# opensoundscape

***Release 0.6.2***

**Mar 25, 2022**

# Contents

OpenSoundscape is free and open source software for the analysis of bioacoustic recordings (GitHub). Its main goals are to allow users to train their own custom species classification models using a variety of frameworks (including convolutional neural networks) and to use trained models to predict whether species are present in field recordings. OpSo can be installed and run on a single computer or in a cluster or cloud environment.

OpenSoundcape is developed and maintained by the Kitzes Lab at the University of Pittsburgh.

The Installation section below provides guidance on installing OpSo. The Tutorials pages below are written as Jupyter Notebooks that can also be downloaded from the project repository on GitHub.

# CHAPTER 1

# Mac and Linux

OpenSoundscape can be installed on Mac and Linux machines with Python 3.7 (or 3.8) using the pip command `pip install opensoundscape==0.6.2`. We recommend installing OpenSoundscape in a virtual environment to prevent dependency conflicts.

Below are instructions for installation with two package managers:

- `conda`: Python and package management through Anaconda, a package manager popular among scientific programmers
- `venv`: Python's included virtual environment manager, `venv`

Feel free to use another virtual environment manager (e.g. `virtualenvwrapper`) if desired.

## 1.1 Installation via Anaconda

- Install Anaconda if you don't already have it.
  - Download the installer here, or
  - follow the installation instructions for your operating system.
- Create a Python 3.7 (or 3.8) conda environment for opensoundscape: `conda create --name opensoundscape pip python=3.7`
- Activate the environment: `conda activate opensoundscape`
- Install opensoundscape using pip: `pip install opensoundscape==0.6.2`
- Deactivate the environment when you're done using it: `conda deactivate`

## 1.2 Installation via `venv`

Download Python 3.7 (or 3.8) from this website.

Run the following commands in your bash terminal:

- Check that you have installed Python 3.7 (or 3.8)._: `python3 --version`
- Change directories to where you wish to store the environment: `cd [path for environments folder]`
  - Tip: You can use this folder to store virtual environments for other projects as well, so put it somewhere that makes sense for you, e.g. in your home directory.
- Make a directory for virtual environments and `cd` into it: `mkdir .venv && cd .venv`
- Create an environment called `opensoundscape` in the directory: `python3 -m venv opensoundscape`
- Activate/use the environment: `source opensoundscape/bin/activate`
- Install OpenSoundscape in the environment: `pip install opensoundscape==0.6.2`
- Once you are done with OpenSoundscape, deactivate the environment: `deactivate`
- To use the environment again, you will have to refer to absolute path of the virtual environments folder. For instance, if I were on a Mac and created `.venv` inside a directory `/Users/MyFiles/Code` I would activate the virtual environment using: `source /Users/MyFiles/Code/.venv/opensoundscape/bin/activate`

For some of our functions, you will need a version of `ffmpeg >= 0.4.1`. On Mac machines, `ffmpeg` can be installed via `brew`.

# CHAPTER 2

# Windows

We recommend that Windows users install and use OpenSoundscape using Windows Subsystem for Linux, because some of the machine learning and audio processing packages required by OpenSoundscape do not install easily on Windows computers. Below we describe the typical installation method. This gives you access to a Linux operating system (we recommend Ubuntu 20.04) in which to use Python and install and use OpenSoundscape. Using Ubuntu 20.04 is as simple as opening a program on your computer.

## 2.1 Get Ubuntu shell

If you don't already use Windows Subsystem for Linux (WSL), activate it using the following:

- Search for the "Powershell" program on your computer
- Right click on "Powershell," then click "Run as administrator" and in the pop-up, allow it to run as administrator
- Install WSL2 (more information: https://docs.microsoft.com/en-us/windows/wsl/install-win10):

```
wsl --install
```

- Restart your computer

Once you have WSL, follow these steps to get an Ubuntu shell on your computer:

- Open Windows Store, search for "Ubuntu" and click "Ubuntu 20.04 LTS"
- Click "Get", wait for the program to download, then click "Launch"
- An Ubuntu shell will open. Wait for Ubuntu to install.
- Set username and password to something you will remember
- Run `sudo apt update` and type in the password you just set

## 2.2 Download Anaconda

We recommend installing OpenSoundscape in a package manager. We find that the easiest package manager for new users is "Anaconda," a program which includes Python and tools for managing Python packages. Below are instructions for downloading Anaconda in the Ubuntu environment.

- Open this page and scroll down to the "Anaconda Installers" section. Under the Linux section, right click on the link "64-Bit (x86) Installer" and click "Copy link"‘
- Download the installer:
  - Open the Ubuntu terminal
  - Type in `wget` then paste the link you copied, e.g.: (the filename of your file may differ)

  ```
  wget https://repo.anaconda.com/archive/Anaconda3-2020.07-Linux-x86_64.sh
  ```

- Execute the downloaded installer, e.g.: (the filename of your file may differ)

  ```
  bash Anaconda3-2020.07-Linux-x86_64.sh
  ```

  - Press ENTER, read the installation requirements, press Q, then type "yes" and press enter to install
  - Wait for it to install
  - If your download hangs, press CTRL+C, `rm -rf ~/anaconda3` and try again
- Type "yes" to initialize `conda`
  - If you skipped this step, initialize your conda installation: run `source ~/anaconda3/bin/activate` and then after that command has run, `conda init`.
- Remove the downloaded file after installation, e.g. `rm Anaconda3-2020.07-Linux-x86_64.sh`
- Close and reopen terminal window to have access to the initialized Anaconda distribution

You can now manage packages with `conda`.

## 2.3 Install OpenSoundscape in virtual environment

- Create a Python 3.7 (or 3.8) conda environment for opensoundscape: `conda create --name opensoundscape pip python=3.7`
- Activate the environment: `conda activate opensoundscape`
- Install opensoundscape using pip: `pip install opensoundscape==0.6.2`

If you see an error that says "No matching distribution found. . . ", your best bet is to use these commands to download then install the package:

```
cd
git clone https://github.com/kitzeslab/opensoundscape.git
cd opensoundscape/
pip install .
```

If you run into this error and you are on a Windows 10 machine:

```
(opensoundscape_environment) username@computername:~$ pip install opensoundscape==0.6.
↪2
WARNING: Retrying (Retry(total=4, connect=None, read=None, redirect=None,␣
↪status=None)) after connection broken by 'NewConnectionError('<pip._vendor.urllib3.
↪connection.HTTPSConnection object at 0x7f7603c5da90>: Failed to establish a new␣
↪connection: [Errno -2] Name or service not known')': /simple/opensoundscape/
```

You may be able to solve it by going to System Settings, searching for "Proxy Settings," and beneath "Automatic proxy setup," turning "Automatically detect settings" OFF. Restart your terminal for changes to take effect. Then activate the environment and install OpenSoundscape using pip.

# CHAPTER 3

# Contributors

Contributors and advanced users can use this workflow to install OpenSoundscape using Poetry. Poetry installation allows direct use of the most recent version of the code. This workflow allows advanced users to use the newest features in OpenSoundscape, and allows developers/contributors to build and test their contributions.

## 3.1 Poetry installation

- Install poetry
- Create a new virtual environment for the OpenSoundscape installation. If you are using Anaconda, you can create a new environment with `conda create -n opso-dev python==3.8` where `opso-dev` is the name of the new virtual environment. Use `conda activate opso-dev` to enter the environment to work on OpenSoundscape and `conda deactivate opso-dev` to return to your base Python installation. If you are not using Anaconda, other packages such as `virtualenv` should work as well. Ensure that the Python version is compatible with the current version of OpenSoundscape.
- **Internal Contributors**: Clone this github repository to your machine: `git clone https://github.com/kitzeslab/opensoundscape.git`
- **External Contributors**: Fork this github repository and clone the fork to your machine
- Ensure you are in the top-level directory of the clone
- Switch to the development branch of OpenSoundscape: `git checkout develop`
- Install OpenSoundscape using `poetry install`. This will install OpenSoundscape and its dependencies into the `opso-dev` virtual environment. By default it will install OpenSoundscape in develop mode, so that updated code in the respository can be imported without reinstallation.
  - If you are on a Mac and poetry install fails to install `numba`, contact one of the developers for help troubleshooting your issues.
- Install the `ffmpeg` dependency. On a Mac, `ffmpeg` can be installed using Homebrew.
- Run the test suite to ensure that everything installed properly. From the top-level directory, run the command `pytest`.

## 3.2 Contribution workflow

### 3.2.1 Contributing to code

Make contributions by editing the code in your repo. Create branches for features by starting with the `develop` branch and then running `git checkout -b feature_branch_name`. Once work is complete, push the new branch to remote using `git push -u origin feature_branch_name`. To merge a feature branch into the development branch, use the GitHub web interface to create a merge or a pull request. Before opening a PR, do the following to ensure the code is consistent with the rest of the package:

- Run the test suite using `pytest`
- Format the code with `black` style (from the top level of the repo): `black .`

### 3.2.2 Contributing to documentation

Build the documentation using `sphinx-build docs docs/_build`

# CHAPTER 4

# Jupyter

To use OpenSoundscape in JupyterLab or in a Jupyter Notebook, you may either start Jupyter from within your OpenSoundscape virtual environment and use the "Python 3" kernel in your notebooks, or create a separate "OpenSoundscape" kernel using the instructions below

The following steps assume you have already used your operating system-specific installation instructions to create a virtual environement containing OpenSoundscape and its dependencies.

## 4.1 Use virtual environment

- Activate your virtual environment
- Start JupyterLab or Jupyter Notebook from inside the conda environment, e.g.: `jupyter lab`
- Copy and paste the JupyterLab link into your web browser

With this method, the default "Python 3" kernel will be able to import `opensoundscape` modules.

## 4.2 Create independent kernel

Use the following steps to create a kernel that appears in any notebook you open, not just notebooks opened from your virtual environment.

- Activate your virtual environment to have access to the `ipykernel` package
- Create ipython kernel with the following command, replacing `ENV_NAME` with the name of your OpenSoundscape virtual environment.

```
python -m ipykernel install --user --name=ENV_NAME --display-name=OpenSoundscape
```

- Now when you make a new notebook on JupyterLab, or change kernels on an existing notebook, you can choose to use the "OpenSoundscape" Python kernel

Contributors: if you include Jupyter's `autoreload`, any changes you make to the source code installed via poetry will be reflected whenever you run the `%autoreload` line magic in a cell:

```
%load_ext autoreload
%autoreload
```

CHAPTER 5

# Audio and spectrograms

This tutorial demonstrates how to use OpenSoundscape to open and modify audio files and spectrograms.

Audio files can be loaded into OpenSoundscape and modified using its `Audio` class. The class gives access to modifications such as trimming short clips from longer recordings, splitting a long clip into multiple segments, bandpassing recordings, and extending the length of recordings by looping them. Spectrograms can be created from `Audio` objects using the `Spectrogram` class. This class also allows useful features like measuring the amplitude signal of a recording, trimming a spectrogram in time and frequency, and converting the spectrogram to a saveable image.

To download the tutorial as a Jupyter Notebook, click the "Edit on GitHub" button at the top right of the tutorial. Using it requires that you install OpenSoundscape and follow the instructions for using it in Jupyter.

For the sake of example, we will downlaod a file from the Kitzes Lab box using the code below, and use it throughout the tutorial. To use your own file for the following examples, change the string assigned to `audio_filename` to any audio file on your computer.

[2]:
```
import subprocess
subprocess.run(['curl',
               'https://pitt.box.com/shared/static/z73eked7quh1t2pp93axzrrpq6wwydx0.
↪wav',
                '-L', '-o', '1min_audio.wav'])
audio_filename = './1min_audio.wav'
```

```
  % Total    % Received % Xferd  Average Speed   Time    Time     Time  Current
                                 Dload  Upload   Total   Spent    Left  Speed
  0     0    0     0    0     0      0      0 --:--:-- --:--:-- --:--:--     0
  0     0    0     0    0     0      0      0 --:--:-- --:--:-- --:--:--     0
100     7    0     7    0     0      5      0 --:--:--  0:00:01 --:--:--     0
100 3750k  100 3750k    0     0  1245k      0  0:00:03  0:00:03 --:--:-- 4157k
```

## 5.1 Quick start

Import the `Audio` and `Spectrogram` classes from OpenSoundscape. (For more information about Python imports, review this article.)

[3]:
```
# import Audio and Spectrogram classes from OpenSoundscape
from opensoundscape.audio import Audio
from opensoundscape.spectrogram import Spectrogram
```

These classes provide a variety of tools to load and manipulate audio and spectrograms. The code below demonstrates a basic pipeline:

- load an audio file
- generate a spectrogram with default parameters
- create a 224px x 224px-sized image of the spectrogram
- save the image to a file

[4]:
```
from pathlib import Path

# Settings
image_shape = (224, 224) #(height, width) not (width, height)
image_save_path = Path('./saved_spectrogram.png')

# Load audio file as Audio object
audio = Audio.from_file(audio_filename)

# Create Spectrogram object from Audio object
spectrogram = Spectrogram.from_audio(audio)

# Convert Spectrogram object to PIL Image
image = spectrogram.to_image(shape=image_shape)

# Save image to file
image.save(image_save_path)
```

The above function calls could even be condensed to a single line:

[7]:
```
Spectrogram.from_audio(Audio.from_file(audio_filename)).to_image(shape=image_shape).
↪save(image_save_path)
```

Clean up by deleting the spectrogram saved above.

[8]:
```
image_save_path.unlink()
```

## 5.2 Audio loading

The `Audio` class in OpenSoundscape allows loading and manipulation of audio files.

### 5.2.1 Load .wavs

Load the example audio from file:

[10]:
```
audio_object = Audio.from_file(audio_filename)
```

### 5.2.2 Load .mp3s

OpenSoundscape uses a package called `librosa` to help load audio files. Librosa automatically supports `.wav` files, but loading `.mp3` files requires that you also install `ffmpeg` or an alternative. See Librosa's installation tips for more information.

### 5.2.3 load a segment of a file

We can directly load a section of a `.wav` file very quickly (even if the audio file is large) using the `offset` and `duration` parameters.

For example, let's load 1 second of audio from 2.0-3.0 seconds:

```
[11]: audio_segment = Audio.from_file(audio_filename,offset=2.0,duration=1.0)
      audio_segment.duration()
```

```
[11]: 1.0
```

### 5.2.4 Audio properties

The properties of an `Audio` object include its samples (the actual audio data) and the sample rate (the number of audio samples taken per second, required to understand the samples). After an audio file has been loaded, these properties can be accessed using the `samples` and `sample_rate` attributes, respectively.

```
[12]: print(f"How many samples does this audio object have? {len(audio_object.samples)}")
      print(f"What is the sampling rate? {audio_object.sample_rate}")
```

```
How many samples does this audio object have? 1920000
What is the sampling rate? 32000
```

### 5.2.5 Resample audio during load

By default, an audio object is loaded with the same sample rate as the source recording.

The `sample_rate` parameter of `Audio.from_file` allows you to re-sample the file during the creation of the object. This is useful when working with multiple files to ensure that all files have a consistent sampling rate.

Let's load the same audio file as above, but specify a sampling rate of 22050 Hz.

```
[13]: audio_object_resample = Audio.from_file(audio_filename, sample_rate=22050)
      audio_object_resample.sample_rate
```

```
[13]: 22050
```

For other options when loading audio objects, see the Audio.from_file() documentation.

## 5.3 Audio methods

The `Audio` class gives access to a variety of tools to change audio files, load them with special properties, or get information about them. Various examples are shown below.

For a description of the entire `Audio` object API, see the API documentation.

### 5.3.1 NOTE: Out-of-place operations

Functions that modify `Audio` (and `Spectrogram`) objects are "out of place", meaning that they return a new, modified instance of `Audio` instead of modifying the original instance. This means that running a line

```
audio_object.resample(22050) # WRONG!
```

will **not** change the sample rate of `audio_object`! If your goal was to overwrite `audio_object` with the new, resampled audio, you would instead write

```
audio_object = audio_object.resample(22050)
```

### 5.3.2 Save audio to file

Opensoundscape currently supports saving Audio objects to `.wav` formats **only**. It does not currently support saving metadata (tags) along with wav files - only the samples and sample rate will be preserved in the file.

[14]:
```
audio_object.save('./my_audio.wav')
```

clean up: delete saved file

[15]:
```
from pathlib import Path
Path('./my_audio.wav').unlink()
```

### 5.3.3 Get duration

The `.duration()` method returns the length of the audio in seconds

[16]:
```
length = audio_object.duration()
print(length)
```

```
60.0
```

### 5.3.4 Trim

The `.trim()` method extracts audio from a specified time period in seconds (relative to the start of the audio object).

[17]:
```
trimmed = audio_object.trim(0,5)
trimmed.duration()
```

[17]:
```
5.0
```

### 5.3.5 Split Audio into clips

The `.split()` method divides audio into even-lengthed clips, optionally with overlap between adjacent clips (default is no overlap). See the function's documentation for options on how to handle the last clip.

The function returns a list containing Audio objects for each clip and a DataFrame giving the start and end times of each clip with respect to the original file.

### split

[18]:
```
#split into 5-second clips with no overlap between adjacent clips
clips, clip_df = audio_object.split(clip_duration=5,clip_overlap=0,final_clip=None)

#check the duration of the Audio object in the first returned element
print(f"duration of first clip: {clips[0].duration()}")

print(f"head of clip_df")
clip_df.head(3)
```

```
duration of first clip: 5.0
head of clip_df
```

[18]:

| | start_time | end_time |
|---|---|---|
| 0 | 0.0 | 5.0 |
| 1 | 5.0 | 10.0 |
| 2 | 10.0 | 15.0 |

### split with overlap

if we want overlap between consecutive clips

Note that a negative "overlap" value would leave *gaps* between consecutive clips.

[19]:
```
_, clip_df = audio_object.split(clip_duration=5,clip_overlap=2.5,final_clip=None)
print(f"head of clip_df")
clip_df.head()
```

```
head of clip_df
```

[19]:

| | start_time | end_time |
|---|---|---|
| 0 | 0.0 | 5.0 |
| 1 | 2.5 | 7.5 |
| 2 | 5.0 | 10.0 |
| 3 | 7.5 | 12.5 |
| 4 | 10.0 | 15.0 |

### split and save

The `Audio.split_and_save()` method splits audio into clips and immediately saves them to files in a specified location. You provide it with a naming prefix, and it will add on a suffix indicating the start and end times of the clip (eg `_5.0-10.0s.wav`). It returns just a DataFrame with the paths and start/end times for each clip (it does not return Audio objects).

The splitting options are the same as `.split()`: clip_duration, clip_overlap, and final_clip

[20]:
```
#split into 5-second clips with no overlap between adjacent clips
Path('./temp_audio').mkdir(exist_ok=True)
clip_df = audio_object.split_and_save(
    destination='./temp_audio',
    prefix='audio_clip_',
    clip_duration=5,
    clip_overlap=0,
    final_clip=None
)
```

(continues on next page)

(continued from previous page)

```
print(f"head of clip_df")
clip_df.head()
```

```
head of clip_df
```

[20]:

```
                                           start_time  end_time
file
./temp_audio/audio_clip__0.0s_5.0s.wav            0.0       5.0
./temp_audio/audio_clip__5.0s_10.0s.wav           5.0      10.0
./temp_audio/audio_clip__10.0s_15.0s.wav         10.0      15.0
./temp_audio/audio_clip__15.0s_20.0s.wav         15.0      20.0
./temp_audio/audio_clip__20.0s_25.0s.wav         20.0      25.0
```

The folder `temp_audio` should now contain 12 5-second clips created from the 60-second audio file.

clean up: delete temp folder of saved audio clips

[21]:

```
from shutil import rmtree
rmtree('./temp_audio')
```

### split_and_save dry run

we can use the `dry_run=True` option to produce only the clip_df but not actually process the audio. this is useful as a quick test to see if the function is behaving as expected, before doing any (potentially slow) splitting on huge audio files.

Just for fun, we'll use an overlap of -5 in this example (5 second gap between each consecutive clip)

This function returns a DataFrame of clips, but does not actually process the audio files or write any new files.

[22]:

```
clip_df = audio_object.split_and_save(
    destination='./temp_audio',
    prefix='audio_clip_',
    clip_duration=5,
    clip_overlap=-5,
    final_clip=None,
    dry_run=True,
)
clip_df
```

[22]:

```
                                           start_time  end_time
file
./temp_audio/audio_clip__0.0s_5.0s.wav            0.0       5.0
./temp_audio/audio_clip__10.0s_15.0s.wav         10.0      15.0
./temp_audio/audio_clip__20.0s_25.0s.wav         20.0      25.0
./temp_audio/audio_clip__30.0s_35.0s.wav         30.0      35.0
./temp_audio/audio_clip__40.0s_45.0s.wav         40.0      45.0
./temp_audio/audio_clip__50.0s_55.0s.wav         50.0      55.0
```

## 5.3.6 Extend and loop

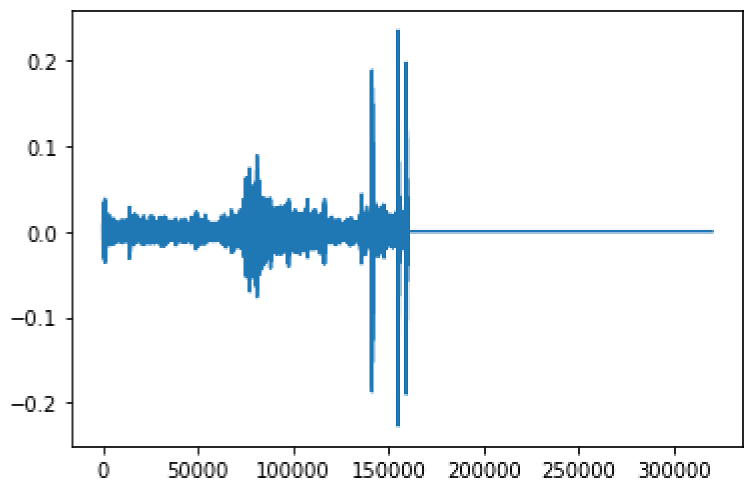
The `.extend()` method extends an audio file to a desired length by adding silence to the end.

The `.loop()` method extends an audio file to a desired length (or number of repetitions) by looping the audio.

extend() example: create an Audio object twice as long as the original, extending with silence (0 valued samples)

[23]:
```
import matplotlib.pyplot as plt

# create an audio object twice as long, extending the end with silence (zero-values)
extended = trimmed.extend(trimmed.duration() * 2)

print(f"duration of original clip: {trimmed.duration()}")
print(f"duration of extended clip: {extended.duration()}")
print(f"samples of extended clip:")
plt.plot(extended.samples)
plt.show()
```

```
duration of original clip: 5.0
duration of extended clip: 10.0
samples of extended clip:
```

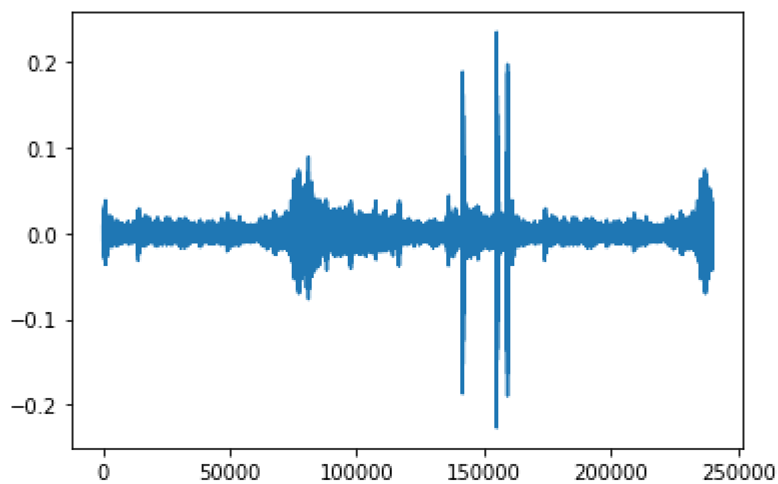



Looping example: create an audio object 1.5x as long, extending the end by looping

[24]:
```
looped = trimmed.loop(trimmed.duration() * 1.5)
print(looped.duration())
plt.plot(looped.samples)
```

```
7.5
```

[24]:
```
[<matplotlib.lines.Line2D at 0x7fc0346abf90>]
```

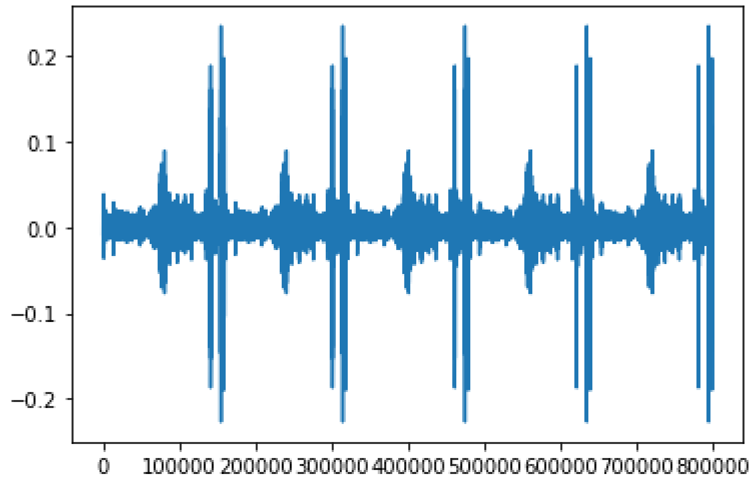


create an audio object that loops the original object 5 times and plot the samples

[21]:
```
looped = trimmed.loop(n=5)
print(looped.duration())
plt.plot(looped.samples)
```

```
25.0
```

[21]:
```
[<matplotlib.lines.Line2D at 0x7fdb48afb310>]
```




### 5.3.7 Resample

The `.resample()` method resamples the audio object to a new sampling rate (can be lower or higher than the original sampling rate)

[25]:
```
resampled = trimmed.resample(sample_rate=48000)
resampled.sample_rate
```

[25]:
```
48000
```

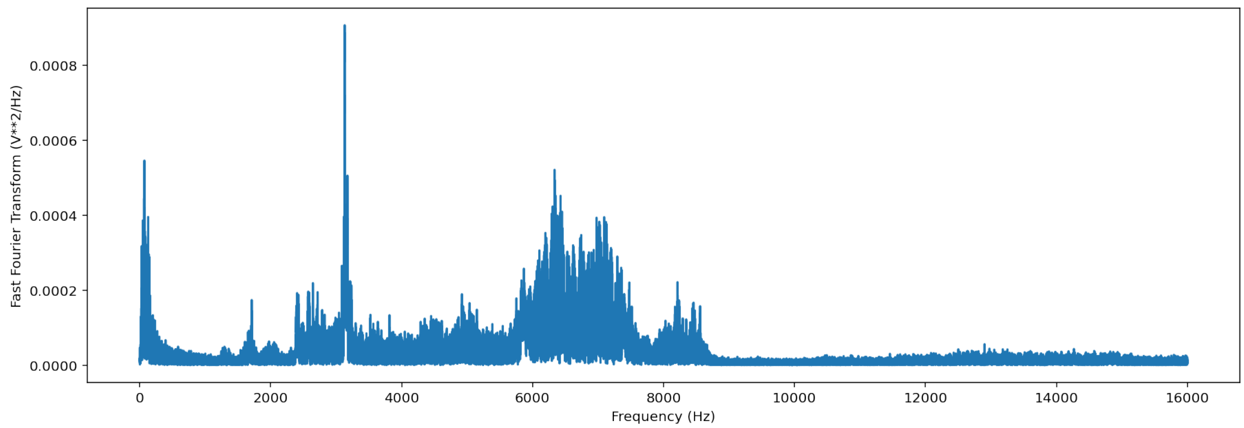
### 5.3.8 Generate a frequency spectrum

The `.spectrum()` method provides an easy way to compute a Fast Fourier Transform on an audio object to measure its frequency composition.

[26]:
```
# calculate the fft
fft_spectrum, frequencies = trimmed.spectrum()

#plot settings
from matplotlib import pyplot as plt
plt.rcParams['figure.figsize']=[15,5] #for big visuals
%config InlineBackend.figure_format = 'retina'

# plot
plt.plot(frequencies,fft_spectrum)
plt.ylabel('Fast Fourier Transform (V**2/Hz)')
plt.xlabel('Frequency (Hz)')
```

```
/Users/SML161/opt/miniconda3/envs/opso/lib/python3.7/site-packages/matplotlib_inline/
↪config.py:75: DeprecationWarning: InlineBackend._figure_format_changed is␣
↪deprecated in traitlets 4.1: use @observe and @unobserve instead.
  def _figure_format_changed(self, name, old, new):
```

[26]:
```
Text(0.5, 0, 'Frequency (Hz)')
```



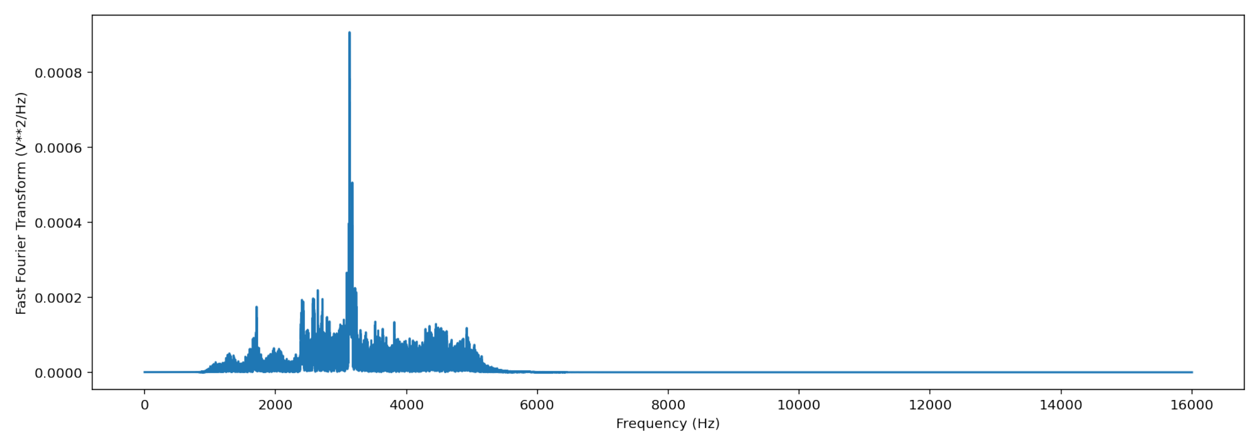

### 5.3.9 Bandpass

Bandpass the audio file to limit its frequency range to 1000 Hz to 5000 Hz. The bandpass operation uses a Butterworth filter with a user-provided order.

[27]:
```python
# apply a bandpass filter
bandpassed = trimmed.bandpass(low_f = 1000, high_f = 5000, order=9)

# calculate the bandpassed audio's spectrum
fft_spectrum, frequencies = bandpassed.spectrum()

# plot
print('spectrum after bandpassing the audio:')
plt.plot(frequencies,fft_spectrum)
plt.ylabel('Fast Fourier Transform (V**2/Hz)')
plt.xlabel('Frequency (Hz)')
```

```
spectrum after bandpassing the audio:
```

[27]:
```
Text(0.5, 0, 'Frequency (Hz)')
```




# 5.4 Spectrogram creation

## 5.4.1 Load spectrogram

A `Spectrogram` object can be created from an audio object using the `from_audio()` method.

[28]:
```
audio_object = Audio.from_file(audio_filename)
spectrogram_object = Spectrogram.from_audio(audio_object)
```

Spectrograms can also be loaded from saved images using the `from_file()` method.

## 5.4.2 Spectrogram properties

To check the time and frequency axes of a spectrogram, you can look at its `times` and `frequencies` attributes. The `times` attribute is the list of the spectrogram windows' centers' times in seconds relative to the beginning of the audio. The `frequencies` attribute is the list of frequencies represented by each row of the spectrogram. These are not the actual values of the spectrogram — just the values of the axes.

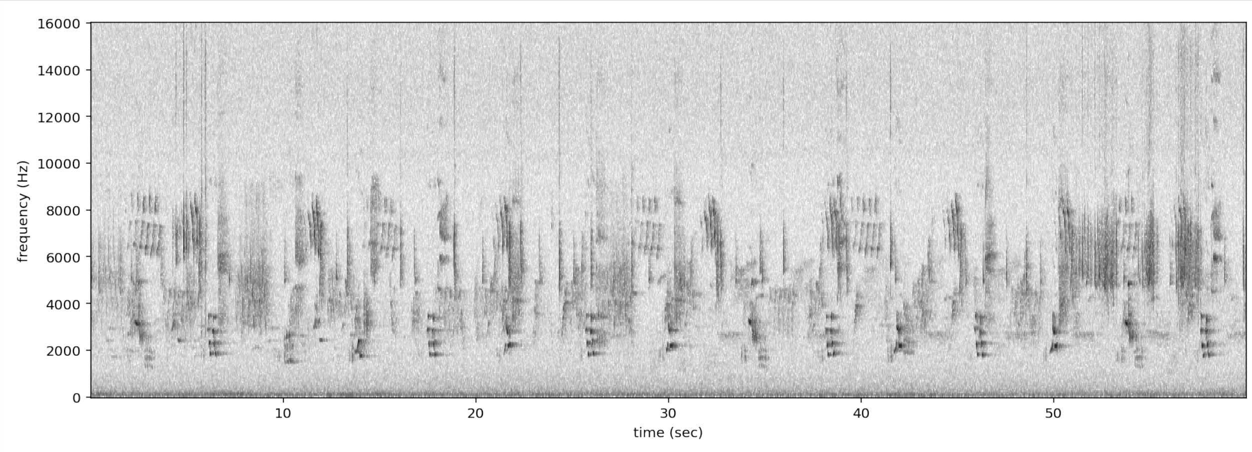
[29]:
```
spec = Spectrogram.from_audio(Audio.from_file(audio_filename))
print(f'the first few times: {spec.times[0:5]}')
print(f'the first few frequencies: {spec.frequencies[0:5]}')
```

```
the first few times: [0.008 0.016 0.024 0.032 0.04 ]
the first few frequencies: [  0.    62.5 125.   187.5 250. ]
```

## 5.4.3 Plot spectrogram

A `Spectrogram` object can be visualized using its `plot()` method.

[30]:
```
audio_object = Audio.from_file(audio_filename)
spectrogram_object = Spectrogram.from_audio(audio_object)
spectrogram_object.plot()
```




### 5.4.4 Spectrogram parameters

Spectrograms are created using "windows." A window is a subset of consecutive samples of the original audio that is analyzed to create one pixel in the horizontal direction (one "column") on the resulting spectrogram. The appearance of a spectrogram depends on two parameters that control the size and spacing of these windows:

#### Samples per window, `window_samples`

This parameter is the length (in audio samples) of each spectrogram window. Choosing the value for `window_samples` represents a trade-off between frequency resolution and time resolution:

- Larger value for `window_samples` –> higher frequency resolution (more rows in a single spectrogram column)
- Smaller value for `window_samples` –> higher time resolution (more columns in the spectrogram per second)

#### Overlap of consecutive windows, `overlap_samples`

`overlap_samples`: this is the number of audio samples that will be re-used (overlap) between two consecutive Specrogram windows. It must be less than `window_samples` and greater than or equal to zero. Zero means no overlap between windows, while a value of `window_samples`/2 would give 50% overlap between consecutive windows. Using higher overlap percentages can sometimes yield better time resolution in a spectrogram, but will take more computational time to generate.

#### Relationship

When there is zero overlap between windows, the number of columns per second is equal to the size in Hz of each spectrogram row. Consider the relationship between time resolution (columns in the spectrogram per second) and frequency resolution (rows in a given frequency range) in the following example:

- Let `sample_rate=48000`, `window_samples=480`, and `overlap_samples=0`
- Each window ("spectrogram column") represents `480/48000 = 1/100 = 0.01` seconds of audio
- There will be `1/(length of window in seconds) = 1/0.01` = 100 columns in the spectrogram per second.

- Each pixel will span 100 Hz in the frequency dimension, i.e., the lowest pixel spans 0-100 Hz, the next lowest 100-200 Hz, then 200-300 Hz, etc.

If `window_samples=4800`, then the spectrogram would have better time resolution (each window represents only 4800/48000 = 0.001s of audio) but worse frequency resolution (each row of the spectrogram would represent 1000 Hz in the frequency range).

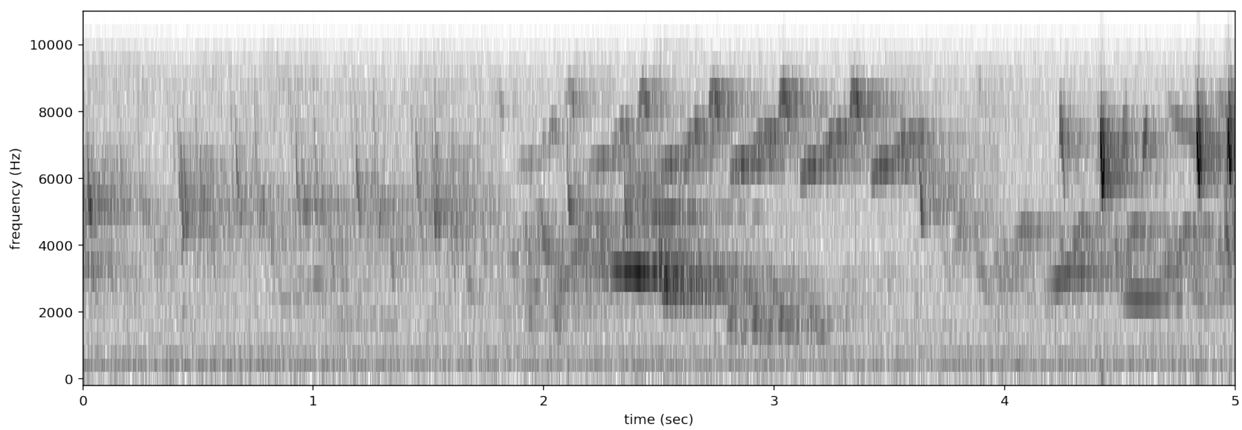
As an example, let's create two spectrograms, one with hight time resolution and another with high frequency resolution.

[31]:
```
# Load audio
audio = Audio.from_file(audio_filename, sample_rate=22000).trim(0,5)
```

### Create a spectrogram with high time resolution

Using `window_samples=55` and `overlap_samples=0` gives 55/22000 = 0.0025 seconds of audio per window, or 1/0.0025 = 400 windows per second. Each spectrogram pixel spans 400 Hz.

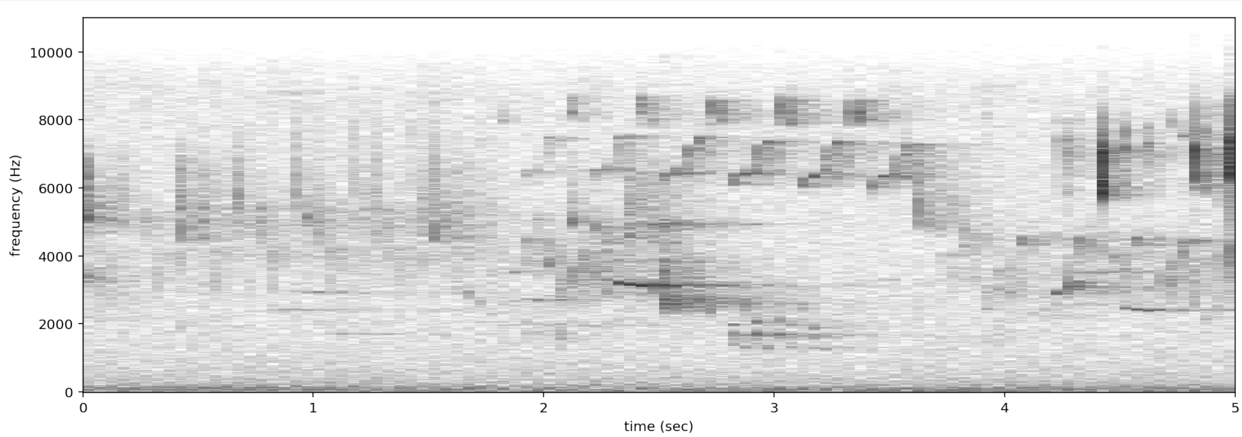
[32]:
```
spec = Spectrogram.from_audio(audio, window_samples=55, overlap_samples=0)
spec.plot()
```




### Create a spectrogram with high time frequency resolution

Using `window_samples=1100` and `overlap_samples=0` gives 1100/22000 = 0.05 seconds of audio per window, or 1/0.05 = 20 windows per second. Each spectrogram pixel spans 20 Hz.

[33]:
```
spec = Spectrogram.from_audio(audio, window_samples=1100, overlap_samples=0)
spec.plot()
```



For other options when loading spectrogram objects from audio objects, see the `from_audio()` documentation.

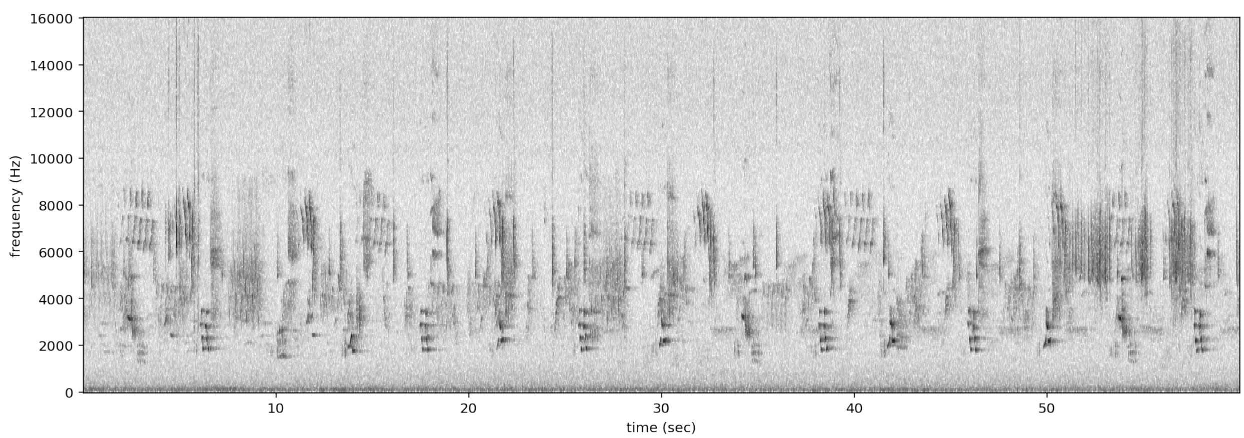
## 5.5 Spectrogram methods

The tools and features of the spectrogram class are demonstrated here, including plotting; how spectrograms can be generated from modified audio; saving a spectrogram as an image; customizing a spectrogram; trimming and bandpassing a spectrogram; and calculating the amplitude signal from a spectrogram.

### 5.5.1 Plot

A `Spectrogram` object can be plotted using its `plot()` method.

[34]:
```
audio_object = Audio.from_file(audio_filename)
spectrogram_object = Spectrogram.from_audio(audio_object)
spectrogram_object.plot()
```

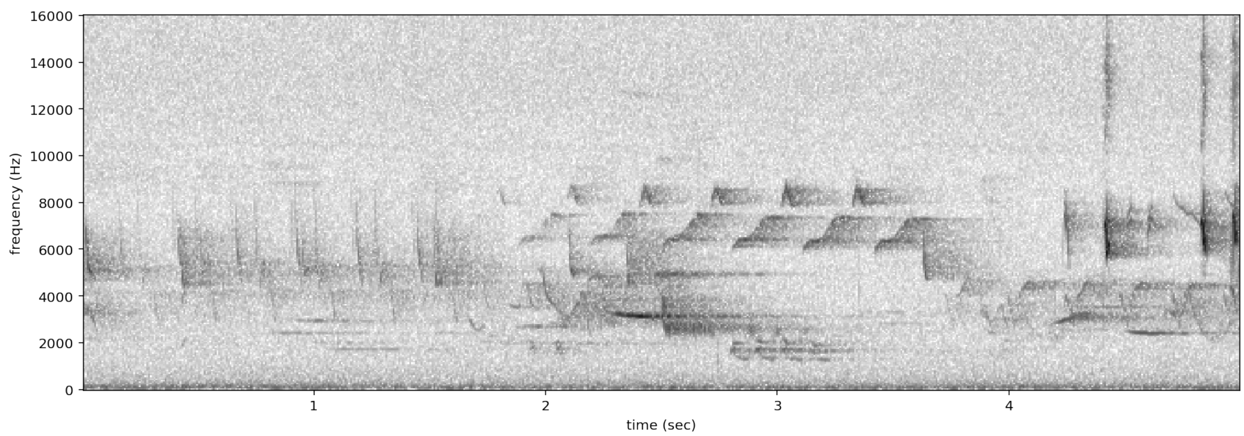



### 5.5.2 Load modified audio

Sometimes, you may wish to trim or modify an audio object before creating a spectrogram. In this case, you should first modify the Audio object, then call `Spectrogram.from_audio()`.

For example, the code below demonstrates creating a spectrogram from a 5 second long trim of the audio object. Compare this plot to the plot above.

[35]:
```
# Trim the original audio
trimmed = audio_object.trim(0, 5)

# Create a spectrogram from the trimmed audio
spec = Spectrogram.from_audio(trimmed)

# Plot the spectrogram
spec.plot()
```




### 5.5.3 Save spectrogram to file

To save the created spectrogram, first convert it to an image. It will no longer be an OpenSoundscape `Spectrogram` object, but instead a Python Image Library (PIL) `Image` object.

[36]:
```
print("Type of `spectrogram_audio` (before conversion):", type(spectrogram_object))
spectrogram_image = spectrogram_object.to_image()
print("Type of `spectrogram_image` (after conversion):", type(spectrogram_image))
```

```
Type of `spectrogram_audio` (before conversion): <class 'opensoundscape.spectrogram.
↪Spectrogram'>
Type of `spectrogram_image` (after conversion): <class 'PIL.Image.Image'>
```

Save the PIL Image using its `save()` method, supplying the filename at which you want to save the image.

[37]:
```
image_path = Path('./saved_spectrogram.png')
spectrogram_image.save(image_path)
```

To save the spectrogram at a desired size, specify the image shape when converting the `Spectrogram` to a PIL `Image`.

[38]:
```
image_shape = (512,512)
large_image_path = Path('./saved_spectrogram_large.png')
spectrogram_image = spectrogram_object.to_image(shape=image_shape)
spectrogram_image.save(large_image_path)
```

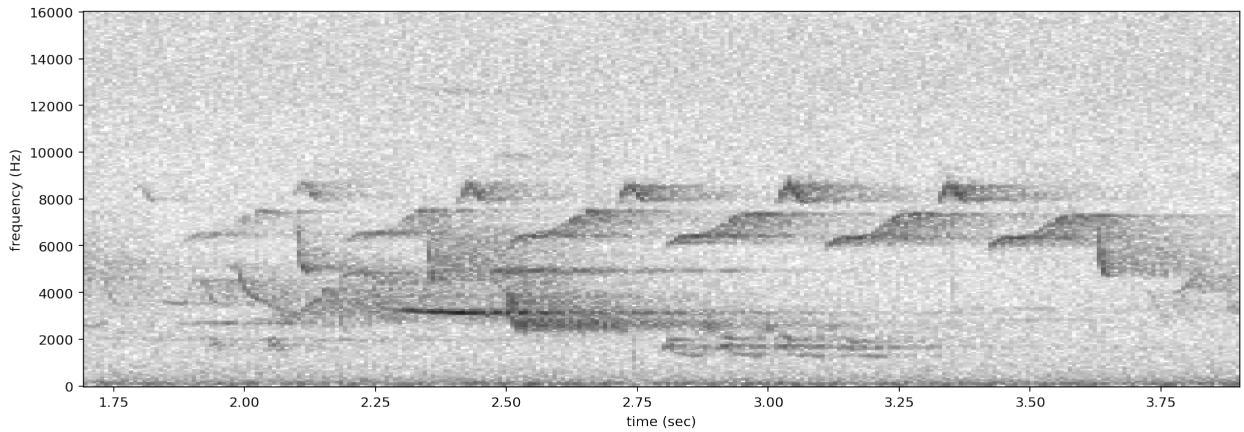
Delete the files created above.

[39]:
```
image_path.unlink()
large_image_path.unlink()
```

### 5.5.4 Trim

Spectrograms can be trimmed in time using `trim()`. Trim the above spectrogram to zoom in on one vocalization.

[40]:
```
spec_trimmed = spec.trim(1.7, 3.9)
spec_trimmed.plot()
```




### 5.5.5 Bandpass

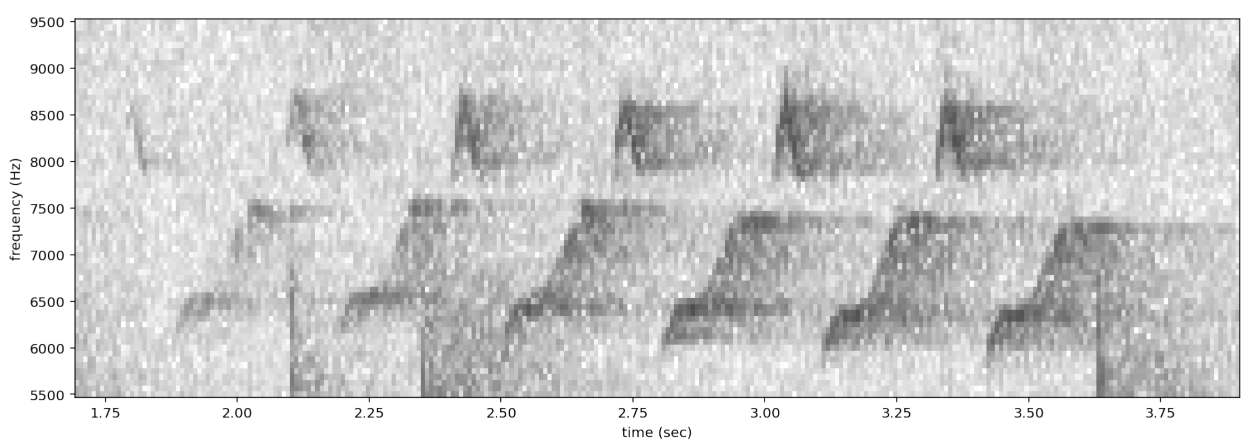
Spectrograms can be trimmed in frequency using `bandpass()`. This simply subsets the Spectrogram array rather than performing an audio-domain filter.

For instance, the vocalization zoomed in on above is the song of a Black-and-white Warbler (*Mniotilta varia*), one of the highest-frequency bird songs in our area. Set its approximate frequency range.

[41]:
```
baww_low_freq = 5500
baww_high_freq = 9500
```

Bandpass the above time-trimmed spectrogram in frequency as well to limit the spectrogram view to the vocalization of interest.

[42]:
```
spec_bandpassed = spec_trimmed.bandpass(baww_low_freq, baww_high_freq)
spec_bandpassed.plot()
```

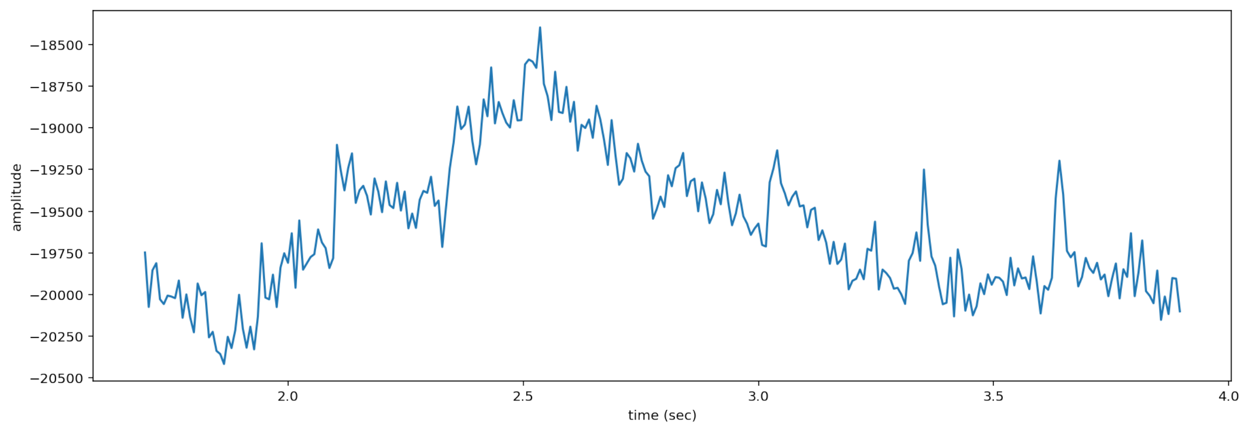



### 5.5.6 Calculate amplitude signal

The `.amplitude()` method sums the columns of the spectrogram to create a one-dimensional amplitude versus time vector.

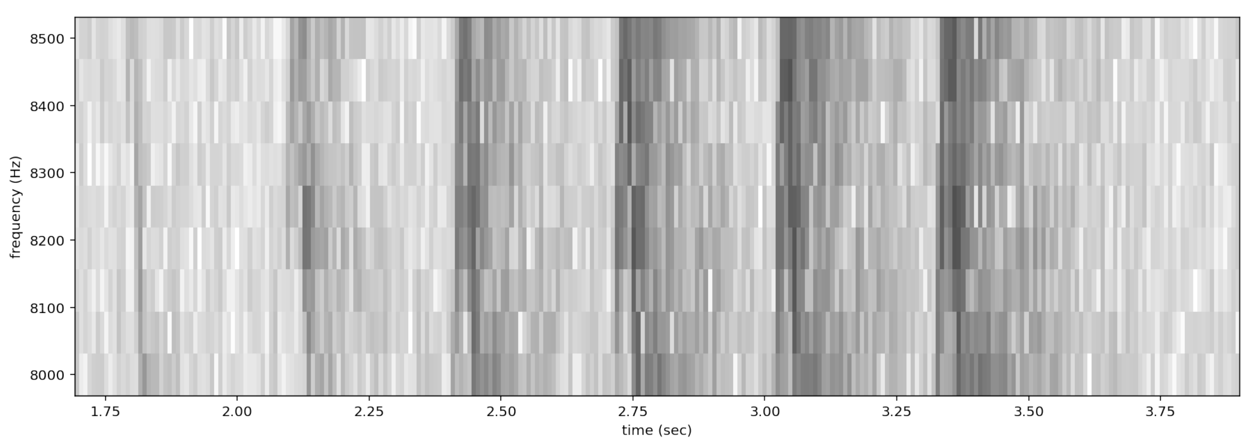
Note: the amplitude of the Spectrogram (and FFT) has units of power (V**2) over frequency (Hz)

[43]:
```
# calculate amplitude signal
high_freq_amplitude = spec_trimmed.amplitude()

# plot
from matplotlib import pyplot as plt
plt.plot(spec_trimmed.times,high_freq_amplitude)
plt.xlabel('time (sec)')
plt.ylabel('amplitude')
plt.show()
```




It is also possible to get the amplitude signal from a restricted range of frequencies, for instance, to look at the amplitude in the frequency range of a species of interest. For example, get the amplitude signal from the 8000 Hz to 8500 Hz range of the audio (displayed below):

[44]:
```
spec_bandpassed = spec_trimmed.bandpass(8000, 8500)
spec_bandpassed.plot()
```



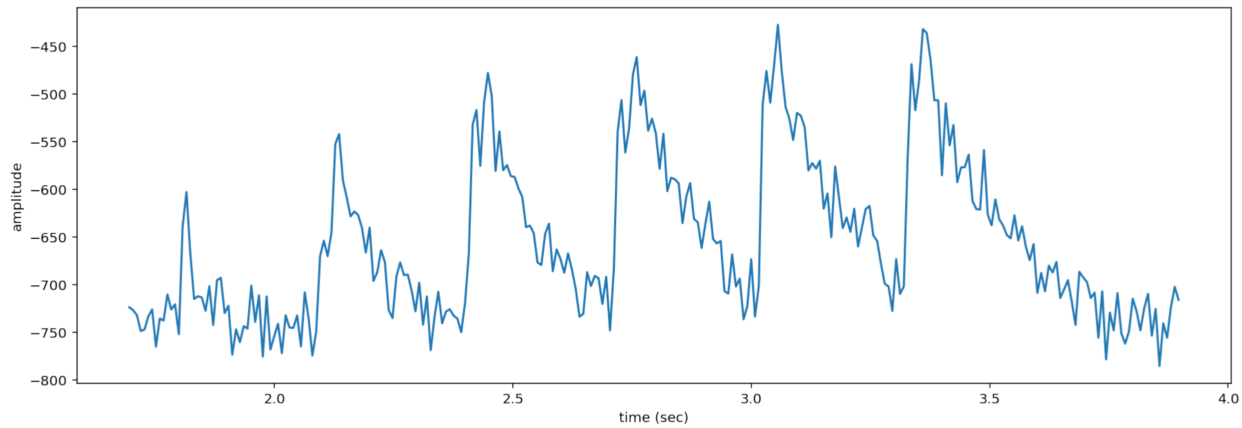

Get and plot the amplitude signal of only 8-8.5 kHz.

[45]:
```
# Get amplitude signal
high_freq_amplitude = spec_trimmed.amplitude(freq_range=[8000,8500])

# Get amplitude signal
high_freq_amplitude = spec_trimmed.amplitude(freq_range=[8000,8500])

# Plot signal
```

(continues on next page)

(continued from previous page)

```
plt.plot(spec_trimmed.times, high_freq_amplitude)
plt.xlabel('time (sec)')
plt.ylabel('amplitude')
plt.show()
```




Amplitude signals like these can be used to identify periodic calls, like those by many species of frogs. A pulsing-call identification pipeline called RIBBIT is implemented in OpenSoundscape.

Amplitude signals may not be the most reliable method of identification for species like birds. In this case, it is possible to create a machine learning algorithm to identify calls based on their appearance on spectrograms.

The developers of OpenSoundscape have trained machine learning models for over 500 common North American bird species; for examples of how to download demonstration models, see the "Prediction with pretrained models" tutorial.

### 5.5.7 clean up

[46]:
```
#delete the file we downloaded for the tutorial
Path('1min_audio.wav').unlink()
```

CHAPTER 6

# Manipulating audio annotations

This notebook demonstrates how to use the `annotations` module of OpenSoundscape to

- load annotations from Raven files
- create a set of one-hot labels corresponding to fixed-length audio clips
- split a set of labeled audio files into clips and create labels dataframe for all clips

The audio recordings used in thise notebook were recorded by Andrew Spencer and are available under a Creative Commons License (CC BY-NC-ND 2.5) from xeno-canto.org. Annotations were performed in Raven Pro software by our team.

[1]:
```
from opensoundscape.audio import Audio
from opensoundscape.spectrogram import Spectrogram
from opensoundscape.annotations import BoxedAnnotations

import numpy as np
import pandas as pd
from glob import glob

from matplotlib import pyplot as plt
plt.rcParams['figure.figsize']=[15,5] #for big visuals
%config InlineBackend.figure_format = 'retina'
```

## 6.1 download example files

Run the code below to download a set of example audio and raven annotations files for this tutorial.

[2]:
```
import subprocess
subprocess.run(['curl','https://pitt.box.com/shared/static/
↪nzdzwwmyr3tkr6ig6sltw4b7jg3ptfe4.gz','-L', '-o','gwwa_audio_and_raven_annotations.
↪tar.gz']) # Download the data
subprocess.run(["tar","-xzf", "gwwa_audio_and_raven_annotations.tar.gz"]) # Unzip the
↪downloaded tar.gz file
```

(continues on next page)

(continued from previous page)

```
subprocess.run(["rm", "gwwa_audio_and_raven_annotations.tar.gz"]) # Remove the file␣
↪after its contents are unzipped
```

```
  % Total    % Received % Xferd  Average Speed   Time    Time     Time  Current
                                 Dload  Upload   Total   Spent    Left  Speed
  0     0    0     0    0     0      0      0 --:--:-- --:--:-- --:--:--     0
  0     0    0     0    0     0      0      0 --:--:-- --:--:-- --:--:--     0
100     7    0     7    0     0      4      0 --:--:--  0:00:01 --:--:--     0
100 1036k  100 1036k    0     0   466k      0  0:00:02  0:00:02 --:--:-- 2894k
```

[2]:
```
CompletedProcess(args=['rm', 'gwwa_audio_and_raven_annotations.tar.gz'], returncode=0)
```

### 6.1.1 Load a single Raven annotation table from a txt file

We can use the BoxedAnnotation class's `from_raven_file` method to load a Raven txt file into OpenSoundscape. This table contains the frequency and time limits of rectangular "boxes" representing each annotation that was created in Raven.

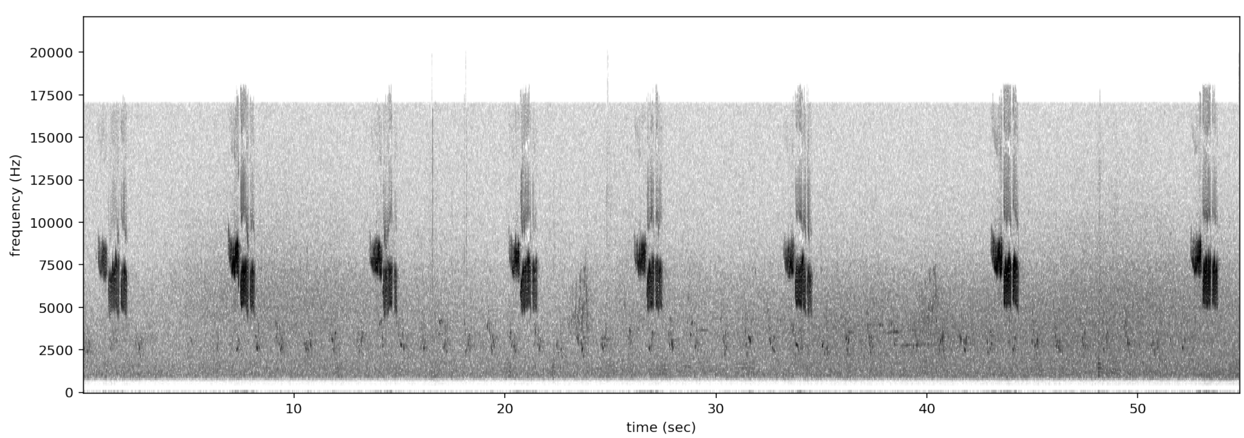
Note that we need to specify the name of the column containing annotations, since it can be named anything in Raven. The column will be renamed to "annotation".

This table looks a lot like what you would see in the Raven interface.

[3]:
```
# specify an audio file and corresponding raven annotation file
audio_file = './gwwa_audio_and_raven_annotations/GWWA_XC/13738.mp3'
annotation_file = './gwwa_audio_and_raven_annotations/GWWA_XC_AnnoTables/13738.Table.
↪1.selections.txt'
```

let's look at a spectrogram of the audio file to see what we're working with

[4]:
```
Spectrogram.from_audio(Audio.from_file(audio_file)).plot()
```




now, let's load the annotations from the Raven annotation file

[5]:
```
#create an object from Raven file
annotations = BoxedAnnotations.from_raven_file(annotation_file,annotation_column=
↪'Species')

#inspect the object's .df attribute, which contains the table of annotations
annotations.df.head()
```

```
[5]:   Selection           View  Channel  start_time   end_time   low_f   high_f  \
0           1  Spectrogram 1        1    0.459636   2.298182  4029.8  17006.4
1           2  Spectrogram 1        1    6.705283   8.246417  4156.6  17031.7
2           3  Spectrogram 1        1   13.464641  15.005775  3903.1  17082.4
3           4  Spectrogram 1        1   20.128208  21.601748  4055.2  16930.3
4           5  Spectrogram 1        1   26.047590  27.521131  4207.2  17057.1

   annotation  Notes
0   GWWA_song    NaN
1   GWWA_song    NaN
2           ?    NaN
3   GWWA_song    NaN
4   GWWA_song    NaN
```

we could instead choose to load it with only the necessary columns, plus the "Notes" column

```
[6]: annotations = BoxedAnnotations.from_raven_file(annotation_file,annotation_column=
↪'Species',keep_extra_columns=['Notes'])
annotations.df.head()
```

```
[6]:   start_time   end_time   low_f   high_f annotation  Notes
0     0.459636   2.298182  4029.8  17006.4  GWWA_song    NaN
1     6.705283   8.246417  4156.6  17031.7  GWWA_song    NaN
2    13.464641  15.005775  3903.1  17082.4          ?    NaN
3    20.128208  21.601748  4055.2  16930.3  GWWA_song    NaN
4    26.047590  27.521131  4207.2  17057.1  GWWA_song    NaN
```

### 6.1.2 Convert or correct annotations

We can provide a DataFrame (e.g., from a .csv file) or a dictionary to convert original values to new values.

Let's load up a little csv file that specifies a set of conversions we'd like to make. The csv file should have two columns, but it doesn't matter what they are called. If you create a table in Microsoft Excel, you can export it to a .csv file to use it as your conversion table.

```
[8]: conversion_table = pd.read_csv('./gwwa_audio_and_raven_annotations/conversion_table.
↪csv')
conversion_table
```

```
[8]:    original   new
0  gwwa_song  gwwa
```

alternatively, we could simply write a Python dictionary for the conversion table. For instance:

```
[9]: conversion_table = {
    "GWWA_song":"GWWA",
    "?":np.nan
}
```

now, we can apply the conversions in the table to our annotations.

This will create a new BoxedAnnotations object rather than modifying the original object ("out of place operation")

```
[10]: annotations_corrected = annotations.convert_labels(conversion_table)
annotations_corrected.df
```

[10]:

```
   start_time   end_time   low_f   high_f annotation  Notes
0    0.459636   2.298182  4029.8  17006.4       GWWA    NaN
1    6.705283   8.246417  4156.6  17031.7       GWWA    NaN
2   13.464641  15.005775  3903.1  17082.4        NaN    NaN
3   20.128208  21.601748  4055.2  16930.3       GWWA    NaN
4   26.047590  27.521131  4207.2  17057.1       GWWA    NaN
5   33.121946  34.663079  4207.2  17082.4       GWWA    NaN
6   42.967925  44.427946  4181.9  17057.1       GWWA    NaN
7   52.417508  53.891048  4232.6  16930.3       GWWA    NaN
```

## 6.2 View a subset of annotations

Specify a list of classes to include in the subset

for example, we can subset to only annotations marked as '?'

[11]:

```
classes_to_keep = ['?']
annotations_only_unsure = annotations.subset(classes_to_keep)
annotations_only_unsure.df
```

[11]:

```
   start_time   end_time   low_f   high_f annotation  Notes
2   13.464641  15.005775  3903.1  17082.4          ?    NaN
```

## 6.3 saving annotations to Raven-compatible file

We can always save our BoxedAnnotations object to a Raven-compatible txt file, which can be opened in Raven along with an audio file just like the files Raven creates itself. You must specify a path for the save file that ends with `.txt`.

[14]:

```
annotations_only_unsure.to_raven_file('./gwwa_audio_and_raven_annotations/13738_
↪unsure.txt')
```

### 6.3.1 Splitting annotations along with audio

Often, we want to train or validate models on short audio segments (e.g., 5 seconds) rather than on long files (e.g., 2 hours).

We can accomplish this in three ways:

(1) Split the annotations (`.one_hot_labels_like()`) using the DataFrame returned by `Audio.split()` (this dataframe includes the start and end times of each clip)

(2) Create a dataframe of start and end times, and split the audio accordingly

(3) directly split the labels with `.one_hot_clip_labels()`, using splitting parameters that match Audio.split()

All three methods are demonstrated below.

## 6.4 1. Split Audio object, then split annotations to match

After splitting audio with audio.split(), we'll use BoxedAnnotation's `one_hot_labels_like()` function to extract the labels for each audio clip. This function requires that we specify the minimum overlap of the label (in seconds) with the clip for the clip to be labeled positive. We also specify the list of classes for one-hot labels (if we give classes=None, it will make a column for every unique label in the annotations).

[15]:
```
# load the Audio and Annotations
audio = Audio.from_file(audio_file)
annotations = BoxedAnnotations.from_raven_file(annotation_file,annotation_column=
↪'Species')

# split the audio into 5 second clips with no overlap (we use _ because we don't␣
↪really need to save the audio clip objects for this demo)
_, clip_df = audio.split(clip_duration=5.0, clip_overlap=0.0)

labels_df = annotations.one_hot_labels_like(clip_df,min_label_overlap=0.25,classes=[
↪'GWWA_song'])

#the returned dataframe of one-hot labels (0/1 for each class and each clip) has rows␣
↪corresponding to each audio clip
labels_df.head()
```

[15]:
```
                     GWWA_song
start_time end_time
0.0        5.0             1.0
5.0        10.0            1.0
10.0       15.0            0.0
15.0       20.0            0.0
20.0       25.0            1.0
```

## 6.5 2. Split annotations into labels (without audio splitting)

The function in the previous example, `one_hot_labels_like()`, splits the labels according to start and end times from a DataFrame. But how would we get that DataFrame if we aren't actually splitting Audio files?

We can create the dataframe with a helper function that takes the same splitting parameters as Audio.split(). Notice that we need to specify one additional parameter: the entire duration to be split (`full_duration`).

[16]:
```
# generate clip start/end time DataFrame
from opensoundscape.helpers import generate_clip_times_df
clip_df = generate_clip_times_df(full_duration=60,clip_duration=5.0, clip_overlap=0.0)

#we can use the clip_df to split the Annotations in the same way as before
labels_df = annotations.one_hot_labels_like(clip_df,min_label_overlap=0.25,classes=[
↪'GWWA_song'])

#the returned dataframe of one-hot labels (0/1 for each class and each clip) has rows␣
↪corresponding to each audio clip
labels_df.head()
```

[16]:
```
                     GWWA_song
start_time end_time
0.0        5.0             1.0
5.0        10.0            1.0
10.0       15.0            0.0
15.0       20.0            0.0
20.0       25.0            1.0
```

## 6.6 3. Split annotations directly using splitting parameters

Though we recommend using one of the above methods, you can also split annotations by directly calling `one_hot_clip_labels()`. This method combines the two steps in the examples above (creating a clip df and splitting the annotations), and requires that you specify the parameters for both of those steps.

Here's an example that produces equivalent results to the previous examples:

[17]:
```
labels_df = annotations.one_hot_clip_labels(
    full_duration=60,
    clip_duration=5,
    clip_overlap=0,
    classes=['GWWA_song'],
    min_label_overlap=0.25,
)
labels_df.head()
```

[17]:
```
                     GWWA_song
start_time end_time
0          5               1.0
5          10              1.0
10         15              0.0
15         20              0.0
20         25              1.0
```

### 6.6.1 Create audio clips and one-hot labels from many audio and annotation files

Let's get to the useful part - you have tons of audio files (with corresponding Raven files) and you need to create one-hot labels for 5 second clips on all of them. Can't we just give you the code you need to get this done?!

Sure :)

but be warned, matching up the correct raven and audio files might require some finagling

## 6.7 find all the Raven and audio files, and see if they match up one-to-one

caveat: you'll need to be careful about matching up the correct Raven files and audio files. In this example, we'll assume our Raven files have exactly the same name (ignoring the extensions like ".Table.1.selections.txt") as our audio files, *and* that these file names *are unique (!)* - that is, no two audio files have the same name.

[24]:
```
# specify folder containing Raven annotations
raven_files_dir = "./gwwa_audio_and_raven_annotations/GWWA_XC_AnnoTables/"

# find all .txt files (we'll naively assume all txt files are Raven files!)
raven_files = glob(f"{raven_files_dir}/*.txt")
print(f"found {len(raven_files)} annotation files")

#specify folder containing audio files
audio_files_dir = "./gwwa_audio_and_raven_annotations/GWWA_XC/"

# find all audio files (we'll assume they are .wav, .WAV, or .mp3)
audio_files = glob(f"{audio_files_dir}/*.wav")+glob(f"{audio_files_dir}/*.WAV")+glob(f
↪"{audio_files_dir}/*.mp3")
```

(continues on next page)

(continued from previous page)

```
print(f"found {len(audio_files)} audio files")

# pair up the raven and audio files based on the audio file name
from pathlib import Path
audio_df = pd.DataFrame({'audio_file':audio_files})
audio_df.index = [Path(f).stem for f in audio_files]

#check that there aren't duplicate audio file names
print('\n audio files with duplicate names:')
audio_df[audio_df.index.duplicated(keep=False)]
```

```
found 3 annotation files
found 3 audio files

 audio files with duplicate names:
```

[24]:
```
Empty DataFrame
Columns: [audio_file]
Index: []
```

[25]:
```
raven_df = pd.DataFrame({'raven_file':raven_files})
raven_df.index = [Path(f).stem.split('.Table')[0] for f in raven_files]

#check that there aren't duplicate audio file names
print('\n raven files with duplicate names:')
raven_df[raven_df.index.duplicated(keep=False)]
```

```

 raven files with duplicate names:
```

[25]:
```
                                                raven_file
13738  ./gwwa_audio_and_raven_annotations/GWWA_XC_Ann...
13738  ./gwwa_audio_and_raven_annotations/GWWA_XC_Ann...
```

Once we've resolved any issues with duplicate names, we can match up raven and audio files.

[26]:
```
#remove the second selection table for file 13738.mp3
raven_df=raven_df[raven_df.raven_file.apply(lambda x: "selections2" not in x)]
```

[27]:
```
paired_df = audio_df.join(raven_df,how='outer')
```

check if any audio files don't have annotation files

[28]:
```
print(f"audio files without raven file: {len(paired_df[paired_df.raven_file.
↪apply(lambda x:x!=x)])}")
paired_df[paired_df.raven_file.apply(lambda x:x!=x)]
```

```
audio files without raven file: 2
```

[28]:
```
                                                audio_file raven_file
135601  ./gwwa_audio_and_raven_annotations/GWWA_XC/135...        NaN
13742   ./gwwa_audio_and_raven_annotations/GWWA_XC/137...        NaN
```

check if any raven files don't have audio files

[29]:
```
#look at unmatched raven files
print(f"raven files without audio file: {len(paired_df[paired_df.audio_file.
↪apply(lambda x:x!=x)])}")
```

(continues on next page)

(continued from previous page)

```
paired_df[paired_df.audio_file.apply(lambda x:x!=x)]
```

```
raven files without audio file: 1
```

[29]:
```
      audio_file                                        raven_file
16989        NaN  ./gwwa_audio_and_raven_annotations/GWWA_XC_Ann...
```

In this example, let's discard any unpaired raven or audio files

[30]:
```
paired_df = paired_df.dropna()
```

[31]:
```
paired_df
```

[31]:
```
                                              audio_file  \
13738  ./gwwa_audio_and_raven_annotations/GWWA_XC/137...

                                              raven_file
13738  ./gwwa_audio_and_raven_annotations/GWWA_XC_Ann...
```

## 6.8 split and save the audio and annotations

Now we have a set of paired up raven and audio files.

Let's split each of the audio files and create the corresponding labels.

We'll want to keep the names of the audio clips that we create using Audio.split_and_save() so that we can correspond them with one-hot clip labels.

Note: it will be confusing and annoying if your Raven files use different names for the annotation column. Ideally, all of your raven files should have the same column name for the annotations.

[32]:
```
%%bash
mkdir -p ./temp_clips
```

[33]:
```
#choose settings for audio splitting
clip_duration = 3
clip_overlap = 0
final_clip = None
clip_dir = './temp_clips'

#choose settings for annotation splitting
classes = None#['GWWA_song','GWWA_dzit'] #list of all classes, or None
min_label_overlap = 0.1


#store the label dataframes from each audio file so that we can aggregate them later
#Note: if you have a huge number (millions) of annotations, this might get very large.
#an alternative would be to save the individual dataframes to files, then concatenate␣
↪them later.
all_labels = []

cnt = 0

for i, row in paired_df.iterrows():
```

(continues on next page)

(continued from previous page)

```
    #load the audio into an Audio object
    audio = Audio.from_file(row['audio_file'])

    #in this example, only the first 60 seconds of audio is annotated
    #so trim the audio to 60 seconds max
    audio = audio.trim(0,60)

    #split the audio and save the clips
    clip_df = audio.split_and_save(
        clip_dir,
        prefix=row.name,
        clip_duration=clip_duration,
        clip_overlap=clip_overlap,
        final_clip=final_clip,
        dry_run=False
    )

    #load the annotation file into a BoxedAnnotation object
    annotations = BoxedAnnotations.from_raven_file(row['raven_file'],annotation_
↪column='Species')

    #since we trimmed the audio, we'll also trim the annotations for consistency
    annotations = annotations.trim(0,60)

    #split the annotations to match the audio
    #we choose to keep_index=True so that we retain the audio clip's path in the␣
↪final label dataframe
    labels = annotations.one_hot_labels_like(clip_df,classes=classes,min_label_
↪overlap=min_label_overlap,keep_index=True)

    #since we have saved short audio clips, we can discard the start_time and end_
↪time indices
    labels = labels.reset_index(level=[1,2],drop=True)
    all_labels.append(labels)

    cnt+=1
    if cnt>2:
        break

#make one big dataframe with all of the labels. We could use this for training, for␣
↪instance.
all_labels = pd.concat(all_labels)
```

[34]:

```
all_labels
```

[34]:

```
                                      ?   GWWA_song
file
./temp_clips/13738_0.0s_3.0s.wav    0.0        1.0
./temp_clips/13738_3.0s_6.0s.wav    0.0        0.0
./temp_clips/13738_6.0s_9.0s.wav    0.0        1.0
./temp_clips/13738_9.0s_12.0s.wav   0.0        0.0
./temp_clips/13738_12.0s_15.0s.wav  1.0        0.0
./temp_clips/13738_15.0s_18.0s.wav  0.0        0.0
./temp_clips/13738_18.0s_21.0s.wav  0.0        1.0
./temp_clips/13738_21.0s_24.0s.wav  0.0        1.0
./temp_clips/13738_24.0s_27.0s.wav  0.0        1.0
./temp_clips/13738_27.0s_30.0s.wav  0.0        1.0
```

(continues on next page)

(continued from previous page)

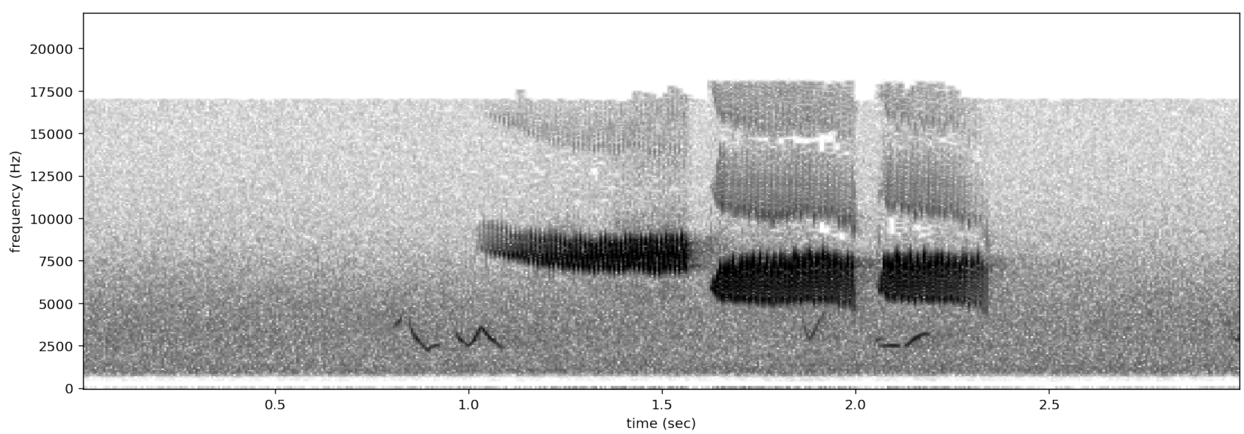
```
./temp_clips/13738_30.0s_33.0s.wav  0.0        0.0
./temp_clips/13738_33.0s_36.0s.wav  0.0        1.0
./temp_clips/13738_36.0s_39.0s.wav  0.0        0.0
./temp_clips/13738_39.0s_42.0s.wav  0.0        0.0
./temp_clips/13738_42.0s_45.0s.wav  0.0        1.0
./temp_clips/13738_45.0s_48.0s.wav  0.0        0.0
./temp_clips/13738_48.0s_51.0s.wav  0.0        0.0
./temp_clips/13738_51.0s_54.0s.wav  0.0        1.0
```

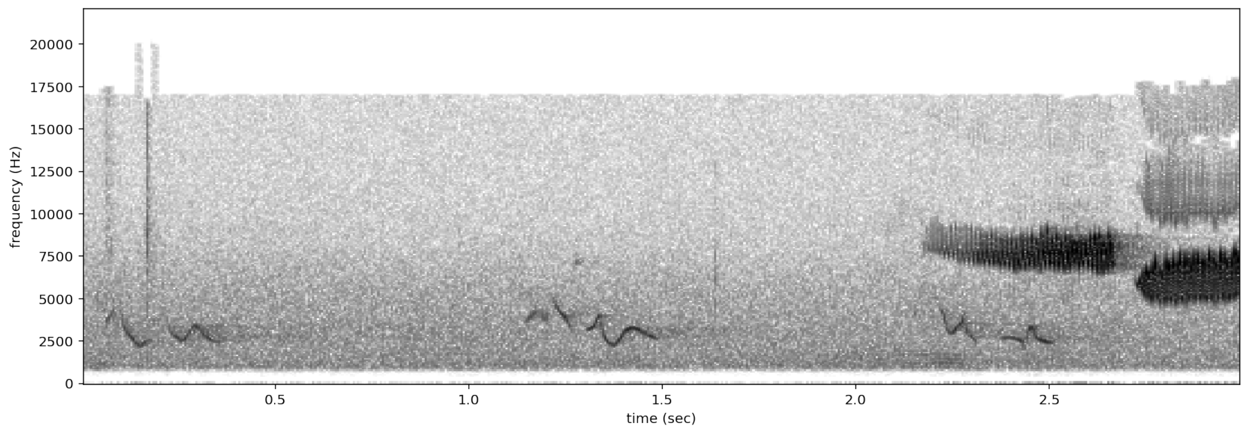
## 6.9 sanity check: look at spectrograms of clips labeled 0 and 1

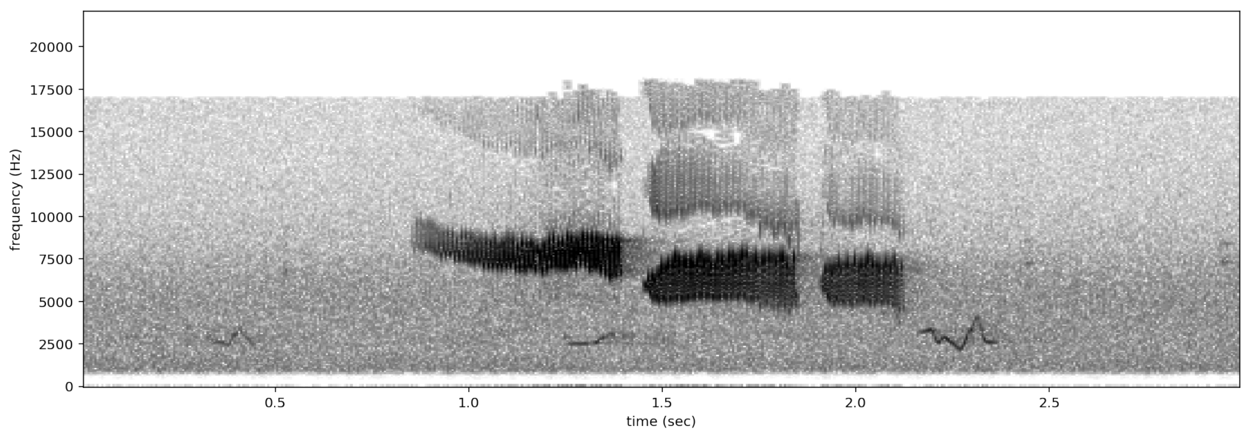
[35]:
```
# ignore the "?" annotations for this visualization
all_labels = all_labels[all_labels["?"]==0]
```

[36]:
```
# plot spectrograms for 3 random positive clips
positives = all_labels[all_labels['GWWA_song']==1].sample(3,random_state=0)
print("spectrograms of 3 random positive clips (label=1)")
for positive_clip in positives.index.values:
    Spectrogram.from_audio(Audio.from_file(positive_clip)).plot()

# plot spectrograms for 5 random negative clips
negatives = all_labels[all_labels['GWWA_song']==0].sample(3,random_state=0)
print("spectrogram of 3 random negative clips (label=0)")
for negative_clip in negatives.index.values:
    Spectrogram.from_audio(Audio.from_file(negative_clip)).plot()
```

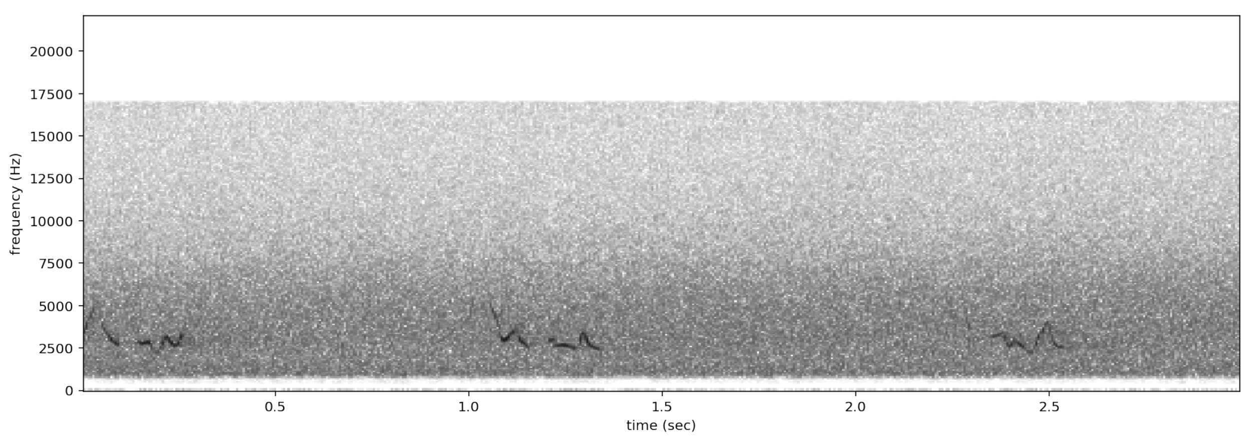
```
spectrograms of 3 random positive clips (label=1)
```

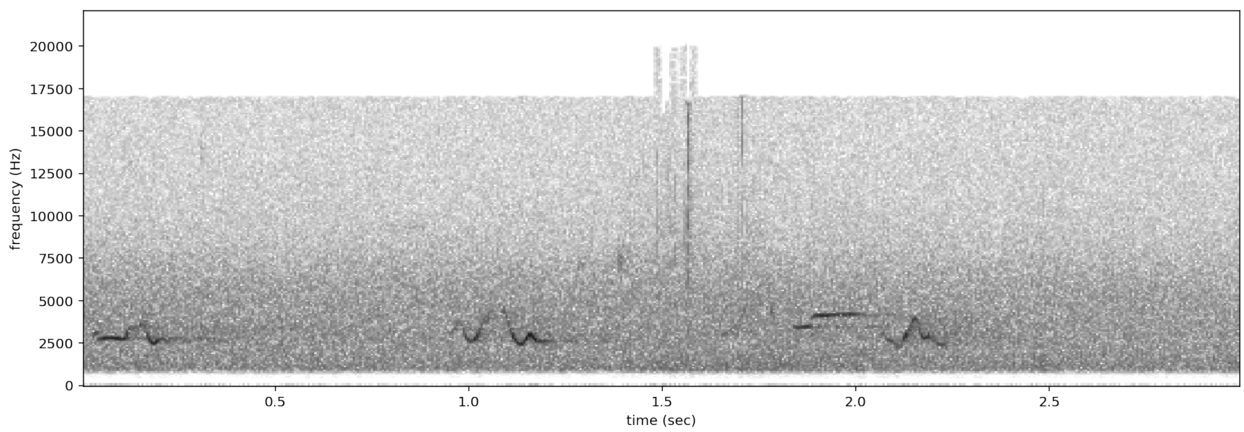


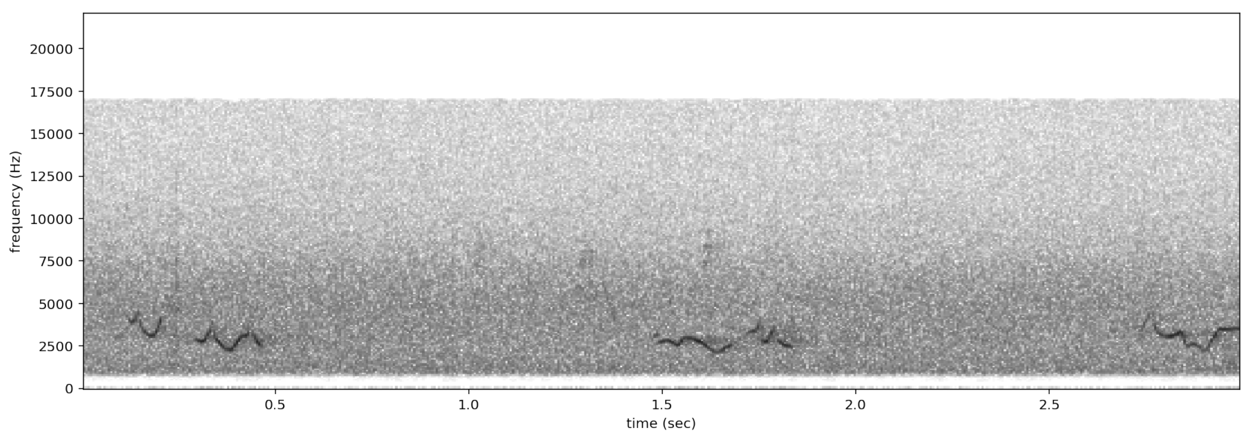



```
spectrogram of 3 random negative clips (label=0)
```






clean up: remove temp_clips directory

[37]:
```
import shutil
shutil.rmtree('./gwwa_audio_and_raven_annotations')
shutil.rmtree('./temp_clips')
```

CHAPTER 7

# Prediction with pre-trained CNNs

This notebook contains all the code you need to use a pre-trained OpenSoundscape convolutional neural network model (CNN) to make predictions on your own data. Before attempting this tutorial, install OpenSoundscape by following the instructions on the OpenSoundscape website, opensoundscape.org. More detailed tutorials about data preprocessing, training CNNs, and customizing prediction methods can also be found on this site.

Note that prediction no longer requires you to split your files into clips ahead of time - you can simply create a list of audio files of arbitrary length. Prediction scores will be generated on windows of a fixed length, eg 5 seconds, for the duration of each audio file.

## 7.1 Load required packages

The `cnn` module provides a function `load_model` to load saved opensoundscape models

[1]:
```
from opensoundscape.torch.models.cnn import load_model, load_outdated_model
import opensoundscape
```

load some additional packages and perform some setup for the Jupyter notebook.

[2]:
```
# Other utilities and packages
import torch
from pathlib import Path
import numpy as np
import pandas as pd
from glob import glob
import subprocess
```

[3]:
```
#set up plotting
from matplotlib import pyplot as plt
plt.rcParams['figure.figsize']=[15,5] #for large visuals
%config InlineBackend.figure_format = 'retina'
```

create and save a model object to use for demonstration in this notebook:

[4]:
```
from opensoundscape.torch.models.cnn import PytorchModel
PytorchModel('resnet18',[0,1,2]).save('./temp.model')
```

```
created PytorchModel model object with 3 classes
```

## 7.2 Load a saved model

For this example, let's download a pre-trained model from the Kitzes Lab box to use as an example. This 2-class model is not actually good at recognizing any particular species, but it's useful for illustrating how prediction works.

[5]:
```
subprocess.run(['curl',
                'https://pitt.box.com/shared/static/s9lydizgspwsimo4p5l5j4nf9yeg319k.
↪model',
                '-L', '-o', 'example.model'])
```

```
  % Total    % Received % Xferd  Average Speed   Time    Time     Time  Current
                                 Dload  Upload   Total   Spent    Left  Speed
  0     0    0     0    0     0      0      0 --:--:-- --:--:-- --:--:--     0
  0     0    0     0    0     0      0      0 --:--:-- --:--:-- --:--:--     0
100     8    0     8    0     0      6      0 --:--:--  0:00:01 --:--:--     0
100 85.4M  100 85.4M    0     0  4049k      0  0:00:21  0:00:21 --:--:-- 5221k
```

[5]:
```
CompletedProcess(args=['curl', 'https://pitt.box.com/shared/static/
↪s9lydizgspwsimo4p5l5j4nf9yeg319k.model', '-L', '-o', 'example.model'], returncode=0)
```

load the model object using the `load_model` function

[6]:
```
model = load_model('./example.model')
```

### 7.2.1 Choose audio files for prediction

Create a list of audio files to predict on. They can be of any length. Consider using `glob` to find many files at once.

For this example, let's download a 1-minute audio clip from the Kitzes Lab box to use as an example.

[7]:
```
subprocess.run(['curl',
                'https://pitt.box.com/shared/static/z73eked7quh1t2pp93axzrrpq6wwydx0.
↪wav',
                '-L', '-o', '1min_audio.wav'])
```

```
  % Total    % Received % Xferd  Average Speed   Time    Time     Time  Current
                                 Dload  Upload   Total   Spent    Left  Speed
  0     0    0     0    0     0      0      0 --:--:-- --:--:-- --:--:--     0
  0     0    0     0    0     0      0      0 --:--:-- --:--:-- --:--:--     0
100     7    0     7    0     0      5      0 --:--:--  0:00:01 --:--:--     5
100 3750k  100 3750k    0     0  1220k      0  0:00:03  0:00:03 --:--:-- 3357k
```

[7]:
```
CompletedProcess(args=['curl', 'https://pitt.box.com/shared/static/
↪z73eked7quh1t2pp93axzrrpq6wwydx0.wav', '-L', '-o', '1min_audio.wav'], returncode=0)
```

[8]:
```
from glob import glob
audio_files = glob('./*.wav') #match all .wav files in the current directory
audio_files
```

[8]:
```
['./1min_audio.wav']
```

### 7.2.2 Prepare a dataframe and dataset for prediction

The prediction dataframe will have the names of each file and the start and end time of each window that we want to generate predictions for. OpenSoundscape provides a helper function to create this dataframe in the case where we want to predict on fixed-length windows with a fixed overlap between consecutive windows. Note that we need to know the duration of clips that the model expects, eg 5 second clips for the model we downloaded above.

[9]:
```
from opensoundscape.helpers import make_clip_df
clip_df = make_clip_df(files=audio_files,clip_duration=5.0)
clip_df.head()
```

[9]:
```
                  start_time  end_time
file
./1min_audio.wav         0.0       5.0
./1min_audio.wav         5.0      10.0
./1min_audio.wav        10.0      15.0
./1min_audio.wav        15.0      20.0
./1min_audio.wav        20.0      25.0
```

note that we might need to change the preprocessing parameters of our Preprocessor object to match the model's preprocessing used during training (e.g. spectrogram parameters or bandpassing)

[10]:
```
from opensoundscape.preprocess.preprocessors import ClipLoadingSpectrogramPreprocessor
prediction_dataset = ClipLoadingSpectrogramPreprocessor(clip_df)
```

we can check on the parameters used during trainig by accessing model.train_dataset. For instance, check the band-passing behavior of the training dataset:

(Note that an empty params dictionary indicates that default values were used)

[11]:
```
model.train_dataset.actions.bandpass.params
```

[11]:
```
{'min_f': 0, 'max_f': 11025, 'out_of_bounds_ok': False}
```

## 7.3 generate predictions with the model

The model returns a dataframe with a MultiIndex of file, start_time, and end_time. There is one column for each class.

[12]:
```
scores, _, _ = model.predict(prediction_dataset)
scores.head()
```

```
(12, 2)
```

[12]:
```
                                        absent   present
file             start_time end_time
./1min_audio.wav 0.0        5.0       0.277278 -0.293570
                 5.0        10.0      0.359079 -0.363364
                 10.0       15.0     -1.124166  1.038807
                 15.0       20.0      0.350859 -0.332194
                 20.0       25.0     -3.864331  3.613130
```

## 7.4 Using models from older OpenSoundscape versions

Models trained and saved with OpenSoundscape versions prior to 0.6.1 need to be loaded in a different way, and require that you know the architecture of the saved model.

For example, one set of our publicly availably binary models for 500 species was created with an older version of OpenSoundscape. These models require a little bit of manipulation to load into OpenSoundscape 0.5.x and onward. From the model notes page, we know that these models were trained with a resnet18 architecture. We can load them into a PytorchModel class.

First, let's download one of these models (it's stored in a .tar format) and save it to the same directory as this notebook in a file called `opso_04_model_acanthis-flammea.tar`

[13]:
```
subprocess.run(['curl',
                'https://pitt.box.com/shared/static/1glpty35omjhmq6cdz8cfudm43nn2t9f.
↪tar',
                '-L', '-o', 'opso_04_model_acanthis-flammea.tar'])
```

```
  % Total    % Received % Xferd  Average Speed   Time    Time     Time  Current
                                 Dload  Upload   Total   Spent    Left  Speed
  0     0    0     0    0     0      0      0 --:--:-- --:--:-- --:--:--     0
  0     0    0     0    0     0      0      0 --:--:-- --:--:-- --:--:--     0
100     8    0     8    0     0      6      0 --:--:--  0:00:01 --:--:--     6
100 42.9M  100 42.9M    0     0  2720k      0  0:00:16  0:00:16 --:--:-- 5099k
```

[13]:
```
CompletedProcess(args=['curl', 'https://pitt.box.com/shared/static/
↪1glpty35omjhmq6cdz8cfudm43nn2t9f.tar', '-L', '-o', 'opso_04_model_acanthis-flammea.
↪tar'], returncode=0)
```

[14]:
```
from opensoundscape.torch.models.cnn import load_outdated_model
from opensoundscape.torch.architectures import cnn_architectures
```

the load_outdated_model function will expect us to specify the model class (we'll use PytorchModel) and architecture constructor (we'll use cnn_architectures.resnet18). In this case, we also want to specify that the model should be single-tartet (models are multi-target by default)

[15]:
```
model = load_outdated_model('./opso_04_model_acanthis-flammea.tar',model_class =␣
↪PytorchModel,architecture_constructor=cnn_architectures.resnet18)
model.single_target = True
```

```
created PytorchModel model object with 2 classes
<All keys matched successfully>
```

The model is now fully compatible with OpenSoundscape, and can be used as above. For example:

[16]:
```
scores, _, _ = model.predict(prediction_dataset)
scores.head()
```

```
(12, 2)
```

[16]:
```
                                      acanthis-flammea-absent  \
file              start_time end_time
./1min_audio.wav  0.0        5.0                     5.777371
                  5.0        10.0                    4.891728
                  10.0       15.0                    5.632080
                  15.0       20.0                    4.748437
                  20.0       25.0                    4.424040

                                      acanthis-flammea-present
file              start_time end_time
./1min_audio.wav  0.0        5.0                    -5.517636
                  5.0        10.0                   -4.772002
                  10.0       15.0                   -5.395757
                  15.0       20.0                   -5.166635
                  20.0       25.0                   -5.115609
```

## 7.5 Options for prediction

The code above returns the raw predictions of the model without any post-processing (such as a softmax layer or a sigmoid layer).

For details on how to use the `predict()` function for post-processing of predictions and to generate binary 0/1 predictions of class presence, see the "Basic training and prediction with CNNs" tutorial notebook. But, as a quick example, let's add a softmax layer to make the prediction scores for both classes sum to 1. We can also use the `binary_preds` argument to generate 0/1 predictions for each sample and class. For presence/absence models, use the option `binary_preds='single_target'`. For multi-class models, think about whether each clip should be labeled with only one class (single target) or whether each clip could contain multiple classes (`binary_preds='multi_target'`)

[17]:
```
scores, binary_predictions, _ = model.predict(
    prediction_dataset,
    activation_layer='softmax',
    binary_preds='single_target'
)
```

```
(12, 2)
```

As before, the `scores` are continuous variables, but now have been softmaxed:

[18]:
```
scores.head()
```

[18]:
```
                                          acanthis-flammea-absent  \
file              start_time end_time
./1min_audio.wav  0.0        5.0                         0.999988
                  5.0        10.0                        0.999936
                  10.0       15.0                        0.999984
                  15.0       20.0                        0.999951
                  20.0       25.0                        0.999928

                                          acanthis-flammea-present
file              start_time end_time
./1min_audio.wav  0.0        5.0                         0.000012
                  5.0        10.0                        0.000064
                  10.0       15.0                        0.000016
                  15.0       20.0                        0.000049
                  20.0       25.0                        0.000072
```

We also have an additional output, the binary 0/1 ("absent" vs "present") predictions generated by the model:

[19]:
```
binary_predictions.head()
```

[19]:
```
                                          acanthis-flammea-absent  \
file              start_time end_time
./1min_audio.wav  0.0        5.0                              1.0
                  5.0        10.0                             1.0
                  10.0       15.0                             1.0
                  15.0       20.0                             1.0
                  20.0       25.0                             1.0

                                          acanthis-flammea-present
file              start_time end_time
./1min_audio.wav  0.0        5.0                              0.0
                  5.0        10.0                             0.0
                  10.0       15.0                             0.0
```

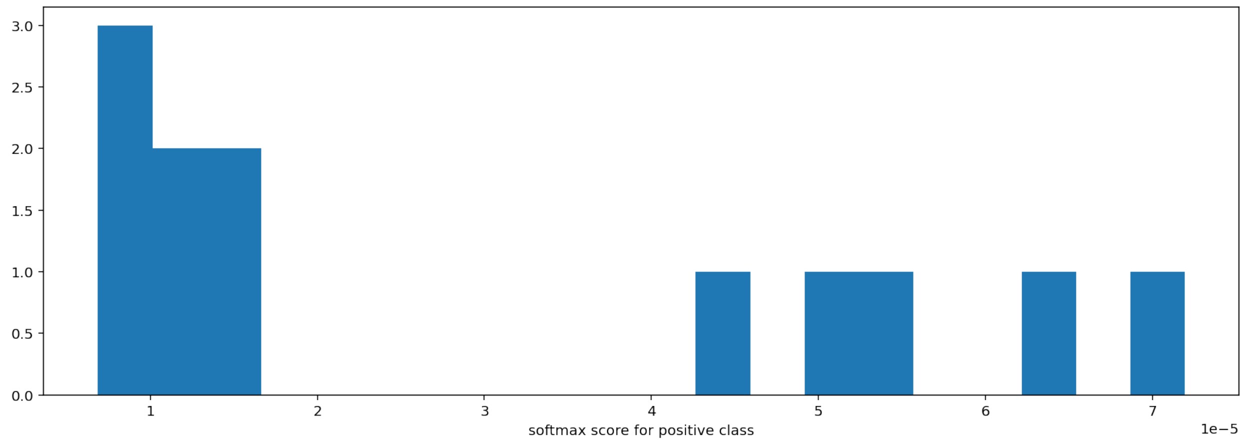
(continues on next page)

(continued from previous page)

```
              15.0        20.0                            0.0
              20.0        25.0                            0.0
```

It is sometimes helpful to look at a histogram of the scores:

```
[20]: _ = plt.hist(scores['acanthis-flammea-present'],bins=20)
_ = plt.xlabel('softmax score for positive class')
```




## 7.6 Deprecated: Using LongAudioPreprocessor to predict on (unsplit) audio files

It's also possible to run predictions on long audio files by loading entire files and letting OpenSoundscape split them while predicting. This is deprecated in favor of the approach shown above and has high memory (RAM) requirements. In this case, OpenSoundscape will internally split the audio into short segments during prediction. The input dataframe in this case is simply a dataframe with file paths. The model.split_and_predict() method expects the user to provide the audio clip length.

Let's look at an example. We'll use the 1 minute audio file contained within OpenSoundscape's test folder as a "long" audio file. In practice, you can split files that are multiple hours long - the limiting factor is your computer's memory ("RAM"), which must be able to hold the entire audio file.

```
[21]: import opensoundscape
from opensoundscape.preprocess.preprocessors import LongAudioPreprocessor

#get audio path from opensoundscape's tests folder
long_audio_prediction_df = pd.DataFrame(index=audio_files)
img_shape = [224,224]

#the audio will be split during prediction. choose the clip length and overlap of␣
↪sequential clips (0 for no overlap)
clip_length = 5.0
clip_overlap = 0.0
long_audio_prediction_ds = LongAudioPreprocessor(
    long_audio_prediction_df,
    audio_length=clip_length,
    clip_overlap=clip_overlap,
    out_shape=img_shape,
```

(continues on next page)

(continued from previous page)

```
)
```

```
/Users/SML161/opt/miniconda3/envs/opso/lib/python3.7/site-packages/ipykernel_launcher.
↪py:15: DeprecationWarning: Call to deprecated class LongAudioPreprocessor. (Use␣
↪ClipLoadingSpectrogramPreprocessorfor similar functionality with lower memory␣
↪requirements.) -- Deprecated since version 0.6.1.
  from ipykernel import kernelapp as app
```

in addition to the scores (and potentially, predictions) the function returns a list of "unsafe" samples that caused errors during preprocessing.

[22]:
```
score_df, pred_df, unsafe_samples = model.split_and_predict(
    long_audio_prediction_ds,
    file_batch_size=1,
    num_workers=0,
    activation_layer=None,
    binary_preds='single_target',
    threshold=0.5,
    clip_batch_size=4,
    error_log=None,
)
score_df.head()
```

```
/Users/SML161/opt/miniconda3/envs/opso/lib/python3.7/site-packages/ipykernel_launcher.
↪py:9: DeprecationWarning: Call to deprecated method split_and_predict. (Use␣
↪ClipLoadingSpectrogramPreprocessorwith model.predict() for similar functionality␣
↪but lower memory requirements.) -- Deprecated since version 0.6.1.
  if __name__ == '__main__':
```

[22]:
```
                                      acanthis-flammea-absent  \
file              start_time end_time
./1min_audio.wav 0.0        5.0                      5.777371
                 5.0        10.0                     4.891728
                 10.0       15.0                     5.632079
                 15.0       20.0                     4.748437
                 20.0       25.0                     4.424040

                                      acanthis-flammea-present
file              start_time end_time
./1min_audio.wav 0.0        5.0                      -5.517637
                 5.0        10.0                     -4.772002
                 10.0       15.0                     -5.395757
                 15.0       20.0                     -5.166635
                 20.0       25.0                     -5.115609
```

### 7.6.1 Clean up: delete model objects

[24]:
```
from glob import glob
from pathlib import Path
for p in Path('.').glob('*.model'):
    p.unlink()
for p in Path('.').glob('*.tar'):
    p.unlink()
Path('1min_audio.wav').unlink()
```

# CHAPTER 8

## Beginner friendly training and prediction with CNNs

Convolutional Neural Networks (CNNs) are a popular tool for developing automated machine learning classifiers on images or image-like samples. By converting audio into a two-dimensional frequency vs. time representation such as a spectrogram, we can generate image-like samples that can be used to train CNNs. This tutorial demonstrates the basic use of OpenSoundscape's `preprocessors` and `cnn` modules for training CNNs and making predictions using CNNs.

Under the hood, OpenSoundscape uses Pytorch for machine learning tasks. By using OpenSoundscape's CNN classes such as `PytorchModel` in combination with preprocessor classes such as `CnnPreprocessor`, you can train and predict with PyTorch's powerful CNN architectures in just a few lines of code.

First, let's import some utilities.

[1]:
```
# Preprocessor classes are used to load, transform, and augment audio samples for use␣
↪in a machine learing model
from opensoundscape.preprocess.preprocessors import CnnPreprocessor

# the cnn module provides classes for training/predicting with various types of CNNs
from opensoundscape.torch.models.cnn import PytorchModel

#other utilities and packages
import torch
import pandas as pd
from pathlib import Path
import numpy as np
import pandas as pd
import random
import subprocess

#set up plotting
from matplotlib import pyplot as plt
plt.rcParams['figure.figsize']=[15,5] #for large visuals
%config InlineBackend.figure_format = 'retina'
```

Set manual seeds for pytorch and python. These ensure the training results are reproducible. You probably don't want to do this when you actually train your model, but it's useful for debugging.

[2]:
```
torch.manual_seed(0)
random.seed(0)
```

## 8.1 Prepare audio data

### 8.1.1 Download labeled audio files

Training a machine learning model requires some pre-labeled data. These data, in the form of audio recordings or spectrograms, are labeled with whether or not they contain the sound of the species of interest. These data can be obtained from online databases such as Xeno-Canto.org, or by labeling one's own ARU data using a program like Cornell's Raven sound analysis software.

The Kitzes Lab has created a small labeled dataset of short clips of American Woodcock vocalizations. You have two options for obtaining the folder of data, called `woodcock_labeled_data`:

1. Run the following cell to download this small dataset. These commands require you to have `tar` installed on your computer, as they will download and unzip a compressed file in `.tar.gz` format.
2. Download a `.zip` version of the files by clicking here. You will have to unzip this folder and place the unzipped folder in the same folder that this notebook is in.

**Note**: Once you have the data, you do not need to run this cell again.

[3]:
```
subprocess.run(['curl','https://pitt.box.com/shared/static/
↪79fi7d715dulcldsy6uogz02rsn5uesd.gz','-L', '-o','woodcock_labeled_data.tar.gz']) #␣
↪Download the data
subprocess.run(["tar","-xzf", "woodcock_labeled_data.tar.gz"]) # Unzip the downloaded␣
↪tar.gz file
subprocess.run(["rm", "woodcock_labeled_data.tar.gz"]) # Remove the file after its␣
↪contents are unzipped
```

```
  % Total    % Received % Xferd  Average Speed   Time    Time     Time  Current
                                 Dload  Upload   Total   Spent    Left  Speed
  0      0    0      0    0     0      0      0 --:--:-- --:--:-- --:--:--     0
  0      0    0      0    0     0      0      0 --:--:-- --:--:-- --:--:--     0
100      7    0      7    0     0      5      0 --:--:--  0:00:01 --:--:--     0
100 4031k  100 4031k    0     0  1110k      0  0:00:03  0:00:03 --:--:-- 2797k
```

[3]:
```
CompletedProcess(args=['rm', 'woodcock_labeled_data.tar.gz'], returncode=0)
```

### 8.1.2 Generate one-hot encoded labels

The folder contains 2s long audio clips taken from an autonomous recording unit. It also contains a file `woodcock_labels.csv` which contains the names of each file and its corresponding label information, created using a program called Specky.

[4]:
```
#load Specky output: a table of labeled audio files
specky_table = pd.read_csv(Path("woodcock_labeled_data/woodcock_labels.csv"))
specky_table.head()
```

[4]:
```
                               filename woodcock sound_type
0  d4c40b6066b489518f8da83af1ee4984.wav  present       song
1  e84a4b60a4f2d049d73162ee99a7ead8.wav   absent         na
2  79678c979ebb880d5ed6d56f26ba69ff.wav  present       song
```

(continues on next page)

(continued from previous page)

```
3   49890077267b569e142440fa39b3041c.wav  present       song
4   0c453a87185d8c7ce05c5c5ac5d525dc.wav  present       song
```

This table must provide an accurate path to the files of interest. For this self-contained tutorial, we can use relative paths (starting with a dot and referring to files in the same folder), but you may want to use absolute paths for your training.

[5]:
```
#update the paths to the audio files
specky_table.filename = ['./woodcock_labeled_data/'+f for f in specky_table.filename]
specky_table.head()
```

[5]:
```
                                            filename woodcock sound_type
0   ./woodcock_labeled_data/d4c40b6066b489518f8da8...  present       song
1   ./woodcock_labeled_data/e84a4b60a4f2d049d73162...   absent         na
2   ./woodcock_labeled_data/79678c979ebb880d5ed6d5...  present       song
3   ./woodcock_labeled_data/49890077267b569e142440...  present       song
4   ./woodcock_labeled_data/0c453a87185d8c7ce05c5c...  present       song
```

We then use the `categorical_to_one_hot` function from `opensoundscape.annotations` to crate "one hot" labels - that is, a column for every class, with 1 for present or 0 for absent in each sample's row. In this case, our classes are simply `'negative'` for files without a woodcock and `'positive'` for files with a woodcock.

We'll need to put the paths to audio files as the index of the DataFrame.

Note that these classes are mutually exclusive, so we have a "single-target" problem, as opposed to a "multi-target" problem where multiple classes can simultaneously be present.

[6]:
```
from opensoundscape.annotations import categorical_to_one_hot
one_hot_labels, classes = categorical_to_one_hot(specky_table[['woodcock']].values)
labels = pd.DataFrame(index=specky_table['filename'],data=one_hot_labels,
↪columns=classes)
labels.head()
```

[6]:
```
                                                    absent  present
filename
./woodcock_labeled_data/d4c40b6066b489518f8da83...       0        1
./woodcock_labeled_data/e84a4b60a4f2d049d73162e...       1        0
./woodcock_labeled_data/79678c979ebb880d5ed6d56...       0        1
./woodcock_labeled_data/49890077267b569e142440f...       0        1
./woodcock_labeled_data/0c453a87185d8c7ce05c5c5...       0        1
```

If we want to, we can always convert one_hot labels back to categorical labels:

[7]:
```
from opensoundscape.annotations import one_hot_to_categorical
categorical_labels = one_hot_to_categorical(one_hot_labels,classes)
categorical_labels[:3]
```

[7]:
```
[['present'], ['absent'], ['present']]
```

### 8.1.3 Split into training and validation sets

We use a utility from `sklearn` to randomly divide the labeled samples into two sets. The first set, `train_df`, will be used to train the CNN, while the second set, `valid_df`, will be used to test how well the model can predict the classes of samples that it was not trained with.

During the training process, the CNN will go through all of the samples once every "epoch" for several (sometimes hundreds of) epochs. Each epoch usually consists of a "learning" step and a "validation" step. In the learning step, the CNN iterates through all of the training samples while the computer program is modifying the weights of the convolutional neural network. In the validation step, the program performs prediction on all of the validation samples and prints out metrics to assess how well the classifier generalizes to unseen data.

[8]:
```
from sklearn.model_selection import train_test_split
train_df,valid_df = train_test_split(labels,test_size=0.2,random_state=1)
```

### 8.1.4 Create preprocessors for training and validation

Preprocessors in OpenSoundscape can be used to process audio data, especially for training and prediction with convolutional neural networks.

To train a CNN, we use `CnnPreprocessor`, which loads audio files, creates spectrograms, performs various augmentations to the spectrograms, and returns a pytorch Tensor to be used in training or prediction. All of the steps in the preprocessing pipeline can be modified or skipped by modifying the preprocessor's `.actions`. For details on how to modify and customize a preprocessor, see the `preprocessing` notebook/tutorial.

Each Preprocessor must be initialized with a very specific dataframe with the following attributes:

- the index of the dataframe provides paths to audio samples
- the columns are the class names
- the values are 0 (absent/False) or 1 (present/True) for each sample and each class.

The `train_df` and `valid_df` we created above meet these needs:

[9]:
```
train_df.head()
```

[9]:
```
                                                  absent  present
filename
./woodcock_labeled_data/49890077267b569e142440f...       0        1
./woodcock_labeled_data/ad90eefb6196ca83f9cf43b...       0        1
./woodcock_labeled_data/e9e7153d11de3ac8fc3f716...       0        1
./woodcock_labeled_data/c057a4486b25cd638850fc0...       0        1
./woodcock_labeled_data/0c453a87185d8c7ce05c5c5...       0        1
```

We next create separate preprocessors for training and for validation. These data will be assessed separately each epoch, as described above.

[10]:
```
from opensoundscape.preprocess.preprocessors import CnnPreprocessor

train_dataset = CnnPreprocessor(train_df)

valid_dataset = CnnPreprocessor(valid_df)
```

### 8.1.5 Inspect training images

Before creating a machine learning algorithm, we strongly recommend making sure the images coming out of the preprocessor look like you expect them to. Here we generate images for a few samples.

First, in order to view the images, we need a helper function that correctly displays the Tensor that comes out of the Preprocessor.

[11]:
```
# helper function for displaying a sample as an image
def show_tensor(sample):
```

(continues on next page)

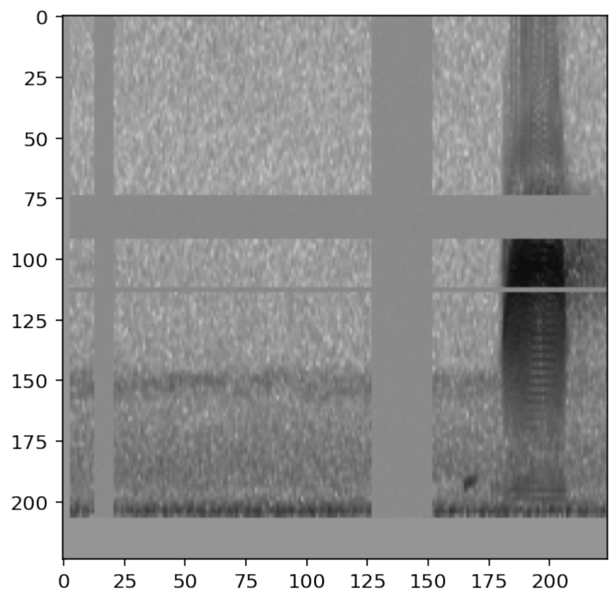
(continued from previous page)

```
    plt.imshow((sample['X'][0,:,:]/2+0.5)*-1,cmap='Greys',vmin=-1,vmax=0)
    plt.show()
```

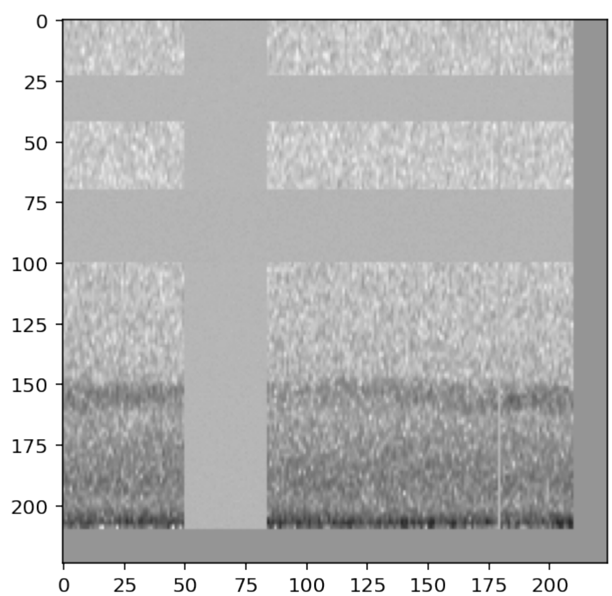
Now, load a handful of random samples, printing the labels and image for each:

[12]:
```
for i, d in enumerate(train_dataset.sample(n=4)):
    print(f"labels: {d['y']}")
    show_tensor(d)
```

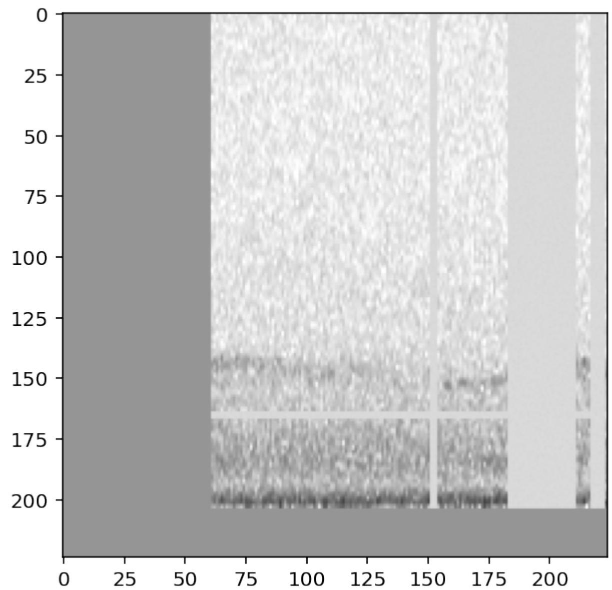
```
labels: tensor([0, 1])
```



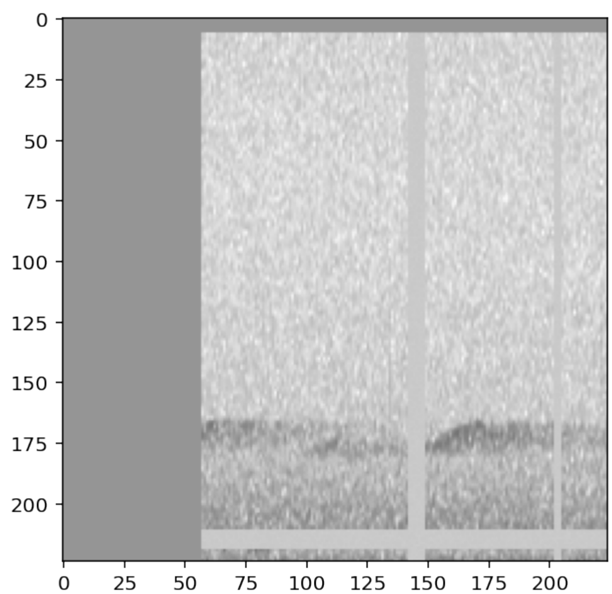

```
labels: tensor([1, 0])
```




```
labels: tensor([0, 1])
```



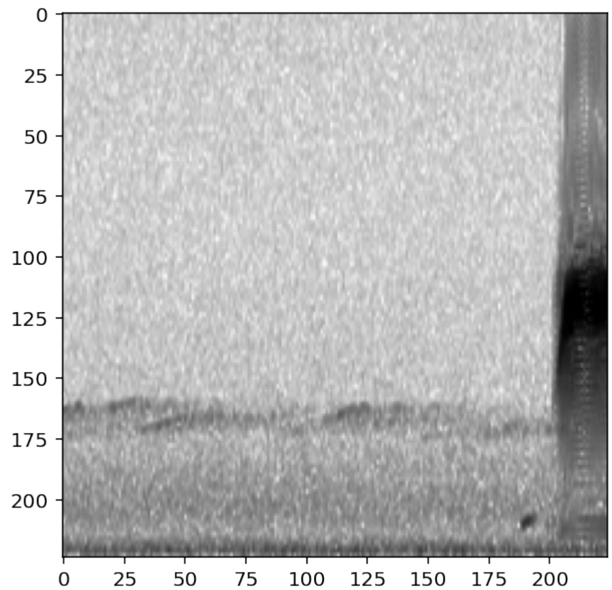

```
labels: tensor([0, 1])
```



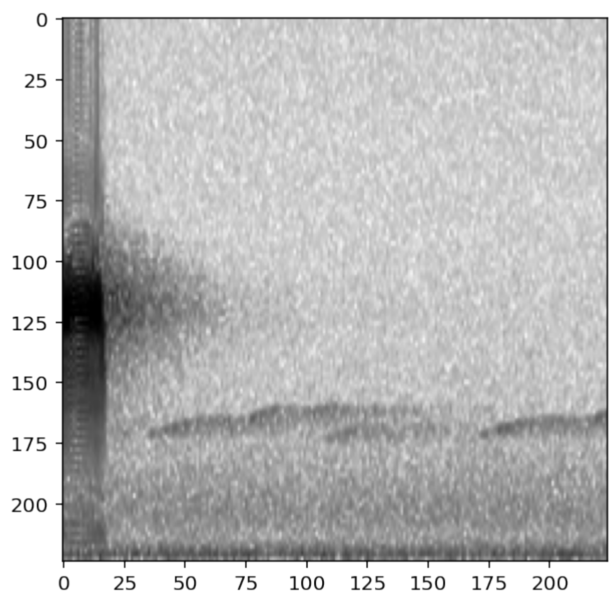

The `CnnPreprocessor` preprocessor allows you to turn all augmentation off or on as desired. Inspect the unaugmented images as well:

[13]:
```
train_dataset.augmentation_off()
for i, d in enumerate(train_dataset.sample(n=4)):
    print(f"labels: {d['y']}")
    show_tensor(d)
#turn augmentation back on when we're done
train_dataset.augmentation_on()
```

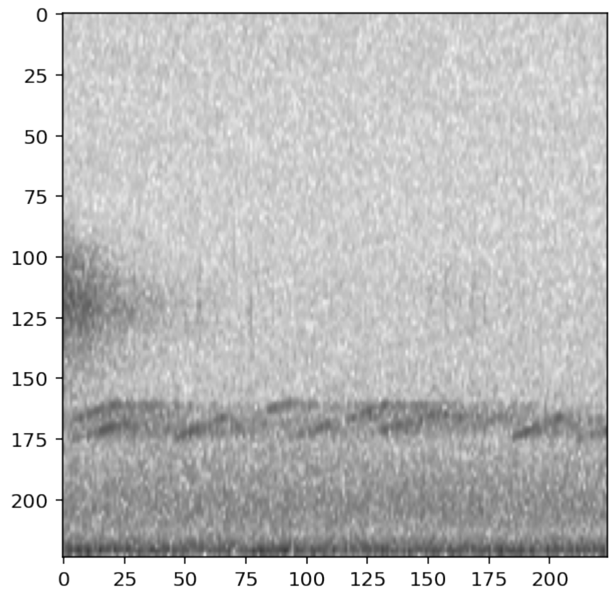
```
labels: tensor([0, 1])
```



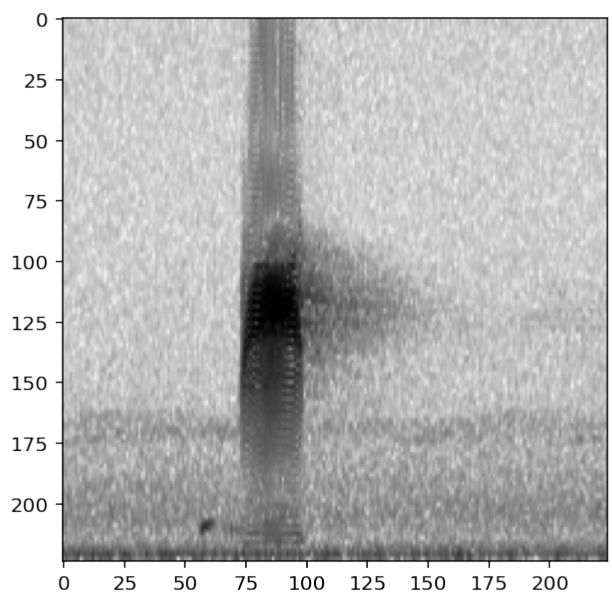

```
labels: tensor([0, 1])
```




```
labels: tensor([1, 0])
```




```
labels: tensor([0, 1])
```




## 8.2 Training

Now, we create a convolutional neural network model object, train it on the `train_dataset` with validation from `valid_dataset`, and use it for prediction.

### 8.2.1 Set up a two-class, single-target model

This demonstrates using a two class, single-target model.

- The two classes in this case are "positive" and "negative."

- The model is "single target," meaning that each sample belongs to exactly one class, "positive" or "negative"

We usually use two-class, single-target models to predict the presence or absence of a single species. We often refer to this as a "binary" model, but be careful not to confuse this for thresholded "binary" output predictions (1 or 0).

The model object should be initialized with a list of class names that matches the class names in the training dataset. Here we'll use the resnet18 architecture, a popular and powerful architecture that makes a good staring point. For more details on other CNN architectures, see the "Advanced CNN Training" tutorial.

[14]:
```
# Create model object
classes = train_df.columns
model = PytorchModel('resnet18',classes,single_target=True)
```

```
created PytorchModel model object with 2 classes
```

### 8.2.2 Train the model

Depending on the speed of your computer, training the CNN may take a few minutes.

We'll only train for 5 epochs on this small dataset as a demonstration, but you'll probably need to train for hundreds of epochs on hundreds of training files (at a minimum) to create a useful model.

In practice, using larger batch sizes (64+) improves stability and generalizability of training, particularly for architectures (such as ResNet) that contain a 'batch norm' layer. Here we use a small batch size to keep the computational reqirements for this tutorial low.

[15]:
```
model.train(
    train_dataset=train_dataset,
    valid_dataset=valid_dataset,
    save_path='./binary_train/',
    epochs=5,
    batch_size=8,
    save_interval=100,
    num_workers=0,
)
```

```
Epoch: 0 [batch 0/3 (0.00%)]
        Jacc: 0.062 Hamm: 0.875 DistLoss: 1.151

Validation.
(6, 2)
         Precision: 0.41666666666666667
         Recall: 0.5
         F1: 0.45454545454545453
Updating best model
Epoch: 1 [batch 0/3 (0.00%)]
        Jacc: 0.250 Hamm: 0.500 DistLoss: 2.262

Validation.
(6, 2)
         Precision: 0.41666666666666667
         Recall: 0.5
         F1: 0.45454545454545453
Epoch: 2 [batch 0/3 (0.00%)]
        Jacc: 0.583 Hamm: 0.250 DistLoss: 0.505

Validation.
(6, 2)
```

(continues on next page)

(continued from previous page)

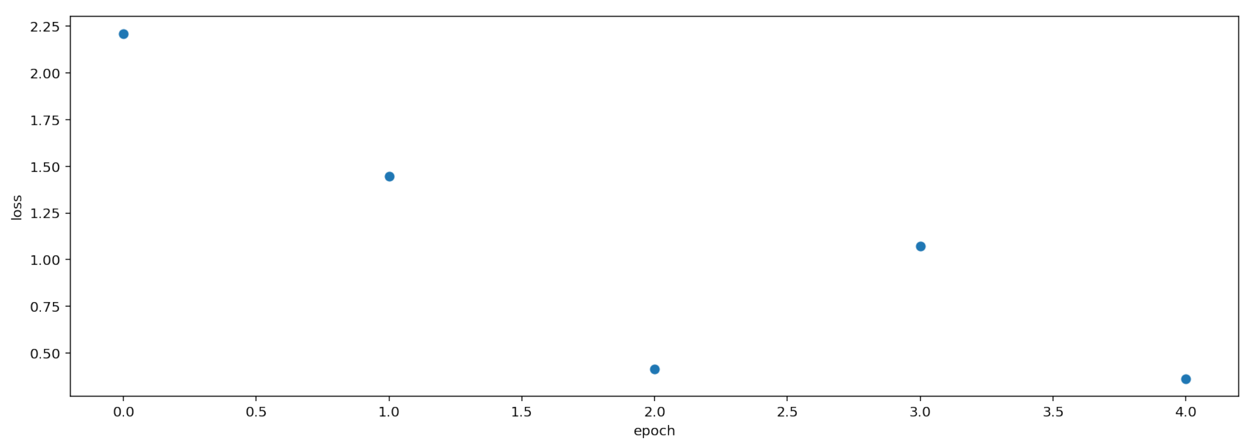
```
          Precision: 0.41666666666666667
          Recall: 0.5
          F1: 0.45454545454545453
Epoch: 3 [batch 0/3 (0.00%)]
         Jacc: 0.375 Hamm: 0.250 DistLoss: 1.272

Validation.
(6, 2)
          Precision: 0.41666666666666667
          Recall: 0.5
          F1: 0.45454545454545453
Epoch: 4 [batch 0/3 (0.00%)]
         Jacc: 0.679 Hamm: 0.125 DistLoss: 0.374

Validation.
(6, 2)
          Precision: 0.41666666666666667
          Recall: 0.5
          F1: 0.45454545454545453
Saving weights, metrics, and train/valid scores.

Best Model Appears at Epoch 0 with F1 0.455.
```

### 8.2.3 Plot the loss history

We can plot the loss from each epoch to check that our loss is declining

[16]:
```
plt.scatter(model.loss_hist.keys(),model.loss_hist.values())
plt.xlabel('epoch')
plt.ylabel('loss')
```

[16]:
```
Text(0, 0.5, 'loss')
```




[17]:
```
model.save('~/Downloads/example.model')
```

## 8.3 Prediction

We haven't actually trained a useful model in 5 epochs, but we can use the trained model to demonstrate how prediction works and show several of the settings useful for prediction.

### 8.3.1 Create preprocessor for prediction

Similar to training, prediction requires the use of a Preprocessor. To ensure that the preprocessing matches that used during model training, we'll create our prediction Preprocessor using the training preprocessor as a starting point. (If you load a trained model from a file, you can access `model.train_dataset`).

In this instance, we'll reuse the validation dataset used above, but in a real application you would likely want to use the model for prediction on a separate dataset, such as a new and unlabeled dataset that you want to classify.

[18]:
```
#create a copy of the training dataset, sampling 0 of the training samples from it
prediction_dataset = model.train_dataset.sample(n=0)
#turn off augmentation on this dataset
prediction_dataset.augmentation_off()
#use the validation samples as test samples for the sake of illustration
prediction_dataset.df = valid_df
```

### 8.3.2 Predict on the validation dataset

We simply call model's `.predict()` method on a Preprocessor instance.

This will return three dataframes:

- scores : numeric predictions from the model for each sample and class (by default these are raw outputs from the model)
- predictions: 0/1 predictions from the model for each sample and class (only generated if `binary_predictions` argument is supplied)
- labels: Original labels from the dataset, if available

[19]:
```
valid_scores_df, valid_preds_df, valid_labels_df = model.predict(prediction_dataset)
valid_scores_df.head()
```

```
(6, 2)
```

[19]:
```
                                                        absent    present
./woodcock_labeled_data/882de25226ed989b31274ee... -34.736469  34.712406
./woodcock_labeled_data/92647ab903049a9ee4125ab... -29.079432  28.833181
./woodcock_labeled_data/75b2f63e032dbd6d1979004... -26.357983  26.485283
./woodcock_labeled_data/01c5d0c90bd4652f308fd9c... -35.237747  35.949291
./woodcock_labeled_data/ad14ac7ffa729060712b442...  -6.998813   8.033541
```

[20]:
```
# None: not generated because the `binary_predictions` argument was not supplied
valid_preds_df
```

[21]:
```
valid_labels_df.head()
```

[21]:
```
                                                   absent  present
./woodcock_labeled_data/882de25226ed989b31274ee...       0        1
./woodcock_labeled_data/92647ab903049a9ee4125ab...       0        1
./woodcock_labeled_data/75b2f63e032dbd6d1979004...       0        1
```

(continues on next page)

(continued from previous page)

```
./woodcock_labeled_data/01c5d0c90bd4652f308fd9c...      0        1
./woodcock_labeled_data/ad14ac7ffa729060712b442...      1        0
```

The `valid_preds` dataframe in the example above is `None` - this is because we haven't specified an option for the `binary_preds` argument of predict. We can choose between `'single_target'` prediction (always predict the highest scoring class and no others) or `'multi_target'` (predict 1 for all classes exceeding a threshold).

### 8.3.3 Create presence/absence (0/1) predictions

Supplying the `binary_preds` argument returns a dataframe in which the scores are transformed from continuous numbers to either 0 or 1.

**Note**: Binary predictions always have some error rates, sometimes large ones. It is not generally advisable to use these binary predictions as scientific observations without a thorough understanding of the model's false-positive and false-negative rates.

If you wish to output binary predictions, three options are available:

- `None`: default. do not create or return binary predictions
- `'single_target'`: predict that the highest-scoring class = 1, all others = 0
- `'multi_target'`: provide a `threshold`. Scores above threshold = 1, others = 0

For instance, using the option `'single_target'` chooses whichever of `'negative'` or `'positive'` is higher.

[22]:
```
scores,preds,labels = model.predict(prediction_dataset,binary_preds='single_target')
preds.head()
```

```
(6, 2)
```

[22]:
```
                                                 absent  present
./woodcock_labeled_data/882de25226ed989b31274ee...     0.0      1.0
./woodcock_labeled_data/92647ab903049a9ee4125ab...     0.0      1.0
./woodcock_labeled_data/75b2f63e032dbd6d1979004...     0.0      1.0
./woodcock_labeled_data/01c5d0c90bd4652f308fd9c...     0.0      1.0
./woodcock_labeled_data/ad14ac7ffa729060712b442...     0.0      1.0
```

The `'multi_target'` option allows you to select a threshold. If a score meets that threshold, the binary prediction is 1; otherwise, it is 0.

Each score will have a function applied to it that takes the score from the real numbers, (-inf, inf), to the range [0, 1] (specifically the logistic sigmoid, or expit function). Whether the score meets this threshold will be based off of the sigmoid, not the raw score.

[23]:
```
score_df, pred_df, label_df = model.predict(
    prediction_dataset,
    binary_preds='multi_target',
    threshold=0.99,
)
pred_df.head()
```

```
(6, 2)
```

[23]:
```
                                                 absent  present
./woodcock_labeled_data/882de25226ed989b31274ee...     0.0      1.0
./woodcock_labeled_data/92647ab903049a9ee4125ab...     0.0      1.0
./woodcock_labeled_data/75b2f63e032dbd6d1979004...     0.0      1.0
```

(continues on next page)

(continued from previous page)

```
./woodcock_labeled_data/01c5d0c90bd4652f308fd9c...      0.0       1.0
./woodcock_labeled_data/ad14ac7ffa729060712b442...      0.0       1.0
```

Note that in some of the above predictions, both the negative and positive classes are predicted to be present. This is because the `'multi_target'` option assumes that the classes are not mutually exclusive. For a presence/absence model like the one above, the `'single_target'` option is more appropriate.

### 8.3.4 Change the activation layer

We can modify the final activation layer to change the scores returned by the `predict()` function. Note that this does not impact the results of the binary predictions (described above), which are always calcuated using a sigmoid transformation (for multi-target models) or softmax function (for single-target models).

Options include:

- `None`: default. Just the raw outputs of the network, which are in (-inf, inf)
- `'softmax'`: scores across all classes will sum to 1 for each sample
- `'softmax_and_logit'`: softmax the scores across all classes so they sum to 1, then apply the "logit" transformation to these scores, taking them from [0,1] back to (-inf,inf)
- `'sigmoid'`: transforms each score individually to [0, 1] without requiring they sum to 1

In this case, since we are choosing between two mutually exclusive classes, we want to use the `'softmax'` activation.

[24]:
```
valid_scores, valid_preds, valid_labels = model.predict(prediction_dataset,␣
↪activation_layer='softmax')
```

```
(6, 2)
```

Compare the softmax scores to the true labels for this dataset, side-by-side:

[25]:
```
valid_scores.columns = ['pred_negative','pred_positive']
valid_dataset.df.join(valid_scores).sample(5)
```

[25]:
```
                                                    absent  present  \
filename
./woodcock_labeled_data/92647ab903049a9ee4125ab...       0        1
./woodcock_labeled_data/ad14ac7ffa729060712b442...       1        0
./woodcock_labeled_data/4afa902e823095e03ba23eb...       0        1
./woodcock_labeled_data/75b2f63e032dbd6d1979004...       0        1
./woodcock_labeled_data/01c5d0c90bd4652f308fd9c...       0        1

                                                    pred_negative  \
filename
./woodcock_labeled_data/92647ab903049a9ee4125ab...   7.061090e-26
./woodcock_labeled_data/ad14ac7ffa729060712b442...   2.961637e-07
./woodcock_labeled_data/4afa902e823095e03ba23eb...   3.963297e-28
./woodcock_labeled_data/75b2f63e032dbd6d1979004...   1.123211e-23
./woodcock_labeled_data/01c5d0c90bd4652f308fd9c...   1.212999e-31

                                                    pred_positive
filename
./woodcock_labeled_data/92647ab903049a9ee4125ab...            1.0
./woodcock_labeled_data/ad14ac7ffa729060712b442...            1.0
./woodcock_labeled_data/4afa902e823095e03ba23eb...            1.0
```

(continues on next page)

(continued from previous page)

```
./woodcock_labeled_data/75b2f63e032dbd6d1979004...          1.0
./woodcock_labeled_data/01c5d0c90bd4652f308fd9c...          1.0
```

### 8.3.5 Parallelizing prediction

Two parameters can be used to increase prediction efficiency, depending on the computational resources available:

- `num_workers`: Pytorch's method of parallelizing across cores (CPUs) - choose 0 to predict on the root process, or >1 if you want to use more than 1 CPU
- `batch_size`: number of samples to predict on simultaneously

[26]:
```
score_df, pred_df, label_df = model.predict(
    valid_dataset,
    batch_size=8,
    num_workers=0,
    binary_preds='multi_target'
)
```

```
(6, 2)
```

## 8.4 Multi-class models

A multi-class model can have any number of classes, and can be either

- multi-target: any number of classes can be positive for one sample
- single-target: exactly one class is positive for each sample

Models that are multi-target benefit from a modified loss function, and we have implemented a special class called CnnResampleLoss specifically designed for multi-target problems. We can use it similarly to the PytorchModel class:

[27]:
```
from opensoundscape.torch.models.cnn import CnnResampleLoss
model = CnnResampleLoss('resnet18',classes)
print("model.single_target:", model.single_target)
```

```
created PytorchModel model object with 2 classes
model.single_target: False
```

If you want a single-target model, uncomment and run the following line.

[28]:
```
#model.single_target = True
```

### 8.4.1 Train

Training looks the same as in two-class models.

[29]:
```
model.train(
    train_dataset=train_dataset,
    valid_dataset=valid_dataset,
    save_path='./multilabel_train/',
    epochs=1,
    batch_size=16,
```

(continues on next page)

(continued from previous page)

```
    save_interval=100,
    num_workers=0
)
```

```
Epoch: 0 [batch 0/2 (0.00%)]
        Jacc: 0.500 Hamm: 0.500 DistLoss: 22.018

Validation.
(6, 2)
         Precision: 0.4166666666666667
         Recall: 0.5
         F1: 0.45454545454545453
Saving weights, metrics, and train/valid scores.
Updating best model

Best Model Appears at Epoch 0 with F1 0.455.
```

### 8.4.2 Predict

Prediction looks the same as demonstrated above, but make sure to think carefully:

- What `activation_layer` do I want?
- If outputting binary predictions for each sample and class, is my model single-target (`binary_preds='single_target'`) or multi-target (`binary_preds='multi_target'`)?

For more detail on these choices, see the sections about activation layers and binary predictions above.

[30]:
```
train_preds,_,_ = model.predict(train_dataset)
train_preds.columns = ['pred_negative','pred_positive']
train_dataset.df.join(train_preds).head()
```

```
(23, 2)
```

[30]:
```
                                                    absent  present  \
filename
./woodcock_labeled_data/49890077267b569e142440f...       0        1
./woodcock_labeled_data/ad90eefb6196ca83f9cf43b...       0        1
./woodcock_labeled_data/e9e7153d11de3ac8fc3f716...       0        1
./woodcock_labeled_data/c057a4486b25cd638850fc0...       0        1
./woodcock_labeled_data/0c453a87185d8c7ce05c5c5...       0        1

                                                    pred_negative  \
filename
./woodcock_labeled_data/49890077267b569e142440f...      -4.728383
./woodcock_labeled_data/ad90eefb6196ca83f9cf43b...      -5.338425
./woodcock_labeled_data/e9e7153d11de3ac8fc3f716...      -6.712691
./woodcock_labeled_data/c057a4486b25cd638850fc0...      -4.538961
./woodcock_labeled_data/0c453a87185d8c7ce05c5c5...      -4.409285

                                                    pred_positive
filename
./woodcock_labeled_data/49890077267b569e142440f...       3.845540
./woodcock_labeled_data/ad90eefb6196ca83f9cf43b...       4.401108
./woodcock_labeled_data/e9e7153d11de3ac8fc3f716...       5.315771
./woodcock_labeled_data/c057a4486b25cd638850fc0...       3.375217
./woodcock_labeled_data/0c453a87185d8c7ce05c5c5...       3.186363
```

## 8.5 Save and load models

Models can be easily saved to a file and loaded at a later time. If the model was saved with OpenSoundscape version >=0.6.1, the entire model object will be saved - including the class, cnn architecture, loss function, and training/validation datasets. Models saved with earlier versions of OpenSoundscape do not contain all of this information and may require that you know their class and architecture (see below).

### 8.5.1 Save

OpenSoundscape saves models automatically during training:

- The model saves weights to `self.save_path` to `epoch-X.model` automatically during training every `save_interval` epochs
- The model keeps the file `best.model` updated with the weights that achieve the best F1 score on the validation dataset

You can also save the model manually at any time with `model.save(path)`.

[31]:
```
model1 = PytorchModel('resnet18',classes,single_target=True)
# Save every 2 epochs
model1.train(
    train_dataset=train_dataset,
    valid_dataset=valid_dataset,
    epochs=3,
    batch_size=8,
    save_path='./binary_train/',
    save_interval=2,
    num_workers=0
)
model1.save('./binary_train/my_favorite.model')
```

```
created PytorchModel model object with 2 classes
Epoch: 0 [batch 0/3 (0.00%)]
        Jacc: 0.314 Hamm: 0.500 DistLoss: 0.727

Validation.
(6, 2)
         Precision: 0.4166666666666667
         Recall: 0.5
         F1: 0.45454545454545453
Updating best model
Epoch: 1 [batch 0/3 (0.00%)]
        Jacc: 0.250 Hamm: 0.500 DistLoss: 1.237

Validation.
(6, 2)
         Precision: 0.4166666666666667
         Recall: 0.5
         F1: 0.45454545454545453
Saving weights, metrics, and train/valid scores.
Epoch: 2 [batch 0/3 (0.00%)]
        Jacc: 0.375 Hamm: 0.250 DistLoss: 0.549

Validation.
(6, 2)
         Precision: 0.4166666666666667
```

(continues on next page)

(continued from previous page)

```
        Recall: 0.5
        F1: 0.45454545454545453
Saving weights, metrics, and train/valid scores.

Best Model Appears at Epoch 0 with F1 0.455.
```

### 8.5.2 Load

Models created with OpenSoundscape 0.6.1 and above can be loaded in their entirety with the `load_model` function:

[32]:
```
from opensoundscape.torch.models.cnn import load_model
model = load_model('./binary_train/best.model')
```

The model can now be used for prediction (`model.predict()`) or to continue training (`model.train()`).

## 8.6 Predict using saved model

Using a saved or downloaded model to run predictions on audio files is as simple as

1. Loading a previously svaed model
2. Creating an instance of a preprocessor class for prediction
3. Running `model.predict()` on the preprocessor

[33]:
```
# load the saved model
model = load_model('./binary_train/best.model')

# create a Preprocessor instance with the audio samples
# use the model.train_dataset as a starting point to ensure that our preprocessing␣
↪matches what the model expects
prediction_dataset = model.train_dataset.sample(n=0)
prediction_dataset.augmentation_off()
prediction_dataset.df = valid_df

#predict on a dataset
scores,_,_ = model.predict(prediction_dataset, activation_layer='softmax_and_logit')
```

```
(6, 2)
```

## 8.7 Continue training from saved model

Similar to predicting using a saved model, we can also continue to train a model after loading it from a saved file.

By default, `.load()` loads the optimizer parameters and learning rate parameters from the saved model, in addition to the network weights.

[34]:
```
# Create architecture
model = load_model('./binary_train/best.model')

# Continue training from the checkpoint where the model was saved
model.train(train_dataset,valid_dataset,save_path='.',epochs=0)
```

```
Best Model Appears at Epoch 0 with F1 0.000.
```

## 8.8 Next steps

You now have seen the basic usage of training CNNs with OpenSoundscape and generating predictions.

Additional tutorials you might be interested in are: * Custom preprocessing: how to change spectrogram parameters, modify augmentation routines, etc. * Custom training: how to modify and customize model training * Predict with pre-trained CNNs: details on how to predict with pre-trained CNNs. Much of this information was covered in the tutorial above, but this tutorial also includes information about using models made with previous versions of OpenSoundscape

Finally, clean up and remove files created during this tutorial:

[35]:
```
import shutil
dirs = ['./multilabel_train', './binary_train', './woodcock_labeled_data']
[shutil.rmtree(d) for d in dirs]
```

[35]:
```
[None, None, None]
```

# CHAPTER 9

# Custom preprocessing

Preprocessors in OpenSoundscape perform all of the preprocessing steps from loading a file from the disk up to providing a sample to the machine learning algorithm for training or prediction. These classes are used when (a) training a machine learning model in OpenSoundscape, or (b) making predictions with a machine learning model in OpenSoundscape.

If you are already familiar with PyTorch, you might notice that Preprocessors take the place of, and are children of, PyTorch's Dataset classes to provide each sample to PyTorch as a Tensor.

Preprocessors are designed to be flexible and modular, so that each step of the preprocessing pipeline can be modified or removed. This notebook demonstrates:

- preparation of audio data to be used by a preprocessor
- how "Actions" are strung together into "Pipelines" to preprocess data
- modifying the parameters of actions
- turning Actions on and off
- modifying the order and contents of pipelines
- use of the `AudioToSpectrogramPreprocessor` class, including examples of:
  - modifying audio and spectrogram parameters
  - changing the output image shape
  - changing the output type
- use of the `CnnPreprocessor` class, including examples of:
  - choosing between default "augmentation on" and "augmentation off" pipelines
  - modifying augmentation parameters
  - using the "overlay" augmentation
- writing custom preprocessors and actions

First, import the needed packages.

[1]:
```
# Preprocessor classes are used to load, transform, and augment audio samples for use␣
↪in a machine learing model
from opensoundscape.preprocess.preprocessors import BasePreprocessor,␣
↪AudioToSpectrogramPreprocessor, CnnPreprocessor

#other utilities and packages
import torch
import pandas as pd
from pathlib import Path
import numpy as np
import pandas as pd
import random
import subprocess
```

Set up plotting and some helper functions.

[2]:
```
#set up plotting
from matplotlib import pyplot as plt
plt.rcParams['figure.figsize']=[15,5] #for large visuals
%config InlineBackend.figure_format = 'retina'

# helper function for displaying a sample as an image
def show_tensor(sample):
    plt.imshow((sample['X'][0,:,:]/2+0.5)*-1,cmap='Greys',vmin=-1,vmax=0)
    plt.show()
```

Set manual seeds for pytorch and python. These ensure the training results are reproducible. You probably don't want to do this when you actually train your model, but it's useful for debugging.

[3]:
```
torch.manual_seed(0)
random.seed(0)
```

## 9.1 Preparing audio data

### 9.1.1 Download labeled audio files

The Kitzes Lab has created a small labeled dataset of short clips of American Woodcock vocalizations. You have two options for obtaining the folder of data, called `woodcock_labeled_data`:

1. Run the following cell to download this small dataset. These commands require you to have `tar` installed on your computer, as they will download and unzip a compressed file in `.tar.gz` format.
2. Download a `.zip` version of the files by clicking here. You will have to unzip this folder and place the unzipped folder in the same folder that this notebook is in.

**Note**: Once you have the data, you do not need to run this cell again.

[4]:
```
subprocess.run(['curl','https://pitt.box.com/shared/static/
↪79fi7d715dulcldsy6uogz02rsn5uesd.gz','-L', '-o','woodcock_labeled_data.tar.gz']) #␣
↪Download the data
subprocess.run(["tar","-xzf", "woodcock_labeled_data.tar.gz"]) # Unzip the downloaded␣
↪tar.gz file
subprocess.run(["rm", "woodcock_labeled_data.tar.gz"]) # Remove the file after its␣
↪contents are unzipped
```

```
  % Total    % Received % Xferd  Average Speed   Time    Time     Time  Current
                                 Dload  Upload   Total   Spent    Left  Speed
  0     0    0     0    0     0      0      0 --:--:-- --:--:-- --:--:--     0
  0     0    0     0    0     0      0      0 --:--:-- --:--:-- --:--:--     0
100     7    0     7    0     0      5      0 --:--:--  0:00:01 --:--:--     0
100 4031k  100 4031k    0     0  1520k      0  0:00:02  0:00:02 --:--:-- 5069k
```

[4]:
```
CompletedProcess(args=['rm', 'woodcock_labeled_data.tar.gz'], returncode=0)
```

### 9.1.2 Generate one-hot encoded labels

The folder contains 2s long audio clips taken from an autonomous recording unit. It also contains a file `woodcock_labels.csv` which contains the names of each file and its corresponding label information, created using a program called Specky.

We manipulate the label dataframe to give "one hot" labels - that is, a column for every class, with 1 for present or 0 for absent in each sample's row. In this case, our classes are simply 'negative' for files without a woodcock and 'positive' for files with a woodcock. Note that these classes are mutually exclusive, so we have a "single-target" problem (as opposed to a "multi-target" problem where multiple classes can simultaneously be present).

For more details on the steps below, see the basic CNN training and prediction tutorial.

[5]:
```
#load Specky output: a table of labeled audio files
specky_table = pd.read_csv(Path("woodcock_labeled_data/woodcock_labels.csv"))
#update the paths to the audio files
specky_table.filename = ['./woodcock_labeled_data/'+f for f in specky_table.filename]

from opensoundscape.annotations import categorical_to_one_hot
one_hot_labels, classes = categorical_to_one_hot(specky_table[['woodcock']].values)
labels = pd.DataFrame(index=specky_table['filename'],data=one_hot_labels,
↪columns=classes)
labels.head()
```

[5]:

| filename | absent | present |
|---|---|---|
| ./woodcock_labeled_data/d4c40b6066b489518f8da83... | 0 | 1 |
| ./woodcock_labeled_data/e84a4b60a4f2d049d73162e... | 1 | 0 |
| ./woodcock_labeled_data/79678c979ebb880d5ed6d56... | 0 | 1 |
| ./woodcock_labeled_data/49890077267b569e142440f... | 0 | 1 |
| ./woodcock_labeled_data/0c453a87185d8c7ce05c5c5... | 0 | 1 |

## 9.2 Intro to Preprocessors

Preprocessors prepare samples for use by machine learning algorithms by stringing together transformations called **Actions** into a **Pipeline**. The preprocessor sequentially applies to the sample each Action in the Pipeline. You can add, remove, and rearrange Actions from the pipeline and change the parameters of each Action.

The currently implemented Preprocessor classes and their Actions include:

- `CnnPreprocessor` - loads audio files, creates spectrograms, performs various augmentations, and returns a pytorch Tensor.
- `AudioToSpectrogramPreprocessor` - loads audio files, creates spectrograms, and returns a pytorch Tensor (no augmentation).

### 9.2.1 Initialize preprocessor

A Preprocessor must be initialized with a very specific dataframe:

- the index of the dataframe provides paths to audio samples
- the columns are the class names
- the values are 0 (absent/False) or 1 (present/True) for each sample and each class.

For example, we've set up the labels dataframe with files as the index and classes as the columns, so we can use it to make an instance of `CnnPreprocessor`:

[6]:
```
from opensoundscape.preprocess.preprocessors import CnnPreprocessor

preprocessor = CnnPreprocessor(labels)
```

### 9.2.2 Access sample from a Preprocessor

A sample is accessed in a preprocessor using indexing, like a list. Each sample is a dictionary with two keys: 'X', the Tensor of the sample, and 'y', the Tensor of labels of the sample.

[7]:
```
preprocessor[0]
```

[7]:
```
{'X': tensor([[[ 0.0000,  0.0000,  0.0000,  ...,  0.0191, -0.0078,  0.0653],
          [ 0.0000,  0.0000,  0.0000,  ...,  0.0958,  0.0501,  0.0597],
          [ 0.0000,  0.0000,  0.0000,  ...,  0.3639,  0.1509,  0.0387],
          ...,
          [ 0.0000,  0.0000,  0.0000,  ...,  0.0000,  0.0000,  0.0000],
          [ 0.0000,  0.0000,  0.0000,  ...,  0.0000,  0.0000,  0.0000],
          [ 0.0000,  0.0000,  0.0000,  ...,  0.0000,  0.0000,  0.0000]],

         [[ 0.0000,  0.0000,  0.0000,  ..., -0.0090, -0.0230,  0.0743],
          [ 0.0000,  0.0000,  0.0000,  ...,  0.1073,  0.0300,  0.0806],
          [ 0.0000,  0.0000,  0.0000,  ...,  0.3479,  0.1474,  0.0241],
          ...,
          [ 0.0000,  0.0000,  0.0000,  ...,  0.0000,  0.0000,  0.0000],
          [ 0.0000,  0.0000,  0.0000,  ...,  0.0000,  0.0000,  0.0000],
          [ 0.0000,  0.0000,  0.0000,  ...,  0.0000,  0.0000,  0.0000]],

         [[ 0.0000,  0.0000,  0.0000,  ...,  0.0079, -0.0237,  0.0630],
          [ 0.0000,  0.0000,  0.0000,  ...,  0.0936,  0.0200,  0.0808],
          [ 0.0000,  0.0000,  0.0000,  ...,  0.3740,  0.1541,  0.0166],
          ...,
          [ 0.0000,  0.0000,  0.0000,  ...,  0.0000,  0.0000,  0.0000],
          [ 0.0000,  0.0000,  0.0000,  ...,  0.0000,  0.0000,  0.0000],
          [ 0.0000,  0.0000,  0.0000,  ...,  0.0000,  0.0000,  0.0000]]]),
 'y': tensor([0, 1])}
```

### 9.2.3 Subset samples from a Preprocessor

Preprocessors allow you to select a subset of samples using `sample()` and `head()` methods (like Pandas DataFrames). For example:

[8]:
```
len(preprocessor)
```

```
[8]: 29
```

Select the first 10 samples (non-random)

```
[9]: len(preprocessor.head(5))
```

```
[9]: 5
```

Randomly select an absolute number of samples

```
[10]: len(preprocessor.sample(n=10))
```

```
[10]: 10
```

Randomly select a fraction of samples

```
[11]: len(preprocessor.sample(frac=0.5))
```

```
[11]: 14
```

## 9.3 Pipelines and actions

Each Preprocessor class has two attributes, `preprocessor.pipeline` and `preprocessor.actions`. Pipelines are comprised of Actions.

### 9.3.1 About Pipelines

The preprocessor's Pipeline is the ordered list of Actions that the preprocessor performs on each sample.

- The Pipeline is stored in the `preprocessor.pipeline` attribute.
- You can modify the contents or order of Preprocessor Actions by overwriting the preprocessor's `.pipeline` attribute. When you modify this attribute, you must provide a list of Actions, where each Action is an instance of a class that sub-classes `opensoundscape.preprocess.BaseAction`.

Inspect the current pipeline.

```
[12]: # inspect the current pipeline (ordered sequence of Actions to take)
preprocessor.pipeline
```

```
[12]: [<opensoundscape.preprocess.actions.AudioLoader at 0x7fba9d6a7ed0>,
 <opensoundscape.preprocess.actions.AudioTrimmer at 0x7fba9d6a78d0>,
 <opensoundscape.preprocess.actions.AudioToSpectrogram at 0x7fba9d6a7590>,
 <opensoundscape.preprocess.actions.SpectrogramBandpass at 0x7fba9d6a7d10>,
 <opensoundscape.preprocess.actions.SpecToImg at 0x7fba9d67ebd0>,
 <opensoundscape.preprocess.actions.BaseAction at 0x7fba9d6afb50>,
 <opensoundscape.preprocess.actions.TorchColorJitter at 0x7fba9d64d850>,
 <opensoundscape.preprocess.actions.ImgToTensor at 0x7fba9d64d690>,
 <opensoundscape.preprocess.actions.TimeMask at 0x7fba9d6dc9d0>,
 <opensoundscape.preprocess.actions.FrequencyMask at 0x7fba9d6dc990>,
 <opensoundscape.preprocess.actions.TensorAddNoise at 0x7fba9d6dc650>,
 <opensoundscape.preprocess.actions.TensorNormalize at 0x7fba9d64d6d0>,
 <opensoundscape.preprocess.actions.TorchRandomAffine at 0x7fba9d6dc690>]
```

### 9.3.2 About actions

Preprocessors come with a set of predefined Actions that are available to the preprocessor. These are not necessarily all included in the preprocessing pipeline; these are just the transformations that are available to be strung together into a pipeline if desired.

- The Actions are stored in the `preprocessor.actions` attribute. Each Action is an instance of a class (described in more detail below).
- Each Action takes a sample (and its labels*), performs some transformation to them, and returns the sample (and its labels*). The code for this transformation is stored in the Action's `.go()` method.
- You can customize Actions using the `.on()` and `.off()` methods to turn the Action on or off, or by changing the action's parameters. Any customizable parameters for performing the Action are stored in a dictionary, `.params`. This dictionary can be modified using the Action's `.set()` method, e.g. `action.set(param=value, param2=value2, ...)`.
- You can view all the available Actions in a preprocessor using the `.list_actions()` method.

[13]:
```
# create a new instance of a CnnPreprocessor
preprocessor = AudioToSpectrogramPreprocessor(labels)

# print all Actions that have been added to the preprocessor
# (Note that this is not the pipeline, just a collection of available actions)
preprocessor.actions.list_actions()
```

[13]:
```
['load_audio',
 'trim_audio',
 'to_spec',
 'bandpass',
 'to_img',
 'to_tensor',
 'normalize']
```

Notice that the Actions in `preprocessor.actions.list_actions()` are not identical to the names listed in the pipeline, but are parallel. For example, in this case, `preprocessor.actions.to_spec` corresponds to an instance of `opensoundscape.preprocess.actions.AudioToSpectrogram`:

[14]:
```
preprocessor.actions.to_spec
```

[14]:
```
<opensoundscape.preprocess.actions.AudioToSpectrogram at 0x7fba9d6ab210>
```

That's because of the structure of actions:

- The `.actions` attribute is an instance of a class called `ActionContainer` (see below)
- The `ActionContainer` has an attribute for each possible action, e.g. `preprocessor.actions.to_spec`
- Each attribute is defined as an instance of an Action class, e.g. `AudioToSpectrogram`
- Each Action class is a child of a class called `BaseAction`; see the `actions` module for examples.

[15]:
```
preprocessor.actions?
```

```
Type:        ActionContainer
String form: <opensoundscape.preprocess.actions.ActionContainer object at␣
↪0x7fba9a836a90>
File:        ~/opt/miniconda3/envs/opso_py37/lib/python3.7/site-packages/
↪opensoundscape/preprocess/actions.py
Docstring:
```

(continues on next page)

(continued from previous page)

```
this is a container object which holds instances of Action child-classes

the Actions it contains each have .go(), .on(), .off(), .set(), .get()

The actions are un-ordered and may not all be used. In preprocessor objects
such as AudioToSpectrogramPreprocessor, Actions from the action
container are listed in a pipeline(list), which defines their order of use.

To add actions to the container: action_container.loader = AudioLoader()
To set parameters of actions: action_container.loader.set(param=value,...)

Methods: list_actions()
```

## 9.4 Modifying Actions

### 9.4.1 View default parameters for an Action

The docstring for an individual action, such as `preprocessor.actions.to_spec`, gives information on what parameters can be changed and what the defaults are.

[16]:
```
preprocessor.actions.to_spec?
```

```
Type:        AudioToSpectrogram
String form: <opensoundscape.preprocess.actions.AudioToSpectrogram object at␣
↪0x7fba9d6ab210>
File:        ~/opt/miniconda3/envs/opso_py37/lib/python3.7/site-packages/
↪opensoundscape/preprocess/actions.py
Docstring:
Action child class for Spectrogram.from_audio() (Audio -> Spectrogram)

see spectrogram.Spectrogram.from_audio for documentation

Args:
    window_type="hann": see scipy.signal.spectrogram docs for description of window␣
↪parameter
    window_samples=512: number of audio samples per spectrogram window (pixel)
    overlap_samples=256: number of samples shared by consecutive windows
    decibel_limits = (-100,-20) : limit the dB values to (min,max) (lower values set␣
↪to min, higher values set to max)
    dB_scale=True : If True, rescales values to decibels, x=10*log10(x)
        - if dB_scale is False, decibel_limits is ignored
```

Any defaults that have been changed will be shown in the `.params` attribute of the action:

[17]:
```
preprocessor.actions.to_spec.params
```

[17]:
```
{}
```

### 9.4.2 Modify Action parameters

In general, Actions are modified using the `set()` method, e.g.:

[18]:
```
preprocessor.actions.to_spec.set(window_samples=256)
```

We can check that the values were actually changed by printing the action's params. This is not guaranteed to print the defaults, but will definitely print the parameters that have actively changed.

[19]:
```
print(preprocessor.actions.load_audio.params)
```

```
{'sample_rate': None}
```

### 9.4.3 Turn individual Actions on or off

Each Action has `.on()` and `.off()` methods which toggle a bypass of the Action in the pipeline. Note that the Actions will still remain in the same order in the pipeline, and can be turned back on again if desired.

[20]:
```
#initialize a preprocessor that includes augmentation
preprocessor = CnnPreprocessor(labels)
preprocessor.pipeline
```

[20]:
```
[<opensoundscape.preprocess.actions.AudioLoader at 0x7fba9d876850>,
 <opensoundscape.preprocess.actions.AudioTrimmer at 0x7fba9d876890>,
 <opensoundscape.preprocess.actions.AudioToSpectrogram at 0x7fba9d8768d0>,
 <opensoundscape.preprocess.actions.SpectrogramBandpass at 0x7fba9d876910>,
 <opensoundscape.preprocess.actions.SpecToImg at 0x7fba9d876950>,
 <opensoundscape.preprocess.actions.BaseAction at 0x7fba9d876a50>,
 <opensoundscape.preprocess.actions.TorchColorJitter at 0x7fba9d876a90>,
 <opensoundscape.preprocess.actions.ImgToTensor at 0x7fba9d8769d0>,
 <opensoundscape.preprocess.actions.TimeMask at 0x7fba9d6f2e90>,
 <opensoundscape.preprocess.actions.FrequencyMask at 0x7fba9d876b10>,
 <opensoundscape.preprocess.actions.TensorAddNoise at 0x7fba9d876b50>,
 <opensoundscape.preprocess.actions.TensorNormalize at 0x7fba9d876a10>,
 <opensoundscape.preprocess.actions.TorchRandomAffine at 0x7fba9d876ad0>]
```

[21]:
```
#turn off augmentations other than noise
preprocessor.actions.color_jitter.off()
preprocessor.actions.add_noise.off()
preprocessor.actions.time_mask.off()
preprocessor.actions.frequency_mask.off()
preprocessor.pipeline
```

[21]:
```
[<opensoundscape.preprocess.actions.AudioLoader at 0x7fba9d876850>,
 <opensoundscape.preprocess.actions.AudioTrimmer at 0x7fba9d876890>,
 <opensoundscape.preprocess.actions.AudioToSpectrogram at 0x7fba9d8768d0>,
 <opensoundscape.preprocess.actions.SpectrogramBandpass at 0x7fba9d876910>,
 <opensoundscape.preprocess.actions.SpecToImg at 0x7fba9d876950>,
 <opensoundscape.preprocess.actions.BaseAction at 0x7fba9d876a50>,
 <opensoundscape.preprocess.actions.TorchColorJitter at 0x7fba9d876a90>,
 <opensoundscape.preprocess.actions.ImgToTensor at 0x7fba9d8769d0>,
 <opensoundscape.preprocess.actions.TimeMask at 0x7fba9d6f2e90>,
 <opensoundscape.preprocess.actions.FrequencyMask at 0x7fba9d876b10>,
 <opensoundscape.preprocess.actions.TensorAddNoise at 0x7fba9d876b50>,
 <opensoundscape.preprocess.actions.TensorNormalize at 0x7fba9d876a10>,
 <opensoundscape.preprocess.actions.TorchRandomAffine at 0x7fba9d876ad0>]
```

[ ]:
```
print('random affine on')
show_tensor(preprocessor[0])
```

(continues on next page)

(continued from previous page)

```
print('random affine off')
preprocessor.actions.random_affine.off()
show_tensor(preprocessor[0])
```

To view whether an individual Action in a pipeline is on or off, inspect its `bypass` attribute:

[ ]:
```
# The AudioLoader Action that is still on
preprocessor.pipeline[0].bypass
```

[ ]:
```
# The TorchRandomAffine Action that we turned off
preprocessor.pipeline[-1].bypass
```

## 9.5 Modifying the pipeline

Sometimes, you may want to change the order or composition of the Preprocessor's pipeline. You can simply overwrite the `.pipeline` attribute, as long as the new pipeline is still a list of Action instances from the preprocessor's `.actions` ActionContainer.

### 9.5.1 Example: return Spectrogram instead of Tensor

Here's an example where we replace the pipeline with one that just loads audio and converts it to a Spectrogram, returning a Spectrogram instead of a Tensor:

[ ]:
```
#initialize a preprocessor
preprocessor = AudioToSpectrogramPreprocessor(labels)
print('original pipeline:')
[print(p) for p in preprocessor.pipeline]

#overwrite the pipeline with a slice of the original pipeline
print('\nnew pipeline:')
preprocessor.pipeline = preprocessor.pipeline[0:3]

[print(p) for p in preprocessor.pipeline]

print('\nwe now have a preprocessor that returns Spectrograms instead of Tensors:')
print(type(preprocessor[0]['X']))
preprocessor[0]['X'].plot()
```

### 9.5.2 Example: custom augmentation pipeline

Here's an example where we add a new Action to the Action container, then overwrite the preprocessing pipeline with one that includes our new action.

Note that each Action requires a specific input Type and may return that same Type or a different Type. So you'll need to be careful about the order of your Actions in your pipeline

This custom pipeline will first performs a Gaussian noise augmentation, then a random affine, then our second noise augmentation (add_noise_2)

[ ]:
```
#initialize a preprocessor
preprocessor = CnnPreprocessor(labels)

#add a new Action to the Action container
from opensoundscape.preprocess.actions import TensorAddNoise
preprocessor.actions.add_noise_2 = TensorAddNoise(std=0.1)

#overwrite the pipeline with a list of Actions from .actions
preprocessor.pipeline = [
    preprocessor.actions.load_audio,
    preprocessor.actions.trim_audio,
    preprocessor.actions.to_spec,
    preprocessor.actions.bandpass,
    preprocessor.actions.to_img,
    preprocessor.actions.to_tensor,
    preprocessor.actions.normalize,
    preprocessor.actions.add_noise,
    preprocessor.actions.random_affine,
    preprocessor.actions.add_noise_2
]

show_tensor(preprocessor[0])
```

### 9.5.3 Use an Action multiple times in a pipeline

If an Action is present multiple times in a pipeline (e.g. multiple overlays), changing the parameters of the Action at one point in the pipeline will change it at all points in the pipeline. For instance, create a pipeline with multiple "add noise" steps:

[ ]:
```
#initialize a preprocessor that includes augmentation
preprocessor = CnnPreprocessor(labels)

# Insert another instance of the "add_noise" action into the pipeline
preprocessor.pipeline.insert(-2, preprocessor.actions.add_noise)
preprocessor.pipeline
```

Note that changing the parameter of one of the `add_noise` steps changes the parameters for both of them.

[ ]:
```
# Print the parameters of both of the TensorAddNoise Actions in the pipeline
print("Parameters of TensorAddNoise actions before changing:")
[print(f"Params of {p}:", p.params) for p in preprocessor.pipeline[-4:-2]]

# Change the parameters of one of the add noise steps
preprocessor.pipeline[-4].set(std=0.01)

# The modification above is the same as:
#preprocessor.actions.add_noise.set(std=0.01)

# See that the parameters for both steps are changed
print("\nParameters of TensorAddNoise actions after changing:")
[print(f"Params of {p}:", p.params) for p in preprocessor.pipeline[-4:-2]];
```

To modify the parameters of Actions individually, add them as separate Actions in the pipeline by adding a new named action to the action container.

[ ]:
```
from opensoundscape.preprocess.actions import TensorAddNoise

# Add a new possible action to the ActionContainer
preprocessor.actions.my_new_action = TensorAddNoise(std=0.005)

# Replace one of the old actions in the pipeline with the new one with different␣
↪parameters
preprocessor.pipeline[-3] = preprocessor.actions.my_new_action
```

Now notice that the two instances of the `TensorAddNoise` action can have different parameters.

[ ]:
```
[print(f"Params of {p}:", p.params) for p in preprocessor.pipeline[-4:-2]];
```

## 9.6 Customizing AudioToSpectrogramPreprocessor

Below are various examples of how to modify parameters of the Actions of the `AudioToSpectrogramPreprocessor` class, including the `AudioLoader`, `AudioToSpectrogram`, and `SpectrogramBandpass` actions.

### 9.6.1 Modify the sample rate

Re-sample all loaded audio to a specified rate during the load_audio action

[ ]:
```
preprocessor = AudioToSpectrogramPreprocessor(labels)

preprocessor.actions.load_audio.set(sample_rate=24000)
```

### 9.6.2 Modify spectrogram window length and overlap

(see Spectrogram.from_audio() for detailed documentation)

[ ]:
```
print('default parameters:')
show_tensor(preprocessor[0])

print('high time resolution, low frequency resolution:')
preprocessor.actions.to_spec.set(window_samples=64,overlap_samples=32)

show_tensor(preprocessor[0])
```

### 9.6.3 Bandpass spectrograms

Trim spectrograms to a specified frequency range:

[ ]:
```
preprocessor = AudioToSpectrogramPreprocessor(labels)

print('default parameters:')
show_tensor(preprocessor[0])

print('bandpassed to 2-4 kHz:')
preprocessor.actions.bandpass.set(min_f=2000,max_f=4000)
```

(continues on next page)

(continued from previous page)

```
preprocessor.actions.bandpass.on()
show_tensor(preprocessor[0])
```

### 9.6.4 Change the output image

Change the shape of the output image - note that the shape argument expects (height, width), not (widht, height)

```
[ ]: preprocessor = AudioToSpectrogramPreprocessor(labels)
preprocessor.actions.to_img.set(shape=[500,1000])
show_tensor(preprocessor[0])
```

## 9.7 Customizing CnnPreprocessor

The CnnPreprocessor class can be used to perform both audio and spectrogram transformation as well as augmentation for training with CNNs.

This section describes: * A special method of CnnPreprocessor which allows you to turn all augmentations on or off * Examples of modifying augmentation parameters for standard augmentations * Detailed descriptions of the useful "Overlay" augmentation

### 9.7.1 Turn all augmentation on or off

With CnnPreprocessor, we can easily choose between a pipeline that contains augmentations and a pipeline with no augmentations using the shortcuts augmentation_off() and augmentation_on() methods. Using these methods will overwrite any changes made to the pipeline, so apply them first before further customizing an instance of CnnPreprocessor.

```
[ ]: preprocessor = CnnPreprocessor(labels)
preprocessor.augmentation_off()
preprocessor.pipeline
```

```
[ ]: preprocessor.augmentation_on()
preprocessor.pipeline
```

### 9.7.2 Modify augmentation parameters

CnnPreprocessor includes several augmentations with customizable parameters. Here we provide a couple of illustrative examples - see any action's documentation for details on how to use its parameters.

```
[ ]: #initialize a preprocessor
preprocessor = CnnPreprocessor(labels)

#turn off augmentations other than overlay
preprocessor.actions.color_jitter.off()
preprocessor.actions.random_affine.off()
preprocessor.actions.random_affine.off()
preprocessor.actions.time_mask.off()

# allow up to 20 horizontal masks, each spanning up to 0.1x the height of the image.
```

(continues on next page)

(continued from previous page)

```
preprocessor.actions.frequency_mask.set(max_width = 0.1, max_masks=20)
show_tensor(preprocessor[0])
```

[ ]:
```
#turn off frequency mask and turn on gaussian noise
preprocessor.actions.add_noise.on()
preprocessor.actions.frequency_mask.off()

# increase the intensity of gaussian noise added to the image
preprocessor.actions.add_noise.set(std=0.2)
show_tensor(preprocessor[0])
```

### 9.7.3 Overlay augmentation

Overlay is a powerful Action that allows additional samples to be overlayed or blended with the original sample.

The additional samples are chosen from the `overlay_df` that is provided to the preprocessor when it is initialized. The index of the `overlay_df` must be paths to audio files. The dataframe can be simply an index containing audio files with no other columns, or it can have the same columns as the sample dataframe for the preprocessor.

Samples for overlays are chosen based on their class labels, according to the parameter `overlay_class`:

- `None` - Randomly select any file from `overlay_df`
- `"different"` - Select a random file from `overlay_df` containing none of the classes this file contains
- specific class name - always choose files from this class

Samples can be drawn from dataframes in a few general ways (each is demonstrated below):

1. Using a separate dataframe where any sample can be overlayed (`overlay_class=None`)
2. Using the same dataframe as training, where the overlay class is "different," i.e., does not contain overlapping labels with the original sample
3. Using the same dataframe as training, where samples from a specific class are used for overlays

By default, the overlay Action does **not** change the labels of the sample it modifies. However, if you wish to add the labels from overlayed samples to the original sample's labels, you can set `update_labels=True` (see example below).

[ ]:
```
#initialize a preprocessor and provide a dataframe with samples to use as overlays
preprocessor = CnnPreprocessor(labels, overlay_df=labels)

#turn off augmentations other than overlay
preprocessor.actions.color_jitter.off()
preprocessor.actions.random_affine.off()
preprocessor.actions.random_affine.off()
preprocessor.actions.time_mask.off()
preprocessor.actions.frequency_mask.off()
```

#### Modify `overlay_weight`

We'll first overlay a random sample with 30% of the final mix coming from the overlayed sample (70% coming from the original) by using `overlay_weight=0.3`.

To demonstrate this, let's show what happens if we overlay samples from the "negative" class, resulting in the final sample having a higher or lower signal-to-noise ratio. By default, the overlay Action chooses a random file from the overlay dataframe. Instead, choose a sample from the class called `"absent"` using the `overlay_class` parameter.

[ ]:
```
preprocessor.actions.overlay.set(
    overlay_class='absent',
    overlay_weight=0.3
)
show_tensor(preprocessor[0])
```

Now use `overlay_weight=0.8` to increase the contribution of the overlayed sample (80%) compared to the original sample (20%).

[ ]:
```
preprocessor.actions.overlay.set(overlay_weight=0.8)
show_tensor(preprocessor[0])
```

### Overlay samples from a specific class

As demonstrated above, you can choose a specific class to choose samples from. Here, instead, we choose samples from the "positive" class.

[ ]:
```
preprocessor.actions.overlay.set(
    overlay_class='present',
    overlay_weight=0.4
)
show_tensor(preprocessor[0])
```

### Overlaying samples from any class

By default, or by specifying `overlay_class=None`, the overlay sample is chosen randomly from the overlay_df with no restrictions

[ ]:
```
preprocessor.actions.overlay.set(overlay_class=None)
show_tensor(preprocessor[0])
```

### Overlaying samples from a "different" class

The `'different'` option for `overlay_class` chooses a sample to overlay that has non-overlapping labels with the original sample.

In the case of this example, this has the same effect as drawing samples from the `"negative"` class a demonstrated above. In multi-class examples, this would draw from any of the samples not labeled with the class(es) of the original sample.

We'll again use `overlay_weight=0.8` to exaggerate the importance of the overlayed sample (80%) compared to the original sample (20%).

[ ]:
```
preprocessor.actions.overlay.set(update_labels=False,overlay_class='different',
↪overlay_weight=0.8)
show_tensor(preprocessor[0])
```

### Updating labels

By default, the overlay Action does **not** change the labels of the sample it modifies.

For instance, if the overlayed sample has labels [1,0] and the original sample has labels [0,1], the default behavior will return a sample with labels [0,1] not [1,1].

If you wish to add the labels from overlayed samples to the original sample's labels, you can set `update_labels=True`.

[ ]:
```
print('default: labels do not update')
preprocessor.actions.overlay.set(update_labels=False,overlay_class='different')
print(f"\t resulting labels: {preprocessor[0]['y'].numpy()}")

print('Using update_labels=True')
preprocessor.actions.overlay.set(update_labels=True,overlay_class='different')
print(f"\t resulting labels: {preprocessor[0]['y'].numpy()}")
```

This example is a single-target problem: the two classes represent "woodcock absent" and "woodcock present." Because the labels are mutually exclusive, labels [1,1] do not make sense. So, for this single-target problem, we would not want to use `update_labels=True`, and it would probably make most sense to only overlay absent recordings, e.g., `overlay_class='absent'`.

## 9.8 Creating a new Preprocessor class

If you have a specific augmentation routine you want to perform, you may want to create your own Preprocessor class rather than modifying an existing one.

Your subclass might add a different set of Actions, define a different pipeline, or even override the `__getitem__` method of BasePreprocessor.

Here's an example of a customized preprocessor that subclasses `AudioToSpectrogramPreprocessor` and creates a pipeline that depends on the `magic_parameter` input.

[ ]:
```
from opensoundscape.preprocess.actions import TensorAddNoise
class MyPreprocessor(AudioToSpectrogramPreprocessor):
    """Child of AudioToSpectrogramPreprocessor with weird augmentation routine"""

    def __init__(
        self,
        df,
        magic_parameter,
        audio_length=None,
        return_labels=True,
        out_shape=[224, 224],
    ):

        super(MyPreprocessor, self).__init__(
            df,
            audio_length=audio_length,
            out_shape=out_shape,
            return_labels=return_labels,
        )

        self.actions.add_noise = TensorAddNoise(std=0.1*magic_parameter)
```

(continues on next page)

(continued from previous page)

```
        self.pipeline = [
            self.actions.load_audio,
            self.actions.trim_audio,
            self.actions.to_spec,
            self.actions.bandpass,
            self.actions.to_img,
            self.actions.to_tensor,
            self.actions.normalize,
        ] + [self.actions.add_noise for i in range(magic_parameter)]
```

[ ]:
```
p = MyPreprocessor(labels, magic_parameter=2)
show_tensor(p[0])
```

[ ]:
```
p = MyPreprocessor(labels, magic_parameter=3)
show_tensor(p[0])
```

## 9.9 Defining new Actions

You can define new Actions to include in your Preprocessor pipeline. They should subclass `opensoundscape.actions.BaseAction`.

You will need to define a `.go()` method for all actions. If you provide default parameter values, you will also need to define an `__init__()` method.

### 9.9.1 Without default parameters

If the Action does not need to have default arguments, it's trivial to create by defining a `go()` method.

[ ]:
```
from opensoundscape.preprocess.actions import BaseAction
class SquareSamples(BaseAction):
    """Square values of every audio sample

    Audio in, Audio out
    """
    def go(self, audio):
        samples = np.array(audio.samples)**2
        return Audio(samples, audio.sample_rate)
```

Test it out:

[ ]:
```
from opensoundscape.audio import Audio

square_action = SquareSamples(threshold=0.2)

audio = Audio.from_file('./woodcock_labeled_data/01c5d0c90bd4652f308fd9c73feb1bf5.wav
↪')
print(np.mean(audio.samples))
audio = square_action.go(audio)
print(np.mean(audio.samples))
```

### 9.9.2 With default parameters

Here we overwrite the `__init__` method to provide a default parameter value. The Action below removes low-amplitude audio samples, acting somewhat as a "denoiser".

```
[ ]: class AudioGate(BaseAction):
         """Replace audio samples below a threshold with 0

         Audio in, Audio out

         Args:
             threshold: sample values below this will become 0
         """

         def __init__(self, **kwargs):
             super(AudioGate, self).__init__(**kwargs)

             # default parameters
             self.params["threshold"] = 0.1

             # update/add any parameters passed to __init__
             self.params.update(kwargs)

         def go(self, audio):
             samples = np.array([0 if np.abs(s)<self.params["threshold"] else s for s in␣
     ↪audio.samples])
             return Audio(samples, audio.sample_rate)
```

Test it out:

```
[ ]: gate_action = AudioGate(threshold=0.2)

     print('histogram of samples')
     audio = Audio.from_file('./woodcock_labeled_data/01c5d0c90bd4652f308fd9c73feb1bf5.wav
     ↪')
     _ = plt.hist(audio.samples,bins=100)
     plt.semilogy()
     plt.show()

     print('histogram of samples after audio gate')
     audio_gated = gate_action.go(audio)
     _ = plt.hist(audio_gated.samples,bins=100)
     plt.semilogy()
```

Clean up files created during this tutorial:

```
[ ]: import shutil
     shutil.rmtree('./woodcock_labeled_data')
```

```
[ ]:
```

# CHAPTER 10

## Advanced CNN training

This notebook demonstrates how to use classes from `opensoundscape.torch.models.cnn` and architectures created using `opensoundscape.torch.architectures.cnn_architectures` to

- choose between single-target and multi-target model behavior
- modify learning rates, learning rate decay schedule, and regularization
- choose from various CNN architectures
- train a multi-target model with a special loss function
- use strategic sampling for imbalanced training data
- customize preprocessing: train on spectrograms with a bandpassed frequency range

Rather than demonstrating their effects on training (model training is slow!), most examples in this notebook either don't train the model or "train" it for 0 epochs for the purpose of demonstration.

For introductory demos (basic training, prediction, saving/loading models), see the "Beginner-friendly training and prediction with CNNs" tutorial (cnn.ipynb).

[1]:
```
from opensoundscape.preprocess import preprocessors
from opensoundscape.torch.models import cnn
from opensoundscape.torch.architectures import cnn_architectures

import torch
import pandas as pd
from pathlib import Path
import numpy as np
import random
import subprocess

from matplotlib import pyplot as plt
plt.rcParams['figure.figsize']=[15,5] #for big visuals
%config InlineBackend.figure_format = 'retina'
```

## 10.1 Prepare audio data

### 10.1.1 Download labeled audio files

The Kitzes Lab has created a small labeled dataset of short clips of American Woodcock vocalizations. You have two options for obtaining the folder of data, called `woodcock_labeled_data`:

1. Run the following cell to download this small dataset. These commands require you to have `tar` installed on your computer, as they will download and unzip a compressed file in `.tar.gz` format.
2. Download a `.zip` version of the files by clicking here. You will have to unzip this folder and place the unzipped folder in the same folder that this notebook is in.

If you already have these files, you can skip or comment out this cell

[2]:
```
subprocess.run(['curl','https://pitt.box.com/shared/static/
↪79fi7d715dulcldsy6uogz02rsn5uesd.gz','-L', '-o','woodcock_labeled_data.tar.gz']) #␣
↪Download the data
subprocess.run(["tar","-xzf", "woodcock_labeled_data.tar.gz"]) # Unzip the downloaded␣
↪tar.gz file
subprocess.run(["rm", "woodcock_labeled_data.tar.gz"]) # Remove the file after its␣
↪contents are unzipped
```

```
  % Total    % Received % Xferd  Average Speed   Time    Time     Time  Current
                                 Dload  Upload   Total   Spent    Left  Speed
  0     0    0     0    0     0      0      0 --:--:-- --:--:-- --:--:--     0
  0     0    0     0    0     0      0      0 --:--:-- --:--:-- --:--:--     0
100     7    0     7    0     0      6      0 --:--:--  0:00:01 --:--:--     0
100 4031k  100 4031k    0     0  1405k      0  0:00:02  0:00:02 --:--:-- 3158k
```

[2]:
```
CompletedProcess(args=['rm', 'woodcock_labeled_data.tar.gz'], returncode=0)
```

### 10.1.2 Create one-hot encoded labels

See the “Basic training and prediction with CNNs” tutorial for more details.

The audio data includes 2s long audio clips taken from an autonomous recording unit and a CSV of labels. We manipulate the label dataframe to give “one hot” labels - that is, a column for every class, with 1 for present or 0 for absent in each sample’s row. In this case, our classes are simply ‘negative’ for files without a woodcock and ‘positive’ for files with a woodcock. Note that these classes are mutually exclusive, so we have a “single-target” problem (as opposed to a “multi-target” problem where multiple classes can simultaneously be present).

For more details on the steps below, see the “basic training and prediction with CNNs” tutorial.

[3]:
```
#load Specky output: a table of labeled audio files
specky_table = pd.read_csv(Path("woodcock_labeled_data/woodcock_labels.csv"))
#update the paths to the audio files
specky_table.filename = ['./woodcock_labeled_data/'+f for f in specky_table.filename]

from opensoundscape.annotations import categorical_to_one_hot
one_hot_labels, classes = categorical_to_one_hot(specky_table[['woodcock']].values)
labels = pd.DataFrame(index=specky_table['filename'],data=one_hot_labels,
↪columns=classes)
labels.head()
```

[3]:
```
                                                    absent  present
filename
```

(continues on next page)

(continued from previous page)

```
./woodcock_labeled_data/d4c40b6066b489518f8da83...        0         1
./woodcock_labeled_data/e84a4b60a4f2d049d73162e...        1         0
./woodcock_labeled_data/79678c979ebb880d5ed6d56...        0         1
./woodcock_labeled_data/49890077267b569e142440f...        0         1
./woodcock_labeled_data/0c453a87185d8c7ce05c5c5...        0         1
```

### 10.1.3 Split into train and validation sets

Randomly split the data into training data and validation data.

[4]:
```
from sklearn.model_selection import train_test_split
train_df, valid_df = train_test_split(labels, test_size=0.2, random_state=0)
# for multi-class need at least a few images for each batch
len(train_df)
```

[4]:
```
23
```

### 10.1.4 Create Preprocessors

Preprocessors take the audio data specified by the dataframe created above and prepare it for use by Pytorch, e.g., creating spectrograms and performing augmentation. The class CnnPreprocessor contains a set of preprocessing and augmentation parameters that we have developed as a good starting point for general bioacoustics recognition problems. You can modify the preprocessing and augmentation parameters after creating the object. For more detail, see the "Basic training and prediction with CNNs" tutorial and the "Custom preprocessors" tutorial.

[5]:
```
train_dataset = preprocessors.CnnPreprocessor(train_df, overlay_df=train_df)

valid_dataset = preprocessors.CnnPreprocessor(valid_df, overlay_df=valid_df, return_
↪labels=True)
```

[6]:
```
train_dataset.audio_length
```

## 10.2 Creating a model

In general, we initialize a model object by providing the architecture object (ie a pytorch model) and a list of classes.

[7]:
```
arch = cnn_architectures.resnet50(num_classes=len(classes))
model = cnn.PytorchModel(arch,classes)
```

```
created PytorchModel model object with 2 classes
```

Alternatively, we can specify the name of an architecture as a string (see Cnn Architectures below for details)

[8]:
```
model = cnn.PytorchModel('resnet18',classes)
```

```
created PytorchModel model object with 2 classes
```

### 10.2.1 Single-target versus multi-target

One important decision is whether your model is single-target (exactly one label per sample) or multi-target (any number of labels per sample, including 0). Single-target models have a softmax activation layer which forces the sum of all class scores to be 1.0. By default, models are created as multi-target, but you can set `single_target=True` either when creating the object or afterwards.

[9]:
```
#change the model to be single_target
model.single_target = True

#or specify single_target when you create the object
model = cnn.PytorchModel(arch,classes,single_target=True)
```

```
created PytorchModel model object with 2 classes
```

## 10.3 Model training parameters

We can modify various parameters about model training, including:

- The learning rate
- The learning rate schedule
- Weight decay for regularization

Let's take a peek at the current parameters, stored in a dictionary.

[10]:
```
model.optimizer_params
```

[10]:
```
{'lr': 0.01, 'momentum': 0.9, 'weight_decay': 0.0005}
```

### 10.3.1 Learning rates

The learning rate determines how much the model's weights change every time it calculates the loss function.

Faster learning rates improve the speed of training and help the model leave local minima as it learns to classify, but if the learning rate is too fast, the model may not successfully fit the data or its fitting might be unstable.

Often after training a model for a while at a relatively high learning rate (think 0.01), we might want to "fine tune" the model by training for a few epochs with a lower learning rate. Let's set a low learning rate for fine tuning:

[11]:
```
model.optimizer_params['lr']=0.001
```

### 10.3.2 Separate learning rates for feature and classifier blocks

In the `Resnet18Multiclass` and `Resnet18Binary` classes, we can modify the learning rates for the feature extration and classification blocks of the network separately. For example, we can specify a relatively fast learning rate for classifier and slower one for features, if we think the features from a pre-trained model are close to optimal but we have a different set of classes than the pre-trained model.

[12]:
```
r18_model = cnn.Resnet18Binary(classes)
print(r18_model.optimizer_params)
r18_model.optimizer_params['feature']['lr'] = 0.001
r18_model.optimizer_params['classifier']['lr'] = 0.01
```

```
created PytorchModel model object with 2 classes
{'feature': {'lr': 0.001, 'momentum': 0.9, 'weight_decay': 0.0005}, 'classifier': {'lr
↪': 0.01, 'momentum': 0.9, 'weight_decay': 0.0005}}
```

### 10.3.3 Learning rate schedule

It's often helpful to decrease the learning rate over the course of training. By reducing the amount that the model's weights are updated as time goes on, this causes the learning to gradually switch from coarsely searching across possible weights to fine-tuning the weights.

By default, the learning rates are multiplied by 0.7 (the learning rate "cooling factor") once every 10 epochs (the learning rate "update interval").

Let's modify that for a very fast training schedule, where we want to multiply the learning rates by 0.1 every epoch.

[13]:
```
model.lr_cooling_factor = 0.1
model.lr_update_interval = 1
```

### 10.3.4 Regularization weight decay

Pytorch optimizers perform L2 regularization, giving the optimizer an incentive for the model to have small weights rather than large weights. The goal of this regularization is to reduce overfitting to the training data by reducing the complexity of the model.

Depending on how much emphasis you want to place on the L2 regularization, you can change the weight decay parameter. By default, it is 0.0005. The higher the value for the "weight decay" parameter, the more the model training algorithm prioritizes smaller weights.

[14]:
```
model.optimizer_params['weight_decay']=0.001
```

## 10.4 Selecting CNN architectures

The `` `opensoundscape.torch.architectures.cnn_architectures `` <https://github.com/kitzeslab/opensoundscape/blob/master/opensoundscape/torch/architectures/cnn_architectures.py>`__ module provides functions to create several common CNN architectures. These architectures are built in to pytorch, but the OpenSoundscape module helps us out by reshaping the final layer to match the number of classes we have.

You could also create a custom architecture by subclassing an existing pytorch model or writing one from scratch (the minimum requirement is that it subclasses `torch.nn.Module` - it should at least have `.forward()` and `.backward()` methods.

In general, we can create any pytorch model architecture and pass it to the `architecture` argument when creating a model in opensoundscape. We can choose whether to use pre-trained (ImageNet) weights or start from scratch (`use_pretrained=False` for random weights). For instance, lets create an alexnet architecture with random weights:

[15]:
```
my_arch = cnn_architectures.alexnet(num_classes=len(classes),use_pretrained=False)
```

For convenience, we can also initialize a model object by providing the name of an architecture as a string, rather than the architecture object. For a list of valid architecture names, use `cnn_architectures.list_architectures()`. Note that these will use default architecture parameters, including using pre-trained ImageNet weights.

[16]:
```
print(cnn_architectures.list_architectures())
```

```
['resnet18', 'resnet34', 'resnet50', 'resnet101', 'resnet152', 'alexnet', 'vgg11_bn',
↪'squeezenet1_0', 'densenet121', 'inception_v3']
```

[17]:
```
model = cnn.PytorchModel(architecture='resnet18',classes=classes)
```

```
created PytorchModel model object with 2 classes
```

### 10.4.1 Pretrained weights

In OpenSoundscape, by default, model architectures are initialized with weights pretrained on the ImageNet image database. It takes some time for pytorch to download these weights from an online repository the first time an instance of a particular architecture is created with pretrained weights - pytorch will do this automatically and only once.

Using pretrained weights often speeds up training significantly, as the representation learned from ImageNet is a good start at beginning to interpret spectrograms, even though they are not true "pictures."

If you prefer not to use pre-trained weights, or if you don't have an internet connection, you can specify `use_pretrained` argument to `False`, when creating an architecture:

[18]:
```
arch = cnn_architectures.alexnet(num_classes=10,use_pretrained=False)
```

### 10.4.2 Freezing the feature extractor

Convolutional Neural Networks can be thought of as having two parts: a **feature extractor** which learns how to represent/"see" the input data, and a **classifier** which takes those representations and transforms them into predictions about the class identity of each sample.

You can freeze the feature extractor if you only want to train the final classification layer of the network but not modify any other weights. This could be useful for applying pre-trained classifiers to new data, i.e. "transfer learning". To do so, set the `freeze_feature_extractor` argument to `True` when you create an architecture.

[19]:
```
# See "InceptionV3 architecture" section below for more information
arch = cnn_architectures.resnet50(num_classes=10, freeze_feature_extractor=True, use_
↪pretrained=False)
```

### 10.4.3 InceptionV3 class

The Inception architecture requires slightly different training and preprocessing from the ResNet architectures and the other architectures implemented in OpenSoundscape (see below), because:

1) the input image shape must be 299x299, and
2) Inception's forward pass gives output + auxiliary output.

The InceptionV3 class in `cnn` handles the necessary modifications in training and prediction for you, but you'll need to make sure to pass images of the correct shape from your Preprocessor. Here's an example:

[20]:
```
from opensoundscape.torch.models.cnn import InceptionV3

#generate an Inception model
model = InceptionV3(classes=classes,use_pretrained=False)

#create a copy of the training dataset from above
inception_dataset = train_dataset.sample(frac=1)

#modify the preprocessor to give 299x299 image shape
inception_dataset.actions.to_img.set(shape=[299,299])
```

(continues on next page)

(continued from previous page)

```
#train and validate for 1 epoch
#note that Inception will complain if batch_size=1
model.train(inception_dataset,inception_dataset,epochs=0,batch_size=4)

#predict
preds, _, _ = model.predict(inception_dataset)
```

```
/Users/SML161/opt/miniconda3/envs/opso_py37/lib/python3.7/site-packages/torchvision/
↪models/inception.py:83: FutureWarning: The default weight initialization of␣
↪inception_v3 will be changed in future releases of torchvision. If you wish to keep␣
↪the old behavior (which leads to long initialization times due to scipy/scipy
↪#11299), please set init_weights=True.
  ' due to scipy/scipy#11299), please set init_weights=True.', FutureWarning)
```

```
created PytorchModel model object with 2 classes

Best Model Appears at Epoch 0 with F1 0.000.
(23, 2)
```

### 10.4.4 Changing the architecture of an existing model

The architecture is stored in the model object's `.newtork` attribute. We can access parameters of the network or even replace it entirely:

[21]:
```
#initialize the AlexNet architecture
new_arch = cnn_architectures.densenet121(num_classes=2, use_pretrained=False)

# replace the alexnet architecture with the densenet architecture
model.network = new_arch
```

## 10.5 Sampling for imbalanced training data

The imbalanced data sampler will help to ensure that a single batch contains only a few classes during training, and that the classes will recieve approximately equal representation within the batch. This may be useful for *imbalanced* training data (when some classes have far fewer training samples than others). However, in practice it may be better to upsample your training data for equal class representation.

[22]:
```
model = cnn.PytorchModel('resnet18',classes)
model.sampler = 'imbalanced' #default is None

#...you can now train your model as normal
model.train(train_dataset, valid_dataset, epochs=0)

#once we run train(), we can see that the train_loader is using an␣
↪ImbalancedDatasetSampler
print('sampler:')
model.train_loader.sampler
```

```
created PytorchModel model object with 2 classes

Best Model Appears at Epoch 0 with F1 0.000.
sampler:
```

[22]:
```
<opensoundscape.torch.sampling.ImbalancedDatasetSampler at 0x7fda3cb19510>
```

## 10.6 Multi-target training with CnnResampleLoss

Training multi-target models (a.k.a. multi-label: there can be any number of positive labels on each sample) is challenging and can benefit from using a modified loss function. OpenSoundscape provides a subclass of PytorchModel called CnnResampleLoss, which implements a loss function designed for training multi-target models. We recommend using this class rather than PytorchModel when training multi-target models. The use of the class is identical:

[23]:
```
model = cnn.CnnResampleLoss('resnet18',classes)
#use as normal...
#model.train(...)
#model.predict(...)
```

```
created PytorchModel model object with 2 classes
```

## 10.7 Training and predicting with custom preprocessors

The preprocessing tutorial gives in-depth descriptions of how to customize your preprocessing pipeline.

Here, we'll just give a quick example of tweaking the preprocessing pipeline: providing the CNN with a bandpassed spectrogram object instead of the full frequency range.

It's good practice to create the validation from the training dataset (after any modifications are made), so that they perform the same preprocessing. You may or may not want to use augmentation on the validation dataset.

### 10.7.1 Bandpassed spectrograms

[24]:
```
model = cnn.PytorchModel('resnet18', classes)

# turn on the bandpass action
train_dataset.actions.bandpass.on()

# specify the min and max frequencies for the bandpass action
train_dataset.actions.bandpass.set(min_f=3000, max_f=5000)

# create a validation dataset that matches the modified train_dataset
valid_dataset = train_dataset.sample(n=0)
valid_dataset.df = valid_df
#valid_dataset.augmentation_off() #uncomment to turn off augmentation on validation␣
↪set

# now we can train and validate on the bandpassed spectrograms
# don't forget that you'll need to apply the same bandpass actions to
# any datasets that you use for prediction as well
model.train(train_dataset, valid_dataset, epochs=0)
```

```
created PytorchModel model object with 2 classes

Best Model Appears at Epoch 0 with F1 0.000.
```

### 10.7.2 Matching preprocessing parameters during prediction

If we predict using this model later (even if we load it from a saved file), we can create a dataset with the correct preprocessing parameters using `model.train_dataset`:

[25]:
```
model.save('./saved.model')
```

[26]:
```
model_from_saved = cnn.load_model('./saved.model')
prediction_preprocessor = model_from_saved.train_dataset.sample(n=0)
#turn off augmentation for prediction
prediction_preprocessor.augmentation_off()
prediction_preprocessor.df = valid_df
print('Bandpassing parameters of prediction preprocessor:')
print(prediction_preprocessor.actions.bandpass.params)
```

```
Bandpassing parameters of prediction preprocessor:
{'min_f': 3000, 'max_f': 5000, 'out_of_bounds_ok': False}
```

### 10.7.3 clean up

remove files

[27]:
```
import shutil
shutil.rmtree('./woodcock_labeled_data')

for p in Path('.').glob('*.model'):
    p.unlink()
```

# CHAPTER 11

# RIBBIT Pulse Rate model demonstration

RIBBIT (Repeat-Interval Based Bioacoustic Identification Tool) is a tool for detecting vocalizations that have a repeating structure.

This tool is useful for detecting vocalizations of frogs, toads, and other animals that produce vocalizations with a periodic structure. In this notebook, we demonstrate how to select model parameters for the Great Plains Toad, then run the model on data to detect vocalizations.

This work is described in:

- 2021 paper, "Automated detection of frog calls and choruses by pulse repetition rate"
- 2020 poster, "Automatic Detection of Pulsed Vocalizations"

RIBBIT is also available as an R package.

This notebook demonstrates how to use the RIBBIT tool implemented in opensoundscape as `opensoundscape.ribbit.ribbit()`

For help instaling OpenSoundscape, see the documentation

## 11.1 Import packages

[1]:
```
# suppress warnings
import warnings
warnings.simplefilter('ignore')

#import packages
import numpy as np
from glob import glob
import pandas as pd
from matplotlib import pyplot as plt
import subprocess

#local imports from opensoundscape
```
(continues on next page)

(continued from previous page)

```
from opensoundscape.audio import Audio
from opensoundscape.spectrogram import Spectrogram
from opensoundscape.ribbit import ribbit

# create big visuals
plt.rcParams['figure.figsize']=[15,8]
pd.set_option('display.precision', 2)
```

## 11.2 Download example audio

First, let's download some example audio to work with.

You can run the cell below, **OR** visit this link to downlaod the data (whichever you find easier):

https://pitt.box.com/shared/static/0xclmulc4gy0obewtzbzyfnsczwgr9we.zip

If you download using the link above, first un-zip the folder (double-click on mac or right-click -> extract all on Windows). Then, move the `great_plains_toad_dataset` folder to the same location on your computer as this notebook. Then you can skip this cell:

[2]:
```
#download files from box.com to the current directory
subprocess.run(['curl', 'https://pitt.box.com/shared/static/
↪9mrxib85y1jmf1ybbjvbr0tv171iekvy.gz','-L', '-o', 'great_plains_toad_dataset.tar.gz
↪']) # Download the data
subprocess.run(["tar","-xzf", "great_plains_toad_dataset.tar.gz"]) # Unzip the␣
↪downloaded tar.gz file
subprocess.run(["rm", "great_plains_toad_dataset.tar.gz"]) # Remove the file after␣
↪its contents are unzipped
```

[2]:
```
CompletedProcess(args=['rm', 'great_plains_toad_dataset.tar.gz'], returncode=0)
```

now, you should have a folder in the same location as this notebook called `great_plains_toad_dataset`

if you had trouble accessing the data, you can try using your own audio files - just put them in a folder called `great_plains_toad_dataset` in the same location as this notebook, and this notebook will load whatever is in that folder

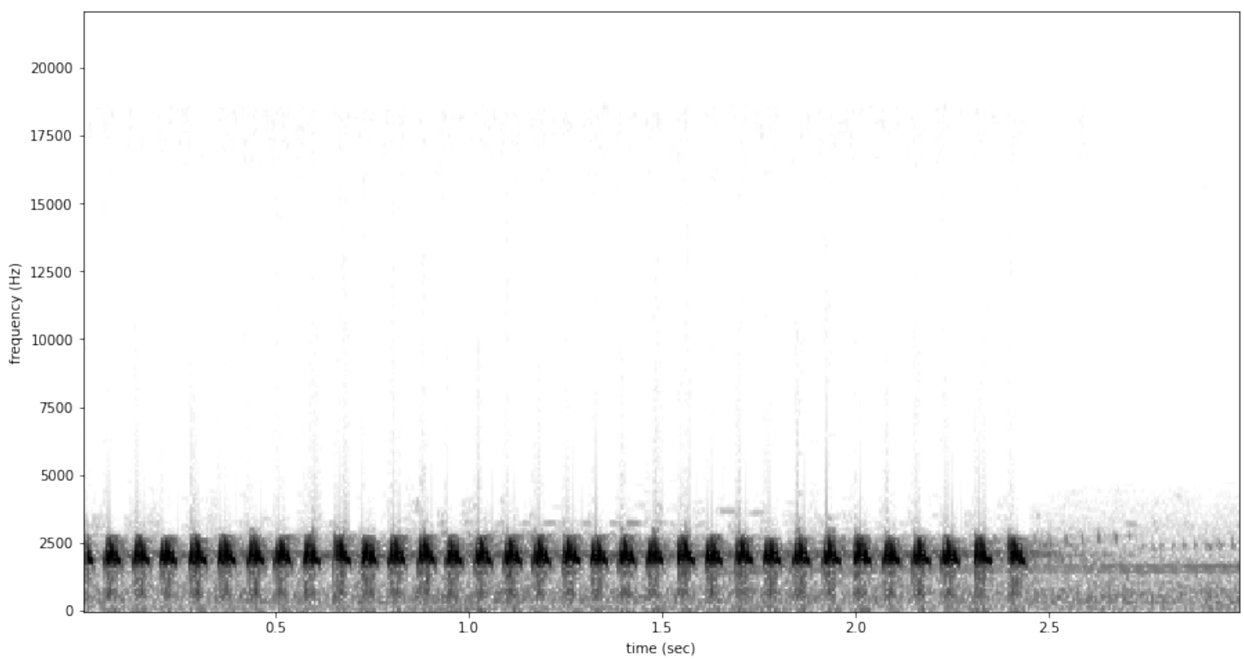
### 11.2.1 Load an audio file and create a spectrogram

[3]:
```
audio_path = np.sort(glob('./great_plains_toad_dataset/*'))[0]

#load the audio file into an OpenSoundscape Audio object
audio = Audio.from_file(audio_path)

#trim the audio to the time from 0-3 seconds for a closer look
audio = audio.trim(0,3)

#create a Spectrogram object
spectrogram = Spectrogram.from_audio(audio)
```

### 11.2.2 Show the Great Plains Toad spectrogram as an image

A spectrogram is a visual representation of audio with frequency on the vertical axis, time on the horizontal axis, and intensity represented by the color of the pixels

[4]:
```
spectrogram.plot()
```




## 11.3 Select model parameters

RIBBIT requires the user to select a set of parameters that describe the target vocalization. Here is some detailed advice on how to use these parameters.

**Signal Band:** The signal band is the frequency range where RIBBIT looks for the target species. Based on the spectrogram above, we can see that the Great Plains Toad vocalization has the strongest energy around 2000-2500 Hz, so we will specify `signal_band = [2000,2500]`. It is best to pick a narrow signal band if possible, so that the model focuses on a specific part of the spectrogram and has less potential to include erronious sounds.

**Noise Bands:** Optionally, users can specify other frequency ranges called noise bands. Sounds in the `noise_bands` are *subtracted* from the `signal_band`. Noise bands help the model filter out erronious sounds from the recordings, which could include confusion species, background noise, and popping/clicking of the microphone due to rain, wind, or digital errors. It's usually good to include one noise band for very low frequencies – this specifically eliminates popping and clicking from being registered as a vocalization. It's also good to specify noise bands that target confusion species. Another approach is to specify two narrow `noise_bands` that are directly above and below the `signal_band`.

**Pulse Rate Range:** This parameters specifies the minimum and maximum pulse rate (the number of pulses per second, also known as pulse repetition rate) RIBBIT should look for to find the focal species. Looking at the spectrogram above, we can see that the pulse rate of this Great Plains Toad vocalization is about 15 pulses per second. By looking at other vocalizations in different environmental conditions, we notice that the pulse rate can be as slow as 10 pulses per second or as fast as 20. So, we choose `pulse_rate_range = [10, 20]` meaning that RIBBIT should look for pulses no slower than 10 pulses per second and no faster than 20 pulses per second.

**Clip Duration:** This parameter tells the algorithm how many seconds of audio to analyze at one time. Generally, you should choose a `clip_duration` that is ~2x longer than the target species vocalization, or a little bit longer. For very slowly pulsing vocalizations, choose a longer window so that at least 5 pulses can occur in one window (0.5 pulses per second -> 10 second window). Typical values for `clip_duration` are 0.3 to 10 seconds. Here, because the The Great Plains Toad has a vocalization that continues on for many seconds (or minutes!), we chose a 2-second window which will include plenty of pulses.

- we can also set `clip_overlap` if we want overlapping clips. For instance, a `clip_duration` of 2 with `clip_overlap` of 1 results in 50% overlap of each consecutive clip. This can help avoid sounds being split up across two clips, and therefore not being detected.
- `final_clip` determines what should be done when there is less than `clip_duration` audio remaining at the end of an audio file. We'll just use `final_clip=None` to discard any remaining audio that doesn't make a complete clip.

**Plot:** We can choose to show the power spectrum of pulse repetition rate for each window by setting `plot=True`. The default is not to show these plots (`plot=False`).

[5]:
```
# minimum and maximum rate of pulsing (pulses per second) to search for
pulse_rate_range = [8,15]

# look for a vocalization in the range of 1000-2000 Hz
signal_band = [1800,2400]

# subtract the amplitude signal from these frequency ranges
noise_bands = [ [0,1000], [3000,3200] ]

#divides the signal into segments this many seconds long, analyzes each independently
clip_duration = 2 #seconds
clip_overlap = 0 #seconds

#if True, it will show the power spectrum plot for each audio segment
show_plots = True
```

## 11.4 Search for pulsing vocalizations with `ribbit()`

This function takes the parameters we chose above as arguments, performs the analysis, and returns two arrays: - **scores:** the pulse rate score for each window - **times:** the start time in seconds of each window

The scores output by the function may be very low or very high. They do not represent a "confidence" or "probability" from 0 to 1. Instead, the relative values of scores on a set of files should be considered: when RIBBIT detects the target species, the scores will be significantly higher than when the species is not detected.

The file `gpt0.wav` has a Great Plains Toad vocalizing only at the beginning. Let's analyze the file with RIBBIT and look at the scores versus time.

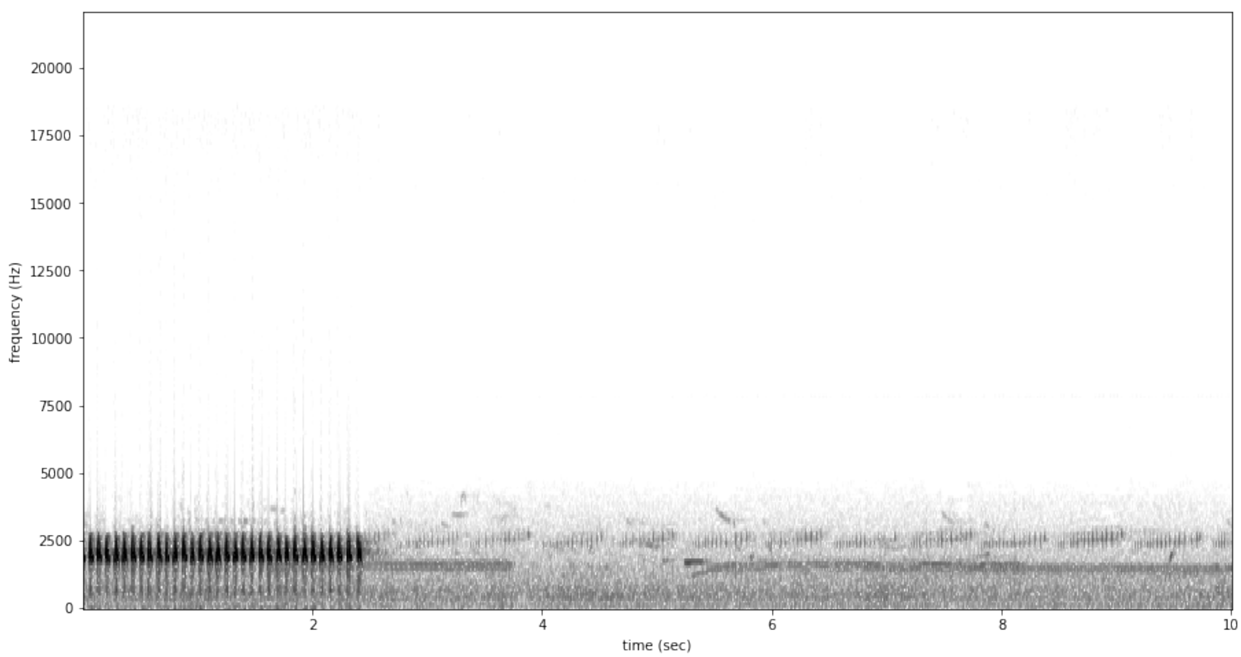
[6]:
```
#get the audio file path
audio_path = np.sort(glob('./great_plains_toad_dataset/*'))[0]

#make the spectrogram
spec = Spectrogram.from_audio(audio.from_file(audio_path))

#run RIBBIT
score_df =  ribbit(
                    spec,
                    pulse_rate_range=pulse_rate_range,
```

(continues on next page)

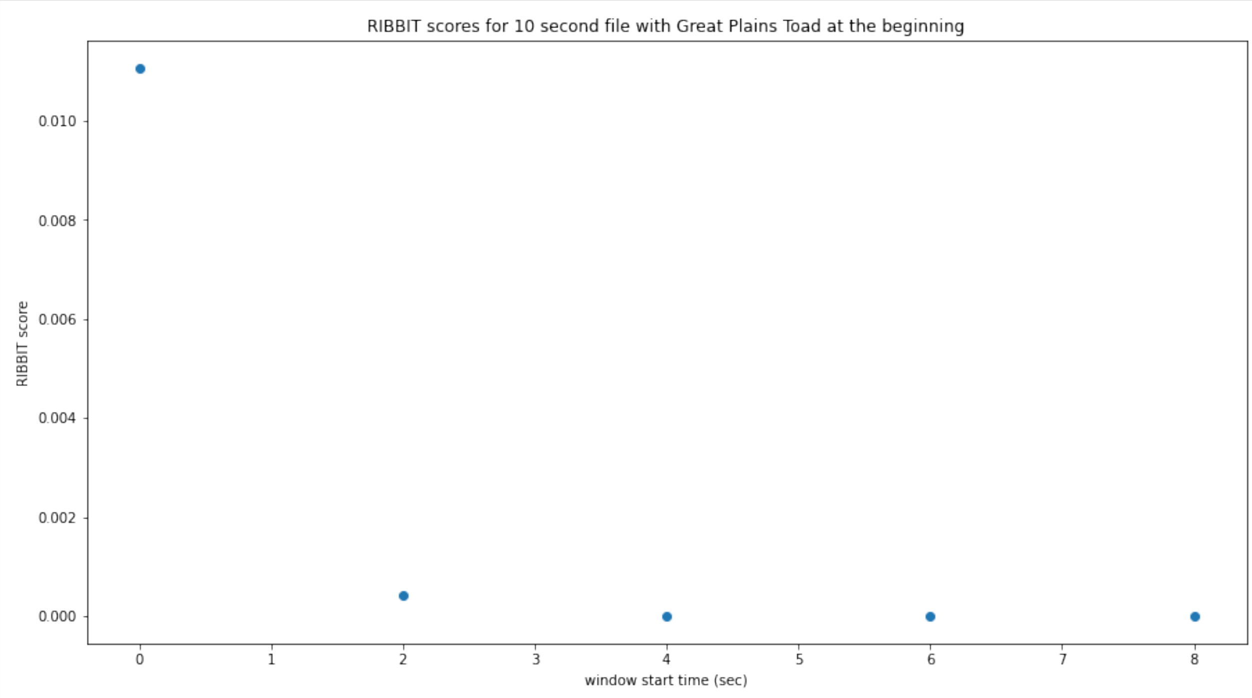
(continued from previous page)

```
                    signal_band=signal_band,
                    clip_duration=clip_duration,
                    noise_bands=noise_bands,
                    plot=False
)


#show the spectrogram
print('spectrogram of 10 second file with Great Plains Toad at the beginning')
spec.plot()

# plot the score vs time of each window
plt.scatter(score_df['start_time'],score_df['score'])
plt.xlabel('window start time (sec)')
plt.ylabel('RIBBIT score')
plt.title('RIBBIT scores for 10 second file with Great Plains Toad at the beginning')
```

```
spectrogram of 10 second file with Great Plains Toad at the beginning
```




```
[6]: Text(0.5, 1.0, 'RIBBIT scores for 10 second file with Great Plains Toad at the␣
↪beginning')
```




as we hoped, RIBBIT outputs a high score during the vocalization (the window from 0-2 seconds) and a low score when the frog is not vocalizing

## 11.5 Analyzing a set of files

[7]:
```
# set up a dataframe for storing files' scores and labels
df = pd.DataFrame(index = glob('./great_plains_toad_dataset/*'),columns=['score',
↪'label'])

# label is 1 if the file contains a Great Plains Toad vocalization, and 0 if it does␣
↪not
df['label'] = [1 if 'gpt' in f else 0 for f in df.index]

# calculate RIBBIT scores
for path in df.index:

    #make the spectrogram
    spec = Spectrogram.from_audio(audio.from_file(path))

    #run RIBBIT
    score_df =  ribbit(
                        spec,
                        pulse_rate_range=[8,20],
                        signal_band=[1900,2400],
                        clip_duration=clip_duration,
                        noise_bands=[[0,1500],[2500,3500]],
                        plot=False)

    # use the maximum RIBBIT score from any window as the score for this file
    # multiply the score by 10,000 to make it easier to read
```

(continues on next page)

(continued from previous page)

```
    df.at[path,'score'] = max(score_df['score']) * 10000

print("Files sorted by score, from highest to lowest:")
df.sort_values(by='score',ascending=False)
```

```
Files sorted by score, from highest to lowest:
```

[7]:

| | score | label |
|---|---|---|
| ./great_plains_toad_dataset/gpt0.mp3 | 1.1e+02 | 1 |
| ./great_plains_toad_dataset/gpt3.mp3 | 29 | 1 |
| ./great_plains_toad_dataset/gpt2.mp3 | 17 | 1 |
| ./great_plains_toad_dataset/gpt1.mp3 | 10 | 1 |
| ./great_plains_toad_dataset/negative9.mp3 | 3 | 0 |
| ./great_plains_toad_dataset/negative8.mp3 | 0.89 | 0 |
| ./great_plains_toad_dataset/negative4.mp3 | 0.76 | 0 |
| ./great_plains_toad_dataset/negative2.mp3 | 0.65 | 0 |
| ./great_plains_toad_dataset/negative1.mp3 | 0.3 | 0 |
| ./great_plains_toad_dataset/negative3.mp3 | 0.3 | 0 |
| ./great_plains_toad_dataset/gpt4.mp3 | 0.12 | 1 |
| ./great_plains_toad_dataset/negative6.mp3 | 0.057 | 0 |
| ./great_plains_toad_dataset/pops2.mp3 | 0.0011 | 0 |
| ./great_plains_toad_dataset/pops1.mp3 | 0.001 | 0 |
| ./great_plains_toad_dataset/negative5.mp3 | 4.3e-05 | 0 |
| ./great_plains_toad_dataset/negative7.mp3 | 0 | 0 |
| ./great_plains_toad_dataset/water.mp3 | 0 | 0 |
| ./great_plains_toad_dataset/silent.mp3 | 0 | 0 |

So, how good is RIBBIT at finding the Great Plains Toad?

We can see that the scores for all of the files with Great Plains Toad (gpt) score above 10 except `gpt4.mp3` (which contains only a very quiet and distant vocalization). All files that do not contain the Great Plains Toad score less than 3.5. So, RIBBIT is doing a good job separating Great Plains Toads vocalizations from other sounds!

Notably, noisy files like `pops1.mp3` score low even though they have lots of periodic energy - our `noise_bands` sucessfully rejected these files. Without using `noise_bands`, files like these would receive very high scores. Also, some birds in "negatives" files that have periodic calls around the same pulsre rate as the Great Plains Toad received low scores. This is also a result of choosing a tight `signal_band` and strategic `noise_bands`. You can try adjusting or eliminating these bands to see their effect on the audio.

(HINT: elimintating the `noise_bands` will result in high scores for the "pops" files)

## 11.6 Run RIBBIT on multiple species simultaneously

If you want to search for multiple species, its best to combine the analysis into one function - that way you only have to load each audio file (and make it's spectrogram) one time, instead of once for each species. (If you have thousands of audio files, this might be a big time saver.)

This code gives a quick exmaple of how you could use a pre-made dataframe (could load it in from a spreadsheet, for instance) of parameters for a set of species to run RIBBIT on all of them.

Note that this example assumes you are using the same spectrogram settings for each species - this might not be the case in practice, if some species require high time-resolution spectrograms and others require high frequency-resolution spectrograms.

[8]:
```
#we'll create a dataframe here, but you could also load it from a spreadsheet
species_df = pd.DataFrame(columns=['pulse_rate_range','signal_band','clip_duration',
↪'noise_bands'])
```

(continues on next page)

(continued from previous page)

```
species_df.loc['great_plains_toad']={
    'pulse_rate_range':[8,20],
    'signal_band':[1900,2400],
    'clip_duration':2.0,
    'noise_bands':[[0,1500],[2500,3500]]
}

species_df.loc['bird_series']={
    'pulse_rate_range':[8,11],
    'signal_band':[5000,6500],
    'clip_duration':2.0,
    'noise_bands':[[0,4000]]
}


species_df
```

[8]:

```
                   pulse_rate_range   signal_band  clip_duration  \
great_plains_toad           [8, 20]  [1900, 2400]            2.0
bird_series                 [8, 11]  [5000, 6500]            2.0

                                noise_bands
great_plains_toad  [[0, 1500], [2500, 3500]]
bird_series                     [[0, 4000]]
```

now let's analyze each audio file for each species.

We'll save the results in a table that has a column for each species.

[9]:

```
# set up a dataframe for storing files' scores and labels
df = pd.DataFrame(index = glob('./great_plains_toad_dataset/*'),columns=species_df.
↪index.values)

# calculate RIBBIT scores
for path in df.index:

    for species, species_params in species_df.iterrows():
    #use RIBBIT for each species in species_df
        #make the spectrogram
        spec = Spectrogram.from_audio(audio.from_file(path))

        #run RIBBIT
        score_df =  ribbit(
                            spec,
                            pulse_rate_range=species_params['pulse_rate_range'],
                            signal_band=species_params['signal_band'],
                            clip_duration=species_params['clip_duration'],
                            noise_bands=species_params['noise_bands'],
                            plot=False)

        # use the maximum RIBBIT score from any window as the score for this file
        # multiply the score by 10,000 to make it easier to read
        df.at[path,species] = max(score_df['score']) * 10000

print("Files with scores for each species, sorted by 'bird_series' score:")
df.sort_values(by='bird_series',ascending=False)
```

```
Files with scores for each species, sorted by 'bird_series' score:
```

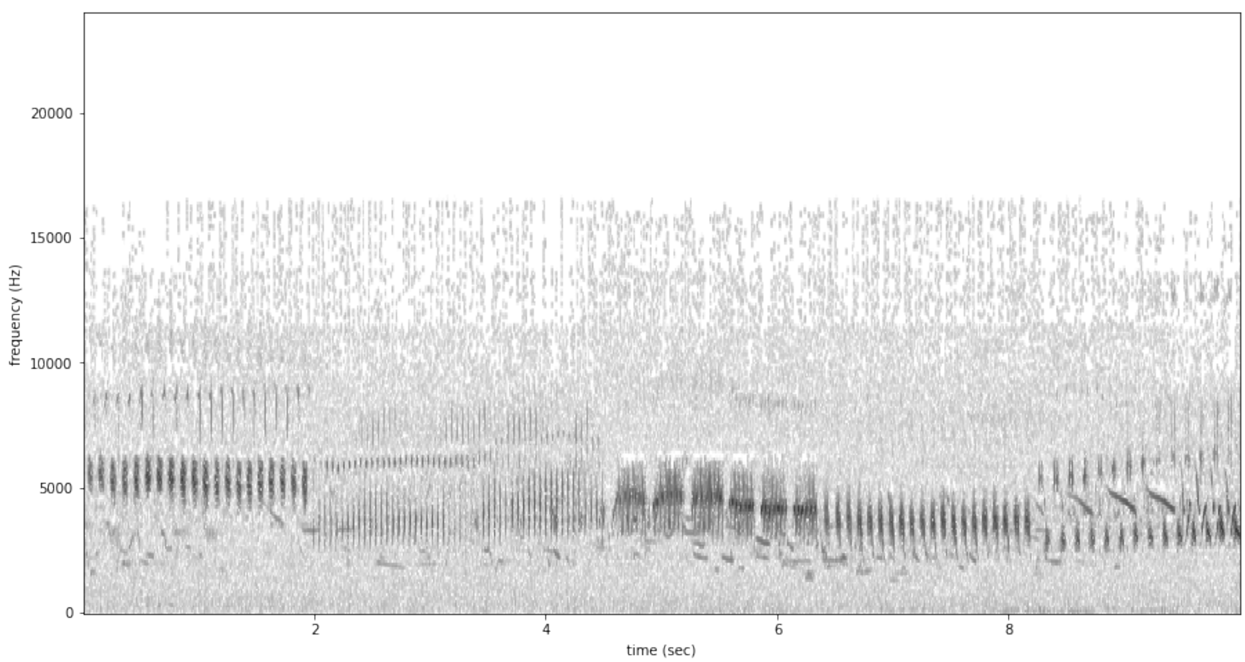
[9]:

```
                                               great_plains_toad bird_series
./great_plains_toad_dataset/negative5.mp3             4.3e-05          94
./great_plains_toad_dataset/negative1.mp3                 0.3          73
./great_plains_toad_dataset/negative3.mp3                 0.3           5
./great_plains_toad_dataset/negative7.mp3                   0         2.9
./great_plains_toad_dataset/negative9.mp3                   3       0.089
./great_plains_toad_dataset/negative2.mp3                0.65       0.016
./great_plains_toad_dataset/negative6.mp3               0.057       0.014
./great_plains_toad_dataset/pops2.mp3                  0.0011      0.0098
./great_plains_toad_dataset/negative8.mp3                0.89      0.0017
./great_plains_toad_dataset/negative4.mp3                0.76      0.0014
./great_plains_toad_dataset/water.mp3                       0      0.0011
./great_plains_toad_dataset/pops1.mp3                   0.001      0.0005
./great_plains_toad_dataset/silent.mp3                      0     0.00037
./great_plains_toad_dataset/gpt4.mp3                     0.12     7.2e-05
./great_plains_toad_dataset/gpt2.mp3                       17           0
./great_plains_toad_dataset/gpt3.mp3                       29           0
./great_plains_toad_dataset/gpt0.mp3                  1.1e+02           0
./great_plains_toad_dataset/gpt1.mp3                       10           0
```

looking at the highest scoring file for 'bird_series', it has the trilled bird sound at 5-6.5 kHz

[10]:

```
Spectrogram.from_audio(audio.from_file('./great_plains_toad_dataset/negative5.mp3')).
↪plot()
```




### 11.6.1 Warning

when loading a dataframe from a file, lists of numbers like [8,20] might be read in as strings ("[8,20]") rather than a list of numbers. Here's a handy little piece of code that will load the values in the desired format

[11]:
```
#let's say we have the species df saved as a csv file
species_df.index.name='species'
species_df.to_csv('species_df.csv')

#define the conversion parameters for each column
import ast
generic = lambda x: ast.literal_eval(x)
conv = {
    'pulse_rate_range':generic,
    'signal_band':generic,
    'noise_bands':generic
}
#tell pandas to use them when loading the csv
species_df=pd.read_csv('./species_df.csv',converters=conv).set_index('species')

#now the species_df has numeric values instead of strings
species_df
```

[11]:
```
                  pulse_rate_range   signal_band  clip_duration  \
species
great_plains_toad          [8, 20]  [1900, 2400]            2.0
bird_series                [8, 11]  [5000, 6500]            2.0

                              noise_bands
species
great_plains_toad  [[0, 1500], [2500, 3500]]
bird_series                     [[0, 4000]]
```

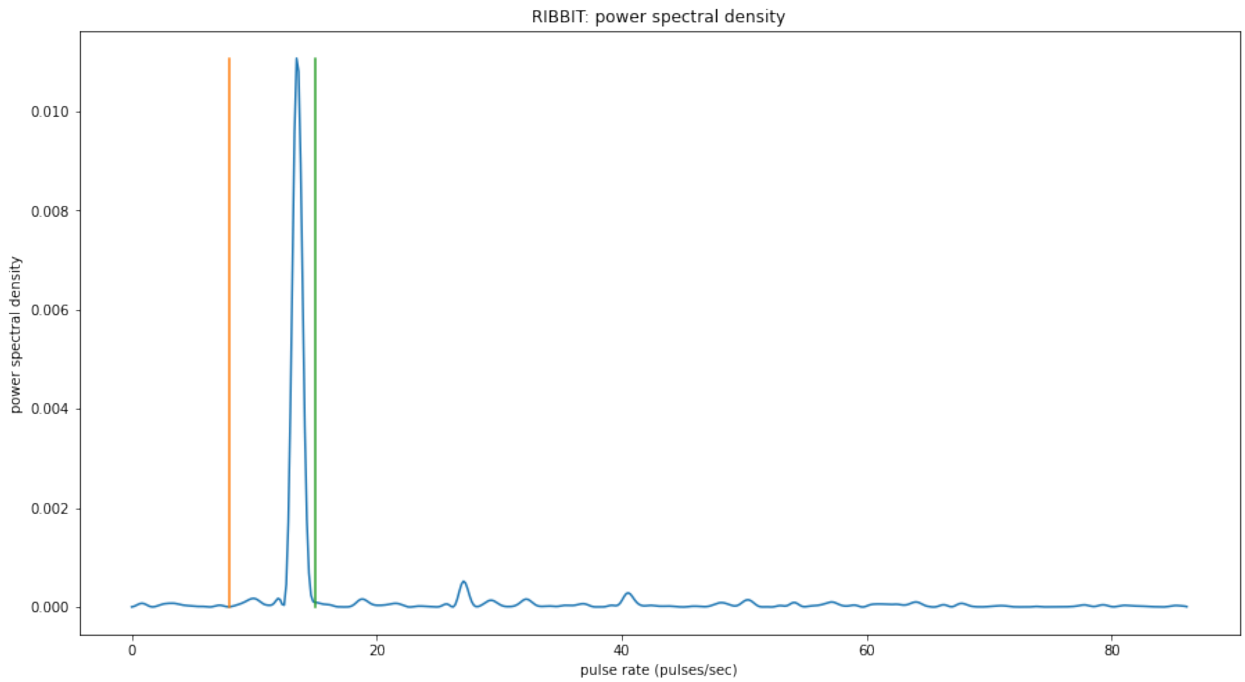
## 11.7 Detail view of RIBBIT method

Now, let's look at one 10 second file and tell ribbit to plot the power spectral density for each window (`plot=True`). This way, we can see if peaks are emerging at the expected pulse rates. Since our `window_length` is 2 seconds, each of these plots represents 2 seconds of audio. The vertical lines on the power spectral density represent the lower and upper `pulse_rate_range` limits.

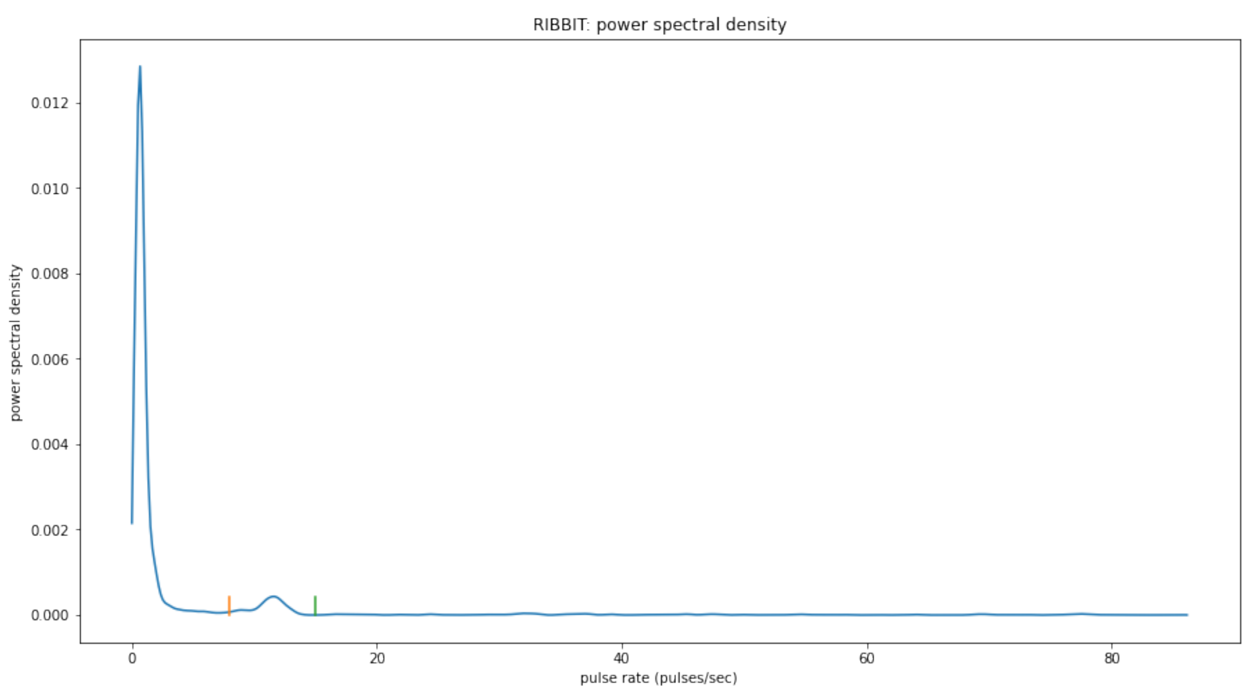
In the file `gpt0.mp3`, the Great Plains Toad vocalizes for a couple seconds at the beginning, then stops. We expect to see a peak in the power spectral density at 15 pulses/sec in the first 2 second window, and maybe a bit in the second, but not later in the audio.

[12]:
```
#create a spectrogram from the file, like above:
# 1. get audio file path
audio_path = np.sort(glob('./great_plains_toad_dataset/*'))[0]
# 2. make audio object and trim (this time 0-10 seconds)
audio = Audio.from_file(audio_path).trim(0,10)
# 3. make spectrogram
spectrogram = Spectrogram.from_audio(audio)

clip_df =  ribbit(
                        spectrogram,
                        pulse_rate_range=pulse_rate_range,
                        signal_band=signal_band,
                        clip_duration=clip_duration,
                        noise_bands=noise_bands,
                        plot=show_plots)
```

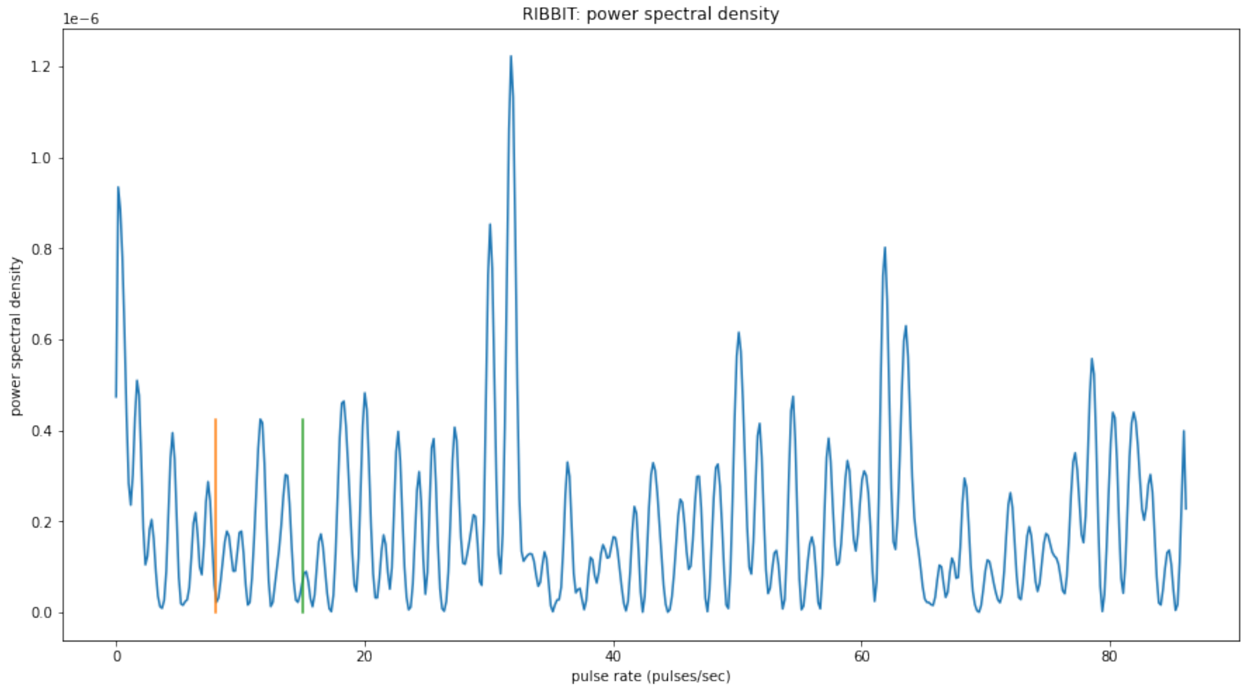
```
window: 0.0 to 2.0 sec
```



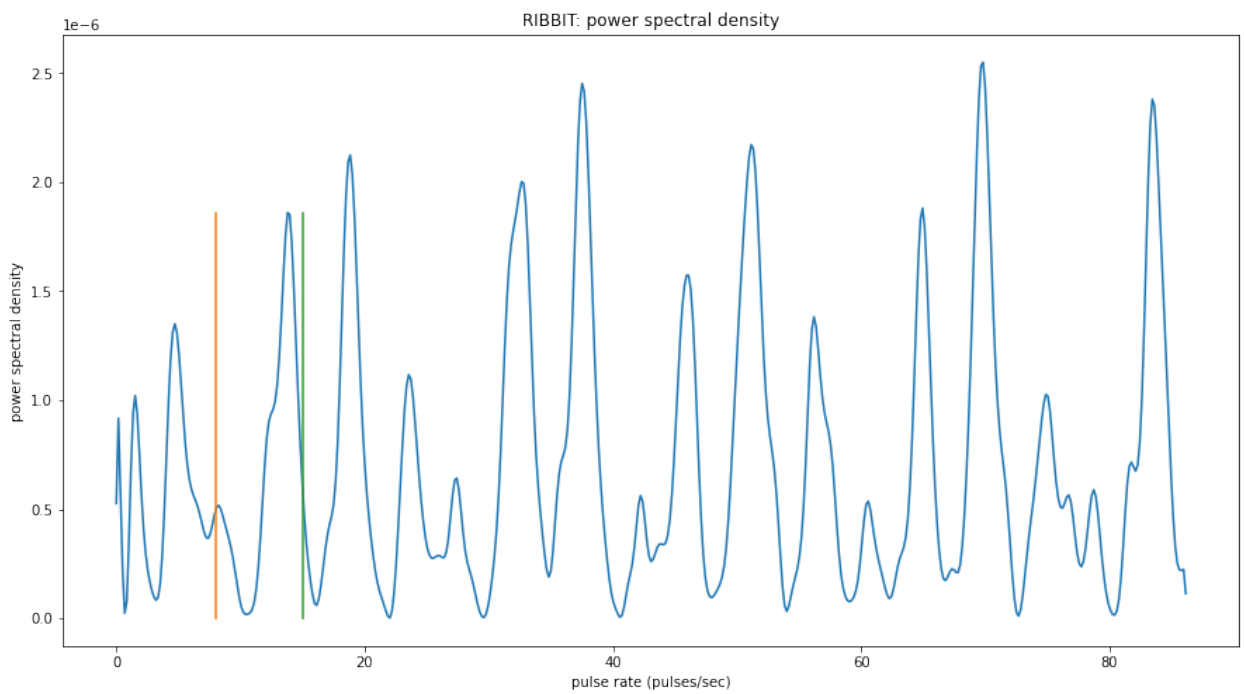

```
window: 2.0 to 4.0 sec
```




```
window: 4.0 to 6.0 sec
```




```
window: 6.0 to 8.0 sec
```




## 11.8 Time to experiment for yourself

Now that you know the basics of how to use RIBBIT, you can try using it on your own data. We recommend spending some time looking at different recordings of your focal species before choosing parameters. Experiment with the noise bands and window length, and get in touch if you have questions!

Sam's email: sam . lapp [at] pitt.edu

this cell will delete the folder `great_plains_toad_dataset`. Only run it if you wish delete that folder and the example audio inside it.

[13]:
```
from pathlib import Path
import shutil
shutil.rmtree('./great_plains_toad_dataset/')
Path('./species_df.csv').unlink()
```

CHAPTER 12

# Audio and Spectrograms

## 12.1 Annotations

functions and classes for manipulating annotations of audio

includes BoxedAnnotations class and utilities to combine or "diff" annotations, etc.

**class** opensoundscape.annotations.**BoxedAnnotations**(*df*, *audio_file=None*)

container for "boxed" (frequency-time) annotations of audio

(for instance, annotations created in Raven software) includes functionality to load annotations from Raven txt files, output one-hot labels for specific clip lengths or clip start/end times, apply corrections/conversions to annotations, and more.

Contains some analogous functions to Audio and Spectrogram, such as trim() [limit time range] and bandpass() [limit frequency range]

**bandpass**(*low_f*, *high_f*, *edge_mode='trim'*)

Bandpass a set of annotations, analogous to Spectrogram.bandpass()

Out-of-place operation: does not modify itself, returns new object

**Parameters**

- **low_f** – low frequency (Hz) bound
- **high_f** – high frequench (Hz) bound
- **edge_mode** – what to do when boxes overlap with edges of trim region - 'trim': trim boxes to bounds - 'keep': allow boxes to extend beyond bounds - 'remove': completely remove boxes that extend beyond bounds

**Returns** a copy of the BoxedAnnotations object on the bandpassed region

**convert_labels**(*conversion_table*)

modify annotations according to a conversion table

Changes the values of 'annotation' column of dataframe. Any labels that do not have specified conversions are left unchanged.

Returns a new BoxedAnnotations object, does not modify itself (out-of-place operation). So use could look like: *my_annotations = my_annotations.convert_labels(table)*

**Parameters** **conversion_table** – current values -> new values. can be either - pd.DataFrame with 2 columns [current value, new values] or - dictionary {current values: new values}

**Returns** new BoxedAnnotations object with converted annotation labels

**classmethod from_raven_file**(*path*, *annotation_column*, *keep_extra_columns=True*, *audio_file=None*)

load annotations from Raven txt file

**Parameters**

- **path** – location of raven .txt file, str or pathlib.Path
- **annotation_column** – (str) column containing annotations
- **keep_extra_columns** – keep or discard extra Raven file columns (always keeps start_time, end_time, low_f, high_f, annotation audio_file). [default: True] - True: keep all - False: keep none - or iterable of specific columns to keep
- **audio_file** – optionally specify the name or path of a corresponding audio file.

**Returns** BoxedAnnotations object containing annotaitons from the Raven file

**global_one_hot_labels**(*classes*)

get a dictionary of one-hot labels for entire duration :param classes: iterable of class names to give 0/1 labels

**Returns** list of 0/1 labels for each class

**one_hot_clip_labels**(*full_duration*, *clip_duration*, *clip_overlap*, *classes*, *min_label_overlap*, *min_label_fraction=1*, *final_clip=None*)

Generate one-hot labels for clips of fixed duration

wraps helpers.generate_clip_times_df() with self.one_hot_labels_like() - Clips are created in the same way as Audio.split() - Labels are applied based on overlap, using self.one_hot_labels_like()

**Parameters**

- **full_duration** – The amount of time (seconds) to split into clips
- **clip_duration** (*float*) – The duration in seconds of the clips
- **clip_overlap** (*float*) – The overlap of the clips in seconds [default: 0]
- **classes** – list of classes for one-hot labels. If None, classes will be all unique values of self.df['annotation']
- **min_label_overlap** – minimum duration (seconds) of annotation within the time interval for it to count as a label. Note that any annotation of length less than this value will be discarded. We recommend a value of 0.25 for typical bird songs, or shorter values for very short-duration events such as chip calls or nocturnal flight calls.
- **min_label_fraction** – [default: None] if >= this fraction of an annotation overlaps with the time window, it counts as a label regardless of its duration. Note that *if either* of the two criterea (overlap and fraction) is met, the label is 1. if None (default), this criterion is not used (i.e., only min_label_overlap is used). A value of 0.5 for ths parameter would ensure that all annotations result in at least one clip being labeled 1 (if there are no gaps between clips).

- **final_clip** (*str*) – Behavior if final_clip is less than clip_duration seconds long. By default, discards remaining time if less than clip_duration seconds long [default: None]. Options:
  - None: Discard the remainder (do not make a clip)
  - "extend": Extend the final clip beyond full_duration to reach clip_duration length
  - "remainder": Use only remainder of full_duration (final clip will be shorter than clip_duration)
  - "full": Increase overlap with previous clip to yield a clip with clip_duration length

**Returns** dataframe with index ['start_time','end_time'] and columns=classes

**one_hot_labels_like** (*clip_df*, *classes*, *min_label_overlap*, *min_label_fraction=None*, *keep_index=False*)

create a dataframe of one-hot clip labels based on given starts/ends

Uses start and end clip times from clip_df to define a set of clips. Then extracts annotatations associated overlapping with each clip. Required overlap parameters are selected by user: annotation must satisfy the minimum time overlap OR minimum % overlap to be included (doesn't require both conditions to be met, only one)

clip_df can be created using opensoundscap.helpers.generate_clip_times_df

**Parameters**

- **clip_df** – dataframe with 'start_time' and 'end_time' columns specifying the temporal bounds of each clip
- **min_label_overlap** – minimum duration (seconds) of annotation within the time interval for it to count as a label. Note that any annotation of length less than this value will be discarded. We recommend a value of 0.25 for typical bird songs, or shorter values for very short-duration events such as chip calls or nocturnal flight calls.
- **min_label_fraction** – [default: None] if >= this fraction of an annotation overlaps with the time window, it counts as a label regardless of its duration. Note that *if either* of the two criterea (overlap and fraction) is met, the label is 1. if None (default), this criterion is not used (i.e., only min_label_overlap is used). A value of 0.5 for ths parameter would ensure that all annotations result in at least one clip being labeled 1 (if there are no gaps between clips).
- **classes** – list of classes for one-hot labels. If None, classes will be all unique values of self.df['annotation']
- **keep_index** – if True, keeps the index of clip_df as an index in the returned DataFrame. [default:False]

**Returns** DataFrame of one-hot labels (multi-index of (start_time, end_time), columns for each class, values 0=absent or 1=present)

**subset** (*classes*)

subset annotations to those from a list of classes

out-of-place operation (returns new filtered BoxedAnnotations object)

**Parameters**

- **classes** – list of classes to retain (all others are discarded)
- **the list can include np.nan or None if you want to keep them** (*–*) –

**Returns** new BoxedAnnotations object containing only annotations in *classes*

**to_raven_file** (*path*)
save annotations to a Raven-compatible tab-separated text file

**Parameters** **path** – path for saved test file (extension must be ".tsv") - can be str or pathlib.Path

**Outcomes:** creates a file containing the annotations in a format compatible with Raven Pro/Lite.

Note: Raven Lite does not support additional columns beyond a single annotation column. Additional columns will not be shown in the Raven Lite interface.

**trim** (*start_time*, *end_time*, *edge_mode='trim'*)
Trim a set of annotations, analogous to Audio/Spectrogram.trim()

Out-of-place operation: does not modify itself, returns new object

**Parameters**

- **start_time** – time (seconds) since beginning for left bound
- **end_time** – time (seconds) since beginning for right bound
- **edge_mode** – what to do when boxes overlap with edges of trim region - 'trim': trim boxes to bounds - 'keep': allow boxes to extend beyond bounds - 'remove': completely remove boxes that extend beyond bounds

**Returns** a copy of the BoxedAnnotations object on the trimmed region. - note that, like Audio.trim(), there is a new reference point for 0.0 seconds (located at start_time in the original object)

**unique_labels** ()
get list of all unique (non-Falsy) labels

opensoundscape.annotations.**categorical_to_one_hot** (*labels*, *classes=None*)
transform multi-target categorical labels (list of lists) to one-hot array

**Parameters**

- **labels** – list of lists of categorical labels, eg [['white','red'],['green','white']] or [[0,1,2],[3]]
- **classes=None** – list of classes for one-hot labels. if None, taken to be the unique set of values in *labels*

**Returns** 2d array with 0 for absent and 1 for present classes: list of classes corresponding to columns in the array

**Return type** one_hot

opensoundscape.annotations.**combine** (*list_of_annotation_objects*)
combine annotations with user-specified preferences Not Implemented.

opensoundscape.annotations.**diff** (*base_annotations*, *comparison_annotations*)
look at differences between two BoxedAnnotations objects Not Implemented.

Compare different labels of the same boxes (Assumes that a second annotator used the same boxes as the first, but applied new labels to the boxes)

opensoundscape.annotations.**one_hot_labels_on_time_interval** (*df*, *classes*, *start_time*, *end_time*, *min_label_overlap*, *min_label_fraction=None*)
generate a dictionary of one-hot labels for given time-interval

Each class is labeled 1 if any annotation overlaps sufficiently with the time interval. Otherwise the class is labeled 0.

**Parameters**

- **df** – DataFrame with columns 'start_time', 'end_time' and 'annotation'
- **classes** – list of classes for one-hot labels. If None, classes will be all unique values of self.df['annotation']
- **start_time** – beginning of time interval (seconds)
- **end_time** – end of time interval (seconds)
- **min_label_overlap** – minimum duration (seconds) of annotation within the time interval for it to count as a label. Note that any annotation of length less than this value will be discarded. We recommend a value of 0.25 for typical bird songs, or shorter values for very short-duration events such as chip calls or nocturnal flight calls.
- **min_label_fraction** – [default: None] if >= this fraction of an annotation overlaps with the time window, it counts as a label regardless of its duration. Note that *if either* of the two criterea (overlap and fraction) is met, the label is 1. if None (default), the criterion is not used (only min_label_overlap is used). A value of 0.5 would ensure that all annotations result in at least one clip being labeled 1 (if no gaps between clips).

**Returns** label 0/1} for all classes

**Return type** dictionary of {class

`opensoundscape.annotations.`**`one_hot_to_categorical`**(*one_hot*, *classes*)

transform one_hot labels to multi-target categorical (list of lists)

**Parameters**

- **one_hot** – 2d array with 0 for absent and 1 for present
- **classes** – list of classes corresponding to columns in the array

**Returns**

**list of lists of categorical labels for each sample, eg** [['white','red'],['green','white']] or [[0,1,2],[3]]

**Return type** labels

## 12.2 Audio

audio.py: Utilities for loading and modifying Audio objects

**Note: Out-of-place operations**

Functions that modify Audio (and Spectrogram) objects are "out of place", meaning that they return a new Audio object instead of modifying the original object. This means that running a line ` audio_object.resample(22050) # WRONG! ` will **not** change the sample rate of *audio_object*! If your goal was to overwrite *audio_object* with the new, resampled audio, you would instead write ` audio_object = audio_object.resample(22050) `

**class** `opensoundscape.audio.`**`Audio`**(*samples*, *sample_rate*, *resample_type='kaiser_fast'*, *max_duration=None*, *metadata=None*)

Container for audio samples

Initialization requires sample array. To load audio file, use *Audio.from_file()*

Initializing an *Audio* object directly requires the specification of the sample rate. Use *Audio.from_file* or *Audio.from_bytesio* with *sample_rate=None* to use a native sampling rate.

**Parameters**

- **samples** (*np.array*) – The audio samples
- **sample_rate** (*integer*) – The sampling rate for the audio samples
- **resample_type** (*str*) – The resampling method to use [default: "kaiser_fast"]
- **max_duration** (*None or integer*) – The maximum duration in seconds allowed for the audio file (longer files will raise an exception)[default: None] If None, no limit is enforced

**Returns** An initialized *Audio* object

**bandpass** (*low_f*, *high_f*, *order*)

Bandpass audio signal with a butterworth filter

Uses a phase-preserving algorithm (scipy.signal's butter and solfiltfilt)

**Parameters**

- **low_f** – low frequency cutoff (-3 dB) in Hz of bandpass filter
- **high_f** – high frequency cutoff (-3 dB) in Hz of bandpass filter
- **order** – butterworth filter order (integer) ~= steepness of cutoff

**duration** ()

Return duration of Audio

**Returns** The duration of the Audio

**Return type** duration (float)

**extend** (*length*)

Extend audio file by adding silence to the end

**Parameters** **length** – the final duration in seconds of the extended audio object

**Returns** a new Audio object of the desired duration

**classmethod from_bytesio** (*bytesio*, *sample_rate=None*, *max_duration=None*, *resample_type='kaiser_fast'*)

Read from bytesio object

Read an Audio object from a BytesIO object. This is primarily used for passing Audio over HTTP.

**Parameters**

- **bytesio** – Contents of WAV file as BytesIO
- **sample_rate** – The final sampling rate of Audio object [default: None]
- **max_duration** – The maximum duration of the audio file [default: None]
- **resample_type** – The librosa method to do resampling [default: "kaiser_fast"]

**Returns** An initialized Audio object

**classmethod from_file** (*path*, *sample_rate=None*, *resample_type='kaiser_fast'*, *max_duration=None*, *metadata=True*, *offset=0*, *duration=None*)

Load audio from files

Deal with the various possible input types to load an audio file Also attempts to load metadata using tinytag.

Audio objects only support mono (one-channel) at this time. Files with multiple channels are mixed down to a single channel.

Optionally, load only a piece of a file using *offset* and *duration*. This will efficiently read sections of a .wav file regardless of where the desired clip is in the audio. For mp3 files, access time grows linearly with time since the beginning of the file.

This function relies on librosa.load(), which supports wav natively but requires ffmpeg for mp3 support.

**Parameters**

- **path** (*str, Path*) – path to an audio file
- **sample_rate** (*int, None*) – resample audio with value and resample_type, if None use source sample_rate (default: None)
- **resample_type** – method used to resample_type (default: kaiser_fast)
- **max_duration** – the maximum length of an input file, None is no maximum (default: None)
- **metadata** (*bool*) – if True, attempts to load metadata from the audio file. If an exception occurs, self.metadata will be *None*. Otherwise self.metadata is a dictionary. Note: will also attempt to parse AudioMoth metadata from the *comment* field, if the *artist* field includes *AudioMoth*. The parsing function for AudioMoth is likely to break when new firmware versions change the *comment* metadata field.
- **offset** – load audio starting at this time (seconds) after the start of the file. Default: 0 seconds.
- **duration** – load audio of this duration (seconds) starting at *offset*. If None, loads all the way to the end of the file.

**Returns** samples, sample_rate, resample_type, max_duration, metadata (dict or None)

**Return type** Audio object with attributes

Note: default sample_rate=None means use file's sample rate, don't resample

**loop**(*length=None*, *n=None*)

Extend audio file by looping it

**Parameters**

- **length** – the final length in seconds of the looped file (cannot be used with n)[default: None]
- **n** – the number of occurences of the original audio sample (cannot be used with length) [default: None] For example, n=1 returns the original sample, and n=2 returns two concatenated copies of the original sample

**Returns** a new Audio object of the desired length or repetitions

**resample**(*sample_rate*, *resample_type=None*)

Resample Audio object

**Parameters**

- **sample_rate** (*scalar*) – the new sample rate
- **resample_type** (*str*) – resampling algorithm to use [default: None (uses self.resample_type of instance)]

**Returns** a new Audio object of the desired sample rate

**save** (*path*)

Save Audio to file

NOTE: currently, only saving to .wav format supported

**Parameters** **path** – destination for output

**spectrum** ()

Create frequency spectrum from an Audio object using fft

**Parameters** **self** –

**Returns** fft, frequencies

**split** (*clip_duration*, *clip_overlap=0*, *final_clip=None*)

Split Audio into even-lengthed clips

The Audio object is split into clips of a specified duration and overlap

**Parameters**

- **clip_duration** (*float*) – The duration in seconds of the clips
- **clip_overlap** (*float*) – The overlap of the clips in seconds [default: 0]
- **final_clip** (*str*) – Behavior if final_clip is less than clip_duration seconds long. By default, discards remaining audio if less than clip_duration seconds long [default: None]. Options:
  - None: Discard the remainder (do not make a clip)
  - "extend": Extend the final clip with silence to reach clip_duration length
  - "remainder": Use only remainder of Audio (final clip will be shorter than clip_duration)
  - "full": Increase overlap with previous clip to yield a clip with clip_duration length

**Returns** list of audio objects - dataframe w/columns for start_time and end_time of each clip

**Return type**

- audio_clips

**split_and_save** (*destination*, *prefix*, *clip_duration*, *clip_overlap=0*, *final_clip=None*, *dry_run=False*)

Split audio into clips and save them to a folder

**Parameters**

- **destination** – A folder to write clips to
- **prefix** – A name to prepend to the written clips
- **clip_duration** – The duration of each clip in seconds
- **clip_overlap** – The overlap of each clip in seconds [default: 0]
- **final_clip** (*str*) – Behavior if final_clip is less than clip_duration seconds long. [default: None] By default, ignores final clip entirely. Possible options (any other input will ignore the final clip entirely),
  - "remainder": Include the remainder of the Audio (clip will not have clip_duration length)
  - "full": Increase the overlap to yield a clip with clip_duration length
  - "extend": Similar to remainder but extend (repeat) the clip to reach clip_duration length
  - None: Discard the remainder

- **dry_run** (*bool*) – If True, skip writing audio and just return clip DataFrame [default: False]

**Returns** pandas.DataFrame containing paths and start and end times for each clip

**time_to_sample** (*time*)
Given a time, convert it to the corresponding sample

**Parameters** **time** – The time to multiply with the sample_rate

**Returns** The rounded sample

**Return type** sample

**trim** (*start_time*, *end_time*)
Trim Audio object in time

If start_time is less than zero, output starts from time 0 If end_time is beyond the end of the sample, trims to end of sample

**Parameters**

- **start_time** – time in seconds for start of extracted clip
- **end_time** – time in seconds for end of extracted clip

**Returns** a new Audio object containing samples from start_time to end_time

**exception** opensoundscape.audio.**OpsoLoadAudioInputError**
Custom exception indicating we can't load input

**exception** opensoundscape.audio.**OpsoLoadAudioInputTooLong**
Custom exception indicating length of audio is too long

## 12.3 AudioMoth

Utilities specifically for audio files recoreded by AudioMoths

opensoundscape.audiomoth.**audiomoth_start_time** (*file*, *filename_timezone='UTC'*, *to_utc=False*)
parse audiomoth file name into a time stamp

AudioMoths create their file name based on the time that recording starts. This function parses the name into a timestamp. Older AudioMoth firmwares used a hexidecimal unix time format, while newer firmwares use a human-readable naming convention. This function handles both conventions.

**Parameters**

- **file** – (str) path or file name from AudioMoth recording
- **filename_timezone** – (str) name of a pytz time zone (for options see pytz.all_timezones). This is the time zone that the AudioMoth uses to record its name, not the time zone local to the recording site. Usually, this is 'UTC' because the AudioMoth records file names in UTC.
- **to_utc** – if True, converts timestamps to UTC localized time stamp. Otherwise, will return timestamp localized to *timezone* argument [default: False]

**Returns** localized datetime object - if to_utc=True, datetime is always "localized" to UTC

opensoundscape.audiomoth.**parse_audiomoth_metadata** (*metadata*)
parse a dictionary of AudioMoth .wav file metadata

-parses the comment field -adds keys for gain_setting, battery_state, recording_start_time -if available (firmware >=1.4.0), addes temperature

Notes on comment field: - Starting with Firmware 1.4.0, the audiomoth logs Temperature to the

metadata (wav header) eg "and temperature was 11.2C."

- At some point the firmware shifted from writing "gain setting 2" to "medium gain setting". Should handle both modes.

**Tested for AudioMoth firmware versions:** 1.5.0

**Parameters** **metadata** – dictionary with audiomoth metadata

**Returns** metadata dictionary with added keys and values

## 12.4 Audio Tools

audio_tools.py: set of tools that filter or modify audio files or sample arrays (not Audio objects)

opensoundscape.audio_tools.**bandpass_filter**(*signal*, *low_f*, *high_f*, *sample_rate*, *order=9*)

perform a butterworth bandpass filter on a discrete time signal using scipy.signal's butter and solfiltfilt (phase-preserving version of sosfilt)

**Parameters**

- **signal** – discrete time signal (audio samples, list of float)
- **low_f** – -3db point (?) for highpass filter (Hz)
- **high_f** – -3db point (?) for highpass filter (Hz)
- **sample_rate** – samples per second (Hz)
- **order=9** – higher values -> steeper dropoff

**Returns** filtered time signal

opensoundscape.audio_tools.**butter_bandpass**(*low_f*, *high_f*, *sample_rate*, *order=9*)

generate coefficients for bandpass_filter()

**Parameters**

- **low_f** – low frequency of butterworth bandpass filter
- **high_f** – high frequency of butterworth bandpass filter
- **sample_rate** – audio sample rate
- **order=9** – order of butterworth filter

**Returns** set of coefficients used in sosfiltfilt()

opensoundscape.audio_tools.**clipping_detector**(*samples*, *threshold=0.6*)

count the number of samples above a threshold value

**Parameters**

- **samples** – a time series of float values
- **threshold=0.6** – minimum value of sample to count as clipping

**Returns** number of samples exceeding threshold

`opensoundscape.audio_tools.`**`convolve_file`**(*in_file*, *out_file*, *ir_file*, *input_gain=1.0*)

apply an impulse_response to a file using ffmpeg's afir convolution

ir_file is an audio file containing a short burst of noise recorded in a space whose acoustics are to be recreated

this makes the files 'sound as if' it were recorded in the location that the impulse response (ir_file) was recorded

**Parameters**

- **`in_file`** – path to an audio file to process
- **`out_file`** – path to save output to
- **`ir_file`** – path to impulse response file
- **`input_gain=1.0`** – ratio for in_file sound's amplitude in (0,1)

**Returns** os response of ffmpeg command

`opensoundscape.audio_tools.`**`mixdown_with_delays`**(*files_to_mix*, *destination*, *delays=None*, *levels=None*, *duration='first'*, *verbose=0*, *create_txt_file=False*)

use ffmpeg to mixdown a set of audio files, each starting at a specified time (padding beginnings with zeros)

**Parameters**

- **`files_to_mix`** – list of audio file paths
- **`destination`** – path to save mixdown to
- **`delays=None`** – list of delays (how many seconds of zero-padding to add at beginning of each file)
- **`levels=None`** – optionally provide a list of relative levels (amplitudes) for each input
- **`duration='first'`** – ffmpeg option for duration of output file: match duration of 'longest','shortest',or 'first' input file
- **`verbose=0`** – if >0, prints ffmpeg command and doesn't suppress ffmpeg output (command line output is returned from this function)
- **`create_txt_file=False`** – if True, also creates a second output file which lists all files that were included in the mixdown

**Returns** ffmpeg command line output

`opensoundscape.audio_tools.`**`silence_filter`**(*filename*, *smoothing_factor=10*, *window_len_samples=256*, *overlap_len_samples=128*, *threshold=None*)

Identify whether a file is silent (0) or not (1)

Load samples from an mp3 file and identify whether or not it is likely to be silent. Silence is determined by finding the energy in windowed regions of these samples, and normalizing the detected energy by the average energy level in the recording.

If any windowed region has energy above the threshold, returns a 0; else returns 1.

**Parameters**

- **filename** (*str*) – file to inspect
- **smoothing_factor** (*int*) – modifier to window_len_samples
- **window_len_samples** – number of samples per window segment
- **overlap_len_samples** – number of samples to overlap each window segment
- **threshold** – threshold value (experimentally determined)

**Returns** 0 if file contains no significant energy over bakcground 1 if file contains significant energy over bakcground

If threshold is None: returns net_energy over background noise

opensoundscape.audio_tools.**window_energy**(*samples*, *window_len_samples=256*, *overlap_len_samples=128*)

Calculate audio energy with a sliding window

Calculate the energy in an array of audio samples

**Parameters**

- **samples** (*np.ndarray*) – array of audio samples loaded using librosa.load
- **window_len_samples** – samples per window
- **overlap_len_samples** – number of samples shared between consecutive windows

**Returns** list of energy level (float) for each window

## 12.5 Spectrogram

spectrogram.py: Utilities for dealing with spectrograms

**class** opensoundscape.spectrogram.**MelSpectrogram**(*spectrogram*, *frequencies*, *times*, *decibel_limits*, *window_samples=None*, *overlap_samples=None*, *window_type=None*, *audio_sample_rate=None*)

Immutable mel-spectrogram container

A mel spectrogram is a spectrogram with pseudo-logarithmically spaced frequency bins (see literature) rather than linearly spaced bins.

See Spectrogram class an Librosa's melspectrogram for detailed documentation.

NOTE: Here we rely on scipy's spectrogram function (via Spectrogram) rather than on librosa's _spectrogram or melspectrogram, because the amplitude of librosa's spectrograms do not match expectations. We only use the mel frequency bank from Librosa.

**classmethod from_audio**(*audio*, *n_mels=64*, *window_samples=512*, *overlap_samples=256*, *decibel_limits=(-100, -20)*, *htk=False*, *norm='slaney'*, *window_type='hann'*, *dB_scale=True*)

Create a MelSpectrogram object from an Audio object

First creates a spectrogram and a mel-frequency filter bank, then computes the dot product of the filter bank with the spectrogram.

The kwargs for the mel frequency bank are documented at: - https://librosa.org/doc/latest/generated/librosa.feature.melspectrogram.html#librosa.feature.melspectrogram - https://librosa.org/doc/latest/generated/librosa.filters.mel.html?librosa.filters.mel

**Parameters**

- **n_mels** – Number of mel bands to generate [default: 128] Note: n_mels should be chosen for compatibility with the Spectrogram parameter *window_samples*. Choosing a value > ~ *window_samples/10* will result in zero-valued rows while small values blend rows from the original spectrogram.
- **window_type** – The windowing function to use [default: "hann"]
- **window_samples** – n samples per window [default: 512]
- **overlap_samples** – n samples shared by consecutive windows [default: 256]
- **htk** – use HTK mel-filter bank instead of Slaney, see Librosa docs [default: False]
- **norm='slanley'** – mel filter bank normalization, see Librosa docs
- **dB_scale=True** – If True, rescales values to decibels, x=10*log10(x) - if dB_scale is False, decibel_limits is ignored

**Returns** opensoundscape.spectrogram.MelSpectrogram object

**plot**(*inline=True*, *fname=None*, *show_colorbar=False*)

Plot the mel spectrogram with matplotlib.pyplot

We can't use pcolormesh because it will smash pixels to achieve a linear y-axis, rather than preserving the mel scale.

**Parameters**

- **inline=True** –
- **fname=None** – specify a string path to save the plot to (ending in .png/.pdf)
- **show_colorbar** – include image legend colorbar from pyplot

**class** opensoundscape.spectrogram.**Spectrogram**(*spectrogram*, *frequencies*, *times*, *decibel_limits*, *window_samples=None*, *overlap_samples=None*, *window_type=None*, *audio_sample_rate=None*)

Immutable spectrogram container

Can be initialized directly from spectrogram, frequency, and time values or created from an Audio object using the .from_audio() method.

**frequencies**

(list) discrete frequency bins generated by fft

**times**

(list) time from beginning of file to the center of each window

**spectrogram**

a 2d array containing 10*log10(fft) for each time window

**decibel_limits**

minimum and maximum decibel values in .spectrogram

**window_samples**

number of samples per window when spec was created [default: none]

**overlap_samples**

number of samples overlapped in consecutive windows when spec was created [default: none]

**window_type**
window fn used to make spectrogram, eg 'hann' [default: none]

**audio_sample_rate**
sample rate of audio from which spec was created [default: none]

**amplitude** (*freq_range=None*)
create an amplitude vs time signal from spectrogram

by summing pixels in the vertical dimension

**Args** freq_range=None: sum Spectrogrm only in this range of [low, high] frequencies in Hz (if None, all frequencies are summed)

**Returns** a time-series array of the vertical sum of spectrogram value

**bandpass** (*min_f*, *max_f*, *out_of_bounds_ok=True*)
extract a frequency band from a spectrogram

crops the 2-d array of the spectrograms to the desired frequency range

**Parameters**

- **min_f** – low frequency in Hz for bandpass
- **max_f** – high frequency in Hz for bandpass
- **out_of_bounds_ok** – (bool) if False, raises ValueError if min_f or max_f are not within the range of the original spectrogram's frequencies [default: True]

**Returns** bandpassed spectrogram object

**duration** ()
calculate the ammount of time represented in the spectrogram

Note: time may be shorter than the duration of the audio from which the spectrogram was created, because the windows may align in a way such that some samples from the end of the original audio were discarded

**classmethod from_audio** (*audio*, *window_type='hann'*, *window_samples=512*, *overlap_samples=256*, *decibel_limits=(-100, -20)*, *dB_scale=True*)
create a Spectrogram object from an Audio object

**Parameters**

- **window_type="hann"** – see scipy.signal.spectrogram docs for description of window parameter
- **window_samples=512** – number of audio samples per spectrogram window (pixel)
- **overlap_samples=256** – number of samples shared by consecutive windows
- **=** (*decibel_limits*) – limit the dB values to (min,max) (lower values set to min, higher values set to max)
- **dB_scale=True** – If True, rescales values to decibels, x=10*log10(x) - if dB_scale is False, decibel_limits is ignored

**Returns** opensoundscape.spectrogram.Spectrogram object

**classmethod from_file** ()
create a Spectrogram object from a file

**Parameters** **file** – path of image to load

**Returns** opensoundscape.spectrogram.Spectrogram object

**limit_db_range** (*min_db=-100*, *max_db=-20*)
Limit the decibel values of the spectrogram to range from min_db to max_db

values less than min_db are set to min_db values greater than max_db are set to max_db

similar to Audacity's gain and range parameters

**Parameters**

- **min_db** – values lower than this are set to this
- **max_db** – values higher than this are set to this

**Returns** Spectrogram object with db range applied

**linear_scale** (*feature_range=(0, 1)*)
Linearly rescale spectrogram values to a range of values using in_range as decibel_limits

**Parameters** **feature_range** – tuple of (low,high) values for output

**Returns** Spectrogram object with values rescaled to feature_range

**min_max_scale** (*feature_range=(0, 1)*)
Linearly rescale spectrogram values to a range of values using in_range as minimum and maximum

**Parameters** **feature_range** – tuple of (low,high) values for output

**Returns** Spectrogram object with values rescaled to feature_range

**net_amplitude** (*signal_band*, *reject_bands=None*)
create amplitude signal in signal_band and subtract amplitude from reject_bands

rescale the signal and reject bands by dividing by their bandwidths in Hz (amplitude of each reject_band is divided by the total bandwidth of all reject_bands. amplitude of signal_band is divided by badwidth of signal_band. )

**Parameters**

- **signal_band** – [low,high] frequency range in Hz (positive contribution)
- **band** (`reject`) – list of [low,high] frequency ranges in Hz (negative contribution)

return: time-series array of net amplitude

**plot** (*inline=True*, *fname=None*, *show_colorbar=False*)
Plot the spectrogram with matplotlib.pyplot

**Parameters**

- **inline=True** –
- **fname=None** – specify a string path to save the plot to (ending in .png/.pdf)
- **show_colorbar** – include image legend colorbar from pyplot

**to_image** (*shape=None*, *mode='RGB'*, *colormap=None*)
Create a Pillow Image from spectrogram

Linearly rescales values in the spectrogram from self.decibel_limits to [255,0]

Default of self.decibel_limits on load is [-100, -20], so, e.g., -20 db is loudest -> black, -100 db is quietest -> white

**Parameters**

- **destination** – a file path (string)
- **shape=None** – tuple of image dimensions as (height, width),

- **mode="RGB"** – RGB for 3-channel output "L" for 1-channel output
- **colormap=None** – if None, greyscale spectrogram is generated Can be any matplotlib colormap name such as 'jet' Note: if mode="L", colormap will have no effect on output

**Returns** Pillow Image object

**trim**(*start_time*, *end_time*)
extract a time segment from a spectrogram

**Parameters**

- **start_time** – in seconds
- **end_time** – in seconds

**Returns** spectrogram object from extracted time segment

**window_length**()
calculate length of a single fft window, in seconds:

**window_start_times**()
get start times of each window, rather than midpoint times

**window_step**()
calculate time difference (sec) between consecutive windows' centers

# CHAPTER 13

## Machine Learning

### 13.1 Convolutional Neural Networks

classes for pytorch machine learning models in opensoundscape

For tutorials, see notebooks on opensoundscape.org

**class** opensoundscape.torch.models.cnn.**CnnResampleLoss**(*architecture*, *classes*, *single_target=False*)

Subclass of PytorchModel with ResampleLoss.

ResampleLoss may perform better than BCE Loss for multitarget problems in some scenarios.

**Parameters**

- **architecture** – a model architecture object, for example one generated with the torch.architectures.cnn_architectures module
- **classes** – list of class names. Must match with training dataset classes.
- **single_target** –
  - True: model expects exactly one positive class per sample
  - False: samples can have an number of positive classes

  [default: False]

**class** opensoundscape.torch.models.cnn.**InceptionV3**(*classes*, *freeze_feature_extractor=False*, *use_pretrained=True*, *single_target=False*)

**train_epoch**()

perform forward pass, loss, backpropagation for one epoch

need to override parent because Inception returns different outputs from the forward pass (final and auxiliary layers)

Returns: (targets, predictions, scores) on training files

**class** opensoundscape.torch.models.cnn.**InceptionV3ResampleLoss**(*classes*, *freeze_feature_extractor=False*, *use_pretrained=True*, *single_target=False*)

**class** opensoundscape.torch.models.cnn.**PytorchModel**(*architecture*, *classes*, *single_target=False*)

Generic Pytorch Model with .train(), .predict(), and .save()

flexible architecture, optimizer, loss function, parameters

for tutorials and examples see opensoundscape.org

**Parameters**

- **architecture** – *EITHER* a pytorch model object (subclass of torch.nn.Module), for example one generated with the *cnn_architectures* module *OR* a string matching one of the architectures listed by cnn_architectures.list_architectures(), eg 'resnet18'. - If a string is provided, uses default parameters

  (including use_pretrained=True)
- **classes** – list of class names. Must match with training dataset classes if training.
- **single_target** –
  - True: model expects exactly one positive class per sample
  - False: samples can have an number of positive classes

  [default: False]

**predict**(*prediction_dataset*, *batch_size=1*, *num_workers=0*, *activation_layer=None*, *binary_preds=None*, *threshold=0.5*, *error_log=None*)

Generate predictions on a dataset

Choose to return any combination of scores, labels, and single-target or multi-target binary predictions. Also choose activation layer for scores (softmax, sigmoid, softmax then logit, or None).

Note: the order of returned dataframes is (scores, preds, labels)

**Parameters**

- **prediction_dataset** – a Preprocessor or DataSset object that returns tensors, such as AudioToSpectrogramPreprocessor (no augmentation) or CnnPreprocessor (w/augmentation) from opensoundscape.datasets
- **batch_size** – Number of files to load simultaneously [default: 1]
- **num_workers** – parallelization (ie cpus or cores), use 0 for current process [default: 0]
- **activation_layer** – Optionally apply an activation layer such as sigmoid or softmax to the raw outputs of the model. options: - None: no activation, return raw scores (ie logit, [-inf:inf]) - 'softmax': scores all classes sum to 1 - 'sigmoid': all scores in [0,1] but don't sum to 1 - 'softmax_and_logit': applies softmax first then logit [default: None]
- **binary_preds** – Optionally return binary (thresholded 0/1) predictions options: - 'single_target': max scoring class = 1, others = 0 - 'multi_target': scores above threshold = 1, others = 0 - None: do not create or return binary predictions [default: None]
- **threshold** – prediction threshold(s) for sigmoid scores. Only relevant when binary_preds == 'multi_target'

- **error_log** – if not None, saves a list of files that raised errors to the specified file location [default: None]

**Returns: 3 DataFrames (or Nones), w/index matching prediciton_dataset.df** scores: post-activation_layer scores predictions: 0/1 preds for each class labels: labels from dataset (if available)

**Note: if loading an audio file raises a PreprocessingError, the scores** and predictions for that sample will be np.nan

Note: if no return type selected for labels/scores/preds, returns None instead of a DataFrame in the returned tuple

**split_and_predict**(*prediction_dataset*, *file_batch_size=1*, *num_workers=0*, *activation_layer=None*, *binary_preds=None*, *threshold=0.5*, *error_log=None*, *clip_batch_size=None*)

Generate predictions on long audio files

This function integrates in-pipline splitting of audio files into shorter clips with clip-level prediction.

The input dataset should be a LongAudioPreprocessor object

Choose to return any combination of scores, labels, and single-target or multi-target binary predictions. Also choose activation layer for scores (softmax, sigmoid, softmax then logit, or None).

**Parameters**

- **prediction_dataset** – a LongAudioPreprocessor object
- **file_batch_size** – Number of audio files to load simultaneously [default: 1]
- **num_workers** – parallelization (ie cpus or cores), use 0 for current process [default: 0]
- **activation_layer** – Optionally apply an activation layer such as sigmoid or softmax to the raw outputs of the model. options: - None: no activation, return raw scores (ie logit, [-inf:inf]) - 'softmax': scores all classes sum to 1 - 'sigmoid': all scores in [0,1] but don't sum to 1 - 'softmax_and_logit': applies softmax first then logit [default: None]
- **binary_preds** – Optionally return binary (thresholded 0/1) predictions options: - 'single_target': max scoring class = 1, others = 0 - 'multi_target': scores above threshold = 1, others = 0 - None: do not create or return binary predictions [default: None]
- **threshold** – prediction threshold for sigmoid scores. Only relevant when binary_preds == 'multi_target'
- **clip_batch_size** – batch size of preprocessed samples for CNN prediction
- **error_log** – if not None, saves a list of files that raised errors to the specified file location [default: None]

**Returns: DataFrames with multi-index: path, clip start & end times** scores: post-*activation_layer* scores predictions: 0/1 preds for each class, if *binary_preds* given unsafe_samples: list of samples that failed to preprocess

**Note: if loading an audio file raises a PreprocessingError, the scores** and predictions for that sample will be np.nan

Note: if no return type selected for scores/preds, returns None instead of a DataFrame for predictions

Note: currently does not support passing labels. Meaning of a label is ambiguous since the original files are split into clips during prediction (output values are for clips, not entire file)

**train**(*train_dataset*, *valid_dataset*, *epochs=1*, *batch_size=1*, *num_workers=0*, *save_path='.'*, *save_interval=1*, *log_interval=10*, *unsafe_sample_log='./unsafe_samples.log'*)

train the model on samples from train_dataset

If customized loss functions, networks, optimizers, or schedulers are desired, modify the respective attributes before calling .train().

**Parameters**

- **train_dataset** – a Preprocessor that loads sample (audio file + label) to Tensor in batches (see docs/tutorials for details)
- **valid_dataset** – a Preprocessor for evaluating performance
- **epochs** – number of epochs to train for [default=1] (1 epoch constitutes 1 view of each training sample)
- **batch_size** – number of training files to load/process before re-calculating the loss function and backpropagation
- **num_workers** – parallelization (ie, cores or cpus) Note: use 0 for single (root) process (not 1)
- **save_path** – location to save intermediate and best model objects [default=".", ie current location of script]
- **save_interval** – interval in epochs to save model object with weights [default:1] Note: the best model is always saved to best.model in addition to other saved epochs.
- **log_interval** – interval in epochs to evaluate model with validation dataset and print metrics to the log
- **unsafe_sample_log** – file path: log all samples that failed in preprocessing (file written when training completes) - if None, does not write a file

**train_epoch**()

perform forward pass, loss, backpropagation for one epoch

Returns: (targets, predictions, scores) on training files

**class** opensoundscape.torch.models.cnn.**Resnet18Binary**(*classes*, *use_pretrained=True*)

Subclass of PytorchModel with Resnet18 architecture

This subclass allows separate training parameters for the feature extractor and classifier via optimizer_params

If you do not need separate training parameters for the feature extraction and classification blocks, you can create a model with resnet18 architecture simply by using PytorchModel('resnet18',classes…).

**Parameters**

- **classes** – list of class names. Must match with training dataset classes.
- **single_target** –
  - True: model expects exactly one positive class per sample
  - False: samples can have an number of positive classes

  [default: False]

**class** opensoundscape.torch.models.cnn.**Resnet18Multiclass**(*classes*, *single_target=False*, *use_pretrained=True*)

Multi-class model with resnet18 architecture and ResampleLoss.

### Notes

Allows separate parameters for feature & classifier blocks via self.optimizer_params's keys: "feature" and "classifier".

If you do not need separate training parameters for the feature extraction and classification blocks, you can create a model with resnet18 architecture simply by using PytorchModel('resnet18',classes. . . ).

Can be single or multi-target.

Uses "ResampleLoss" loss function.

**Parameters**

- **classes** – list of class names. Must match with training dataset classes.
- **single_target** –
  - True: model expects exactly one positive class per sample
  - False: samples can have an number of positive classes

  [default: False]

`opensoundscape.torch.models.cnn.`**`load_model`**(*path*, *device=None*)

load a saved model object

**Parameters**

- **path** – file path of saved model
- **device** – which device to load into, eg 'cuda:1'
- **[default** – None] will choose first gpu if available, otherwise cpu

**Returns** a model object with loaded weights

`opensoundscape.torch.models.cnn.`**`load_outdated_model`**(*path*, *model_class*, *architecture_constructor=None*, *device=None*)

load a CNN saved with a previous version of OpenSoundscape

This function enables you to load models saved with opso 0.4.x, 0.5.x, and 0.6.0 when using >=0.6.1. For models created with 0.6.1 and above, use load_model(path) which is more robust.

Note: If you are loading a model created with opensoundscape 0.4.x, you most likely want to specify *model_class = opensoundscape.torch.models.CnnResnet18Binary*. If your model was created with opensoundscape 0.5.x or 0.6.0, you need to choose the appropriate class.

Note: for future use of the loaded model, you can simply call *model.save(path)* after creating it, then reload it with *model = load_model(path)*. The saved model will be fully compatible with opensoundscape >=0.6.1.

Examples: ``‘ #load a binary resnet18 model from opso 0.4.x, 0.5.x, or 0.6.0 from opensoundscape.torch.models.cnn import Resnet18Binary model = load_outdated_model('old_model.tar',model_class=Resnet18Binary)

#load a resnet50 model of class PytorchModel created with opso 0.5.0 from opensoundscape.torch.models.cnn import PytorchModel from opensoundscape.torch.architectures.cnn_architectures import resnet50 model_050 = load_outdated_model('opso050_pytorch_model_r50.model',model_class=PytorchModel,architecture_constructor=resnet50) ``‘

**Parameters**

- **path** – path to model file, ie .model or .tar file

- **model_class** – the opensoundscape class to create, eg PytorchModel, CnnResampleLoss, or Resnet18Binary from opensoundscape.torch.models.cnn
- **architecture_constructor** – the *function* that creates desired cnn architecture eg opensoundscape.torch.architectures.cnn_architectures.resnet18 Note: this is only required for classes that take the architecture as an input, for instance PytorchModel or CnnResampleLoss. It's not required for e.g. Resnet18Binary or InceptionV3 which internally create a specific architecture.
- **device** – optionally specify a device to map tensors onto, eg 'cpu', 'cuda:0', 'cuda:1'[default: None] - if None, will choose cuda:0 if cuda is available, otherwise chooses cpu

**Returns** a cnn model object with the weights loaded from the saved model

**class** opensoundscape.torch.models.utils.**BaseModule**

Base class for a pytorch model pipeline class.

All child classes should define load, save, etc

opensoundscape.torch.models.utils.**apply_activation_layer**(*x*, *activation_layer=None*)

applies an activation layer to a set of scores

**Parameters**

- **x** – input values
- **activation_layer** –
  - None [default]: return original values
  - 'softmax': apply softmax activation
  - 'sigmoid': apply sigmoid activation
  - 'softmax_and_logit': apply softmax then logit transform

**Returns** values with activation layer applied

opensoundscape.torch.models.utils.**cas_dataloader**(*dataset*, *batch_size*, *num_workers*)

Return a dataloader that uses the class aware sampler

Class aware sampler tries to balance the examples per class in each batch. It selects just a few classes to be present in each batch, then samples those classes for even representation in the batch.

**Parameters**

- **dataset** – a pytorch dataset type object
- **batch_size** – see DataLoader
- **num_workers** – see DataLoader

opensoundscape.torch.models.utils.**collate_lists_of_audio_clips**(*batch*)

Collate function for splitting + prediction of long audio files

Puts each data field into a tensor with outer dimension batch size

Additionally, concats the dfs from each audio file into one long df for the entire batch

opensoundscape.torch.models.utils.**get_batch**(*array*, *batch_size*, *batch_number*)

get a single slice of a larger array

using the batch size and batch index, from zero

**Parameters**

- **array** – iterable to split into batches
- **batch_size** – num elements per batch
- **batch_number** – index of batch

**Returns** one batch (subset of array)

Note: the final elements are returned as the last batch even if there are fewer than batch_size

### Example

if array=[1,2,3,4,5,6,7] then:

- get_batch(array,3,0) returns [1,2,3]
- get_batch(array,3,3) returns [7]

opensoundscape.torch.models.utils.**get_dataloader**(*safe_dataset*, *batch_size=64*, *num_workers=1*, *shuffle=False*, *sampler=''*)

Create a DataLoader from a DataSet - chooses between normal pytorch DataLoader and ImbalancedDatasetSampler. - Sampler: None -> default DataLoader; 'imbalanced'->ImbalancedDatasetSampler

opensoundscape.torch.models.utils.**tensor_binary_predictions**(*scores*, *mode*, *threshold=None*)

generate binary 0/1 predictions from continuous scores

**Parameters**

- **scores** – torch.Tensor of dim (batch_size, n_classes) with input scores [-inf:inf]
- **mode** – 'single_target', 'multi_target', or None (return empty tensor)
- **threshold** – minimum score to predict 1, if mode=='multi_target'. threshold
- **be a single value for all classes or a list of class-specific values.** (*can*) –

**Returns** torch.Tensor of 0/1 predictions in same shape as scores

Note: expects real-valued (unbounded) input scores, i.e. scores take values in [-inf, inf]. Sigmoid layer is applied before multi-target prediction, so the threshold should be in [0,1].

Module to initialize PyTorch CNN architectures with custom output shape

This module allows the use of several built-in CNN architectures from PyTorch. The architecture refers to the specific layers and layer input/output shapes (including convolution sizes and strides, etc) - such as the ResNet18 or Inception V3 architecture.

We provide wrappers which modify the output layer to the desired shape (to match the number of classes). The way to change the output layer shape depends on the architecture, which is why we need a wrapper for each one. This code is based on pytorch.org/tutorials/beginner/finetuning_torchvision_models_tutorial.html

To use these wrappers, for example, if your model has 10 output classes, write

*my_arch=resnet18(10)*

Then you can initialize a model object from *opensoundscape.torch.models.cnn* with your architecture:

*model=PytorchModel(my_arch,classes)*

or override an existing model's architecture:

*model.network = my_arch*

Note: the InceptionV3 architecture must be used differently than other architectures - the easiest way is to simply use the InceptionV3 class in opensoundscape.torch.models.cnn.

`opensoundscape.torch.architectures.cnn_architectures.`**`alexnet`**(*num_classes*, *freeze_feature_extractor=False*, *use_pretrained=True*)

Wrapper for AlexNet architecture

input size = 224

**Parameters**

- **`num_classes`** – number of output nodes for the final layer
- **`freeze_feature_extractor`** – if False (default), entire network will have gradients and can train if True, feature block is frozen and only final layer is trained
- **`use_pretrained`** – if True, uses pre-trained ImageNet features from Pytorch's model zoo.

`opensoundscape.torch.architectures.cnn_architectures.`**`densenet121`**(*num_classes*, *freeze_feature_extractor=False*, *use_pretrained=True*)

Wrapper for densenet121 architecture

input size = 224

**Parameters**

- **`num_classes`** – number of output nodes for the final layer
- **`freeze_feature_extractor`** – if False (default), entire network will have gradients and can train if True, feature block is frozen and only final layer is trained
- **`use_pretrained`** – if True, uses pre-trained ImageNet features from Pytorch's model zoo.

`opensoundscape.torch.architectures.cnn_architectures.`**`inception_v3`**(*num_classes*, *freeze_feature_extractor=False*, *use_pretrained=True*)

Wrapper for Inception v3 architecture

Input: 229x229

WARNING: expects (299,299) sized images and has auxiliary output. See InceptionV3 class in *opensoundscape.torch.models.cnn* for use.

**Parameters**

- **`num_classes`** – number of output nodes for the final layer
- **`freeze_feature_extractor`** – if False (default), entire network will have gradients and can train if True, feature block is frozen and only final layer is trained
- **`use_pretrained`** – if True, uses pre-trained ImageNet features from Pytorch's model zoo.

`opensoundscape.torch.architectures.cnn_architectures.`**`resnet101`**(*num_classes*, *freeze_feature_extractor=False*, *use_pretrained=True*)

Wrapper for ResNet101 architecture

input_size = 224

**Parameters**

- **num_classes** – number of output nodes for the final layer
- **freeze_feature_extractor** – if False (default), entire network will have gradients and can train if True, feature block is frozen and only final layer is trained
- **use_pretrained** – if True, uses pre-trained ImageNet features from Pytorch's model zoo.

`opensoundscape.torch.architectures.cnn_architectures.`**`resnet152`**`(`*num_classes*, *freeze_feature_extractor=False*, *use_pretrained=True*`)`

Wrapper for ResNet152 architecture

input_size = 224

**Parameters**

- **num_classes** – number of output nodes for the final layer
- **freeze_feature_extractor** – if False (default), entire network will have gradients and can train if True, feature block is frozen and only final layer is trained
- **use_pretrained** – if True, uses pre-trained ImageNet features from Pytorch's model zoo.

`opensoundscape.torch.architectures.cnn_architectures.`**`resnet18`**`(`*num_classes*, *freeze_feature_extractor=False*, *use_pretrained=True*`)`

Wrapper for ResNet18 architecture

input_size = 224

**Parameters**

- **num_classes** – number of output nodes for the final layer
- **freeze_feature_extractor** – if False (default), entire network will have gradients and can train if True, feature block is frozen and only final layer is trained
- **use_pretrained** – if True, uses pre-trained ImageNet features from Pytorch's model zoo.

`opensoundscape.torch.architectures.cnn_architectures.`**`resnet34`**`(`*num_classes*, *freeze_feature_extractor=False*, *use_pretrained=True*`)`

Wrapper for ResNet34 architecture

input_size = 224

**Parameters**

- **num_classes** – number of output nodes for the final layer
- **freeze_feature_extractor** – if False (default), entire network will have gradients and can train if True, feature block is frozen and only final layer is trained
- **use_pretrained** – if True, uses pre-trained ImageNet features from Pytorch's model zoo.

`opensoundscape.torch.architectures.cnn_architectures.`**`resnet50`**`(`*num_classes*, *freeze_feature_extractor=False*, *use_pretrained=True*`)`

Wrapper for ResNet50 architecture

input_size = 224

**Parameters**

- **num_classes** – number of output nodes for the final layer
- **freeze_feature_extractor** – if False (default), entire network will have gradients and can train if True, feature block is frozen and only final layer is trained
- **use_pretrained** – if True, uses pre-trained ImageNet features from Pytorch's model zoo.

opensoundscape.torch.architectures.cnn_architectures.**set_parameter_requires_grad**(*model*, *freeze_feature*

if necessary, remove gradients of all model parameters

if freeze_feature_extractor is True, we set requires_grad=False for all features in the feature extraction block. We would do this if we have a pre-trained CNN and only want to change the shape of the final layer, then train only that final classification layer without modifying the weights of the rest of the network.

opensoundscape.torch.architectures.cnn_architectures.**squeezenet1_0**(*num_classes*, *freeze_feature_extractor=False*, *use_pretrained=True*)

Wrapper for squeezenet architecture

input size = 224

**Parameters**

- **num_classes** – number of output nodes for the final layer
- **freeze_feature_extractor** – if False (default), entire network will have gradients and can train if True, feature block is frozen and only final layer is trained
- **use_pretrained** – if True, uses pre-trained ImageNet features from Pytorch's model zoo.

opensoundscape.torch.architectures.cnn_architectures.**vgg11_bn**(*num_classes*, *freeze_feature_extractor=False*, *use_pretrained=True*)

Wrapper for vgg11 architecture

input size = 224

**Parameters**

- **num_classes** – number of output nodes for the final layer
- **freeze_feature_extractor** – if False (default), entire network will have gradients and can train if True, feature block is frozen and only final layer is trained
- **use_pretrained** – if True, uses pre-trained ImageNet features from Pytorch's model zoo.

defines feature extractor and Architecture class for ResNet CNN

This implementation of the ResNet18 architecture allows for separate access to the feature extraction and classification blocks. This can be useful, for instance, to freeze the feature extractor and only train the classifier layer; or to specify different learning rates for the two blocks.

This implementation is used in the Resnet18Binary and Resnet18Multiclass classes of opensoundscape.torch.models.cnn.

**class** opensoundscape.torch.architectures.resnet.**ResNetArchitecture**(*num_cls*, *weights_init='ImageNet'*, *num_layers=18*, *init_classifier_weights=False*)

ResNet architecture with 18 or 50 layers

This implementation enables separate access to feature and classification blocks.

**Parameters**

- **num_cls** – number of classes (int)
- **weights_init** –
  - "ImageNet": load the pre-trained weights for ImageNet dataset
  - path: load weights from a path on your computer or a url
  - None: initialize with random weights
- **num_layers** – 18 for Resnet18 or 50 for Resnet50
- **init_classifier_weights** –
  - if True, load the weights of the classification layer as well as

  feature extraction layers - if False (default), only load the weights of the feature extraction layers

**load**(*init_path*, *init_classifier_weights=True*, *verbose=False*)

load state dict (weights) of the feature+classifier optionally load only feature weights not classifier weights

**Parameters**

- **init_path** –
  - url containing "http": download weights from web
  - path: load weights from local path
- **init_classifier_weights** –
  - if True, load the weights of the classification layer as well as

  feature extraction layers - if False (default), only load the weights of the feature extraction layers
- **verbose** – if True, print missing/unused keys [default: False]

**class** opensoundscape.torch.architectures.resnet.**ResNetFeature**(*block*, *layers*, *zero_init_residual=False*, *groups=1*, *width_per_group=64*, *replace_stride_with_dilation=None*, *norm_layer=None*)

**class** opensoundscape.torch.architectures.utils.**BaseArchitecture**

Base architecture for reference.

**class** opensoundscape.torch.architectures.utils.**CompositeArchitecture**(**args*, ***kwargs*)

Architecture with separate feature and classsifier blocks

## 13.2 Data Selection

`opensoundscape.data_selection.resample(df, n_samples_per_class, upsample=True, downsample=True, random_state=None)`

resample a one-hot encoded label df for a target n_samples_per_class

**Parameters**

- **df** – dataframe with one-hot encoded labels: columns are classes, index is sample name/path
- **n_samples_per_class** – target number of samples per class
- **upsample** – if True, duplicate samples for classes with <n samples to get to n samples
- **downsample** – if True, randomly sample classis with >n samples to get to n samples
- **random_state** – passed to np.random calls. If None, random state is not fixed.

Note: The algorithm assumes that the label df is single-label. If the label df is multi-label, some classes can end up over-represented.

Note 2: The resulting df will have samples ordered by class label, even if the input df had samples in a random order.

`opensoundscape.data_selection.upsample(input_df, label_column='Labels', random_state=None)`

Given a input DataFrame of categorical labels, upsample to maximum value

Upsampling removes the class imbalance in your dataset. Rows for each label are repeated up to *max_count // rows*. Then, we randomly sample the rows to fill up to *max_count*.

The input df is NOT one-hot encoded in this case, but instead contains categorical labels in a specified label_columns

**Parameters**

- **input_df** – A DataFrame to upsample
- **label_column** – The column to draw unique labels from
- **random_state** – Set the random_state during sampling

**Returns** An upsampled DataFrame

**Return type** df

## 13.3 Grad Cam

GradCAM is a method of visualizing the activation of the network on parts of an image

# Author: Kazuto Nakashima # URL: http://kazuto1011.github.io # Created: 2017-05-26

## 13.4 Loss Functions

loss function classes to use with opensoundscape models

**class** `opensoundscape.torch.loss.BCEWithLogitsLoss_hot`

use pytorch's nn.BCEWithLogitsLoss for one-hot labels by simply converting y from long to float

**class** opensoundscape.torch.loss.**CrossEntropyLoss_hot**

use pytorch's nn.CrossEntropyLoss for one-hot labels by converting labels from 1-hot to integer labels

throws a ValueError if labels are not one-hot

**class** opensoundscape.torch.loss.**ResampleLoss**(*class_freq*, *reduction='mean'*, *loss_weight=1.0*)

opensoundscape.torch.loss.**reduce_loss**(*loss*, *reduction*)

Reduce loss as specified.

**Parameters**

- **loss** (*Tensor*) – Elementwise loss tensor.
- **reduction** (*str*) – Options are "none", "mean" and "sum".

**Returns** Reduced loss tensor.

**Return type** Tensor

opensoundscape.torch.loss.**weight_reduce_loss**(*loss*, *weight=None*, *reduction='mean'*, *avg_factor=None*)

Apply element-wise weight and reduce loss.

**Parameters**

- **loss** (*Tensor*) – Element-wise loss.
- **weight** (*Tensor*) – Element-wise weights.
- **reduction** (*str*) – Same as built-in losses of PyTorch.
- **avg_factor** (*float*) – Avarage factor when computing the mean of losses.

**Returns** Processed loss values.

**Return type** Tensor

## 13.5 Safe Dataloading

Dataset wrapper to handle errors gracefully in Preprocessor classes

A SafeDataset handles errors in a potentially misleading way: If an error is raised while trying to load a sample, the SafeDataset will instead load a different sample. The indices of any samples that failed to load will be stored in ._unsafe_indices.

The behavior may be desireable for training a model, but could cause silent errors when predicting a model (replacing a bad file with a different file), and you should always be careful to check for ._unsafe_indices after using a SafeDataset.

based on an implementation by @msamogh in nonechucks (github.com/msamogh/nonechucks/)

**class** opensoundscape.torch.safe_dataset.**SafeDataset**(*dataset*, *unsafe_behavior*, *eager_eval=False*)

A wrapper for a Dataset that handles errors when loading samples

WARNING: When iterating, will skip the failed sample, but when using within a DataLoader, finds the next good sample and uses it for the current index (see __getitem__).

**Parameters**

- **dataset** – a torch Dataset instance or child such as a Preprocessor
- **eager_eval** – If True, checks if every file is able to be loaded during initialization (logs _safe_indices and _unsafe_indices)

Attributes: _safe_indices and _unsafe_indices can be accessed later to check which samples threw errors.

**_build_index**()
tries to load each sample, logs _safe_indices and _unsafe_indices

**__getitem__**(*index*)
If loading an index fails, keeps trying the next index until success

**_safe_get_item**()
Tries to load a sample, returns None if error occurs

**is_index_built**
Returns True if all indices of the original dataset have been classified into safe_samples_indices or _unsafe_samples_indices.

## 13.6 Sampling

classes for strategically sampling within a DataLoader

**class** opensoundscape.torch.sampling.**ClassAwareSampler**(*labels*, *num_samples_cls=1*)
In each batch of samples, pick a limited number of classes to include and give even representation to each class

**class** opensoundscape.torch.sampling.**ImbalancedDatasetSampler**(*dataset*, *indices=None*, *num_samples=None*, *callback_get_label=None*)
Samples elements randomly from a given list of indices for imbalanced dataset :param indices: a list of indices :type indices: list, optional :param num_samples: number of samples to draw :type num_samples: int, optional :param callback_get_label func: a callback-like function which takes two arguments - dataset and index

## 13.7 Performance Metrics

opensoundscape.metrics.**binary_metrics**(*targets, preds, class_names=[0, 1]*)
labels should be single-target

opensoundscape.metrics.**multiclass_metrics**(*targets*, *preds*, *class_names*)
provide a list or np.array of 0,1 targets and predictions

opensoundscape.metrics.**predict**(*scores*, *single_target=False*, *threshold=0.5*)
convert numeric scores to binary predictions

return 0/1 for an array of scores: samples (rows) x classes (columns)

**Parameters**

- **scores** – a 2-d list or np.array. row=sample, columns=classes
- **single_target** – if True, predict 1 for highest scoring class per sample, 0 for other classes. If False, predict 1 for all scores > threshold [default: False]
- **threshold** – Predict 1 for score > threshold. only used if single_target = False. [default: 0.5]

CHAPTER 14

# Preprocessing

## 14.1 Image Augmentation

Transforms and augmentations for PIL.Images

`opensoundscape.preprocess.img_augment.`**`time_split`**(*img*, *seed=None*)

Given a PIL.Image, split into left/right parts and swap

Randomly chooses the slicing location For example, if *h* chosen

**abcdefghijklmnop** ^

hijklmnop + abcdefg

**Parameters** **`img`** – A PIL.Image

**Returns** A PIL.Image

## 14.2 Preprocessing Actions

Actions for augmentation and preprocessing pipelines

This module contains Action classes which act as the elements in Preprocessor pipelines. Action classes have go(), on(), off(), and set() methods. They take a single sample of a specific type and return the transformed or augmented sample, which may or may not be the same type as the original.

See the preprocessor module and Preprocessing tutorial for details on how to use and create your own actions.

**`class`** `opensoundscape.preprocess.actions.`**`ActionContainer`**

this is a container object which holds instances of Action child-classes

the Actions it contains each have .go(), .on(), .off(), .set(), .get()

The actions are un-ordered and may not all be used. In preprocessor objects such as AudioToSpectrogramPreprocessor, Actions from the action container are listed in a pipeline(list), which defines their order of use.

To add actions to the container: action_container.loader = AudioLoader() To set parameters of actions: action_container.loader.set(param=value,. . . )

Methods: list_actions()

**class** opensoundscape.preprocess.actions.**AudioClipLoader**(***kwargs*)

Action to load only a specific segment of an audio file

Loads an audio file or part of a file. see Audio.from_file() for documentation.

**Parameters** **Audio.from_file** (*see*) –

Note: default sample_rate=None means use file's sample rate, don't resample

**class** opensoundscape.preprocess.actions.**AudioLoader**(***kwargs*)

Action child class for Audio.from_file() (path -> Audio)

Loads an audio file or part of a file. see Audio.from_file() for documentation.

**Parameters** **Audio.from_file** (*see*) –

Note: default sample_rate=None means use file's sample rate, don't resample

**class** opensoundscape.preprocess.actions.**AudioToMelSpectrogram**(***kwargs*)

Action child class for MelSpectrogram.from_audio() (Audio -> MelSpectrogram)

see spectrogram.MelSpectrogram.from_audio for documentation

**Parameters**

- **n_mels** – Number of mel bands to generate [default: 128] Note: n_mels should be chosen for compatibility with the Spectrogram parameter *window_samples*. Choosing a value > ~ *window_samples/10* will result in zero-valued rows while small values blend rows from the original spectrogram.
- **window_type** – The windowing function to use [default: "hann"]
- **window_samples** – n samples per window [default: 512]
- **overlap_samples** – n samples shared by consecutive windows [default: 256]
- **htk** – use HTK mel-filter bank instead of Slaney, see Librosa docs [default: False]
- **norm='slanley'** – mel filter bank normalization, see Librosa docs
- **dB_scale=True** – If True, rescales values to decibels, x=10*log10(x) - if dB_scale is False, decibel_limits is ignored

**class** opensoundscape.preprocess.actions.**AudioToSpectrogram**(***kwargs*)

Action child class for Spectrogram.from_audio() (Audio -> Spectrogram)

see spectrogram.Spectrogram.from_audio for documentation

**Parameters**

- **window_type="hann"** – see scipy.signal.spectrogram docs for description of window parameter
- **window_samples=512** – number of audio samples per spectrogram window (pixel)
- **overlap_samples=256** – number of samples shared by consecutive windows
- **=** (*decibel_limits*) – limit the dB values to (min,max) (lower values set to min, higher values set to max)
- **dB_scale=True** – If True, rescales values to decibels, x=10*log10(x) - if dB_scale is False, decibel_limits is ignored

**class** opensoundscape.preprocess.actions.**AudioTrimmer**(***kwargs*)

Action child class for trimming audio (Audio -> Audio)

Trims an audio file to desired length Allows audio to be trimmed from start or from a random time Optionally extends audio shorter than clip_length with silence

**Parameters**

- **audio_length** – desired final length (sec); if None, no trim is performed
- **extend** – if True, clips shorter than audio_length are extended with silence to required length
- **random_trim** – if True, a random segment of length audio_length is chosen from the input audio. If False, the file is trimmed from 0 seconds to audio_length seconds.

**class** opensoundscape.preprocess.actions.**BaseAction**(***kwargs*)

Parent class for all Actions (used in Preprocessor pipelines)

New actions should subclass this class.

Subclasses should set *self.requires_labels = True* if go() expects (X,y) instead of (X). y is a row of a dataframe (a pd.Series) with index (.name) = original file path, columns=class names, values=labels (0,1). X is the sample, and can be of various types (path, Audio, Spectrogram, Tensor, etc). See ImgOverlay for an example of an Action that uses labels.

**class** opensoundscape.preprocess.actions.**FrequencyMask**(***kwargs*)

add random horizontal bars over image

**Parameters**

- **max_masks** – max number of horizontal bars [default: 3]
- **max_width** – maximum size of horizontal bars as fraction of image height

**go**(*x*)

torch Tensor in, torch Tensor out

**class** opensoundscape.preprocess.actions.**ImgOverlay**(*overlay_df*, *audio_length*, *loader_pipeline*, *update_labels*, ***kwargs*)

iteratively overlay images on top of eachother

Overlays images from overlay_df on top of the sample with probability overlay_prob until stopping condition. If necessary, trims overlay audio to the length of the input audio. Overlays the images on top of each other with a weight.

**Overlays can be used in a few general ways:**

1. a separate df where any file can be overlayed (overlay_class=None)
2. **same df as training, where the overlay class is "different" ie,** does not contain overlapping labels with the original sample
3. **same df as training, where samples from a specific class are used** for overlays

**Parameters**

- **overlay_df** – a labels dataframe with audio files as the index and classes as columns
- **audio_length** – length in seconds of original audio sample
- **loader_pipeline** – the preprocessing pipeline to load audio -> spec
- **update_labels** – if True, add overlayed sample's labels to original sample

- **overlay_class** – how to choose files from overlay_df to overlay Options [default: "different"]: None - Randomly select any file from overlay_df "different" - Select a random file from overlay_df containing none

  of the classes this file contains

  specific class name - always choose files from this class
- **overlay_prob** – the probability of applying each subsequent overlay
- **max_overlay_num** – the maximum number of samples to overlay on original - for example, if overlay_prob = 0.5 and max_overlay_num=2,

  1/2 of images will recieve 1 overlay and 1/4 will recieve an additional second overlay
- **overlay_weight** – a float > 0 and < 1, or a list of 2 floats [min, max] between which the weight will be randomly chosen. e.g. [0.1,0.7] An overlay_weight <0.5 means more emphasis on original image.

**go** (*x*, *x_labels*)
Overlay images from overlay_df

**class** opensoundscape.preprocess.actions.**ImgToTensor** (***kwargs*)
Convert PIL image to RGB Tensor (PIL.Image -> Tensor)

convert PIL.Image w/range [0,255] to torch Tensor w/range [0,1] converts image to RGB (3 channels)

**class** opensoundscape.preprocess.actions.**ImgToTensorGrayscale** (***kwargs*)
Convert PIL image to greyscale Tensor (PIL.Image -> Tensor)

convert PIL.Image w/range [0,255] to torch Tensor w/range [0,1] converts image to grayscale (1 channel)

**class** opensoundscape.preprocess.actions.**SaveTensorToDisk** (*save_path*, ***kwargs*)
save a torch Tensor to disk (Tensor -> Tensor)

Requires x_labels because the index of the label-row (.name) gives the original file name for this sample.

Uses torchvision.utils.save_image. Creates save_path dir if it doesn't exist

**Parameters** **save_path** – a directory where tensor will be saved

**go** (*x*, *x_labels*)
we require x_labels because the .name gives origin file name

**class** opensoundscape.preprocess.actions.**SpecToImg** (***kwargs*)
Action class to transform Spectrogram to PIL image

(Spectrogram -> PIL.Image)

**Parameters**

- **destination** – a file path (string)
- **shape=None** – image dimensions for 1 channel, (height, width)
- **mode="RGB"** – RGB for 3-channel color or "L" for 1-channel grayscale
- **colormap=None** – (str) Matplotlib color map name (if None, greyscale)

**class** opensoundscape.preprocess.actions.**SpectrogramBandpass** (***kwargs*)
Action class for Spectrogram.bandpass() (Spectrogram -> Spectrogram)

see opensoundscape.spectrogram.Spectrogram.bandpass() for documentation

To bandpass the spectrogram from 1kHz to 5Khz: action = SpectrogramBandpass(1000,5000)

**Parameters**

- **min_f** – low frequency in Hz for bandpass
- **max_f** – high frequency in Hz for bandpass
- **out_of_bounds_ok** – if False, raises error if min or max beyond spec limits

**class** opensoundscape.preprocess.actions.**TensorAddNoise**(***kwargs*)
Add gaussian noise to sample (Tensor -> Tensor)

**Parameters** **std** – standard deviation for Gaussian noise [default: 1]

Note: be aware that scaling before/after this action will change the effect of a fixed stdev Gaussian noise

**class** opensoundscape.preprocess.actions.**TensorAugment**(***kwargs*)
combination of 3 augmentations with hard-coded parameters

time warp, time mask, and frequency mask

use (bool) time_warp, time_mask, freq_mask to turn each on/off

Note: This function reduces the image to greyscale then duplicates the image across the 3 channels

**go**(*x*)
torch Tensor in, torch Tensor out

**class** opensoundscape.preprocess.actions.**TensorNormalize**(***kwargs*)
torchvision.transforms.Normalize (WARNING: FIXED shift and scale)

(Tensor->Tensor)

WARNING: This does not perform per-image normalization. Instead, it takes as arguments a fixed u and s, ie for the entire dataset, and performs X=(X-u)/s.

**Params:** mean=0.5 std=0.5

**class** opensoundscape.preprocess.actions.**TimeMask**(***kwargs*)
add random vertical bars over image (Tensor -> Tensor)

**Parameters**

- **max_masks** – maximum number of bars [default: 3]
- **max_width** – maximum width of horizontal bars as fraction of image width
- **[default** – 0.2]

**class** opensoundscape.preprocess.actions.**TimeWarp**(***kwargs*)
Time warp is an experimental augmentation that creates a tilted image.

**Parameters** **warp_amount** – use higher values for more skew and offset (experimental)

Note: this augmentation reduces the image to greyscale and duplicates the result across the 3 channels.

**class** opensoundscape.preprocess.actions.**TorchColorJitter**(***kwargs*)
Action class for torchvision.transforms.ColorJitter

(Tensor -> Tensor) or (PIL Img -> PIL Img)

**Parameters**

- **brightness=0.3** –
- **contrast=0.3** –
- **saturation=0.3** –
- **hue=0** –

**class** opensoundscape.preprocess.actions.**TorchRandomAffine**(***kwargs*)

Action class for torchvision.transforms.RandomAffine

(Tensor -> Tensor) or (PIL Img -> PIL Img)

**Parameters**

- **= 0** (*degrees*) –
- **=** (*fill*) –
- **=** –

Note: If applying per-image normalization, we recommend applying RandomAffine after image normalization. In this case, an intermediate gray value is ~0. If normalization is applied after RandomAffine on a PIL image, use an intermediate fill color such as (122,122,122).

## 14.3 Preprocessors

**class** opensoundscape.preprocess.preprocessors.**AudioLoadingPreprocessor**(*df*, *return_labels=True*, *audio_length=None*)

creates Audio objects from file paths

**Parameters**

- **df** – dataframe of audio clips. df must have audio paths in the index. If df has labels, the class names should be the columns, and the values of each row should be 0 or 1. If data does not have labels, df will have no columns
- **return_labels** – if True, __getitem__ returns {"X":batch_tensors,"y":labels} if False, __getitem__ returns {"X":batch_tensors} [default: True]
- **audio_length** – length in seconds of audio to return - None: do not trim the original audio - seconds (float): trim longer audio to this length. Shorter audio input will raise a ValueError.

**class** opensoundscape.preprocess.preprocessors.**AudioToSpectrogramPreprocessor**(*df*, *audio_length=None*, *out_shape=[224, 224]*, *return_labels=True*)

loads audio paths, creates spectrogram, returns tensor

by default, does not resample audio, but bandpasses to 0-11025 Hz (to ensure all outputs have same scale in y-axis) can change with .actions.load_audio.set(sample_rate=sr)

**Parameters**

- **df** – dataframe of audio clips. df must have audio paths in the index. If df has labels, the class names should be the columns, and the values of each row should be 0 or 1. If data does not have labels, df will have no columns
- **audio_length** – length in seconds of audio clips [default: None] If provided, longer clips trimmed to this length. By default, shorter clips will not be extended (modify actions.AudioTrimmer to change behavior).

- **out_shape** – output shape of tensor in pixels [default: [224,224]]
- **return_labels** – if True, the __getitem__ method will return {X:sample,y:labels} If False, the __getitem__ method will return {X:sample} If df has no labels (no columns), use return_labels=False [default: True]

**class** opensoundscape.preprocess.preprocessors.**BasePreprocessor**(*df*, *return_labels=True*)

Base class for Preprocessing pipelines (use in place of torch Dataset)

Custom Preprocessor classes should subclass this class or its children

**Parameters**

- **df** – dataframe of audio clips. df must have audio paths in the index. If df has labels, the class names should be the columns, and the values of each row should be 0 or 1. If data does not have labels, df will have no columns
- **return_labels** – if True, the __getitem__ method will return {X:sample,y:labels} If False, the __getitem__ method will return {X:sample} If df has no labels (no columns), use return_labels=False [default: True]

**Raises** PreprocessingError if exception is raised during __getitem__

**class_counts_cal**()

count number of each label

**head**(*n=5*)

out-of-place copy of first n samples

performs df.head(n) on self.df

**Parameters**

- **n** – number of first samples to return, see pandas.DataFrame.head()
- **[default** – 5]

**Returns** a new dataset object

**pipeline_summary**()

Generate a DataFrame describing the current pipeline

The DataFrame has columns for name (corresponds to the attribute name, eg 'to_img' for self.actions.to_img), on (not bypassed) / off (bypassed), and action_reference (a reference to the object)

**sample**(***kwargs*)

out-of-place random sample

creates copy of object with n rows randomly sampled from dataframe

Args: see pandas.DataFrame.sample()

**Returns** a new dataset object

**class** opensoundscape.preprocess.preprocessors.**ClipLoadingSpectrogramPreprocessor**(*df*)

load audio samples from long audio files

Directly loads a part of an audio file, eg 5-10 seconds, without loading entire file. This alows for prediction on long audio files without needing to pre-split or load large files into memory.

It will load the requested audio segments into samples, regardless of length

**Parameters** **df** – a dataframe with file paths as index and 2 columns: ['start_time','end_time'] (seconds since beginning of file)

**Returns** ClipLoadingSpectrogramPreprocessor object

Examples: You can quickly create such a df for a set of audio files like this:

` from opensoundscape.helpers import make_clip_df files = glob('/path_to/*/*.WAV') #get list of full-length files clip_duration=5.0 clip_overlap = 0.0 clip_df = make_clip_df(files, clip_duration, clip_overlap) `

If you use this preprocessor with model.predict(), it will work, but the scores/predictions df will only have file paths not the times of clips. You will want to re-add the start and end times of clips as multi-index:

``` score_df = model.predict(clip_loading_ds) #for instance score_df.index = pd.MultiIndex.from_arrays(

[clip_df.index,clip_df['start_time'],clip_df['end_time']]

**class** opensoundscape.preprocess.preprocessors.**CnnPreprocessor**(*df, audio_length=None, return_labels=True, debug=None, overlay_df=None, out_shape=[224, 224]*)

Child of AudioToSpectrogramPreprocessor with full augmentation pipeline

loads audio, creates spectrogram, performs augmentations, returns tensor

by default, does not resample audio, but bandpasses to 0-10 kHz (to ensure all outputs have same scale in y-axis) can change with .actions.load_audio.set(sample_rate=sr)

**Parameters**

- **df** – dataframe of audio clips. df must have audio paths in the index. If df has labels, the class names should be the columns, and the values of each row should be 0 or 1. If data does not have labels, df will have no columns
- **audio_length** – length in seconds of audio clips [default: None] If provided, longer clips trimmed to this length. By default, shorter clips will not be extended (modify actions.AudioTrimmer to change behavior).
- **out_shape** – output shape of tensor in pixels [default: [224,224]]
- **return_labels** – if True, the __getitem__ method will return {X:sample,y:labels} If False, the __getitem__ method will return {X:sample} If df has no labels (no columns), use return_labels=False [default: True]
- **debug** – If a path is provided, generated samples (after all augmentation) will be saved to the path as an image. This is useful for checking that the sample provided to the model matches expectations. [default: None]

**augmentation_off**()
use pipeline that skips all augmentations

**augmentation_on**()
use pipeline containing all actions including augmentations

**exception** opensoundscape.preprocess.utils.**PreprocessingError**
Custom exception indicating that a Preprocessor pipeline failed
```

## 14.4 Tensor Augmentation

Augmentations and transforms for torch.Tensors

These functions were implemented for PyTorch in: https://github.com/zcaceres/spec_augment The original paper is available on https://arxiv.org/abs/1904.08779

`opensoundscape.preprocess.tensor_augment.`**`freq_mask`**(*spec*, *F=30*, *max_masks=3*, *replace_with_zero=False*)

draws horizontal bars over the image

F:maximum frequency-width of bars in pixels

max_masks: maximum number of bars to draw

replace_with_zero: if True, bars are 0s, otherwise, mean img value

`opensoundscape.preprocess.tensor_augment.`**`time_mask`**(*spec*, *T=40*, *max_masks=3*, *replace_with_zero=False*)

draws vertical bars over the image

T:maximum time-width of bars in pixels

max_masks: maximum number of bars to draw

replace_with_zero: if True, bars are 0s, otherwise, mean img value

`opensoundscape.preprocess.tensor_augment.`**`time_warp`**(*spec*, *W=5*)

apply time stretch and shearing to spectrogram

fills empty space on right side with horizontal bars

W controls amount of warping. Random with occasional large warp.

# CHAPTER 15

## Signal Processing

### 15.1 RIBBIT

Detect periodic vocalizations with RIBBIT

This module provides functionality to search audio for periodically fluctuating vocalizations.

opensoundscape.ribbit.**calculate_pulse_score**(*amplitude*, *amplitude_sample_rate*, *pulse_rate_range*, *plot=False*, *nfft=1024*)

Search for amplitude pulsing in an audio signal in a range of pulse repetition rates (PRR)

scores an audio amplitude signal by highest value of power spectral density in the PRR range

**Parameters**

- **amplitude** – a time series of the audio signal's amplitude (for instance a smoothed raw audio signal)
- **amplitude_sample_rate** – sample rate in Hz of amplitude signal, normally ~20-200 Hz
- **pulse_rate_range** – [min, max] values for amplitude modulation in Hz
- **plot=False** – if True, creates a plot visualizing the power spectral density
- **nfft=1024** – controls the resolution of the power spectral density (see scipy.signal.welch)

**Returns** pulse rate score for this audio segment (float)

opensoundscape.ribbit.**ribbit**(*spectrogram*, *signal_band*, *pulse_rate_range*, *clip_duration*, *clip_overlap=0*, *final_clip=None*, *noise_bands=None*, *plot=False*)

Run RIBBIT detector to search for periodic calls in audio

This tool searches for periodic energy fluctuations at specific repetition rates and frequencies.

**Parameters**

- **spectrogram** – opensoundscape.Spectrogram object of an audio file
- **signal_band** – [min, max] frequency range of the target species, in Hz

- **pulse_rate_range** – [min,max] pulses per second for the target species
- **clip_duration** – the length of audio (in seconds) to analyze at one time - each clip is analyzed independently and recieves a ribbit score
- **clip_overlap** (*float*) – overlap between consecutive clips (sec)
- **final_clip** (*str*) – behavior if final clip is less than clip_duration seconds long. By default, discards remaining audio if less than clip_duration seconds long [default: None]. Options: - None: Discard the remainder (do not make a clip) - "remainder": Use only remainder of Audio (final clip will be shorter than clip_duration) - "full": Increase overlap with previous clip to yield a clip with clip_duration length Note that the "extend" option is not supported for RIBBIT.
- **noise_bands** – list of frequency ranges to subtract from the signal_band For instance: [ [min1,max1] , [min2,max2] ] - if *None*, no noise bands are used - default: None
- **plot=False** – if True, plot the power spectral density for each clip

**Returns** DataFrame of index=('start_time','end_time'), columns=['score'], with a row for each clip.

### Notes

__PARAMETERS__ RIBBIT requires the user to select a set of parameters that describe the target vocalization. Here is some detailed advice on how to use these parameters.

**Signal Band:** The signal band is the frequency range where RIBBIT looks for the target species. It is best to pick a narrow signal band if possible, so that the model focuses on a specific part of the spectrogram and has less potential to include erronious sounds.

**Noise Bands:** Optionally, users can specify other frequency ranges called noise bands. Sounds in the *noise_bands* are _subtracted_ from the *signal_band*. Noise bands help the model filter out erronious sounds from the recordings, which could include confusion species, background noise, and popping/clicking of the microphone due to rain, wind, or digital errors. It's usually good to include one noise band for very low frequencies – this specifically eliminates popping and clicking from being registered as a vocalization. It's also good to specify noise bands that target confusion species. Another approach is to specify two narrow *noise_bands* that are directly above and below the *signal_band*.

**Pulse Rate Range:** This parameters specifies the minimum and maximum pulse rate (the number of pulses per second, also known as pulse repetition rate) RIBBIT should look for to find the focal species. For example, choosing *pulse_rate_range = [10, 20]* means that RIBBIT should look for pulses no slower than 10 pulses per second and no faster than 20 pulses per second.

**Clip Duration:** The *clip_duration* parameter tells RIBBIT how many seconds of audio to analyze at one time. Generally, you should choose a *clip_length* that is similar to the length of the target species vocalization, or a little bit longer. For very slowly pulsing vocalizations, choose a longer window so that at least 5 pulses can occur in one window (0.5 pulses per second -> 10 second window). Typical values for are 0.3 to 10 seconds. Also, *clip_overlap* can be used for overlap between sequential clips. This is more computationally expensive but will be more likely to center a target sound in the clip (with zero overlap, the target sound may be split up between adjacent clips).

**Plot:** We can choose to show the power spectrum of pulse repetition rate for each window by setting *plot=True*. The default is not to show these plots (*plot=False*).

__ALGORITHM__ This is the procedure RIBBIT follows: divide the audio into segments of length clip_duration for each clip:

> calculate time series of energy in signal band (signal_band) and subtract noise band energies (noise_bands) calculate power spectral density of the amplitude time series score the file based on the maximum value of power spectral density in the pulse rate range

## 15.2 Signal Processing

Signal processing tools for feature extraction and more

opensoundscape.signal.**cwt_peaks**(*audio*, *center_frequency*, *wavelet='morl'*, *peak_threshold=0.2*, *peak_separation=None*, *plot=False*)

compute a cwt, post-process, then extract peaks

Performs a continuous wavelet transform (cwt) on an audio signal at a single frequency. It then squares, smooths, and normalizes the signal. Finally, it detects peaks in the resulting signal and returns the times and magnitudes of detected peaks. It is used as a feature extractor for Ruffed Grouse drumming detection.

**Parameters**

- **audio** – an Audio object
- **center_frequency** – the target frequency to extract peaks from
- **wavelet** – (str) name of a pywt wavelet, eg 'morl' (see pywt docs)
- **peak_threshold** – minimum height of peaks - if None, no minimum peak height - see "height" argument to scipy.signal.find_peaks
- **peak_separation** – minimum time between detected peaks, in seconds - if None, no minimum distance - see "distance" argument to scipy.signal.find_peaks

**Returns** list of times (from beginning of signal) of each peak peak_levels: list of magnitudes of each detected peak

**Return type** peak_times

---

**Note:** consider downsampling audio to reduce computational cost. Audio must have sample rate of at least 2x target frequency.

---

opensoundscape.signal.**detect_peak_sequence_cwt**(*audio*, *sr=400*, *window_len=60*, *center_frequency=50*, *wavelet='morl'*, *peak_threshold=0.2*, *peak_separation=0.0375*, *dt_range=[0.05, 0.8]*, *dy_range=[-0.2, 0]*, *d2y_range=[-0.05, 0.15]*, *max_skip=3*, *duration_range=[1, 15]*, *points_range=[9, 100]*, *plot=False*)

Use a continuous wavelet transform to detect accellerating sequences

This function creates a continuous wavelet transform (cwt) feature and searches for accelerating sequences of peaks in the feature. It was developed to detect Ruffed Grouse drumming events in audio signals. Default parameters are tuned for Ruffed Grouse drumming detection.

Analysis is performed on analysis windows of fixed length without overlap. Detections from each analysis window across the audio file are aggregated.

**Parameters**

- **audio** – Audio object
- **sr=400** – resample audio to this sample rate (Hz)
- **window_len=60** – length of analysis window (sec)
- **center_frequency=50** – target audio frequency of cwt
- **wavelet='morl'** – (str) pywt wavelet name (see pywavelets docs)

- **peak_threshold=0.2** – height threhsold (0-1) for peaks in normalized signal
- **peak_separation=15/400** – min separation (sec) for peak finding
- **0.8]** (*dt_range=[0.05,*) – sequence detection point-to-point criterion 1 - Note: the upper limit is also used as sequence termination criterion 2
- **0]** (*dy_range=[-0.2,*) – sequence detection point-to-point criterion 2
- **0.15]** (*d2y_range=[-0.05,*) – sequence detection point-to-point criterion 3
- **max_skip=3** – sequence termination criterion 1: max sequential invalid points
- **15]** (*duration_range=[1,*) – sequence criterion 1: length (sec) of sequence
- **100]** (*points_range=[9,*) – sequence criterion 2: num points in sequence
- **plot=False** – if True, plot peaks and detected sequences with pyplot

**Returns** dataframe summarizing detected sequences

Note: for Ruffed Grouse drumming, which is very low pitched, audio is resampled to 400 Hz. This greatly increases the efficiency of the cwt, but will only detect frequencies up to 400/2=200Hz. Generally, choose a resample frequency as low as possible but >=2x the target frequency

Note: the cwt signal is normalized on each analysis window, so changing the analysis window size can change the detection results.

Note: if there is an incomplete window remaining at the end of the audio file, it is discarded (not analyzed).

opensoundscape.signal.**find_accel_sequences**(*t, dt_range=[0.05, 0.8], dy_range=[-0.2, 0], d2y_range=[-0.05, 0.15], max_skip=3, duration_range=[1, 15], points_range=[5, 100]*)

detect accelerating/decelerating sequences in time series

developed for deteting Ruffed Grouse drumming events in a series of peaks extracted from cwt signal

The algorithm computes the forward difference of t, y(t). It iterates through the [y(t), t] points searching for sequences of points that meet a set of conditions. It begins with an empty candidate sequence.

"Point-to-point criterea": Valid ranges for dt, dy, and d2y are checked for each subsequent point and are based on previous points in the candidate sequence. If they are met, the point is added to the candidate sequence.

"Continuation criterea": Conditions for max_skip and the upper bound of dt are used to determine when a sequence should be terminated.

- max_skip: max number of sequential invalid points before terminating
- dt<=dt_range[1]: if dt is long, sequence should be broken

"Sequence criterea": When a sequence is terminated, it is evaluated on conditions for duration_range and points_range. If it meets these conditions, it is saved as a detected sequence.

- duration_range: length of sequence in seconds from first to last point
- points_range: number of points included in sequence

When a sequence is terminated, the search continues with the next point and an empty sequence.

**Parameters**

- **t** – (list or np.array) times of all detected peaks (seconds)
- **dt_range=[0.05,0.8]** – valid values for t(i) - t(i-1)
- **dy_range=[-0.2,0]** – valid values for change in y (grouse: difference in time between consecutive beats should decrease)

- **d2y_range=[-.05,15]** – limit change in dy: should not show large decrease (sharp curve downward on y vs t plot)
- **max_skip=3** – max invalid points between valid points for a sequence (grouse: should not have many noisy points between beats)
- **duration_range=[1,15]** – total duration of sequence (sec)
- **points_range=[9,100]** – total number of points in sequence

**Returns** lists of t and y for each detected sequence

**Return type** sequences_t, sequences_y

`opensoundscape.signal.`**`frequency2scale`**(*frequency*, *wavelet*, *sr*)

determine appropriate wavelet scale for desired center frequency

**Parameters**

- **frequency** – desired center frequency of wavelet in Hz (1/seconds)
- **wavelet** – (str) name of pywt wavelet, eg 'morl' for Morlet
- **sr** – sample rate in Hz (1/seconds)

**Returns** (float) scale parameter for pywt.ctw() to extract desired frequency

**Return type** scale

Note: this function is not exactly an inverse of pywt.scale2frequency(), because that function returns frequency in sample-units (cycles/sample) rather than frequency in Hz (cycles/second). In other words, freuquency_hz = pywt.scale2frequency(w,scale)*sr.

# CHAPTER 16

# Misc tools

## 16.1 Helpers

`opensoundscape.helpers.`**`binarize`**(*x*, *threshold*)
: return a list of 0, 1 by thresholding vector x

`opensoundscape.helpers.`**`bound`**(*x*, *bounds*)
: restrict x to a range of bounds = [min, max]

`opensoundscape.helpers.`**`file_name`**(*path*)
: get file name without extension from a path

`opensoundscape.helpers.`**`generate_clip_times_df`**(*full_duration*, *clip_duration*, *clip_overlap=0*, *final_clip=None*)
: generate start and end times for even-lengthed clips

The behavior for incomplete final clips at the end of the full_duration depends on the final_clip parameter.

This function only creates a dataframe with start and end times, it does not perform any actual trimming of audio or other objects.

**Parameters**

- **`full_duration`** – The amount of time (seconds) to split into clips
- **`clip_duration`** (*`float`*) – The duration in seconds of the clips
- **`clip_overlap`** (*`float`*) – The overlap of the clips in seconds [default: 0]
- **`final_clip`** (*`str`*) – Behavior if final_clip is less than clip_duration seconds long. By default, discards remaining time if less than clip_duration seconds long [default: None]. Options:
  - None: Discard the remainder (do not make a clip)
  - "extend": Extend the final clip beyond full_duration to reach clip_duration length
  - "remainder": Use only remainder of full_duration (final clip will be shorter than clip_duration)

– "full": Increase overlap with previous clip to yield a clip with clip_duration length

**Returns** DataFrame with columns for 'start_time', 'end_time', and 'clip_duration' of each clip (which may differ from *clip_duration* argument for final clip only)

**Return type** clip_df

Note: using "remainder" or "full" with clip_overlap>0 is not recommended. This combination may result in several duplications of the same final clip.

`opensoundscape.helpers.`**`hex_to_time`**(*s*)

convert a hexidecimal, Unix time string to a datetime timestamp in utc

Example usage: ``` # Get the UTC timestamp t = hex_to_time('5F16A04E')

# Convert it to a desired timezone my_timezone = pytz.timezone("US/Mountain") t = t.astimezone(my_timezone) ```

**Parameters** **s** (*string*) – hexadecimal Unix epoch time string, e.g. '5F16A04E'

**Returns** datetime.datetime object representing the date and time in UTC

`opensoundscape.helpers.`**`inrange`**(*x*, *r*)

return true if x is in range [r[0],r1] (inclusive)

`opensoundscape.helpers.`**`isNan`**(*x*)

check for nan by equating x to itself

`opensoundscape.helpers.`**`jitter`**(*x*, *width*, *distribution='gaussian'*)

Jitter (add random noise to) each value of x

**Parameters**

- **x** – scalar, array, or nd-array of numeric type
- **width** – multiplier for random variable (stdev for 'gaussian' or r for 'uniform')
- **distribution** – 'gaussian' (default) or 'uniform' if 'gaussian': draw jitter from gaussian with mu = 0, std = width if 'uniform': draw jitter from uniform on [-width, width]

**Returns** x + random jitter

**Return type** jittered_x

`opensoundscape.helpers.`**`linear_scale`**(*array*, *in_range=(0, 1)*, *out_range=(0, 255)*)

Translate from range in_range to out_range

**Inputs:** in_range: The starting range [default: (0, 1)] out_range: The output range [default: (0, 255)]

**Outputs:** new_array: A translated array

`opensoundscape.helpers.`**`make_clip_df`**(*files*, *clip_duration*, *clip_overlap=0*, *final_clip=None*)

generate df of fixed-length clip times for a set of file_batch_size

Used to prepare a dataframe for ClipLoadingSpectrogramPreprocessor

A typical prediction workflow: ``` #get list of audio files files = glob('./dir/*.WAV')

#generate clip df clip_df = make_clip_df(files,clip_duration=5.0,clip_overlap=0)

#create dataset dataset = ClipLoadingSpectrogramPreprocessor(clip_df)

#generate predictions with a model model = load_model('/path/to/saved.model') scores, _, _ = model.predict(dataset)

This function creates a single dataframe with audio files as the index and columns: 'start_time', 'end_time'. It will list clips of a fixed duration from the beginning to end of each audio file.

**Parameters**

- **files** – list of audio file paths
- **clip_duration** (*float*) – see generate_clip_times_df
- **clip_overlap** (*float*) – see generate_clip_times_df
- **final_clip** (*str*) – see generate_clip_times_df

opensoundscape.helpers.**min_max_scale**(*array*, *feature_range=(0, 1)*)
rescale vaues in an a array linearly to feature_range

opensoundscape.helpers.**overlap**(*r1*, *r2*)
"calculate the amount of overlap between two real-numbered ranges

opensoundscape.helpers.**overlap_fraction**(*r1*, *r2*)
"calculate the fraction of r1 (low, high range) that overlaps with r2

opensoundscape.helpers.**rescale_features**(*X*, *rescaling_vector=None*)
rescale all features by dividing by the max value for each feature

optionally provide the rescaling vector (1xlen(X) np.array), so that you can rescale a new dataset consistently with an old one

returns rescaled feature set and rescaling vector

opensoundscape.helpers.**run_command**(*cmd*)
run a bash command with Popen, return response

opensoundscape.helpers.**sigmoid**(*x*)
sigmoid function

## 16.2 Taxa

a set of utilites for converting between scientific and common names of bird species in different naming systems (xeno canto and bird net)

opensoundscape.taxa.**bn_common_to_sci**(*common*)
convert bird net common name (ignoring dashes, spaces, case) to scientific name as lowercase-hyphenated

opensoundscape.taxa.**common_to_sci**(*common*)
convert bird net common name (ignoring dashes, spaces, case) to scientific name as lowercase-hyphenated

opensoundscape.taxa.**get_species_list**()
list of scientific-names (lowercase-hyphenated) of species in the loaded species table

opensoundscape.taxa.**sci_to_bn_common**(*scientific*)
convert scientific name as lowercase-hyphenated to birdnet common name as lowercasenospaces

opensoundscape.taxa.**sci_to_xc_common**(*scientific*)
convert scientific name as lowercase-hyphenated to xeno-canto common name as lowercasenospaces

opensoundscape.taxa.**xc_common_to_sci**(*common*)
convert xeno-canto common name (ignoring dashes, spaces, case) to scientific name as lowercase-hyphenated

## 16.3 Localization

opensoundscape.localization.**calc_speed_of_sound**(*temperature=20*)
Calculate speed of sound in meters per second

Calculate speed of sound for a given temperature in Celsius (Humidity has a negligible effect on speed of sound and so this functionality is not implemented)

**Parameters** **temperature** – ambient temperature in Celsius

**Returns** the speed of sound in meters per second

opensoundscape.localization.**localize**(*receiver_positions*, *arrival_times*, *temperature=20.0*, *invert_alg='gps'*, *center=True*, *pseudo=True*)

Perform TDOA localization on a sound event

Localize a sound event given relative arrival times at multiple receivers. This function implements a localization algorithm from the equations described in the class handout ("Global Positioning Systems"). Localization can be performed in a global coordinate system in meters (i.e., UTM), or relative to recorder positions in meters.

**Parameters**

- **receiver_positions** – a list of [x,y,z] positions for each receiver Positions should be in meters, e.g., the UTM coordinate system.
- **arrival_times** – a list of TDOA times (onset times) for each recorder The times should be in seconds.
- **temperature** – ambient temperature in Celsius
- **invert_alg** – what inversion algorithm to use (only 'gps' is implemented)
- **center** – whether to center recorders before computing localization result. Computes localization relative to centered plot, then translates solution back to original recorder locations. (For behavior of original Sound Finder, use True)
- **pseudo** – whether to use the pseudorange error (True) or sum of squares discrepancy (False) to pick the solution to return (For behavior of original Sound Finder, use False. However, in initial tests, pseudorange error appears to perform better.)

**Returns** The solution (x,y,z,b) with the lower sum of squares discrepancy b is the error in the pseudorange (distance to mics), b=c*delta_t (delta_t is time error)

opensoundscape.localization.**lorentz_ip**(*u*, *v=None*)

Compute Lorentz inner product of two vectors

For vectors *u* and *v*, the Lorentz inner product for 3-dimensional case is defined as

u[0]*v[0] + u[1]*v[1] + u[2]*v[2] - u[3]*v[3]

Or, for 2-dimensional case as

u[0]*v[0] + u[1]*v[1] - u[2]*v[2]

**Parameters**

- **u** – vector with shape either (3,) or (4,)
- **v** – vector with same shape as x1; if None (default), sets v = u

**Returns** value of Lorentz IP

**Return type** float

opensoundscape.localization.**travel_time**(*source*, *receiver*, *speed_of_sound*)

Calculate time required for sound to travel from a souce to a receiver

**Parameters**

- **source** – cartesian position [x,y] or [x,y,z] of sound source

- **receiver** – cartesian position [x,y] or [x,y,z] of sound receiver
- **speed_of_sound** – speed of sound in m/s

**Returns** time in seconds for sound to travel from source to receiver

# CHAPTER 17

# Index

# CHAPTER 18

## Modules

- modindex

# Python Module Index

## o

# Index

## Symbols



## A



## B

## C



## D



## E



## F



## G

## H



## I



## J



## L



## M



## N



## O

## P



## R



## S

## X