Classification and feature engineering

MACHINE LEARNING FOR TIME SERIES DATA IN PYTHON

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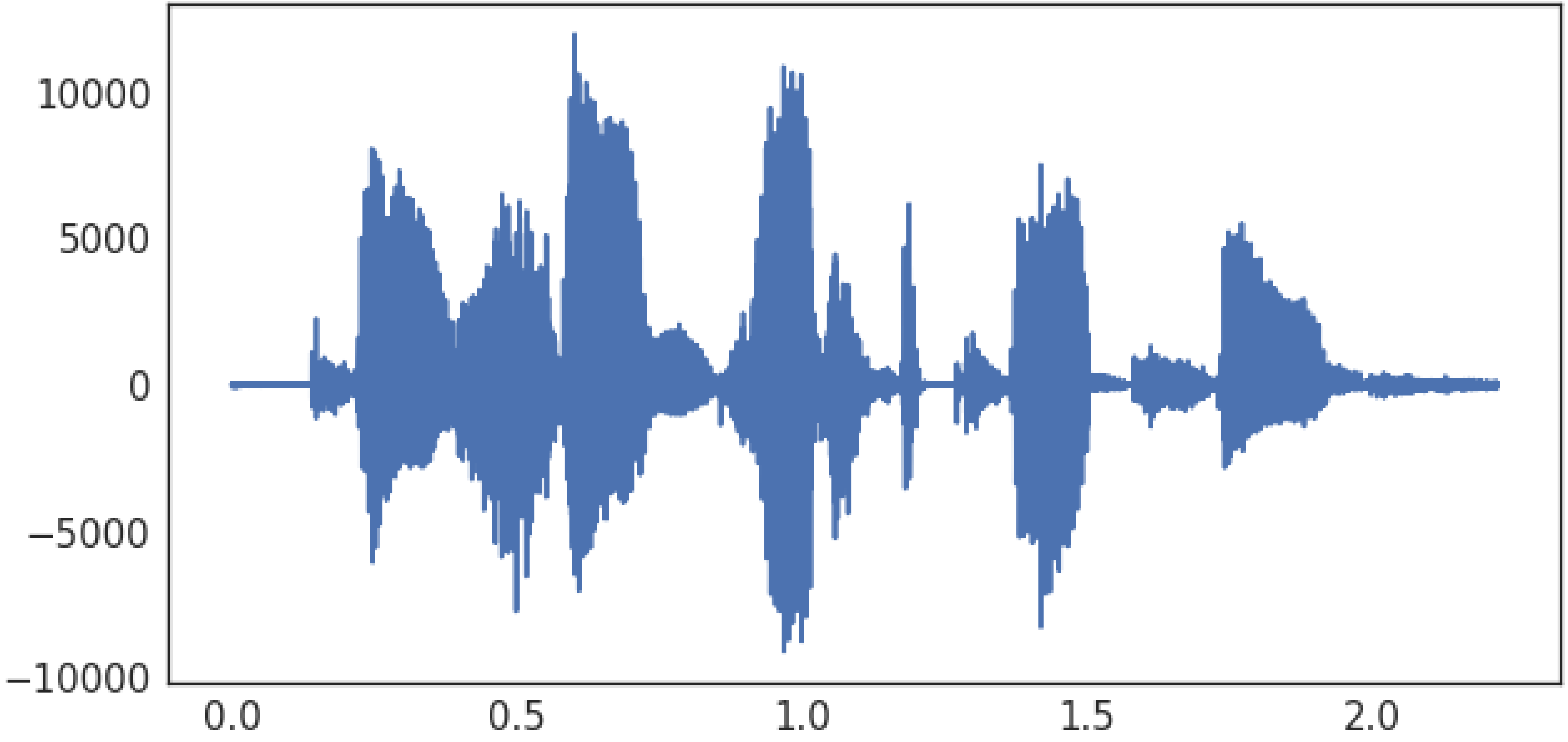
Always visualize raw data before fitting models

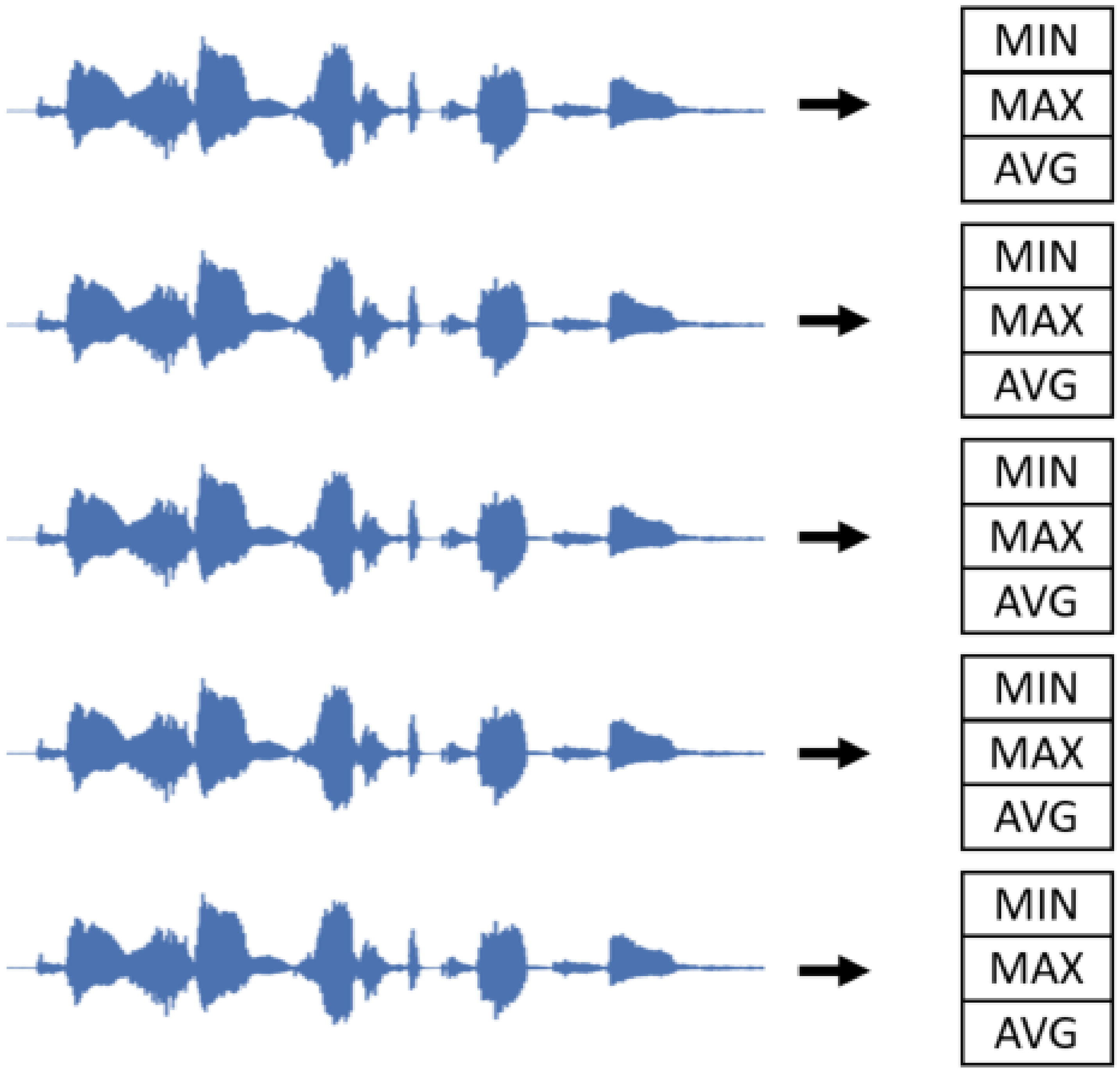
Visualize your timeseries data!

```
ixs = np.arange(audio.shape[-1])
time = ixs / sfreq
fig, ax = plt.subplots()
ax.plot(time, audio)
```



What features to use?

- Using raw timeseries data is too noisy for classification
- We need to calculate features!
- An easy start: summarize your audio data


MIN
MAX
AVG
MIN
MAX
AVG
MIN
MAX
AVG
MIN
MAX
AVG
MIN
MAX
AVG

Calculating multiple features

```
print(audio.shape)
# (n_files, time)
```

```
(20, 7000)
```

```
means = np.mean(audio, axis=-1)
maxs = np.max(audio, axis=-1)
stds = np.std(audio, axis=-1)

print(means.shape)
# (n_files,)
```

```
(20,)
```

Fitting a classifier with scikit-learn

- We've just collapsed a 2-D dataset (samples x time) into several features of a 1-D dataset (samples)
- We can combine each feature, and use it as an input to a model
- If we have a label for each sample, we can use scikit-learn to create and fit a classifier

Preparing your features for scikit-learn

```
# Import a linear classifier
from sklearn.svm import LinearSVC

# Note that means are reshaped to work with scikit-learn
X = np.column_stack([means, maxs, stds])
y = labels.reshape([-1, 1])
model = LinearSVC()
model.fit(X, y)
```

Scoring your scikit-learn model

```
from sklearn.metrics import accuracy_score

# Different input data
predictions = model.predict(X_test)

# Score our model with % correct
# Manually
percent_score = sum(predictions == labels_test) / len(labels_test)
# Using a sklearn scorer
percent_score = accuracy_score(labels_test, predictions)
```

Let's practice!

Improving the features we use for classification

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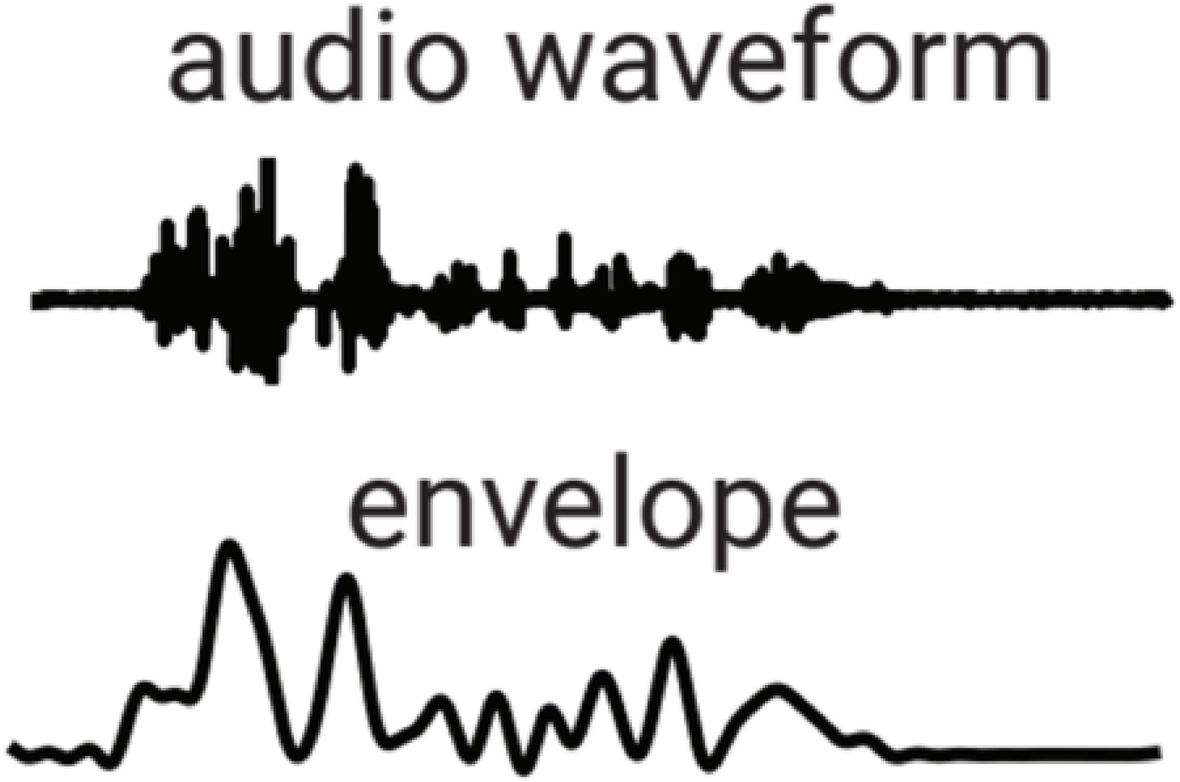
The auditory envelope

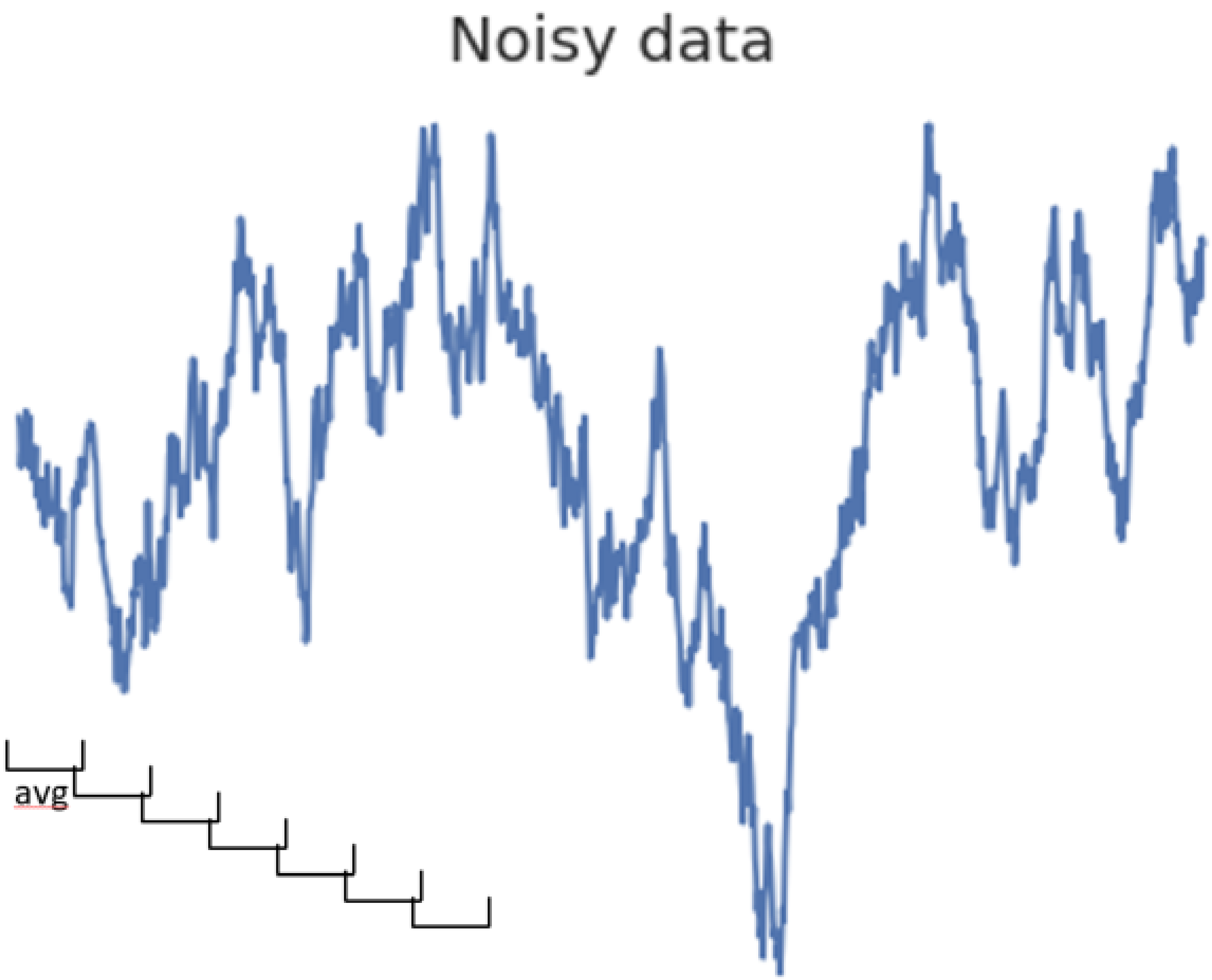
- Smooth the data to calculate the auditory envelope
- Related to the total amount of audio energy present at each moment of time

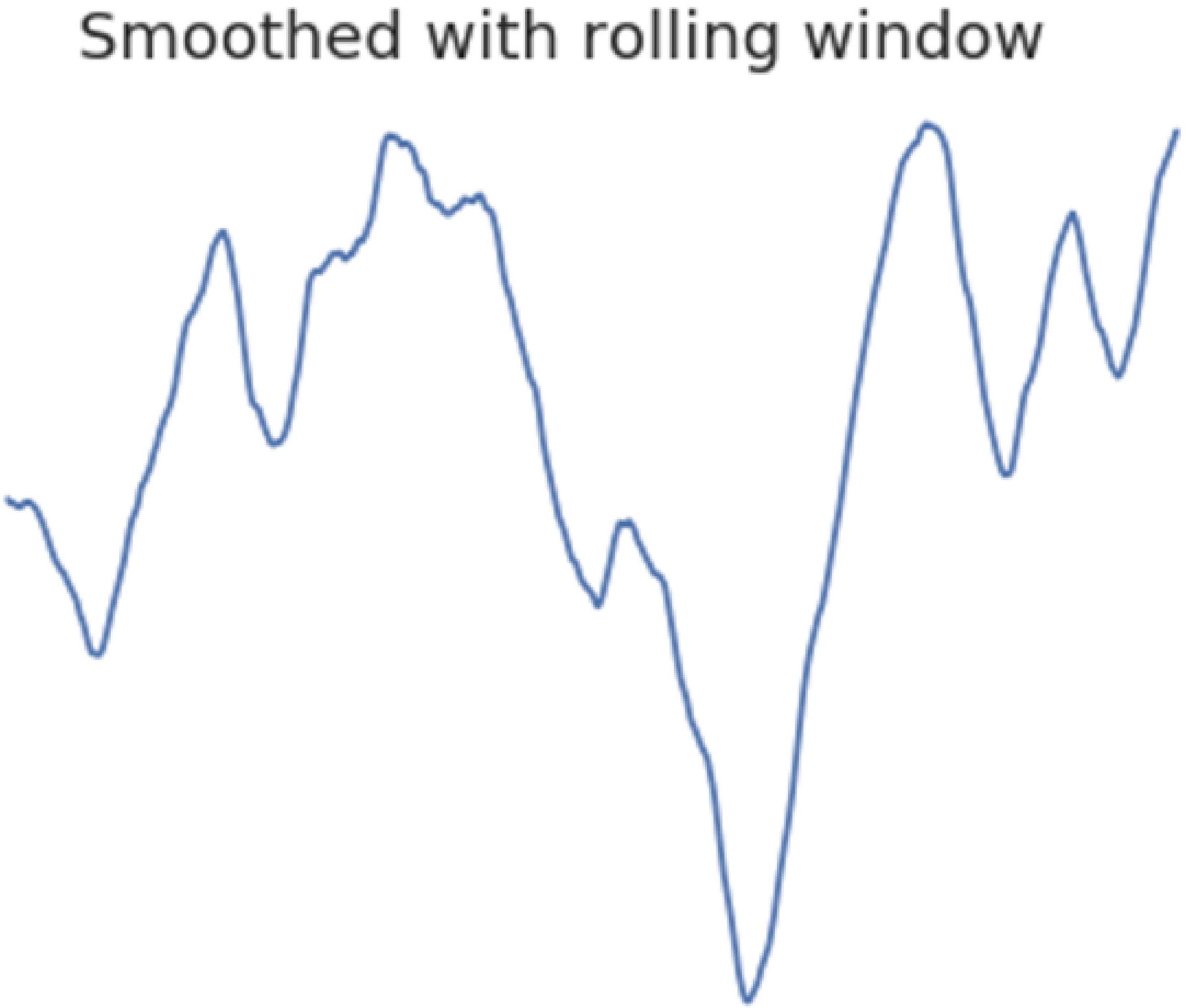


Smoothing over time

- Instead of averaging over *all* time, we can do a *local* average
- This is called *smoothing* your timeseries
- It removes short-term noise, while retaining the general pattern

Smoothing your data





Calculating a rolling window statistic

```
# Audio is a Pandas DataFrame
print(audio.shape)
# (n_times, n_audio_files)
```

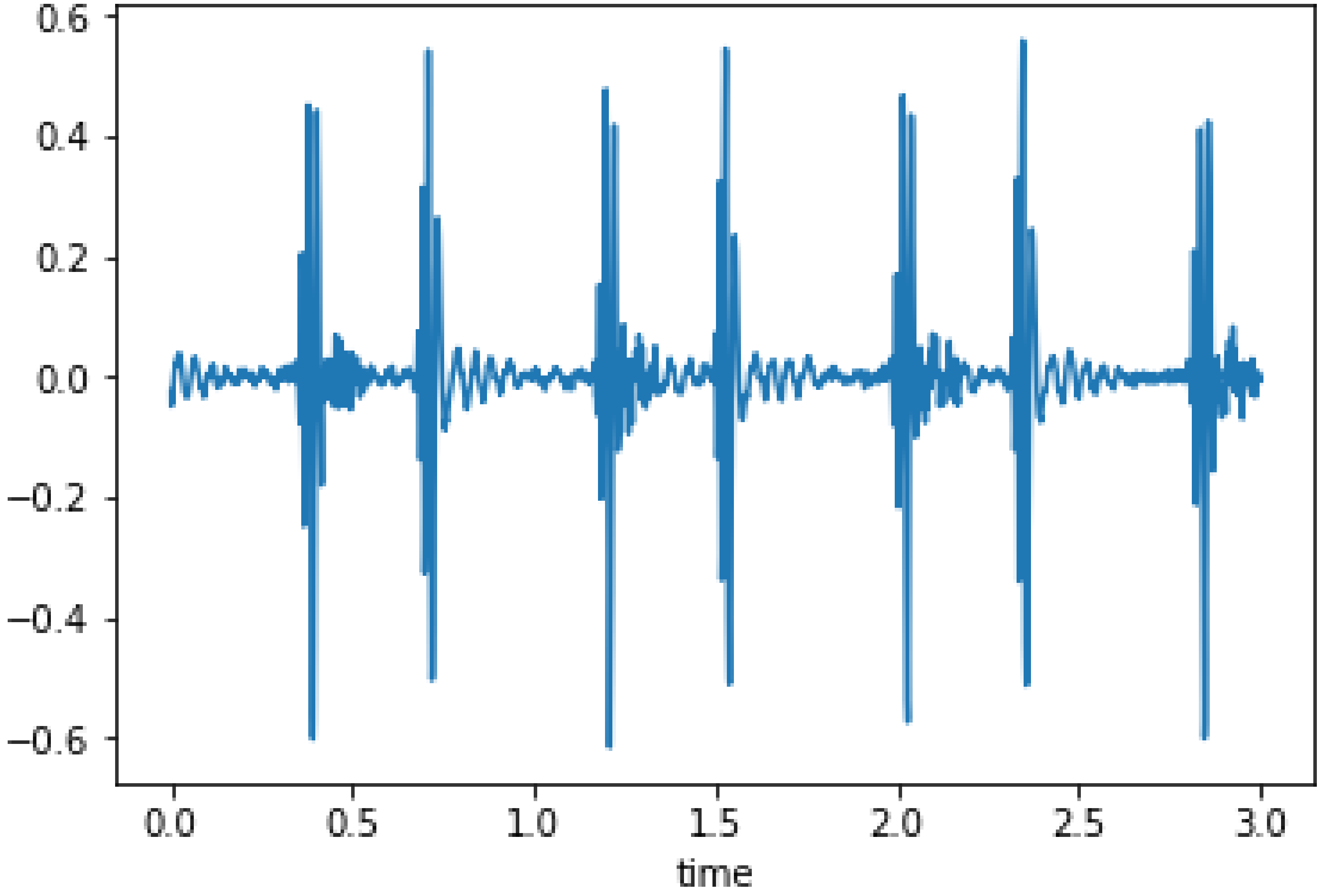
```
(5000, 20)
```

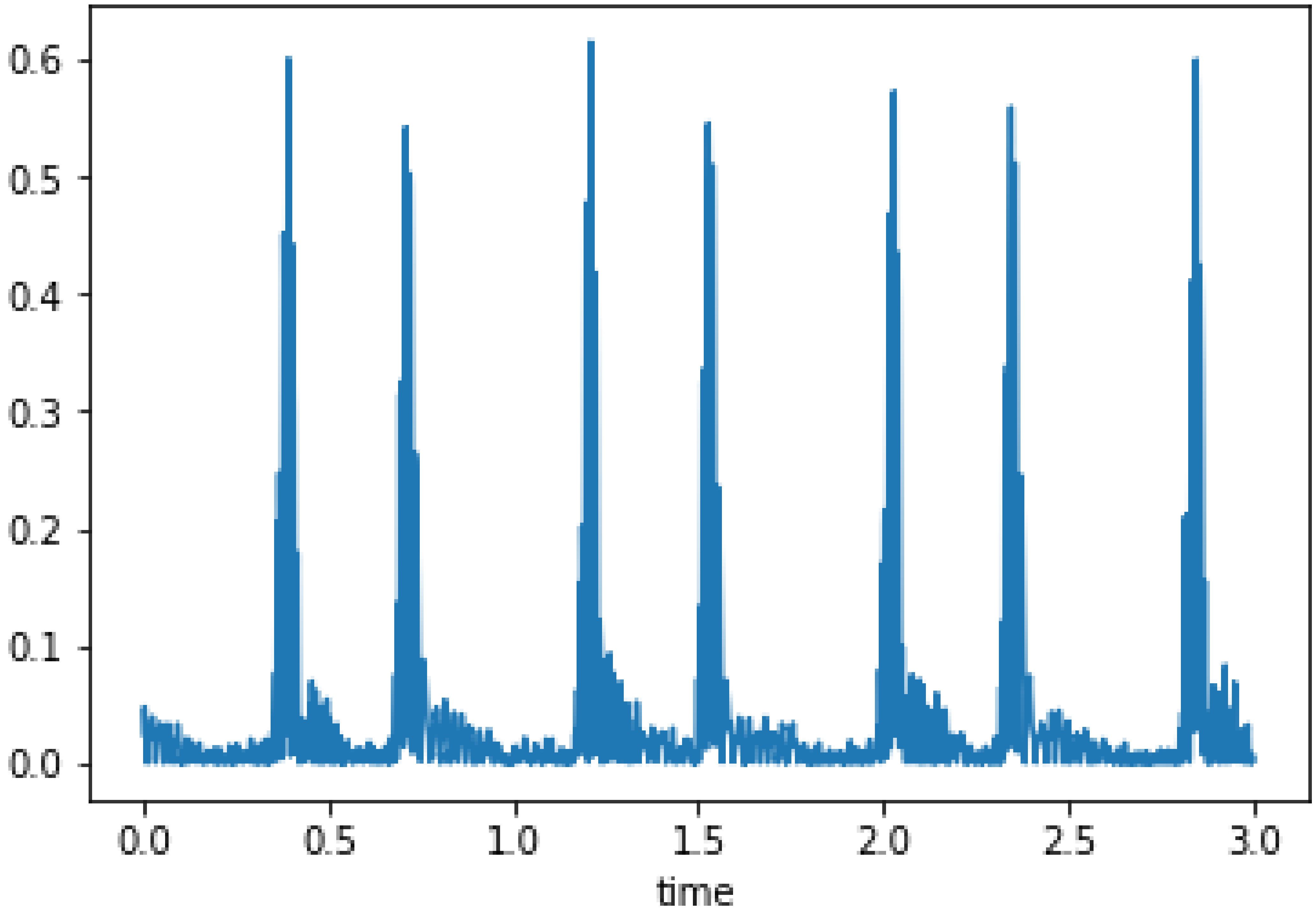
```
# Smooth our data by taking the rolling mean in a window of 50 samples
window_size = 50
windowed = audio.rolling(window=window_size)
audio_smooth = windowed.mean()
```

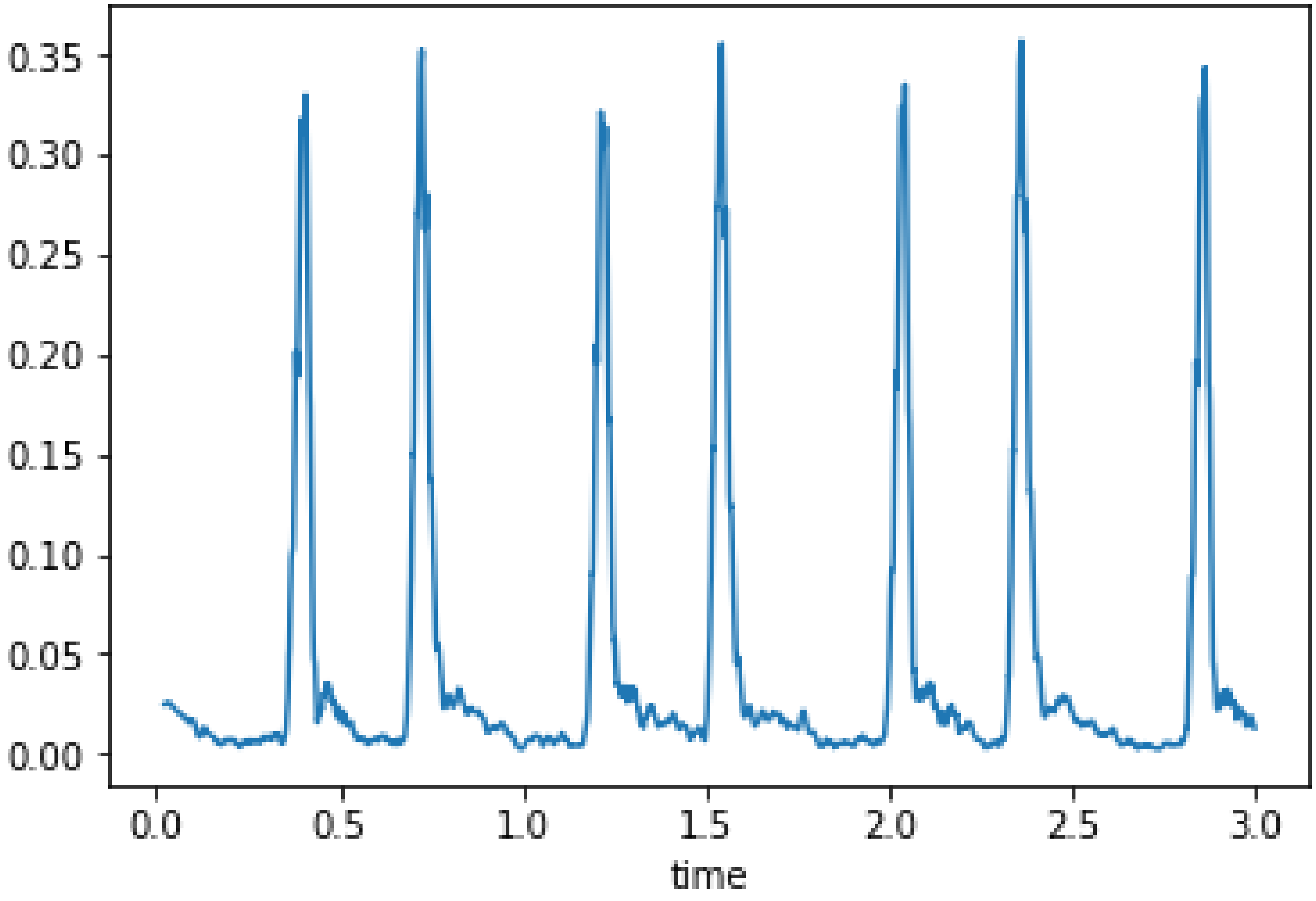
Calculating the auditory envelope

- First *rectify* your audio, then smooth it

```
audio_rectified = audio.apply(np.abs)
audio_envelope = audio_rectified.rolling(50).mean()
```


0.6
0.4
0.2
0.0
−0.2
−0.4
−0.6
0.0
0.5
1.0
1.5
2.0
2.5
3.0
time


0.6
0.5
0.4
0.3
0.2
0.1
0.0
0.0
0.5
1.0
1.5
2.0
2.5
3.0
time


0.35
0.30
0.25
0.20
0.15
0.10
0.05
0.00
0.0
0.5
1.0
1.5
2.0
2.5
3.0
time

Feature engineering the envelope

```
# Calculate several features of the envelope, one per sound
envelope_mean = np.mean(audio_envelope, axis=0)
envelope_std = np.std(audio_envelope, axis=0)
envelope_max = np.max(audio_envelope, axis=0)

# Create our training data for a classifier
X = np.column_stack([envelope_mean, envelope_std, envelope_max])
```

Preparing our features for scikit-learn

```
X = np.column_stack([envelope_mean, envelope_std, envelope_max])
y = labels.reshape([-1, 1])
```

Cross validation for classification

- `cross_val_score` automates the process of:
  - Splitting data into training / validation sets
  - Fitting the model on training data
  - Scoring it on validation data
  - Repeating this process

Using cross_val_score

```
from sklearn.model_selection import cross_val_score

model = LinearSVC()
scores = cross_val_score(model, X, y, cv=3)
print(scores)
```

```
[0.60911642 0.59975305 0.61404035]
```

Auditory features: The Tempogram

- We can summarize more complex temporal information with timeseries-specific functions
- `librosa` is a great library for auditory and timeseries feature engineering
- Here we'll calculate the *tempogram*, which estimates the tempo of a sound over time
- We can calculate summary statistics of tempo in the same way that we can for the envelope

Computing the tempogram

```python
# Import librosa and calculate the tempo of a 1-D sound array
import librosa as lr
audio_tempo = lr.beat.tempo(audio, sr=sfreq,
                            hop_length=2**6, aggregate=None)
```

Let's practice!

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The spectrogram - spectral changes to sound over time

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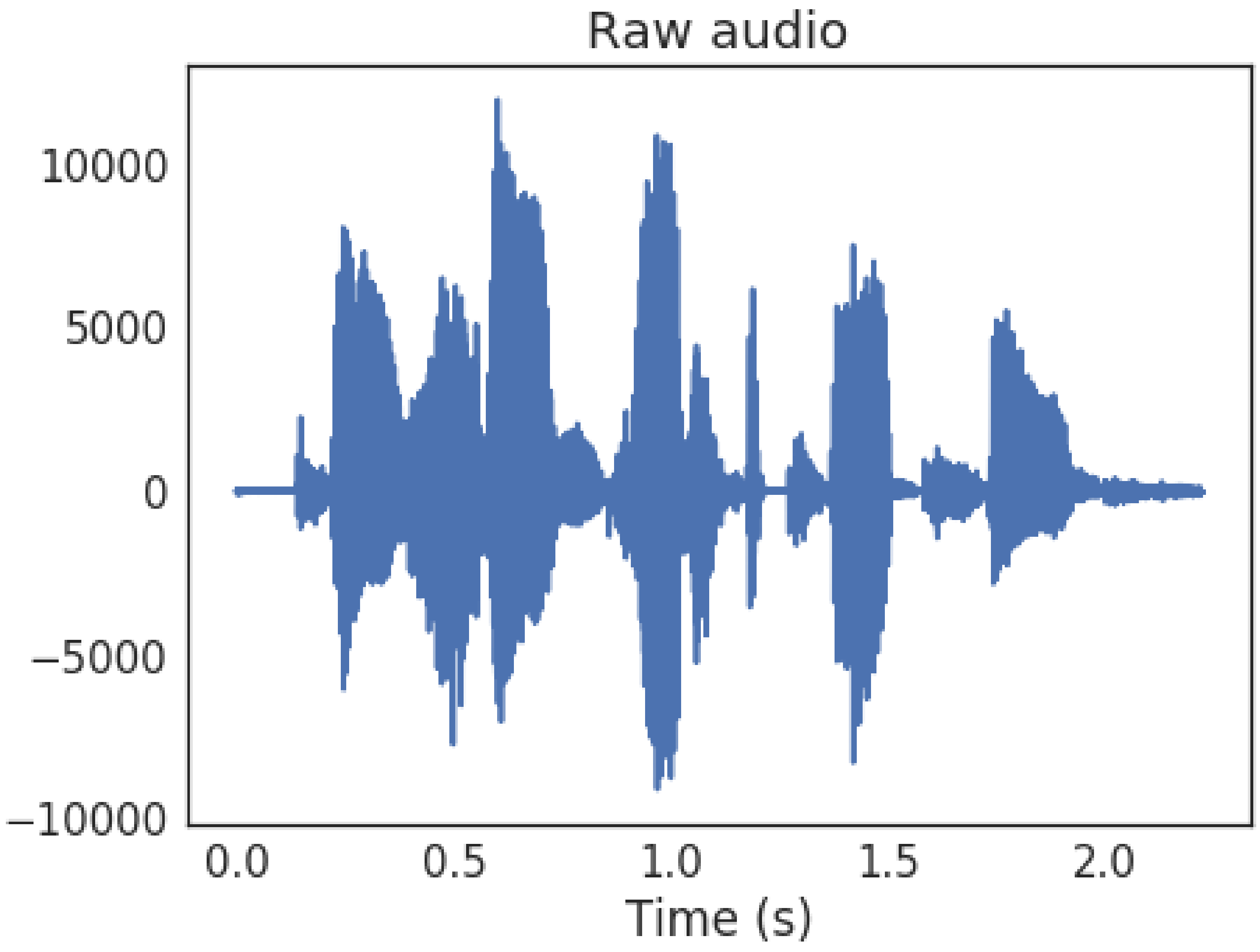
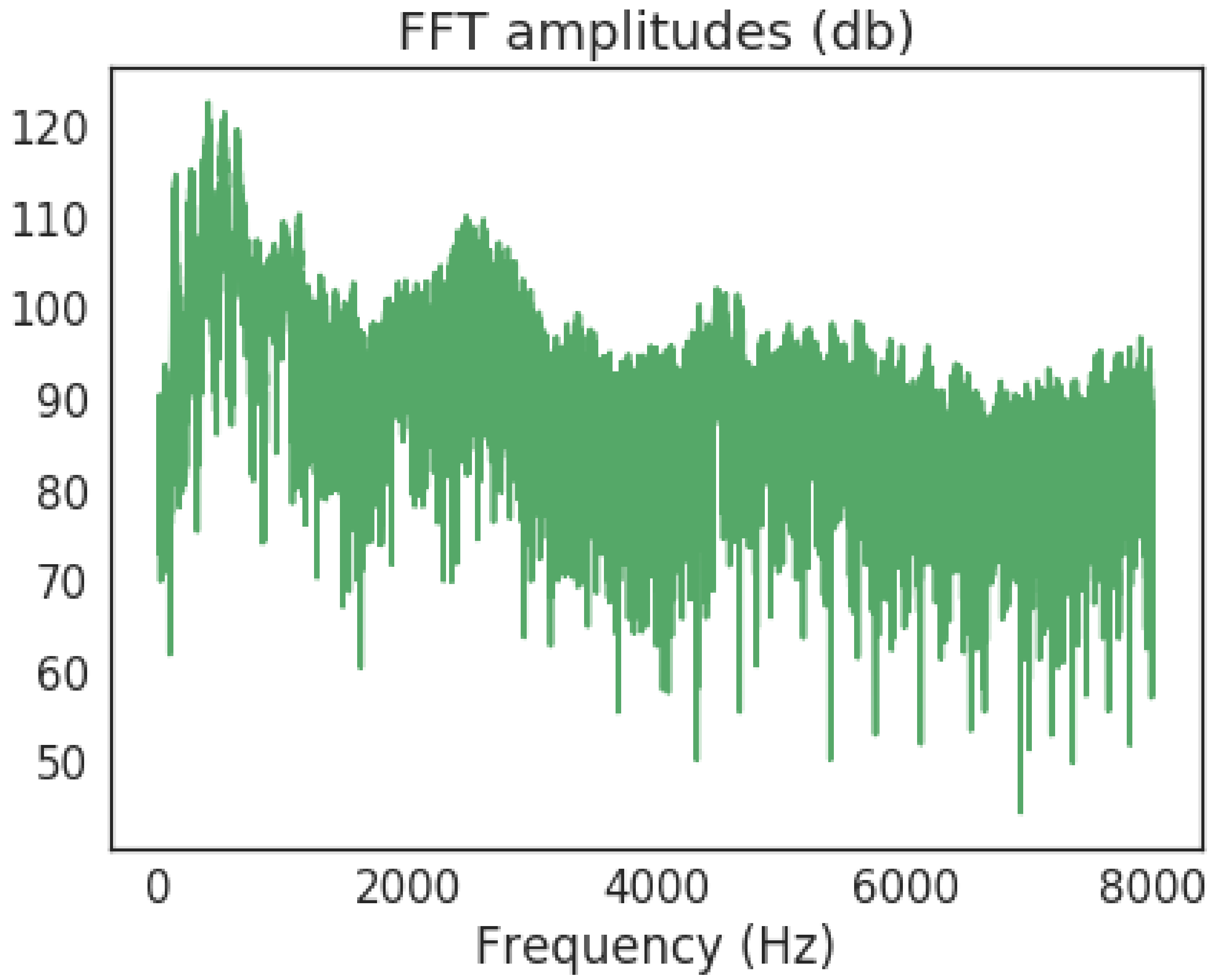
Fourier transforms

- Timeseries data can be described as a combination of quickly-changing things and slowly-changing things
- At each moment in time, we can describe the relative presence of fast- and slow-moving components
- The simplest way to do this is called a *Fourier Transform*
- This converts a single timeseries into an array that describes the timeseries as a combination of oscillations

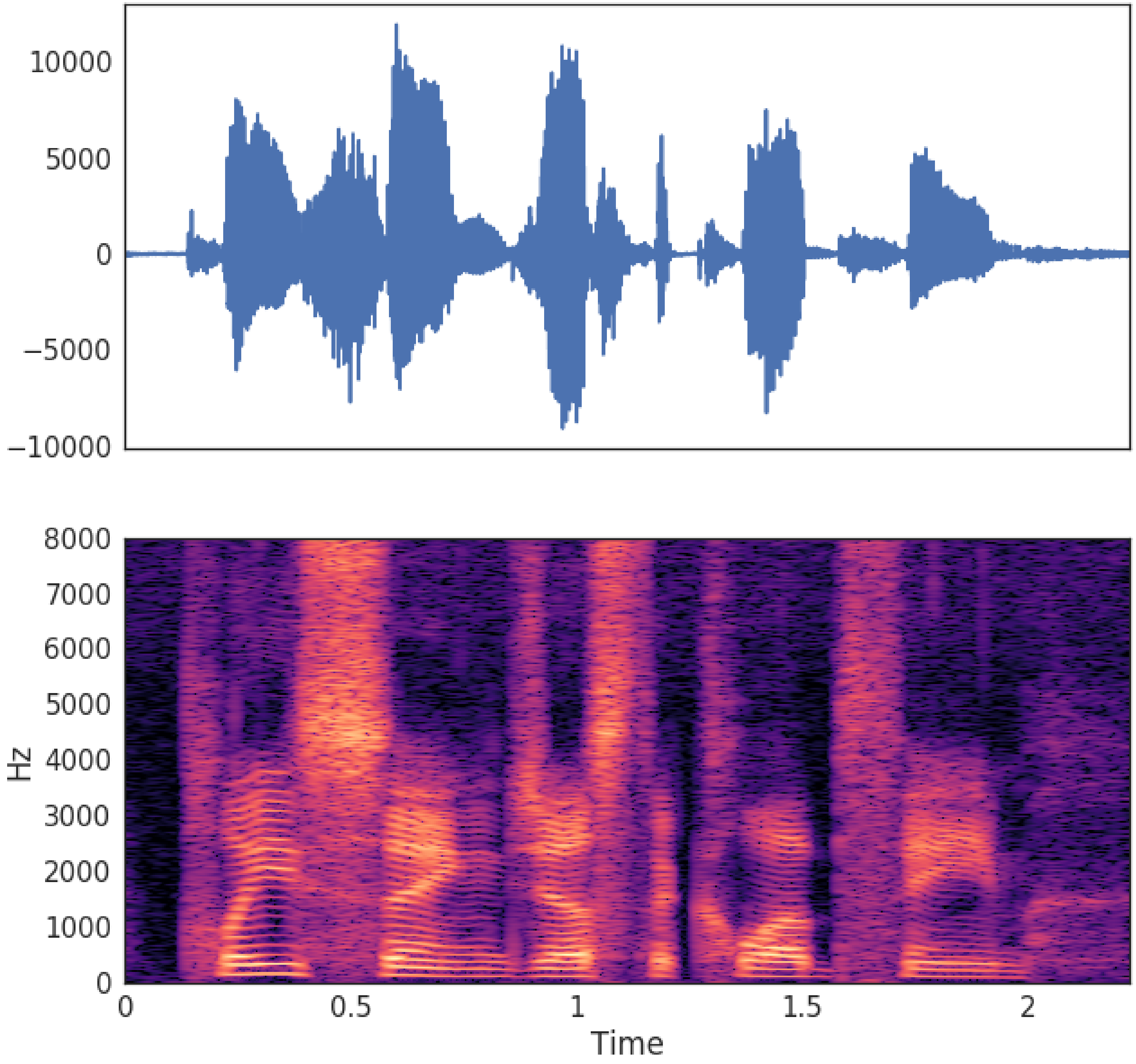
A Fourier Transform (FFT)





Spectrograms: combinations of windows Fourier transforms

- A spectrogram is a collection of windowed Fourier transforms over time
- Similar to how a rolling mean was calculated:
  1. Choose a window size and shape
  2. At a timepoint, calculate the FFT for that window
  3. Slide the window over by one
  4. Aggregate the results
- Called a *Short-Time Fourier Transform* (STFT)


10000
5000
0
−5000
−10000
8000
7000
6000
5000
4000
3000
2000
1000
0
Hz
0
0.5
1
1.5
2
Time

Calculating the STFT

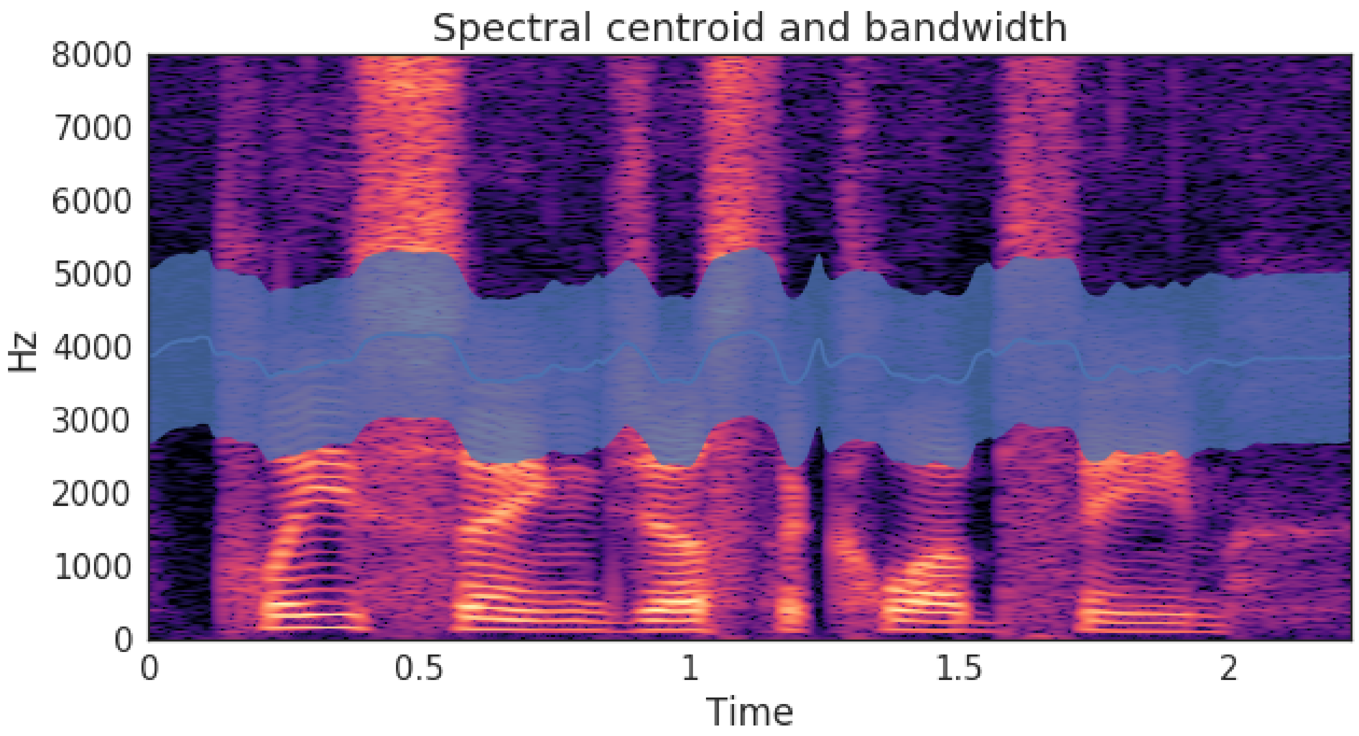
- We can calculate the STFT with `librosa`
- There are several parameters we can tweak (such as window size)
- For our purposes, we'll convert into *decibels* which normalizes the average values of all frequencies
- We can then visualize it with the `specshow()` function

Calculating the STFT with code

```python
# Import the functions we'll use for the STFT
from librosa.core import stft, amplitude_to_db
from librosa.display import specshow

# Calculate our STFT
HOP_LENGTH = 2**4
SIZE_WINDOW = 2**7
audio_spec = stft(audio, hop_length=HOP_LENGTH, n_fft=SIZE_WINDOW)

# Convert into decibels for visualization
spec_db = amplitude_to_db(audio_spec)

# Visualize
specshow(spec_db, sr=sfreq, x_axis='time',
         y_axis='hz', hop_length=HOP_LENGTH)
```

Spectral feature engineering

- Each timeseries has a different spectral pattern.
- We can calculate these spectral patterns by analyzing the spectrogram.
- For example, **spectral bandwidth** and **spectral centroids** describe where most of the energy is at each moment in time



Calculating spectral features

```
# Calculate the spectral centroid and bandwidth for the spectrogram
bandwidths = lr.feature.spectral_bandwidth(S=spec)[0]
centroids = lr.feature.spectral_centroid(S=spec)[0]

# Display these features on top of the spectrogram
ax = specshow(spec, x_axis='time', y_axis='hz', hop_length=HOP_LENGTH)
ax.plot(times_spec, centroids)
ax.fill_between(times_spec, centroids - bandwidths / 2,
                centroids + bandwidths / 2, alpha=0.5)
```

Combining spectral and temporal features in a classifier

```python
centroids_all = []
bandwidths_all = []
for spec in spectrograms:
    bandwidths = lr.feature.spectral_bandwidth(S=lr.db_to_amplitude(spec))
    centroids = lr.feature.spectral_centroid(S=lr.db_to_amplitude(spec))
    # Calculate the mean spectral bandwidth
    bandwidths_all.append(np.mean(bandwidths))
    # Calculate the mean spectral centroid
    centroids_all.append(np.mean(centroids))

# Create our X matrix
X = np.column_stack([means, stds, maxs, tempo_mean,
                     tempo_max, tempo_std, bandwidths_all, centroids_all])
```

Let's practice!

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