Extracting Music Features

April 20, 2022

1 Namaste! So, what is our project about?

1.0.1 Musical Genre Classification of Audio Signals.

- Citation: Tzanetakis, George, and Perry Cook. "Musical genre classification of audio signals," IEEE Transactions on speech and audio processing, 2002.
- Link: https://www.cs.cmu.edu/~gtzan/work/pubs/tsap02gtzan.pdf

1.0.2 Import Libraries

[1]:
```
%matplotlib inline
import librosa
import pandas as pd
import numpy as np
import librosa.display
import sklearn
import matplotlib.pyplot as plt
import IPython.display as ipd
import os, glob
```

1.0.3 Configurations

[2]:
```
config = {
    "dataset": {
#         "input": "test-dataset",
#         "output": "test-data"
        "input": "music-genres-dataset",
        "output": "music-data"
    },
    "counter": 0,
    "max_counter": 5,
    "persist": False
}
```

1.0.4 Load all music files and extract their IDs and genres

[3]:
```
music_data = dict()
for filepath in glob.iglob('data/' + config["dataset"]["input"] + '/**',␣
↪recursive=True):
    if os.path.isfile(filepath):
        # Check if it is a music file
        if filepath.endswith(".wav"):
            music_data[filepath] = dict()
            music_data[filepath]["filepath"] = filepath
            music_data[filepath]["filename"] = filepath.rsplit('/',1)[1]
            music_data[filepath]["genre"] = "UNKNOWN" if "test" in␣
↪config["dataset"]["input"] else music_data[filepath]["filename"].split(".
↪",1)[0]

            config["counter"] += 1
            if config["counter"] == config["max_counter"]:
                break
```

1.0.5 No. of Music files

[4]:
```
len(music_data)
```

[4]: 5

1.0.6 It has the following Genres:

- Pop
- Blues
- Classical
- Country
- Disco
- Hiphop
- Jazz
- Metal
- Pop
- Reggae
- Rock

1.0.7 Let's analyze one SAMPLE_FILE and explore the features it provides..

[5]:
```
SAMPLE_FILE = list(music_data.keys())[0]
SAMPLE_FILE
```

[5]:
```
'data/music-genres-dataset/pop/pop.00027.wav'
```

1.0.8 Play audio

[6]:
```
ipd.Audio(music_data[SAMPLE_FILE]["filepath"])
```

[6]:
```
<IPython.lib.display.Audio object>
```

1.0.9 Duration

[7]:
```
for filepath in music_data.keys():
    music_data[filepath]["duration"] = librosa.get_duration(filename=filepath)

# Show for a sample file
music_data[SAMPLE_FILE]['duration']
```

[7]:
```
30.00018140589569
```

1.1 What does an audio signal comprise?

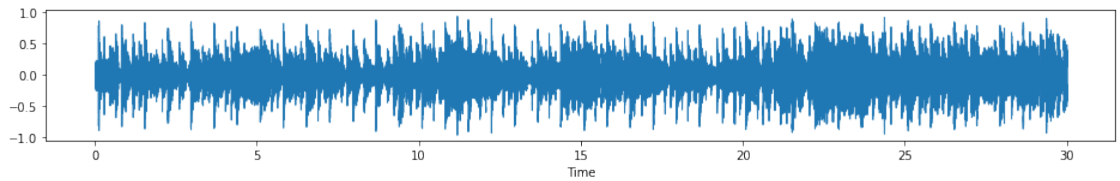
It is a three-dimensional signal in which three axes represent time, amplitude and frequency.

1.1.1 Waveform

A Waveplot lets us know the loudness of the audio at a given time.

Note: The recommended sampling rate and also the default is **22kHz**. We are not overriding it.

[8]:
```
for filepath in music_data.keys():
    music_data[filepath]["waveform"] = music_data[filepath]["waveform"],␣
 ↪music_data[filepath]["sampling_rate"] = librosa.load(filepath)

# Show for a sample file
plt.figure(figsize=(16, 2))
librosa.display.waveshow(music_data[SAMPLE_FILE]['waveform'],␣
 ↪sr=music_data[SAMPLE_FILE]['sampling_rate'], alpha=1)
plt.show()
```



1.1.2 Beats, Tempo, and Predominant local pulse (PLP)

- **Beat**: is the regularly occurring pattern of rhythmic stresses in music.
- **Tempo**: is the speed of the Beat, usually expressed in Beats Per Minute (BPM)
- **Predominant local pulse (PLP)** analyzes the frequency domain to find a locally stable tempo for each frame.

[9]:
```
for filepath in music_data.keys():
    music_data[filepath]["beats"] = librosa.beat.
 ↪beat_track(y=music_data[filepath]['waveform'],␣
 ↪sr=music_data[filepath]['sampling_rate'])[0]
    music_data[filepath]["tempo"] = librosa.beat.
 ↪tempo(y=music_data[filepath]['waveform'],␣
 ↪sr=music_data[filepath]['sampling_rate'])[0]
    music_data[filepath]["plp"] = librosa.beat.
 ↪plp(y=music_data[filepath]['waveform'],␣
 ↪sr=music_data[filepath]['sampling_rate'])[0]

# Show for a sample file
print(f"Beats: {music_data[SAMPLE_FILE]['beats']}")
print(f"Tempo (Beats per minute): {music_data[SAMPLE_FILE]['tempo']}")
print(f"Predominant Local Pulse (PLP): {music_data[SAMPLE_FILE]['plp']}")
```

```
Beats: 83.35433467741936
Tempo (Beats per minute): 83.35433467741936
Predominant Local Pulse (PLP): 0.0
```

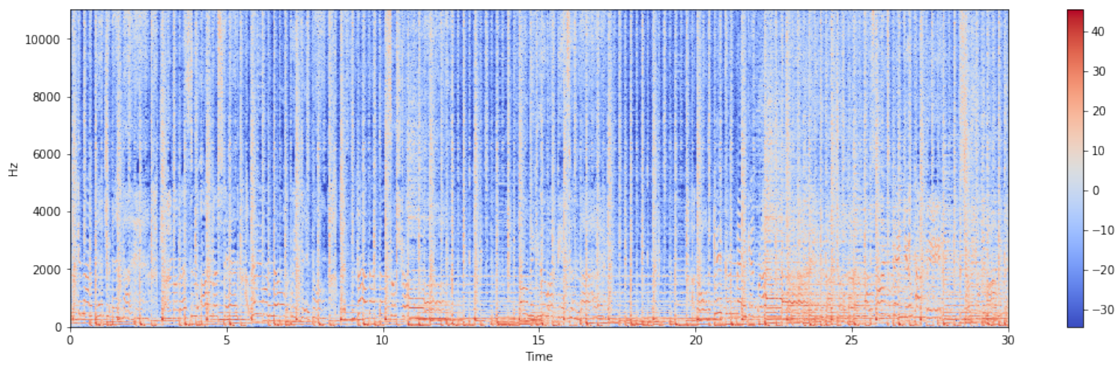
1.1.3 Spectrogram

- A spectrogram shows different frequencies playing at a particular time along with it's amplitude.
- It does so by converting the audio data into short term Fourier transform!

[10]:
```
for filepath in music_data.keys():
    X = librosa.stft(music_data[filepath]['waveform'])
    Xdb = librosa.amplitude_to_db(abs(X))
    music_data[filepath]["spectrogram"] = np.mean(Xdb)
```

```
# Show for a sample file
print(f'Mean of Spectrogram: {music_data[SAMPLE_FILE]["spectrogram"]}')

# Display Spectrogram
X = librosa.stft(music_data[SAMPLE_FILE]['waveform'])
Xdb = librosa.amplitude_to_db(abs(X))
plt.figure(figsize=(18, 5))
librosa.display.specshow(Xdb, sr=music_data[SAMPLE_FILE]["sampling_rate"],␣
↪x_axis='time', y_axis='hz')
plt.colorbar()
plt.show()
```

```
Mean of Spectrogram: -4.269062519073486
```



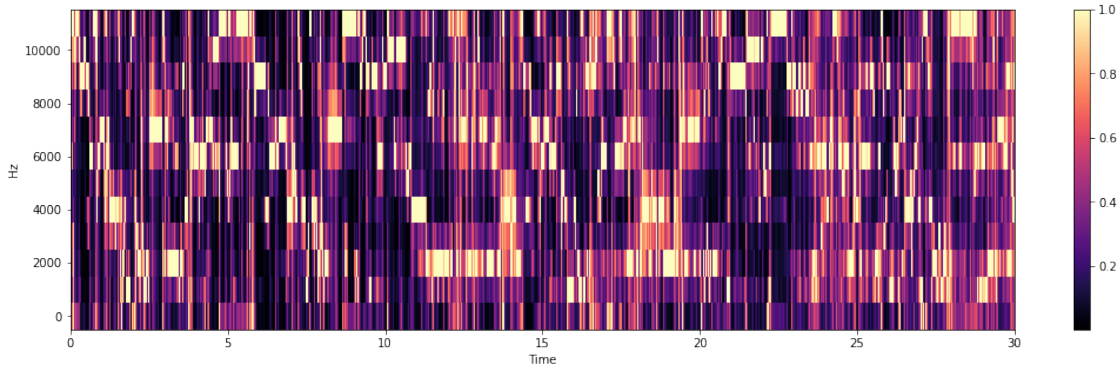
1.1.4 Chromagram

- It represents the intensity of the twelve distinctive pitch classes that are used to study music.
- They can be employed in the differentiation of the pitch class profiles between audio signals.

[11]:
```
for filepath in music_data.keys():
    music_data[filepath]["chromagram"] = np.mean(librosa.feature.
↪chroma_stft(y=music_data[filepath]['waveform'],␣
↪sr=music_data[filepath]['sampling_rate']))

# Show for a sample file
print(f'Mean of Chromagram: {music_data[SAMPLE_FILE]["chromagram"]}')

# Display Chromagram
X = librosa.feature.chroma_stft(y=music_data[SAMPLE_FILE]['waveform'],␣
↪sr=music_data[SAMPLE_FILE]['sampling_rate'])
plt.figure(figsize=(18, 5))
librosa.display.specshow(X, sr=music_data[SAMPLE_FILE]["sampling_rate"],␣
↪x_axis='time', y_axis='hz')
```

```
plt.colorbar()
plt.show()
```

```
Mean of Chromagram: 0.3776119649410248
```

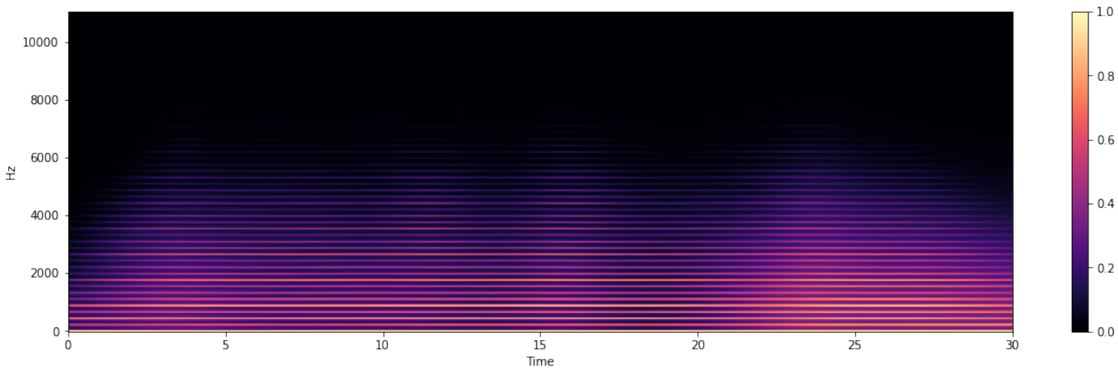


1.1.5 Tempogram

- Tempo can vary locally within a piece.
- Therefore, the tempogram is a feature matrix which indicates the prevalence of certain tempi at each moment in time.

[12]:
```
for filepath in music_data.keys():
    hop_length = 512
    oenv = librosa.onset.onset_strength(y=music_data[filepath]['waveform'],␣
 ↪sr=music_data[filepath]['sampling_rate'], hop_length=hop_length)
    music_data[filepath]["tempogram"] = np.mean(librosa.feature.
 ↪tempogram(onset_envelope=oenv, sr=music_data[filepath]['sampling_rate'],␣
 ↪hop_length=hop_length))

# Show for a sample file
print(f'Mean of Tempogram: {music_data[SAMPLE_FILE]["tempogram"]}')

# Display Tempogram
hop_length = 512
oenv = librosa.onset.onset_strength(y=music_data[SAMPLE_FILE]['waveform'],␣
 ↪sr=music_data[SAMPLE_FILE]['sampling_rate'], hop_length=hop_length)
X = librosa.feature.tempogram(onset_envelope=oenv,␣
 ↪sr=music_data[SAMPLE_FILE]['sampling_rate'], hop_length=hop_length)
plt.figure(figsize=(18, 5))
librosa.display.specshow(X, sr=music_data[SAMPLE_FILE]["sampling_rate"],␣
 ↪x_axis='time', y_axis='hz')
plt.colorbar()
plt.show()
```

```
Mean of Tempogram: 0.1270049797896095
```



1.1.6 Zero Crossings and Zero Crossing Rate

- The zero crossing rate is the rate of sign-changes along a signal, i.e., the rate at which the signal changes from positive to negative or back.
- This feature has been used heavily in both speech recognition and music information retrieval.
- It usually has higher values for highly percussive sounds like those in metal and rock.

[13]:
```
for filepath in music_data.keys():
    music_data[filepath]["zero_crossings"] = sum(librosa.
 ↪zero_crossings(music_data[filepath]['waveform'], pad=False))
    music_data[filepath]["zero_crossing_rate"] = np.mean(librosa.feature.
 ↪zero_crossing_rate(music_data[filepath]['waveform'], pad=False))

# Show for a sample file
print(f'Number of Zero crossings: {music_data[SAMPLE_FILE]["zero_crossings"]}')
print(f'Mean of Zero crossing rate:␣
 ↪{music_data[SAMPLE_FILE]["zero_crossing_rate"]}')
```

```
Number of Zero crossings: 67487
Mean of Zero crossing rate: 0.1018672509425754
```

1.1.7 Spectral Centroid

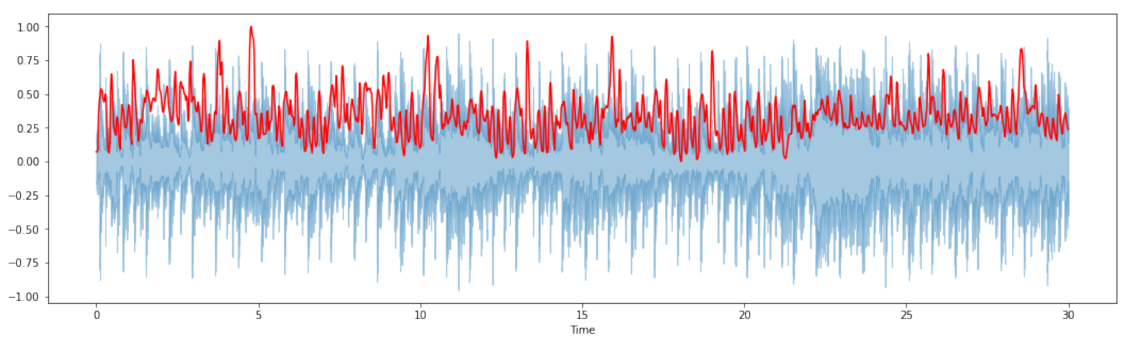
- It indicates where the “centre of mass” for a sound is located.
- It is calculated as the weighted mean of the frequencies present in the sound.
- If the frequencies in music are same throughout then spectral centroid would be around a centre and if there are high frequencies at the end of sound then the centroid would be towards its end.

[14]:
```
for filepath in music_data.keys():
```

```
    spectral_centroids = librosa.feature.
↪spectral_centroid(y=music_data[filepath]['waveform'],␣
↪sr=music_data[filepath]['sampling_rate'])[0]
    music_data[filepath]["spectral_centroid"] = np.mean(spectral_centroids)

    # Computing the time variable for visualization
    frames = range(len(spectral_centroids))
    music_data[filepath]["time_variable"] = librosa.frames_to_time(frames)

# Show for a sample file
print(f'Mean of Spectral Centroid:␣
↪{music_data[SAMPLE_FILE]["spectral_centroid"]}')

# Computing the time variable for visualization
spectral_centroids = librosa.feature.
↪spectral_centroid(y=music_data[SAMPLE_FILE]['waveform'],␣
↪sr=music_data[SAMPLE_FILE]['sampling_rate'])[0]
frames = range(len(spectral_centroids))
t = librosa.frames_to_time(frames)

# Normalising the spectral centroid for visualisation
def normalize(x, axis=0):
    return sklearn.preprocessing.minmax_scale(x, axis=axis)

# Plotting the Spectral Centroid along the waveform
plt.figure(figsize=(18, 5))
librosa.display.waveshow(music_data[SAMPLE_FILE]['waveform'],␣
↪sr=music_data[SAMPLE_FILE]['sampling_rate'], alpha=0.4)
plt.plot(t, normalize(spectral_centroids), color='r')
```

```
Mean of Spectral Centroid: 2682.2841411936142
```

[14]:
```
[<matplotlib.lines.Line2D at 0x7f9ca7c1d6a0>]
```



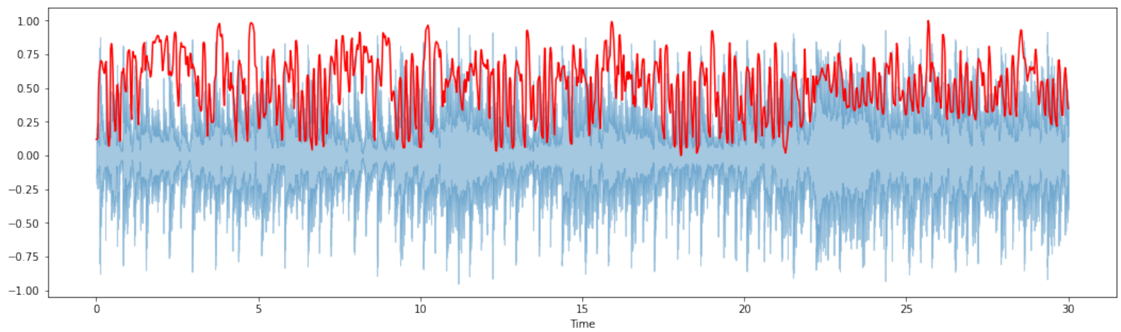
1.1.8 Spectral Rolloff

- It is the per-frame center frequency for a spectrogram bin such that at least roll_percent (0.85 by default) of the energy of the spectrum in this frame is contained in this bin and the bins below.
- This can be used to, e.g., approximate the maximum (or minimum) frequency by setting roll_percent to a value close to 1 (or 0).

[15]:
```
for filepath in music_data.keys():
    music_data[filepath]["spectral_rolloff"] = np.mean(librosa.feature.
 ↪spectral_rolloff(y=music_data[filepath]['waveform'],␣
 ↪sr=music_data[filepath]['sampling_rate'])[0])

# Show for a sample file
print(f'Mean of Spectral Rolloff:␣
 ↪{music_data[SAMPLE_FILE]["spectral_rolloff"]}')

# Plotting the Spectral Rolloff along the waveform
spectral_rolloff = librosa.feature.
 ↪spectral_rolloff(y=music_data[SAMPLE_FILE]['waveform'],␣
 ↪sr=music_data[SAMPLE_FILE]['sampling_rate'])[0]
plt.figure(figsize=(18, 5))
librosa.display.waveshow(music_data[SAMPLE_FILE]['waveform'],␣
 ↪sr=music_data[SAMPLE_FILE]['sampling_rate'], alpha=0.4)
plt.plot(t, normalize(spectral_rolloff), color='r')
```

```
Mean of Spectral Rolloff: 5956.0789882721865
```

[15]:
```
[<matplotlib.lines.Line2D at 0x7f9caa55a7c0>]
```



1.1.9 Spectral Contrast

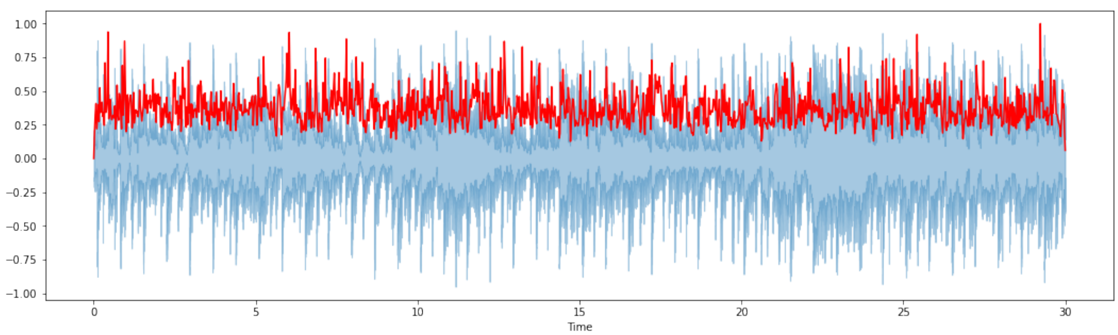
- Each frame of a spectrogram S is first divided into sub-bands.

- Then, for each sub-band, the energy contrast is estimated by comparing the mean energy in the top quantile (peak energy) to that of the bottom quantile (valley energy).
- High contrast values generally correspond to clear, narrow-band signals, while low contrast values correspond to broad-band noise.

[16]:
```
for filepath in music_data.keys():
    music_data[filepath]["spectral_contrast"] = np.mean(librosa.feature.
 ↪spectral_contrast(y=music_data[filepath]['waveform'],␣
 ↪sr=music_data[filepath]['sampling_rate'])[0])

# Show for a sample file
print(f'Mean of Spectral Contrast:␣
 ↪{music_data[SAMPLE_FILE]["spectral_contrast"]}')

# Plotting the Spectral Contrast along the waveform
spectral_contrast = librosa.feature.
 ↪spectral_contrast(y=music_data[SAMPLE_FILE]['waveform'],␣
 ↪sr=music_data[SAMPLE_FILE]['sampling_rate'])[0]
plt.figure(figsize=(18, 5))
librosa.display.waveshow(music_data[SAMPLE_FILE]['waveform'],␣
 ↪sr=music_data[SAMPLE_FILE]['sampling_rate'], alpha=0.4)
plt.plot(t, normalize(spectral_contrast), color='r')
```

```
Mean of Spectral Contrast: 22.257477751200955
```

[16]:
```
[<matplotlib.lines.Line2D at 0x7f9cab0ffb20>]
```



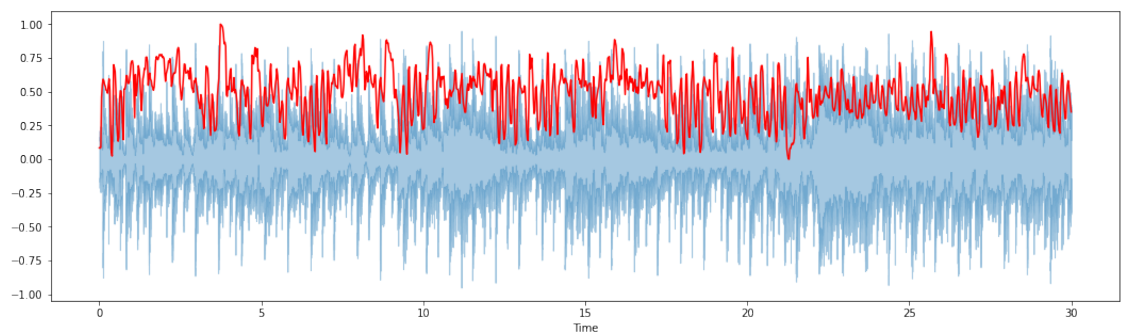
1.1.10 Spectral Bandwidth

- Also called the spectral spread.
- It is the spectral range of interest around the centroid, that is, the variance from the spectral centroid.
- It is directly correlated with the perceived timbre.

[17]:
```python
for filepath in music_data.keys():
    music_data[filepath]["spectral_bandwidth"] = np.mean(librosa.feature.
 ↪spectral_bandwidth(y=music_data[filepath]['waveform'],␣
 ↪sr=music_data[filepath]['sampling_rate'])[0])

# Show for a sample file
print(f'Mean of Spectral Bandwidth:␣
 ↪{music_data[SAMPLE_FILE]["spectral_bandwidth"]}')

# Plotting the Spectral Bandwidth along the waveform
spectral_bandwidth = librosa.feature.
 ↪spectral_bandwidth(y=music_data[SAMPLE_FILE]['waveform'],␣
 ↪sr=music_data[SAMPLE_FILE]['sampling_rate'])[0]
plt.figure(figsize=(18, 5))
librosa.display.waveshow(music_data[SAMPLE_FILE]['waveform'],␣
 ↪sr=music_data[SAMPLE_FILE]['sampling_rate'], alpha=0.4)
plt.plot(t, normalize(spectral_bandwidth), color='r')
```

```
Mean of Spectral Bandwidth: 2923.9677291945763
```

[17]:
```
[<matplotlib.lines.Line2D at 0x7f9cb69c8eb0>]
```



1.1.11 Spectral Flatness

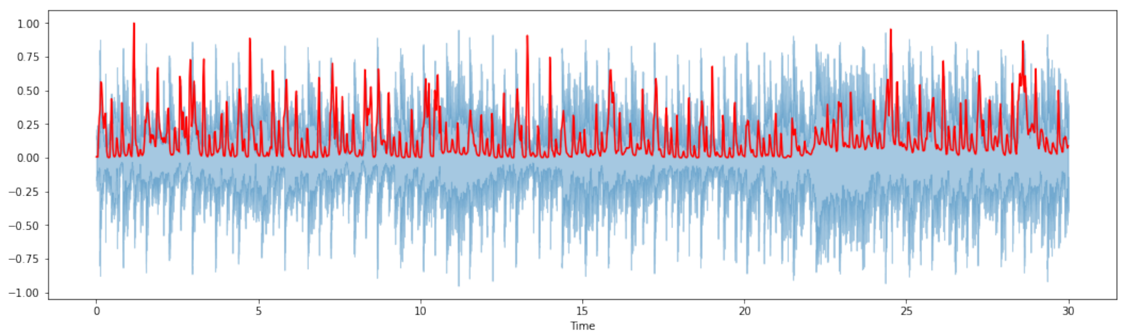
- Also called the Tonality Coefficient.
- It is a measure to quantify how much noise-like a sound is, as opposed to being tone-like.
- A high spectral flatness (closer to 1.0) indicates the spectrum is similar to white noise. It is often converted to decibel.

[18]:
```python
for filepath in music_data.keys():
    music_data[filepath]["spectral_flatness"] = np.mean(librosa.feature.
 ↪spectral_flatness(y=music_data[filepath]['waveform'])[0])

# Show for a sample file
```

```python
print(f'Mean of Spectral Flatness: {music_data[SAMPLE_FILE]["spectral_flatness"]}')

# Plotting the Spectral Flatness along the waveform
spectral_flatness = librosa.feature.spectral_flatness(y=music_data[SAMPLE_FILE]['waveform'])[0]
plt.figure(figsize=(18, 5))
librosa.display.waveshow(music_data[SAMPLE_FILE]['waveform'], sr=music_data[SAMPLE_FILE]['sampling_rate'], alpha=0.4)
plt.plot(t, normalize(spectral_flatness), color='r')
```

```
Mean of Spectral Flatness: 0.047302521765232086
```

[18]: `[<matplotlib.lines.Line2D at 0x7f9c9923a0d0>]`



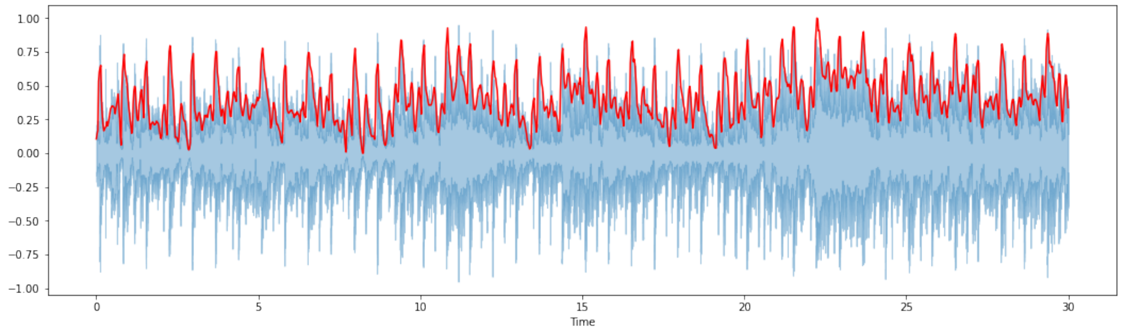
1.1.12 RMS (Root Mean Square) Energy

- Compute root-mean-square (RMS) energy for each frame from the audio samples.
- For audio signals, that roughly corresponds to how loud the signal is.

[19]:
```python
for filepath in music_data.keys():
    music_data[filepath]["rms"] = np.mean(librosa.feature.rms(y=music_data[filepath]['waveform'])[0])

# Show for a sample file
print(f'Mean of RMS (Root Mean Square) Energy: {music_data[SAMPLE_FILE]["rms"]}')

# Plotting the Spectral Flatness along the waveform
rms = librosa.feature.rms(y=music_data[SAMPLE_FILE]['waveform'])[0]
plt.figure(figsize=(18, 5))
librosa.display.waveshow(music_data[SAMPLE_FILE]['waveform'], sr=music_data[SAMPLE_FILE]['sampling_rate'], alpha=0.4)
plt.plot(t, normalize(rms), color='r')
```

```
Mean of RMS (Root Mean Square) Energy: 0.1579022854566574
```

```
[19]: [<matplotlib.lines.Line2D at 0x7f9ca7df9b50>]
```

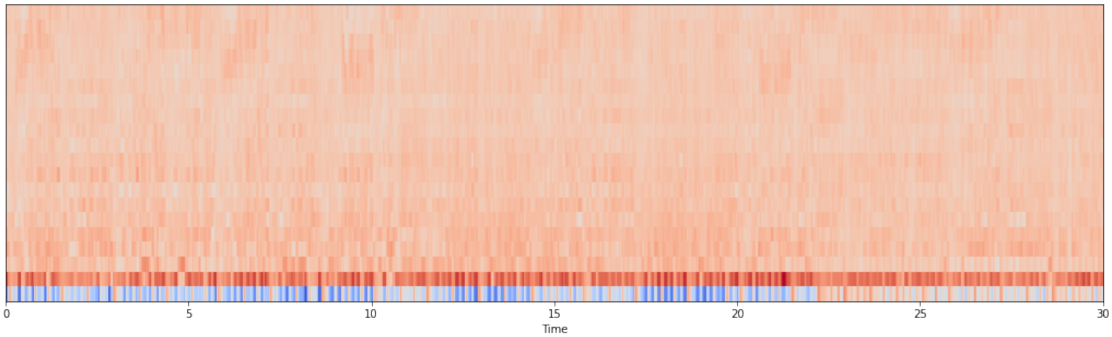


1.1.13 MFCC — Mel-Frequency Cepstral Coefficients

- One of the most important method to extract a feature of an audio signal.
- They are a small set of features (usually about 10–20) which concisely describe the overall shape of a spectral envelope.

```
[20]: for filepath in music_data.keys():
          music_data[filepath]["mfccs"] = np.mean(librosa.feature.
       ↪mfcc(y=music_data[filepath]['waveform'],␣
       ↪sr=music_data[filepath]['sampling_rate']))

      # Show for a sample file
      print(f'Mean of MFCC - Mel-Frequency Cepstral Coefficients:␣
       ↪{music_data[SAMPLE_FILE]["mfccs"]}')

      # Displaying the MFCCs:
      mfccs = librosa.feature.mfcc(y=music_data[SAMPLE_FILE]['waveform'],␣
       ↪sr=music_data[SAMPLE_FILE]['sampling_rate'])
      plt.figure(figsize=(18, 5))
      librosa.display.specshow(mfccs, sr=music_data[SAMPLE_FILE]['sampling_rate'],␣
       ↪x_axis='time')
      plt.show()
```

```
Mean of MFCC - Mel-Frequency Cepstral Coefficients: 2.0804495811462402
```



1.1.14 Prepare Feature Dataset

[21]:
```python
df_feature = pd.DataFrame(music_data.values())
df_feature_with_filenames = df_feature.
 ↪drop(columns=['waveform','time_variable','sampling_rate','duration'])
df_feature_with_filenames.head()
```

[21]:
```
                                      filepath       filename genre  \
0  data/music-genres-dataset/pop/pop.00027.wav  pop.00027.wav   pop
1  data/music-genres-dataset/pop/pop.00033.wav  pop.00033.wav   pop
2  data/music-genres-dataset/pop/pop.00032.wav  pop.00032.wav   pop
3  data/music-genres-dataset/pop/pop.00026.wav  pop.00026.wav   pop
4  data/music-genres-dataset/pop/pop.00030.wav  pop.00030.wav   pop

       beats       tempo       plp  spectrogram  chromagram  tempogram  \
0  83.354335   83.354335  0.000000    -4.269063    0.377612   0.127005
1  99.384014   99.384014  0.000000    -3.781867    0.423036   0.158264
2  95.703125   95.703125  0.519045    -4.358516    0.426769   0.121314
3  75.999540  151.999081  0.000000    -4.899115    0.334962   0.133198
4  95.703125   95.703125  0.472598     0.983008    0.357630   0.140248

   zero_crossings  zero_crossing_rate  spectral_centroid  spectral_rolloff  \
0           67487            0.101867        2682.284141       5956.078988
1           90785            0.137010        2835.119375       5944.979313
2          151492            0.228641        4225.461049       8483.382577
3           68571            0.103494        2525.591959       5552.801896
4           98516            0.148679        3070.672741       6653.076965

   spectral_contrast  spectral_bandwidth  spectral_flatness       rms  \
0          22.257478         2923.967729           0.047303  0.157902
1          18.068245         2731.752387           0.061382  0.139896
2          18.657617         3404.380733           0.125869  0.097861
3          23.054193         2848.409561           0.030347  0.195626
```

```
4          17.128994         2975.765677            0.075034  0.203093

      mfccs
0  2.080450
1  0.843129
2 -0.666234
3  2.070004
4  2.515382
```

1.1.15 Prepare Training Dataset: Drop irrelevant columns

[22]:
```
df_training_data = df_feature.
↪drop(columns=['waveform','time_variable','filepath','sampling_rate','duration',␣
↪'filename'])
df_training_data.head()
```

[22]:
```
  genre      beats      tempo       plp  spectrogram  chromagram  tempogram  \
0   pop  83.354335  83.354335  0.000000    -4.269063    0.377612   0.127005
1   pop  99.384014  99.384014  0.000000    -3.781867    0.423036   0.158264
2   pop  95.703125  95.703125  0.519045    -4.358516    0.426769   0.121314
3   pop  75.999540 151.999081  0.000000    -4.899115    0.334962   0.133198
4   pop  95.703125  95.703125  0.472598     0.983008    0.357630   0.140248

   zero_crossings  zero_crossing_rate  spectral_centroid  spectral_rolloff  \
0           67487            0.101867        2682.284141       5956.078988
1           90785            0.137010        2835.119375       5944.979313
2          151492            0.228641        4225.461049       8483.382577
3           68571            0.103494        2525.591959       5552.801896
4           98516            0.148679        3070.672741       6653.076965

   spectral_contrast  spectral_bandwidth  spectral_flatness       rms  \
0          22.257478         2923.967729           0.047303  0.157902
1          18.068245         2731.752387           0.061382  0.139896
2          18.657617         3404.380733           0.125869  0.097861
3          23.054193         2848.409561           0.030347  0.195626
4          17.128994         2975.765677           0.075034  0.203093

      mfccs
0  2.080450
1  0.843129
2 -0.666234
3  2.070004
4  2.515382
```

1.1.16 Save both datasets

[23]:
```
if config["persist"]:
    df_feature_with_filenames.to_csv("data/" + config["dataset"]["output"] +␣
 ↪"-with-filenames.csv", sep="\t", header=True, index=True)
    df_training_data.to_csv("data/" + config["dataset"]["output"] + ".csv",␣
 ↪sep="\t", header=True, index=True)
```