main

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1 Urban Sound Multiclass Classifier

1.0.1 ML1020 - Machine Learning at Scale - 2019

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1.0.2 Abstract:

The main objective of this project work is the case study of urban sounds audio event identification and classification. This is a supervised learning where we will be working on an audio event dataset with samples of audio data that belong to specific categories (which are the sources of the sounds).

We will be leveraging concepts from transfer learning and deep learning to build a robust classifier whereby, with any given audio sample belonging to one of our pre-determined categories, we should be able to correctly predict the source of this sound. The dataset we will be using is popularly known as the UrbanSound8K dataset. UrbanSounds8K dataset has 8,732 labeled audio sound files (the duration of which are usually equal to or greater than 4 seconds) that contain excerpts from common urban sounds.

1.0.3 Approach:

Document the steps we plan for our approach - either documentation or a diagram - need to finalize

1.1 Data Analysis

The dataset is downloaded from the following link: https://urbansounddataset.weebly.com/urbansound8k.html

Let's load the train data and explore available classes and sample distirubtion between the classes. note: the test data is not labled thus it is useless for the training purpose. We have no choice but employ the train dataset to train and validate the model. The librosa module is an open source Python framework for audio and music analysis. We will be using this for analyzing as well as extracting features from audio data in subsequent sections.

```
In [ ]: # import required libraries
        import pandas as pd
        import numpy as np
        import os
        import matplotlib
```

```python
import matplotlib.pyplot as plt
import seaborn as sns
import librosa
import librosa.display
import IPython.display
import soundfile as sf
import glob
import random

# define the path relative to the notebook source
# expected data structure
# ----------------------------------------------
# project root
# src
#   main.ipynb
# data
#   original
#     train
#       samples
#         *.wav
#       train.csv
#     test
#       samples
#         *.wav
#       test.csv
TRAIN_DATA_PATH = "../data/original/train"
TRAIN_FILE = "train.csv"
# Read the train data classification info
classification = pd.read_csv("{0}/{1}".format(TRAIN_DATA_PATH,TRAIN_FILE),sep = ',')
```

In [89]:
```python
classification.head(10)
```

Out[89]:

	ID	Class
0	0	siren
1	1	street_music
2	2	drilling
3	3	siren
4	4	dog_bark
5	6	children_playing
6	10	street_music
7	11	drilling
8	12	gun_shot
9	15	dog_bark

In [90]:
```python
classification.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5435 entries, 0 to 5434
Data columns (total 2 columns):
```

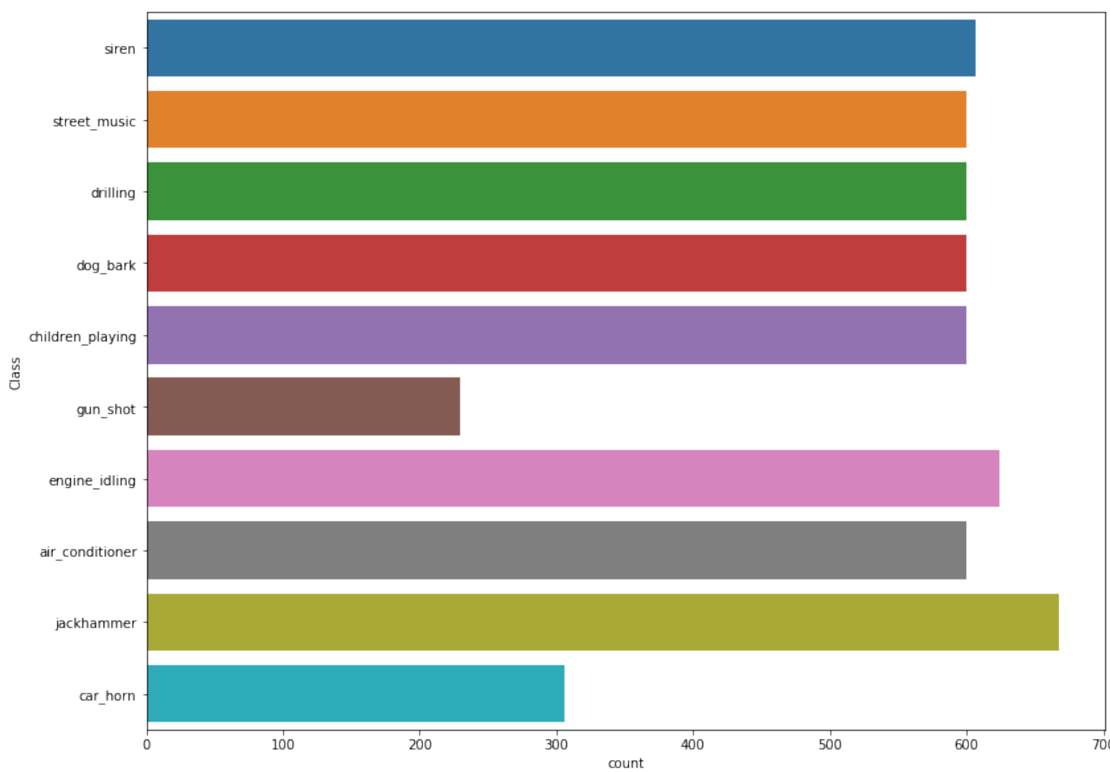
```
ID       5435 non-null int64
Class    5435 non-null object
dtypes: int64(1), object(1)
memory usage: 85.0+ KB
```

Let's examine what classes are available

```
In [91]: classes = classification.Class.unique()
         classes

Out[91]: array(['siren', 'street_music', 'drilling', 'dog_bark',
                'children_playing', 'gun_shot', 'engine_idling', 'air_conditioner',
                'jackhammer', 'car_horn'], dtype=object)

In [92]: print("Number of classes: {0}".format(len(classes)))

Number of classes: 10
```

As per the output above the dataset comprises ten urban sound classes. It is time to take a look at the class population.

```
In [93]: plt.figure(figsize=(13,10))
         p = sns.countplot(data=classification,y='Class')
```



`Gun Shot` and `Car Horn` categories are underpopulated. We could:

- digitize and upsample these categories
- downsample all categories
- add more labeled observations to the smaller categories
- leave as is hoping that the categories with the smaller population stil have enough to train the network

Let's leave the data intact. If during the training we realize that the scarsly popluated categories are not detected well we will take action

1.1.1 Basic Data Stats

Let's explore the sound smaples in depth. Knowning the sample duration ,sample, rate, number of channels, ec. will help us to understnad what the data normalization and prepration must be done prior to feeding the data to a model. We start with the extraction of sound characteristics of each sample...

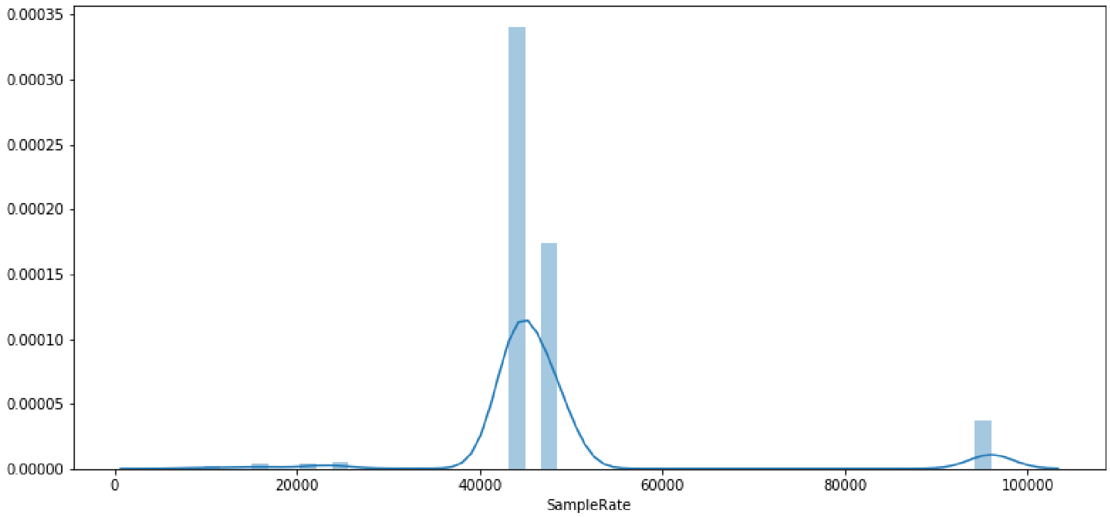
In [94]:
```
def classEncoder(className):
    classMap = {
        'siren':1,
        'street_music':2,
        'drilling':3,
        'dog_bark':4,
        'children_playing':5,
        'gun_shot':6,
        'engine_idling':7,
        'air_conditioner':8,
        'jackhammer':9,
        'car_horn':10
    }
    return classMap.get(className)
```

In [96]:
```
# grab the full paths of all sample files
paths = glob.glob("{0}/samples/*".format(TRAIN_DATA_PATH))
# create a dataframe
sounds = []
for path in paths:
    fn = int(os.path.splitext(os.path.basename(path))[0])
    category = classification[classification.ID == fn]
    audio = sf.SoundFile(path)
    cls = category.Class.values[0]
    sounds.append((fn , classEncoder(cls),cls, audio.name, audio.channels, audio.sampl
    round(audio.frames/audio.samplerate,1),audio.subtype))
df = pd.DataFrame(sounds,columns=['ID','ClassID','Class','Path','Channels','SampleRate
df.head(20)
```

```
Out[96]:        ID  ClassID             Class                                 Path  \
         0     0        1             siren     ../data/original/train/samples\0.wav
         1     1        2      street_music     ../data/original/train/samples\1.wav
         2    10        2      street_music    ../data/original/train/samples\10.wav
         3   100        8  air_conditioner   ../data/original/train/samples\100.wav
         4  1000        2      street_music  ../data/original/train/samples\1000.wav
         5  1001        8  air_conditioner  ../data/original/train/samples\1001.wav
         6  1003        4          dog_bark  ../data/original/train/samples\1003.wav
         7  1004        8  air_conditioner  ../data/original/train/samples\1004.wav
         8  1006        9        jackhammer  ../data/original/train/samples\1006.wav
         9  1007       10          car_horn  ../data/original/train/samples\1007.wav
         10 1008       10          car_horn  ../data/original/train/samples\1008.wav
         11  101        3          drilling   ../data/original/train/samples\101.wav
         12 1014        5  children_playing  ../data/original/train/samples\1014.wav
         13 1015        2      street_music  ../data/original/train/samples\1015.wav
         14 1017        1             siren  ../data/original/train/samples\1017.wav
         15 1018        2      street_music  ../data/original/train/samples\1018.wav
         16 1021        4          dog_bark  ../data/original/train/samples\1021.wav
         17 1022        5  children_playing  ../data/original/train/samples\1022.wav
         18 1024        5  children_playing  ../data/original/train/samples\1024.wav
         19 1025        9        jackhammer  ../data/original/train/samples\1025.wav

             Channels  SampleRate  Frames Format  Length SubType
         0          2       44100  176400    WAV     4.0  PCM_16
         1          1       48000  192000    WAV     4.0  PCM_16
         2          2       44100  176400    WAV     4.0  PCM_16
         3          2       44100  176400    WAV     4.0  PCM_16
         4          2       44100  176400    WAV     4.0  PCM_16
         5          2       44100  176400    WAV     4.0  PCM_16
         6          2       96000  384000  WAVEX     4.0  PCM_24
         7          2       44100  176400    WAV     4.0  PCM_16
         8          2       44100  176400    WAV     4.0  PCM_16
         9          1       16000   64000    WAV     4.0  PCM_16
         10         2       48000   17561    WAV     0.4  PCM_16
         11         2       48000   55200  WAVEX     1.1  PCM_24
         12         2       44100   55125    WAV     1.2  PCM_16
         13         2       48000  192000    WAV     4.0  PCM_16
         14         2       48000  192000  WAVEX     4.0  PCM_24
         15         2       44100  176400    WAV     4.0  PCM_16
         16         1       48000  192000  WAVEX     4.0  PCM_24
         17         2       44100  176400    WAV     4.0  PCM_16
         18         2       48000  192000  WAVEX     4.0  PCM_24
         19         2       44100  176400    WAV     4.0  PCM_16
```

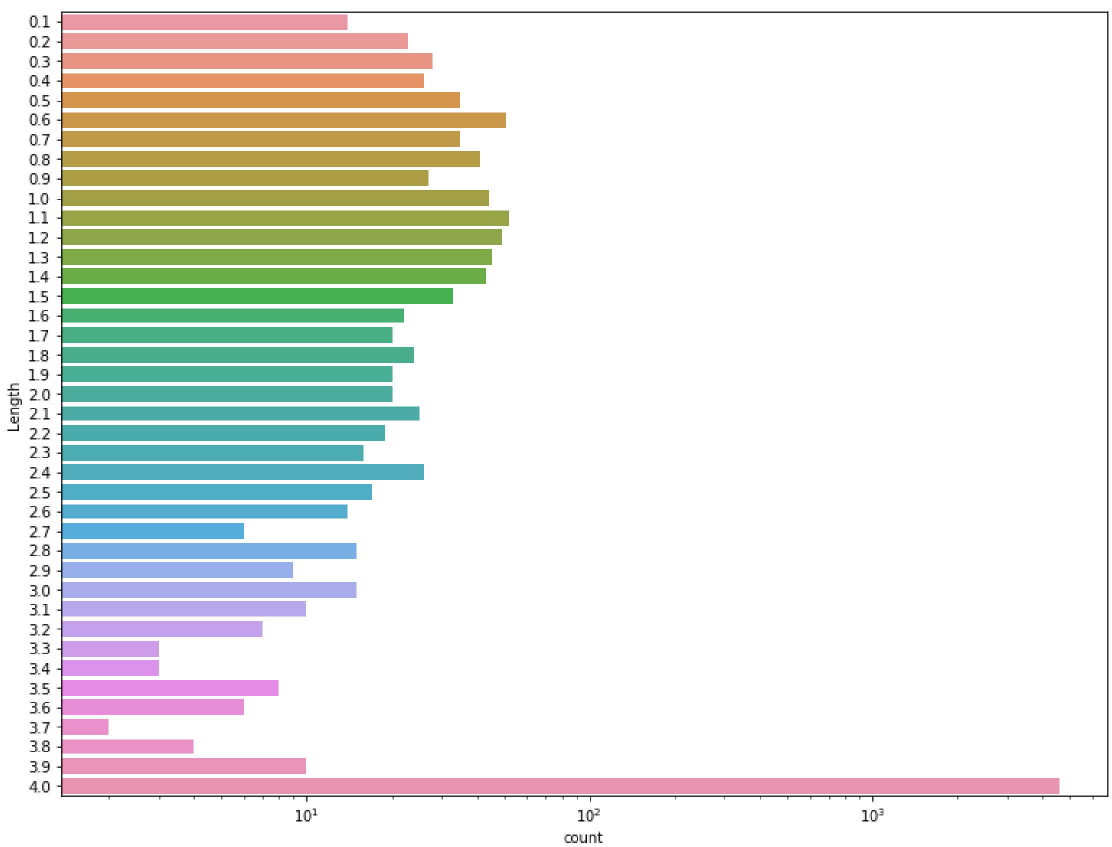
Sample Rate Distribution

```
In [97]: plt.figure(figsize=(13,6))
         sns.distplot(df.SampleRate);
```



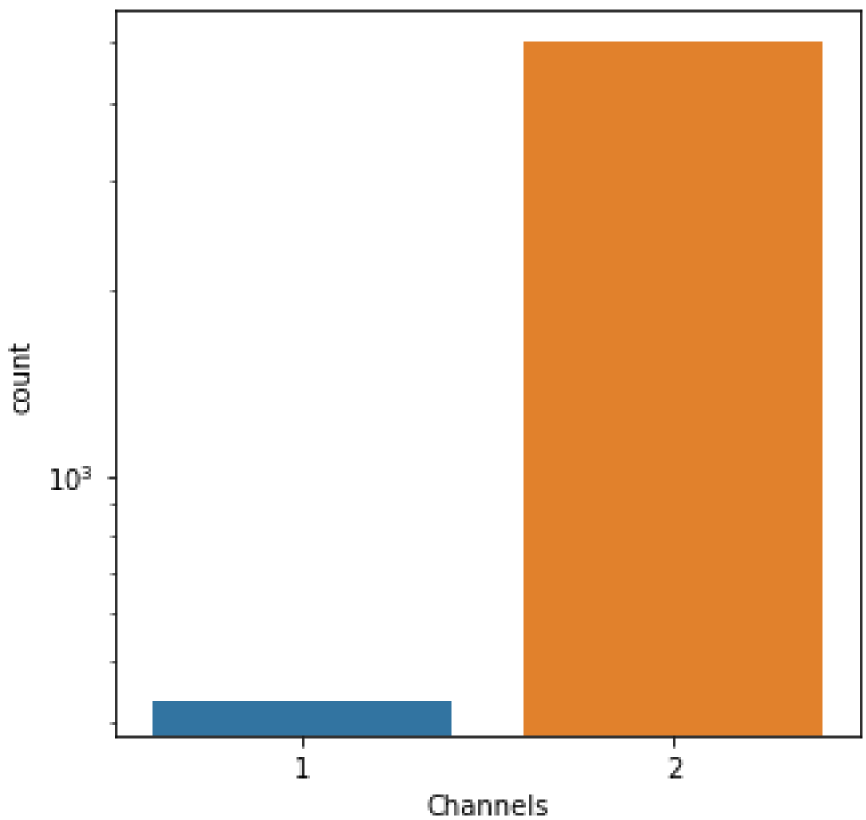
Evidently the sample rate of the sound files varies. We would have to resample the original data to bring it to the same standard. Let's caclulate the length of the sounds

In [98]:
```
plt.figure(figsize=(13,10))
sns.countplot(y=df.Length, log=True);
```



Majority of the sound files are 4 second long. But there are some file that are less than a second long. Designing the model we would have to make sure that the input layer is able to deal with the sound samples of various length and a sample rate. We might also filter out the samples that less than 0.5 second long, because mot likely they do not carry to valuable information. Lastly we are going to verify how many channles the recoded audio file have (stereo vs mono)

```
In [99]: plt.figure(figsize=(5,5))
         sns.countplot(x=df.Channels, log=True);
```



Just a few audo files were recorded in mono. For model training we porbably would need just one channel (TBD)

Sound Characteristics of Each Category There are ten sound classess. Let's take a sample from each class and review its characteristics. **Note:** we will be using librosa library to visualize the feautres of the audio sample.

```
In [100]: sampleDf=df.groupby('Class',as_index = False,group_keys=False).apply(lambda s: s.samp
          sampleDf
```

```
Out[100]:         ID  ClassID             Class  \
          1996  3895        8  air_conditioner
          2950  5299       10          car_horn
          590    189        5  children_playing
          874   2303        4          dog_bark
          4579  7626        3          drilling
          1837  3670        7      engine_idling
          4034  6872        6          gun_shot
          3605  6263        9        jackhammer
          1911  3771        1             siren
          1813  3644        2      street_music

                                              Path  Channels  SampleRate  Frames  \
          1996  ../data/original/train/samples\3895.wav         2       48000  192000
          2950  ../data/original/train/samples\5299.wav         2       48000   60960
          590    ../data/original/train/samples\189.wav         2       48000  192000
          874   ../data/original/train/samples\2303.wav         1       22050   88200
          4579  ../data/original/train/samples\7626.wav         2       44100  176400
          1837  ../data/original/train/samples\3670.wav         2       44100  176400
          4034  ../data/original/train/samples\6872.wav         2       48000  100320
          3605  ../data/original/train/samples\6263.wav         2       96000  384000
          1911  ../data/original/train/samples\3771.wav         1       44100  176400
          1813  ../data/original/train/samples\3644.wav         2       24000   96000

               Format  Length  SubType
          1996  WAVEX     4.0   PCM_24
          2950    WAV     1.3   PCM_16
          590     WAV     4.0   PCM_16
          874     WAV     4.0   PCM_16
          4579    WAV     4.0   PCM_16
          1837    WAV     4.0   PCM_16
          4034    WAV     2.1   PCM_16
          3605  WAVEX     4.0   PCM_24
          1911    WAV     4.0   PCM_16
          1813    WAV     4.0   PCM_16
```

Out of curiosity let's listen a few sounds from our sample collection
Drilling

```
In [101]: IPython.display.Audio(data=sampleDf[sampleDf.Class == 'drilling'].Path.values[0])
```

```
Out[101]: <IPython.lib.display.Audio object>
```

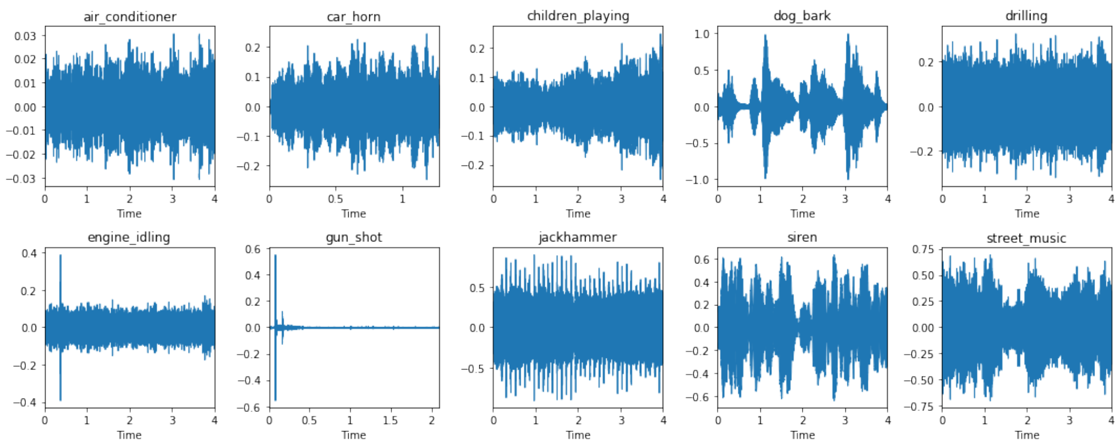
Children Playing

```
In [102]: IPython.display.Audio(data=sampleDf[sampleDf.Class == 'children_playing'].Path.value
```

```
Out[102]: <IPython.lib.display.Audio object>
```

Visualize Data Let's now visualize what these different audio sources look like by plotting their waveforms. This will be a waveform amplitude plot for each audio sample:

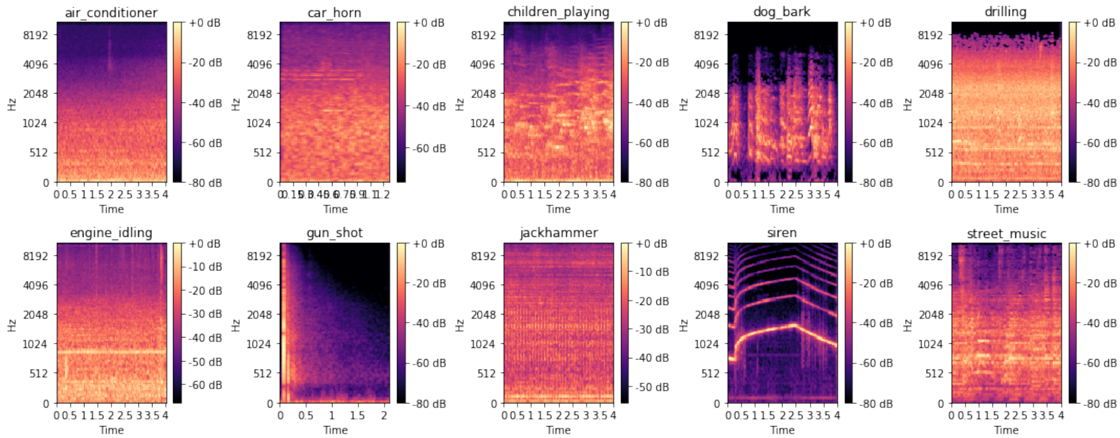
```
In [103]: audio=[sf.read(path) for path in sampleDf["Path"]]
          i = 0
          fig = plt.figure(figsize=(15, 6))
          for sample in audio:
              plt.subplot(2, 5, i+1)
              y = librosa.resample(sample[0].T, sample[1], 22050)
              y = librosa.to_mono(y)
              librosa.display.waveplot(y)
              plt.title(sampleDf["Class"].iloc[[i]].values[0])
              i += 1
          plt.tight_layout()
```



The waveform charts rendered above clearly show that each sound class has distinctive characterisitcs, such as rhythm, amplitude, etc. Though some classes are have more similarities than the other, for example `Air Conditioner` and `Engine Idling` feature rather similar, monotonus sound. Let's apply another popular technique that exposes the features of the sound even better **mel spectogram**. The name mel comes from the word melody. This indicates that the scale is based on pitch comparisons. The melscale is thus a perceptual scale of pitches that have been judged by listeners to be equal in distance from one another.

```
In [104]: i = 0
          fig = plt.figure(figsize=(15, 6))
          for sample in audio:
              plt.subplot(2, 5, i+1)
              y = librosa.resample(sample[0].T, sample[1], 22050)
              y = librosa.to_mono(y)
              M = librosa.feature.melspectrogram(y=y)
              librosa.display.specshow(librosa.power_to_db(M, ref=np.max), y_axis='mel', x_axi
              plt.title(sampleDf["Class"].iloc[[i]].values[0])
              plt.colorbar(format='%+02.0f dB')
```

```
    i += 1
plt.tight_layout()
```



Evidently the mel spectograms have more features than the amplitude/time waveform presentation. Now the distiction between the `Engine Idling` and `Air Conditioner` is much clearer. Another advantage of such data presentation that it could be fed to the **Convolutional Neural Network**.

1.2 Feature Engineering

To be continued...

In [ ]:

1.2.1 Model development:

Document the steps for Transfer Learning

AWS or GCP setup/approach: We need to outline the approach we plan to take in either GCP or AWS for handling big dataset in cloud.

Conclusion: TODO

References: Book - Hands on Transfer Learning With Python - PACKT Publishing
Download Link: https://urbansounddataset.weebly.com/urbansound8k.html

In [ ]:

In [ ]: