eda

January 16, 2024

[1]:
```
from scripts.utils import get_dataset
import pandas as pd
import matplotlib.pyplot as plt
from tqdm.notebook import tqdm
from torchaudio.transforms import MFCC
import torch
from sklearn.manifold import TSNE
import matplotlib as mpl
from IPython.display import display, Audio
from random import randrange
import numpy as np
```

[2]:
```
plt.style.use("ggplot")
```

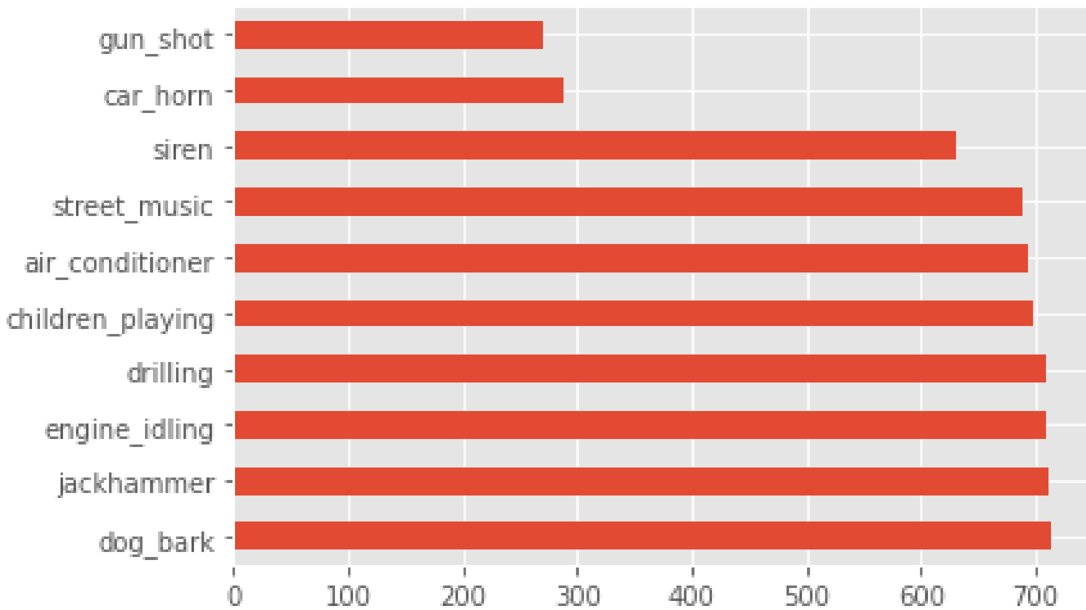
[3]:
```
dataset = get_dataset()
dataset
```

[3]:
```
DatasetDict({
    train: Dataset({
        features: ['audio', 'slice_file_name', 'fsID', 'start', 'end',
'salience', 'fold', 'classID', 'class'],
        num_rows: 6112
    })
    test: Dataset({
        features: ['audio', 'slice_file_name', 'fsID', 'start', 'end',
'salience', 'fold', 'classID', 'class'],
        num_rows: 1310
    })
    valid: Dataset({
        features: ['audio', 'slice_file_name', 'fsID', 'start', 'end',
'salience', 'fold', 'classID', 'class'],
        num_rows: 1310
    })
})
```

Distribution of the labels. Important to know if there is any particular class is present at a higher rate than others.

```
[4]: pd.Series(dataset["train"]["class"]).value_counts().plot(kind="barh")
```

```
[4]: <AxesSubplot:>
```

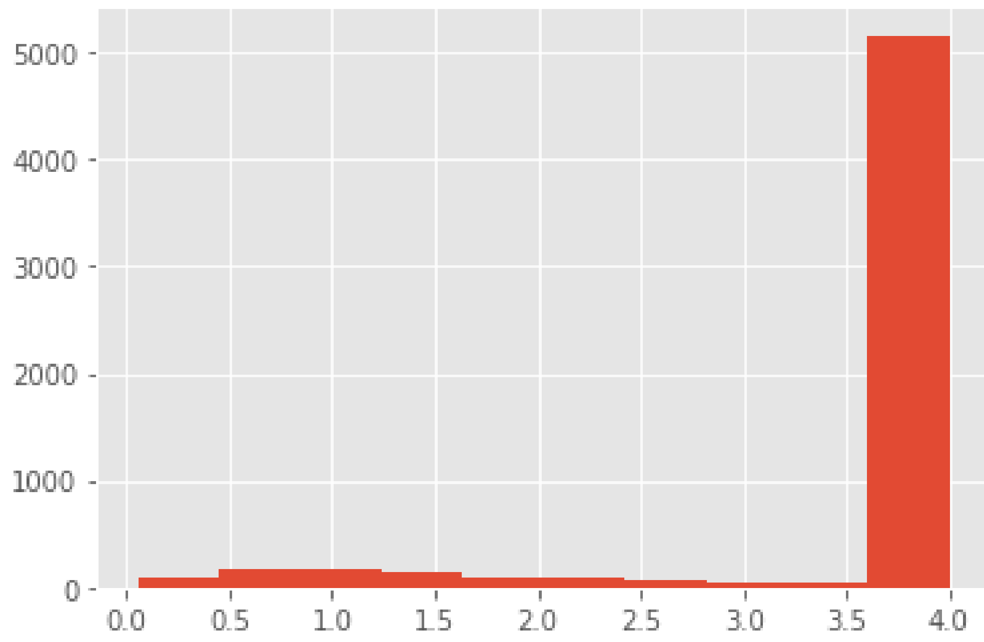


Except for the gun_shot and car_horn classes, labels seem to be equally distributed. Special measures like over or under sampling don't seem necessary

Distribution of duration

```
[5]: (pd.Series(dataset["train"]["end"]) - pd.Series(dataset["train"]["start"])).
     ↪hist()
```

```
[5]: <AxesSubplot:>
```



Most clips seem to be around 4s in duration. For the remaining clips, we'll have to use padding

1 Samples from all classes

[6]:
```
labels = np.array(dataset["train"]["class"])
classes = sorted(list(set(dataset["train"]["class"])))
```

[7]:
```
for x in classes:
    print(x)
    class_subset = dataset["train"].select(np.where(labels == x)[0])
    for _ in range(3):
        sample = class_subset[randrange(0, len(class_subset))]
        display(Audio(sample["audio"]["array"],␣
 ↪rate=sample["audio"]["sampling_rate"]))
```

```
air_conditioner
<IPython.lib.display.Audio object>
<IPython.lib.display.Audio object>
<IPython.lib.display.Audio object>
car_horn
<IPython.lib.display.Audio object>
<IPython.lib.display.Audio object>
```

<IPython.lib.display.Audio object>

children_playing

<IPython.lib.display.Audio object>

<IPython.lib.display.Audio object>

<IPython.lib.display.Audio object>

dog_bark

<IPython.lib.display.Audio object>

<IPython.lib.display.Audio object>

<IPython.lib.display.Audio object>

drilling

<IPython.lib.display.Audio object>

<IPython.lib.display.Audio object>

<IPython.lib.display.Audio object>

engine_idling

<IPython.lib.display.Audio object>

<IPython.lib.display.Audio object>

<IPython.lib.display.Audio object>

gun_shot

<IPython.lib.display.Audio object>

<IPython.lib.display.Audio object>

<IPython.lib.display.Audio object>

jackhammer

<IPython.lib.display.Audio object>

<IPython.lib.display.Audio object>

<IPython.lib.display.Audio object>

siren

<IPython.lib.display.Audio object>

<IPython.lib.display.Audio object>

<IPython.lib.display.Audio object>

street_music

<IPython.lib.display.Audio object>

<IPython.lib.display.Audio object>

```
<IPython.lib.display.Audio object>
```

All the classes seem distinct enough so shouldn't so the it should be possible to get decent performance on the task.

2 Exploring the seperabiliity of the classes

Using a dimensionality reduction technique, such as TSNE, we can get an idea about how separable are the classes with respect to each other

[8]:
```
mfcc_transform = MFCC(n_mfcc=40,␣
↪sample_rate=dataset["train"][0]["audio"]["sampling_rate"])
```

```
/Users/snehalranjan/miniconda3/lib/python3.9/site-
packages/torchaudio/functional/functional.py:571: UserWarning: At least one mel
filterbank has all zero values. The value for `n_mels` (128) may be set too
high. Or, the value for `n_freqs` (201) may be set too low.
  warnings.warn(
```

[9]:
```
mfcc_features = [mfcc_transform(torch.tensor(x["audio"]["array"]).float()).
↪mean(-1).numpy() for x in tqdm(dataset["train"])]
```

```
  0%|          | 0/6112 [00:00<?, ?it/s]
```

[10]:
```
%%time
tsne = TSNE()
reduced_features = tsne.fit_transform(mfcc_features)
reduced_features.shape
```

```
/Users/snehalranjan/miniconda3/lib/python3.9/site-
packages/sklearn/manifold/_t_sne.py:780: FutureWarning: The default
initialization in TSNE will change from 'random' to 'pca' in 1.2.
  warnings.warn(
/Users/snehalranjan/miniconda3/lib/python3.9/site-
packages/sklearn/manifold/_t_sne.py:790: FutureWarning: The default learning
rate in TSNE will change from 200.0 to 'auto' in 1.2.
  warnings.warn(
```

```
CPU times: user 59.8 s, sys: 15 s, total: 1min 14s
Wall time: 11.1 s
```

[10]:
```
(6112, 2)
```

[11]:
```
df = pd.DataFrame(zip(*reduced_features.T, dataset["train"]["class"]),␣
↪columns=["x", "y", "class", ])
print(len(df))
df.head()
```

```
6112
```

[11]:
```
            x          y             class
0  68.179482  43.570770        jackhammer
1 -72.325821  12.808189     engine_idling
2 -43.132973  21.062531  children_playing
3  22.583473  30.926529          dog_bark
4  23.375946 -16.912394   air_conditioner
```

[12]:
```
classes = df["class"].sort_values().unique()
classes.shape
```

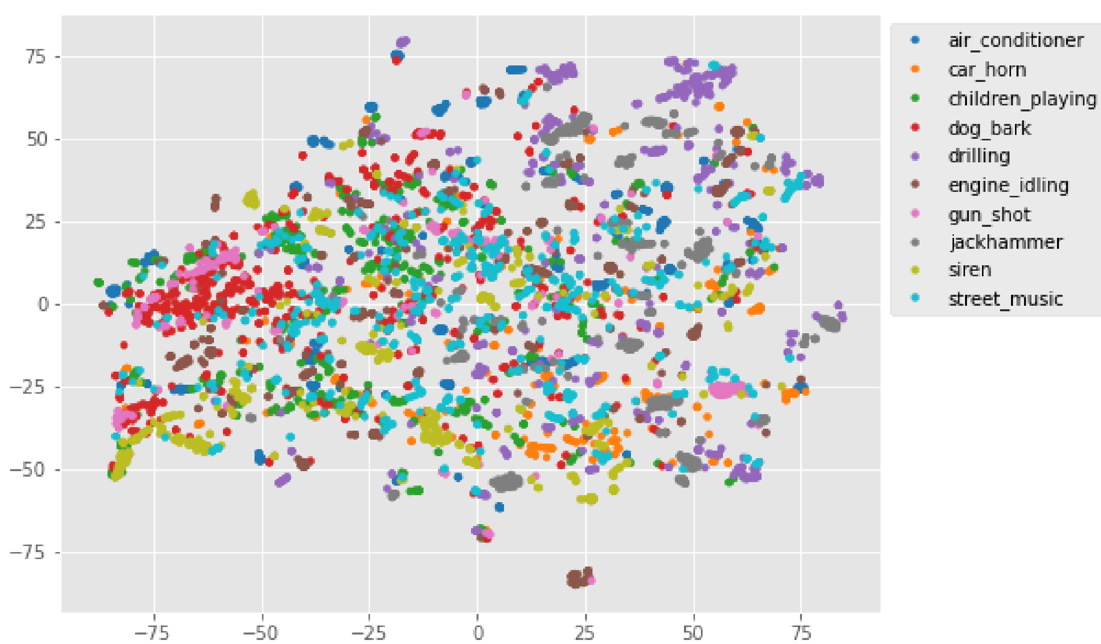
[12]: (10,)

[13]:
```
fig, ax = plt.subplots(1, 1, figsize=(8, 6))

for (classId, className) in enumerate(classes):
    df_class = df[df["class"] == className]
    ax.scatter(
        df_class["x"],
        df_class["y"],
        s=15,
        c=[mpl.cm.tab10.colors[classId] for _ in range(len(df_class))],
        label=classes[classId]
    )

plt.legend(bbox_to_anchor=(1, 1))
```

[13]: <matplotlib.legend.Legend at 0x17ca63fd0>



We can see that certain categories like drilling are easily discernable from other labels but classes like street_music are mixed in with others.

Important to note that the features used here (MFCC) might not be able to represent the information in the best way possible.

[ ]:
```

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```