results-analysis

January 16, 2024

Note: Each model is presented as an independent section for better isolation and ease of understanding

[1]:
```
def get_metrics(labels, preds):
    data_metrics = []
    for metric in metrics:
        metric_name = metric.__name__
        if metric_name == "accuracy_score":
            data_metrics.append((metric_name, metric(labels, preds)))
        else:
            data_metrics.append((metric_name, metric(labels, preds,␣
 ↪average="macro")))

    return pd.DataFrame(data_metrics, columns=["metric", "value"])
```

1 Baseline

Before conducting any experiments, it's important to establish a simple baseline. This helps in making decisions about the model performance in the early stages of development

[2]:
```
import pandas as pd
from sklearn.metrics import precision_score, recall_score, f1_score,␣
 ↪accuracy_score
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
import numpy as np
from tqdm.notebook import tqdm
import matplotlib.pyplot as plt
```

[3]:
```
plt.style.use("ggplot")
```

[4]:
```
df_test = pd.read_csv("preds/mfcc-test.csv")
print(len(df_test))
df_test.head()
```

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```

[4]:
```
            filename             label  air_conditioner  car_horn  \
0  164797-2-0-50.wav  children_playing     8.866575e-01  0.000009
1   17578-5-0-23.wav     engine_idling     5.985906e-05  0.000453
2  207214-2-0-26.wav  children_playing     1.128041e-02  0.002365
3   14470-2-0-14.wav  children_playing     8.298853e-06  0.000204
4   93567-8-0-17.wav             siren     1.277176e-15  0.307760

   children_playing  dog_bark  drilling  engine_idling      gun_shot  \
0      3.810622e-02  0.029240  0.000039   3.133511e-03  1.770535e-03
1      1.342414e-03  0.000029  0.002079   9.932372e-01  1.256412e-07
2      5.206296e-01  0.112187  0.049140   1.356505e-02  1.159514e-01
3      8.744751e-01  0.038185  0.012411   1.595363e-03  1.817845e-02
4      2.747113e-15  0.000004  0.000003   8.254789e-11  3.924732e-10

     jackhammer     siren  street_music
0  3.316693e-09  0.021471      0.019573
1  1.857425e-03  0.000045      0.000897
2  7.473872e-04  0.024246      0.149889
3  1.478383e-06  0.033734      0.021208
4  3.239344e-14  0.692206      0.000027
```

[5]:
```python
classes = df_test.label.sort_values().unique()
```

[6]:
```python
metrics = [precision_score, recall_score, f1_score, accuracy_score]
```

[7]:
```python
preds = df_test[classes].idxmax(axis=1)
```

[8]:
```python
get_metrics(df_test.label, preds)
```

[8]:
```
            metric     value
0  precision_score  0.693671
1     recall_score  0.665230
2         f1_score  0.670525
3   accuracy_score  0.690840
```

This is a decent baseline to compare our models against.

2 Zero Shot (CLAP) Evaluation

[9]:
```python
import pandas as pd
from sklearn.metrics import precision_score, recall_score, f1_score,␣
  ↪accuracy_score
import numpy as np
from tqdm.notebook import tqdm
import matplotlib.pyplot as plt
```

[10]:
```python
plt.style.use("ggplot")
```

[11]:
```python
df_test = pd.read_csv("preds/clap-test.csv")
print(len(df_test))
df_test.head()
```

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```

[11]:
```
             filename              label  air_conditioner  car_horn  \
0  164797-2-0-50.wav  children_playing     2.943992e-03  0.008064
1   17578-5-0-23.wav     engine_idling     2.189460e-02  0.000205
2  207214-2-0-26.wav  children_playing     3.995908e-06  0.000179
3   14470-2-0-14.wav  children_playing     9.924141e-08  0.000002
4   93567-8-0-17.wav             siren     1.587656e-06  0.006024

   children_playing      dog_bark  drilling  engine_idling  gun_shot  \
0          0.952775  4.795736e-04  0.000026       0.000759  0.000759
1          0.000026  1.846368e-04  0.000476       0.965558  0.000054
2          0.992761  2.809861e-06  0.000009       0.000101  0.000042
3          0.999881  4.821749e-07  0.000002       0.000003  0.000018
4          0.000153  1.106603e-04  0.000015       0.000010  0.000009

   jackhammer     siren  street_music
0    0.000116  0.005448      0.028630
1    0.011473  0.000051      0.000077
2    0.000007  0.000857      0.006037
3    0.000042  0.000008      0.000044
4    0.000016  0.984928      0.008732
```

[12]:
```python
classes = df_test.label.sort_values().unique()
```

[13]:
```python
metrics = [precision_score, recall_score, f1_score, accuracy_score]
```

2.1 Selecting the class with the highest probability

The simplest approach to assign classes from the model predictions would be to take the class with the maximum probability

[14]:
```python
preds = df_test[classes].idxmax(axis=1).to_numpy()
```

[15]:
```python
get_metrics(df_test.label, preds)
```

[15]:
```
            metric     value
0  precision_score  0.789655
1     recall_score  0.748847
2         f1_score  0.743472
3   accuracy_score  0.740458
```

For a zero-shot setting, these are suprisingly good numbers. Without any data provided to the model, it was able to correctly identify the classes in 3/4ths of the test dataset. It even beats the MFCC baseline

2.2 Selecting with threshold

A potentially better way of improving the model performance would be use a threshold to filter out predictions where the model is not confident in it's predictions.
We can use a PR curve to determine this threshold.

Since we don't want to overfit on the test set, we'll use the validation set for this task

[16]:
```
df_valid = pd.read_csv("preds/clap-valid.csv")
print(len(df_valid))
df_valid.head()
```

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```

[16]:
```
            filename              label  air_conditioner  car_horn  \
0   49312-2-0-16.wav  children_playing         0.000002  0.000055
1   169466-4-3-9.wav          drilling         0.001141  0.007098
2    39884-5-0-1.wav     engine_idling         0.002819  0.009947
3   167701-4-6-4.wav          drilling         0.001359  0.214464
4   24347-8-0-48.wav             siren         0.000002  0.005404

   children_playing  dog_bark  drilling  engine_idling  gun_shot  jackhammer  \
0          0.998321  0.000009  0.000008       0.000026  0.000020    0.000058
1          0.070889  0.002817  0.007584       0.017082  0.074979    0.751844
2          0.000048  0.000188  0.000043       0.986275  0.000053    0.000401
3          0.002815  0.001745  0.308239       0.056742  0.000485    0.388747
4          0.000871  0.000463  0.000141       0.000293  0.000019    0.000097

      siren  street_music
0  0.000319      0.001182
1  0.022784      0.043782
2  0.000083      0.000142
3  0.022160      0.003244
4  0.914580      0.078131
```

[17]:
```
data = df_valid[classes].to_numpy()

labels = df_valid["label"].tolist()
labels_sparse = np.zeros((len(labels), len(classes)))
for i in range(len(labels)):
    labels_sparse[i] = (classes == labels[i])
```

[18]:
```
thresholds = [0.01, 0.05] + np.linspace(0.1, 0.9, 9).tolist() + [0.95, 0.99]
```

[19]:
```
precisions, recalls = [], []

for threshold in tqdm(thresholds):
    preds = data > threshold
    precisions.append(precision_score(labels_sparse, preds, average="micro"))
    recalls.append(recall_score(labels_sparse, preds, average="micro"))
```

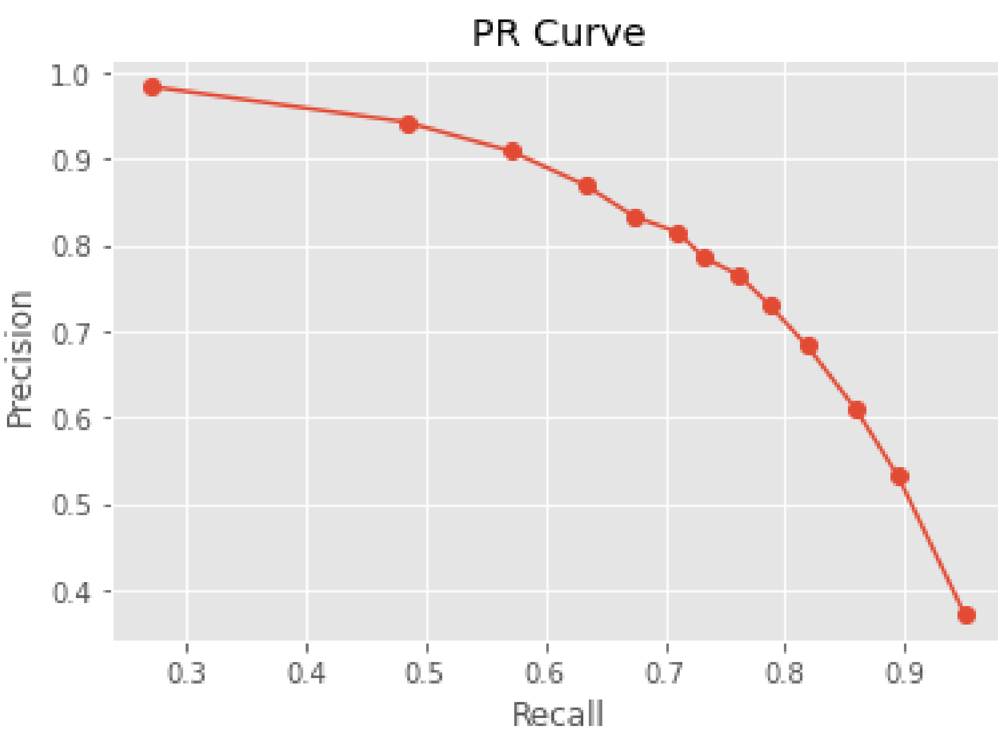
```
  0%|          | 0/13 [00:00<?, ?it/s]
```

[20]:
```
fig, ax = plt.subplots(1, 1)

ax.plot(recalls, precisions, marker='o')

ax.set_xlabel("Recall")
ax.set_ylabel("Precision")

ax.set_title("PR Curve");
```



We can see that the point corresponding to thresholds 0.5 and 0.6 seem to have the best performance

[21]:
```
threshold = 0.55
preds = data > threshold
get_metrics(labels_sparse, preds)
```

[21]:

	metric	value
0	precision_score	0.854083
1	recall_score	0.729168
2	f1_score	0.761264
3	accuracy_score	0.725191

This approach improved the precision with only a slight drop in recall. Consequently, the F1 score also improved. This makes sense as the classification system is now more conservative in it's estimates compared to the earlier version

Depending on the task at hand, the loss in recall might be an acceptable trade-off

3 Wav2Vec2 Evaluation

[22]:

```
import pandas as pd
from sklearn.metrics import precision_score, recall_score, f1_score,␣
↪accuracy_score
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
import numpy as np
from tqdm.notebook import tqdm
import matplotlib.pyplot as plt
```

[23]:

```
plt.style.use("ggplot")
```

[24]:

```
df_test = pd.read_csv("preds/wav2vec2-test.csv")
print(len(df_test))
df_test.head()
```

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[24]:

	filename	label	air_conditioner	car_horn
0	164797-2-0-50.wav	children_playing	0.103794	0.025038
1	17578-5-0-23.wav	engine_idling	0.130853	0.010763
2	207214-2-0-26.wav	children_playing	0.047430	0.137011
3	14470-2-0-14.wav	children_playing	0.017578	0.089363
4	93567-8-0-17.wav	siren	0.004804	0.077267

	children_playing	dog_bark	drilling	engine_idling	gun_shot	jackhammer
0	0.001672	0.009792	0.083255	0.198738	0.000610	0.567548
1	0.000530	0.002195	0.325663	0.178256	0.000008	0.350398
2	0.091758	0.021810	0.282318	0.044008	0.005486	0.324151
3	0.394020	0.032699	0.047640	0.020995	0.001783	0.010209
4	0.043750	0.029088	0.043984	0.032997	0.000891	0.006753

	siren	street_music
0	0.008192	0.001363
1	0.000610	0.000723

```
2  0.025153      0.020877
3  0.149561      0.236151
4  0.757135      0.003332
```

[25]:
```
classes = df_test.label.sort_values().unique()
```

[26]:
```
metrics = [precision_score, recall_score, f1_score, accuracy_score]
```

[27]:
```
preds = df_test[classes].idxmax(axis=1)
```

[28]:
```
get_metrics(df_test.label, preds)
```

[28]:

	metric	value
0	precision_score	0.509989
1	recall_score	0.441267
2	f1_score	0.433847
3	accuracy_score	0.435878

This performance clearly leaves a lot to be desired, let's take a look where the model fails by calculating the metrics at class level

[29]:
```
pd.DataFrame(list(zip(
    classes,
    precision_score(df_test.label, preds, average=None),
    recall_score(df_test.label, preds, average=None),
    f1_score(df_test.label, preds, average=None),

)), columns=["class", "precision", "recall", "f1-score"]).
 ↪sort_values("f1-score").reset_index(drop=True)
```

[29]:

	class	precision	recall	f1-score
0	car_horn	0.204545	0.130435	0.159292
1	air_conditioner	0.522727	0.138554	0.219048
2	engine_idling	0.246201	0.574468	0.344681
3	drilling	0.294118	0.547945	0.382775
4	street_music	0.745098	0.260274	0.385787
5	children_playing	0.612500	0.322368	0.422414
6	jackhammer	0.421875	0.574468	0.486486
7	gun_shot	0.589286	0.687500	0.634615
8	siren	0.739130	0.559211	0.636704
9	dog_bark	0.724409	0.617450	0.666667

The low precision score for classes like car_horn, engine_idling and drilling tells us that the model is often conflating other classes with them.

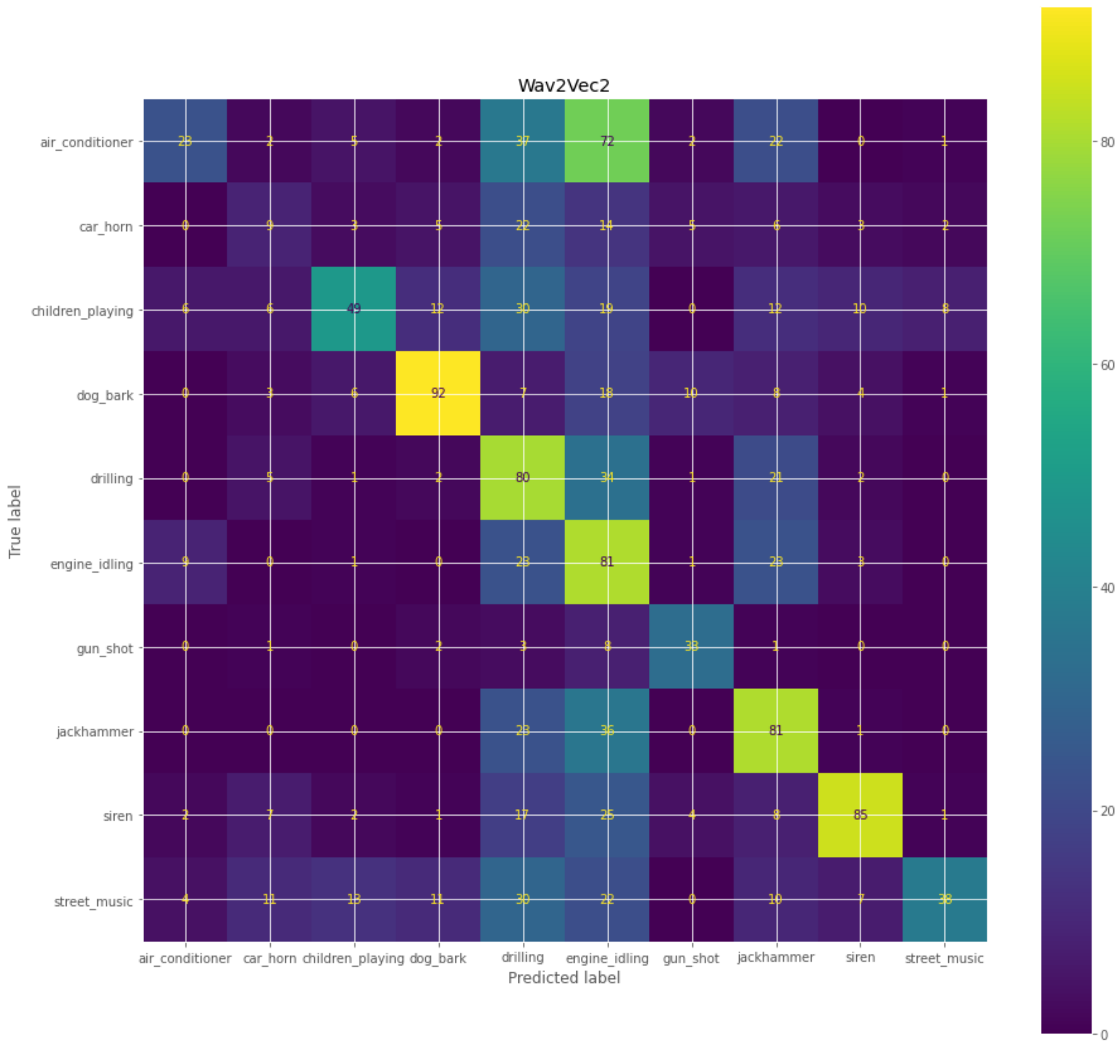
Making a confusion matrix can help us get more information about this

[30]:
```
fig, ax = plt.subplots(1, 1, figsize=(15, 15))

ax.set_title("Wav2Vec2")

ConfusionMatrixDisplay(confusion_matrix(df_test.label, preds),␣
 ↪display_labels=classes).plot(ax=ax)
```

[30]: <sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x14b4c0ac0>



As suspected, the model is often classifying inputs as drilling and engine_idling.

4 MIT-AudioSet Evaluation

[31]:
```
import pandas as pd
from sklearn.metrics import precision_score, recall_score, f1_score,␣
↪accuracy_score
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
import numpy as np
from tqdm.notebook import tqdm
import matplotlib.pyplot as plt
```

[32]:
```
plt.style.use("ggplot")
```

[33]:
```
df_test = pd.read_csv("preds/mit-test.csv")
print(len(df_test))
df_test.head()
```

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[33]:
```
             filename             label  air_conditioner  car_horn  \
0  164797-2-0-50.wav  children_playing         0.003709  0.000305
1   17578-5-0-23.wav     engine_idling         0.027785  0.000359
2  207214-2-0-26.wav  children_playing         0.002041  0.000513
3   14470-2-0-14.wav  children_playing         0.000044  0.000197
4   93567-8-0-17.wav             siren         0.000010  0.000219

   children_playing  dog_bark  drilling  engine_idling  gun_shot  jackhammer  \
0          0.987794  0.001612  0.000068       0.003563  0.000063    0.000093
1          0.000190  0.000461  0.011460       0.871870  0.000017    0.087416
2          0.879849  0.003092  0.000306       0.000149  0.000042    0.000085
3          0.979027  0.000629  0.002236       0.000090  0.000293    0.000199
4          0.000096  0.000051  0.000088       0.000029  0.000003    0.000007

      siren  street_music
0  0.000331      0.002462
1  0.000094      0.000348
2  0.000412      0.113512
3  0.000099      0.017187
4  0.999467      0.000032
```

[34]:
```
classes = df_test.label.sort_values().unique()
```

[35]:
```
metrics = [precision_score, recall_score, f1_score, accuracy_score]
```

[36]:
```
preds = df_test[classes].idxmax(axis=1)
```

[37]:
```
get_metrics(df_test.label, preds)
```

[37]:

	metric	value
0	precision_score	0.940528
1	recall_score	0.935904
2	f1_score	0.937890
3	accuracy_score	0.936641

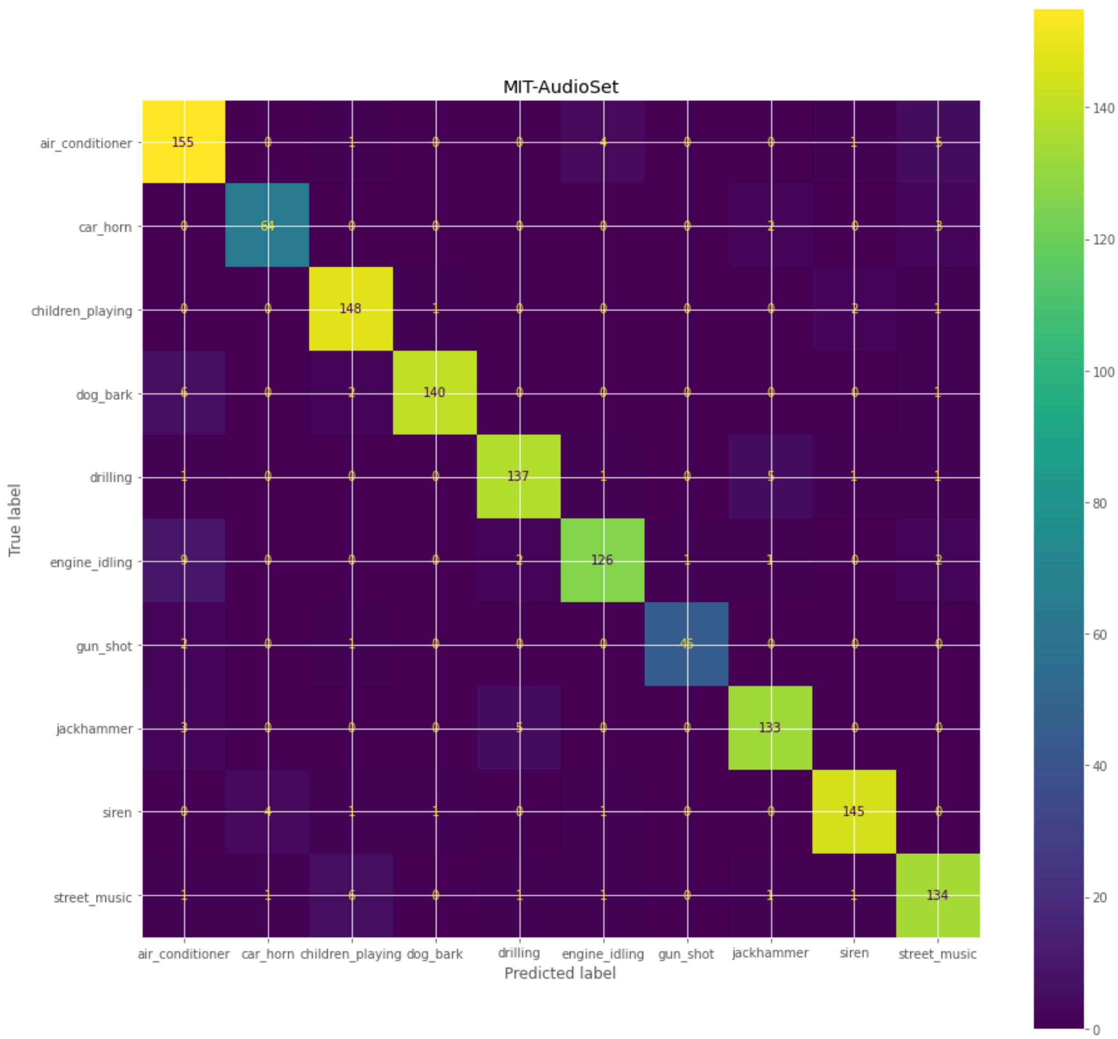
The performance here is significantly better

[38]:
```
fig, ax = plt.subplots(1, 1, figsize=(15, 15))

ax.set_title("MIT-AudioSet")

ConfusionMatrixDisplay(confusion_matrix(df_test.label, preds),␣
 ↪display_labels=classes).plot(ax=ax)
```

[38]: <sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x14b6b7070>



The confusion matrix confirms this with the almost perfect diagonal

[ ]:
```
```