

Final Project Analysis - Evaluating Open Mic Data with MultiClass Classifiers

Tristan Demond, Cole Bailey, Filipp Krasovsky, Andrew Zazueta

University of San Diego

Master of Science, Applied Data Science

Machine Learning

ADS-504-02-SM21

2021

Overview

The Open Mic 2018 dataset contains 20,000 examples of Creative Commons-licensed music available on the Free Music Archive (Humphrey, et. al 2018). Open Mic 2018 was made available through a collaboration between Spotify and MARL@NYU. Each example is a 10-second excerpt which has been partially labeled for the presence or absence of 20 instrument classes by annotators on a crowd-sourcing platform. In this project, researchers describe in detail how the instrument taxonomy was constructed, how the dataset was sampled and annotated, and compare its characteristics to similar, previous data-sets. Finally, we present experimental results and baseline model performance to motivate future work in music recognition in music information retrieval.

Task/Problem/Question

Identification of instruments in polyphonic records is an imperative issue in music information retrieval. This is mainly due to a lack of data available for effective predictive and computational models. With the introduction of this Open Mic 2018 data, we are able to effectively build a model with sufficient data that will correctly identify the instruments playing in polyphonic records. Therefore, the goal of this project is to find a classifier that reduces the error rate to either a local or global minimum across each class or instrument. Multi-instrument recognition is the task of predicting the presence or absence of different instruments within an audio clip, this project aims to effectively do so. The implications of succeeding on this project would enable the team to create deliverables that can identify whether a specific instrument is playing, which could be scaled to machine learning deliverables akin to those used by Shazam and other music recognition services.

Data splitting (training, validation, and test sets)

The data is first loaded and mapped based on their respective instrument. The data is then split using the `squeeze is true` function in Pandas to only have a single array for each instrument rather than parsing through the entire dataframe each runthrough. The testing and training data is split in a 75 to 25 ratio fashion. Then the data was prepared for the baseline model, perceptron, and the following comparative models: Random Forest, Logistic Regression, Neural Network, and Support Vector Machine (SVM). The data was sub-sampled by annotation, and then masked by annotations. Instead of having time-varying features in the original dataset, mean feature vectors were summarized over time. Label likelihood thresholds were at 0.5. This was done for both the test and train datasets and then applied to Perceptron, Random Forest, Logistic Regression, Neural Network, and SVM models for the algorithms.

Validation and testing (model tuning and evaluation)

Across the creation of the models used, several parameters and hyperparameters were imposed on the models to maximize their respective classification rates. After iterating the models several times, the parameters selected were ultimately chosen due to their impact on the precision rates during the classification process.

The parameters selected for the random forest model included the depth of the tree and the number of estimators included at the splits. After iterating the model over several depths, a max depth of eight provided the most significant results. The random forest classified the data at

a depth of 2,4,6,8,10... and 20. It was at a parameter selection of eight that resulted in the highest levels of precision for each instrument.

The next model utilizing several different parameters was the logistic regression model. Logistic regression has the ability to implement a penalty within the model. The first penalty used within the model for classification was 'elastic net'. However, the model performance significantly increased with the inclusion of the 'L1' penalty. This penalty was the most successful in limiting the impact of the variables that are less contributive for classification. The 'liblinear' solver was also included as it pairs with the 'L1' penalty.

The SVM model parameters were set with gamma to 'auto,' kernel to 'poly,' and degree to '2' with the rest of the parameters tuned to their defaults within the function. The advantage to using the gamma as auto over scale is that auto uses the value $[1 / (\text{number of features})]$ rather than the value $[1 / (\text{number of features} * X \text{ variance})]$. The degree hyperparameter can only be used with a polynomial kernel and this function gave the best results over the default value of degree 3.

The final model parameters were established within the creation of the Neural Network model. Similar to the previous models, several iterations of the model were run and parameters were selected on precision rate. For the neural network, this resulted in five hidden layers. With the inclusion of these parameters, the models were able to increase their classification rates by more than 5% in some cases.

Results and final model selection (performance measures etc.)

The model creation began with establishing the baseline model. The baseline model is to be used to compare future models to determine whether the tuning of the parameters and hyperparameters resulted in a positive change in the precision rates. For the baseline model, a perceptron was used. The creation of the baseline model included the mean average over time for each instrument. As a result, the baseline model for each of the instruments was very high in regards to precision. Additionally, the baseline model seemed to always record a higher precision score with performance on the training set rather than the testing set. For example, The precision rate for false classification for the accordion was 93% on the respective training set. The model performance for the accordion testing set saw a small decrease to 90%. The decrease in precision across training and testing sets is more significant for drums. The train/test precision rates in this case were 98% and 92% respectively. With the validation of the baseline model complete and the precision, recall and F-1 scores documented, additional models were created for comparison.

The models all had high precision and recall scores. Each model had at least one instrument classification where it outperformed each of the other models. For example, the Random Forest model recorded a 99% precision rate for the Cello. This is significantly higher than the 82%, 85%, and 83% rates for the perceptron, logistic regression and neural network models respectively. Alternatively, the Neural Network model had the highest rate for voice; Logistic Regression had the highest recorded rate for piano. As a result, the models all outperformed the baseline model in regards to specific instruments. However, in some cases the models failed to beat the baseline rates entirely. None of the models created had a higher precision rate than the perceptron performance on drums. Overall, the Random Forest model recorded the highest average precision rate while the neural network model recorded the lowest averages.

The recorded ‘False’ precision rates in the training data for some of the instruments in the models can be found in Table 1 below.

Instrument	Baseline	Random Forest	Logistic Regression	Neural Network	SVM
Accordion	0.93	0.96	0.88	0.84	0.84
Banjo	0.81	0.98	0.87	0.80	0.81
Bass	0.86	0.98	0.86	0.85	0.81
Cello	0.82	0.91	0.85	0.83	0.83
Clarinet	0.89	0.99	0.94	0.80	0.81
Cymbals	0.85	1.00	0.91	0.97	0.99
Drums	0.98	1.00	0.94	0.94	1.00
Flute	0.96	0.97	0.89	0.76	0.80
Guitar	0.92	1.00	0.96	0.95	0.98
Organ	0.88	0.97	0.92	0.84	0.82
Piano	0.97	0.99	0.98	0.95	0.98

Table 1: The recorded precision rates for models on the training sets.

Discussion and conclusions

In conclusion, the creation of the models were successfully able to identify instruments playing in the polyphonic records. The models had significantly reduced error rates to the local and global minimum across each class and instrument. As discussed previously, instruments in polyphonic records is an imperative issue in music information retrieval.

The data was collected and parsed into testing and training sets. The creation of the training set allowed the models to be fit to the data and then utilized on test data. The benefit of the test data is that it represents information never before “seen” by the model. As a result, it allows overfitting and other potential issues to be observed by monitoring the fall-off of classification rates. The data was free of any nulls and the most optimal parameters were selected. This resulted in the tuning of the max depth for the random forest, penalty implementation for logistic regression, the number of hidden layers for the neural network, and the degree of the polynomial kernel for the SVM. These parameters allowed the models to output their optimal performances that resulted in up to 99% precision rates in some cases.

Each of the models outperformed the others in at least one instrument category. As a result, it would be beneficial to split the data even further. An idea of this is to group all the ‘string’ instruments together (Violin, Cello, etc...) since Logistic Regression had higher average rates for string instruments than the other models. This example would optimize results even further and be stronger than using a one-model-fit-all strategy.

The application of this research can be applied to applications across the music industry. The models had high precision outputs and could be utilized to create deliverables that can identify the instrument being played which can be scaled to music recognition services such as Shazam.

References

Eric Humphrey, Simon Durand, & Brian McFee. (2018). OpenMIC-2018: An Open Data-set for Multiple Instrument Recognition. Proceedings of the 19th International Society for Music Information Retrieval Conference, 438–444.
<https://doi.org/10.5281/zenodo.1492445>

ADS504 project

August 15, 2021

```
[2]: import json
import os
import numpy as np
import pandas as pd

from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report
from sklearn.linear_model import Perceptron
from sklearn.linear_model import LogisticRegression
from sklearn.neural_network import MLPClassifier
from sklearn.metrics import confusion_matrix

#DATA_ROOT = 'C:/Users/mzazu/OneDrive/Documents/USD papers/504/Project/
↳openmic-2018-v1.0.0/openmic-2018-v1.0.0/openmic-2018'
DATA_ROOT = 'D:\ADS504OpenMicDataset\openmic-2018-v1.0.0\openmic-2018-v1.0.
↳0\openmic-2018'

if not os.path.exists(DATA_ROOT):
    raise ValueError('Did you forget to set `DATA_ROOT`?')
```

0.0.1 Loading the data

```
[3]: OPENMIC = np.load(os.path.join(DATA_ROOT, 'openmic-2018.npz'),
↳allow_pickle=True)
```

```
[4]: # What's included?
print(list(OPENMIC.keys()))
```

```
['X', 'Y_true', 'Y_mask', 'sample_key']
```

```
[5]: X, Y_true, Y_mask, sample_key = OPENMIC['X'], OPENMIC['Y_true'],
↳OPENMIC['Y_mask'], OPENMIC['sample_key']
```

0.0.2 Loading the class map

```
[6]: with open(os.path.join(DATA_ROOT, 'class-map.json'), 'r') as f:
      class_map = json.load(f)
```

```
[7]: class_map
```

```
[7]: {'accordion': 0,
      'banjo': 1,
      'bass': 2,
      'cello': 3,
      'clarinet': 4,
      'cymbals': 5,
      'drums': 6,
      'flute': 7,
      'guitar': 8,
      'mallet_percussion': 9,
      'mandolin': 10,
      'organ': 11,
      'piano': 12,
      'saxophone': 13,
      'synthesizer': 14,
      'trombone': 15,
      'trumpet': 16,
      'ukulele': 17,
      'violin': 18,
      'voice': 19}
```

0.0.3 Loading the train-test splits

```
[8]: # We use squeeze=True here to return a single array for each, rather than a
      ↪full DataFrame

      split_train = pd.read_csv(os.path.join(DATA_ROOT, 'partitions/split01_train.
      ↪csv'),
                                header=None, squeeze=True)
      split_test = pd.read_csv(os.path.join(DATA_ROOT, 'partitions/split01_test.csv'),
                                header=None, squeeze=True)
```

```
[9]: # train and test examples are about 75%/25%
      print('# Train: {}, # Test: {}'.format(len(split_train), len(split_test)))
```

```
# Train: 14915, # Test: 5085
```

```
[10]: # sample key maps are easier to use as sets
      train_set = set(split_train)
      test_set = set(split_test)
```

0.0.4 Splitting data

```
[11]: # These loops go through all sample keys, and save their row numbers to either
      ↪idx_train or idx_test
      # This will be useful in the next step for slicing the array data
      idx_train, idx_test = [], []

      for idx, n in enumerate(sample_key):
          if n in train_set:
              idx_train.append(idx)
          elif n in test_set:
              idx_test.append(idx)
          else:
              # This should never happen, but better safe than sorry.
              raise RuntimeError('Unknown sample key={}! Abort!'.
              ↪format(sample_key[n]))

      # Finally, cast the idx_* arrays to numpy structures
      idx_train = np.asarray(idx_train)
      idx_test = np.asarray(idx_test)
```

```
[12]: # split indices to partition the features, labels, and masks
      X_train = X[idx_train]
      X_test = X[idx_test]

      Y_true_train = Y_true[idx_train]
      Y_true_test = Y_true[idx_test]

      Y_mask_train = Y_mask[idx_train]
      Y_mask_test = Y_mask[idx_test]
```

0.0.5 Fitting Baseline Model (Perceptron)

```
[40]: # This dictionary will include the classifiers for each model
      models = dict()

      # We'll iterate over all instrument classes, and fit a model for each one
      # After training, we'll print a classification report for each instrument
      for instrument in class_map:

          # Map the instrument name to its column number
          inst_num = class_map[instrument]

          # Step 1: sub-sample the data

          # First, we need to select down to the data for which we have annotations
          # This is what the mask arrays are for
```

```

train_inst = Y_mask_train[:, inst_num]
test_inst = Y_mask_test[:, inst_num]

# Here, we're using the Y_mask_train array to slice out only the training
→ examples
# for which we have annotations for the given class
X_train_inst = X_train[train_inst]

# Step 2: simplify the data by averaging over time

# Let's arrange the data for a sklearn Perceptron
# Instead of having time-varying features, we'll summarize each track by
→ its mean feature vector over time
X_train_inst_sklearn = np.mean(X_train_inst, axis=1)

# Again, we slice the labels to the annotated examples
# We threshold the label likelihoods at 0.5 to get binary labels
Y_true_train_inst = Y_true_train[train_inst, inst_num] >= 0.5

# Repeat the above slicing and dicing but for the test set
X_test_inst = X_test[test_inst]
X_test_inst_sklearn = np.mean(X_test_inst, axis=1)
Y_true_test_inst = Y_true_test[test_inst, inst_num] >= 0.5

# Step 3.
# Initialize a new classifier
clf = Perceptron(random_state = 0)

# Step 4.
clf.fit(X_train_inst_sklearn, Y_true_train_inst)

# Step 5.
# Finally, we'll evaluate the model on both train and test
Y_pred_train = clf.predict(X_train_inst_sklearn)
Y_pred_test = clf.predict(X_test_inst_sklearn)

print('-' * 52)
print(instrument)
print('\tTRAIN')
print(classification_report(Y_true_train_inst, Y_pred_train))
print('\tTEST')
print(classification_report(Y_true_test_inst, Y_pred_test))

```

 accordion

TRAIN

	precision	recall	f1-score	support
False	0.93	0.81	0.86	1159
True	0.58	0.81	0.67	374
accuracy			0.81	1533
macro avg	0.75	0.81	0.77	1533
weighted avg	0.84	0.81	0.82	1533

TEST				
	precision	recall	f1-score	support
False	0.90	0.74	0.81	423
True	0.43	0.70	0.53	115
accuracy			0.73	538
macro avg	0.66	0.72	0.67	538
weighted avg	0.80	0.73	0.75	538

banjo

TRAIN				
	precision	recall	f1-score	support
False	0.81	0.93	0.87	1148
True	0.81	0.58	0.67	592
accuracy			0.81	1740
macro avg	0.81	0.75	0.77	1740
weighted avg	0.81	0.81	0.80	1740

TEST				
	precision	recall	f1-score	support
False	0.79	0.89	0.84	338
True	0.62	0.42	0.50	140
accuracy			0.76	478
macro avg	0.70	0.66	0.67	478
weighted avg	0.74	0.76	0.74	478

bass

TRAIN				
	precision	recall	f1-score	support
False	0.86	0.89	0.87	1010
True	0.71	0.64	0.67	415

accuracy			0.82	1425
macro avg	0.78	0.77	0.77	1425
weighted avg	0.81	0.82	0.82	1425

TEST

	precision	recall	f1-score	support
False	0.85	0.88	0.86	329
True	0.67	0.61	0.64	134

accuracy			0.80	463
macro avg	0.76	0.75	0.75	463
weighted avg	0.80	0.80	0.80	463

cello

TRAIN

	precision	recall	f1-score	support
False	0.82	0.86	0.84	866
True	0.78	0.74	0.76	598

accuracy			0.81	1464
macro avg	0.80	0.80	0.80	1464
weighted avg	0.81	0.81	0.81	1464

TEST

	precision	recall	f1-score	support
False	0.80	0.81	0.81	259
True	0.78	0.77	0.77	226

accuracy			0.79	485
macro avg	0.79	0.79	0.79	485
weighted avg	0.79	0.79	0.79	485

clarinet

TRAIN

	precision	recall	f1-score	support
False	0.89	0.73	0.81	1349
True	0.44	0.70	0.54	396

accuracy			0.73	1745
macro avg	0.67	0.72	0.67	1745
weighted avg	0.79	0.73	0.75	1745

TEST				
	precision	recall	f1-score	support
False	0.88	0.69	0.77	503
True	0.37	0.66	0.47	137
accuracy			0.68	640
macro avg	0.62	0.67	0.62	640
weighted avg	0.77	0.68	0.71	640

cymbals

TRAIN				
	precision	recall	f1-score	support
False	0.85	0.92	0.88	485
True	0.95	0.91	0.93	814
accuracy			0.91	1299
macro avg	0.90	0.91	0.91	1299
weighted avg	0.91	0.91	0.91	1299

TEST				
	precision	recall	f1-score	support
False	0.85	0.91	0.88	139
True	0.96	0.93	0.94	297
accuracy			0.92	436
macro avg	0.91	0.92	0.91	436
weighted avg	0.92	0.92	0.92	436

drums

TRAIN				
	precision	recall	f1-score	support
False	0.98	0.88	0.93	495
True	0.93	0.99	0.96	828
accuracy			0.95	1323
macro avg	0.95	0.93	0.94	1323
weighted avg	0.95	0.95	0.95	1323

TEST				
	precision	recall	f1-score	support

False	0.92	0.79	0.85	146
True	0.90	0.96	0.93	278
accuracy			0.91	424
macro avg	0.91	0.88	0.89	424
weighted avg	0.91	0.91	0.90	424

flute

TRAIN				
	precision	recall	f1-score	support
False	0.96	0.50	0.66	1050
True	0.46	0.95	0.62	472
accuracy			0.64	1522
macro avg	0.71	0.73	0.64	1522
weighted avg	0.80	0.64	0.65	1522
TEST				
	precision	recall	f1-score	support
False	0.92	0.43	0.58	387
True	0.42	0.92	0.58	175
accuracy			0.58	562
macro avg	0.67	0.67	0.58	562
weighted avg	0.77	0.58	0.58	562

guitar

TRAIN				
	precision	recall	f1-score	support
False	0.92	0.94	0.93	362
True	0.97	0.97	0.97	852
accuracy			0.96	1214
macro avg	0.95	0.95	0.95	1214
weighted avg	0.96	0.96	0.96	1214
TEST				
	precision	recall	f1-score	support
False	0.92	0.95	0.93	150
True	0.97	0.96	0.96	286
accuracy			0.95	436

macro avg	0.95	0.95	0.95	436
weighted avg	0.95	0.95	0.95	436

mallet_percussion

TRAIN

	precision	recall	f1-score	support
False	0.84	0.90	0.87	802
True	0.83	0.73	0.78	522
accuracy			0.83	1324
macro avg	0.83	0.82	0.82	1324
weighted avg	0.83	0.83	0.83	1324

TEST

	precision	recall	f1-score	support
False	0.75	0.88	0.81	267
True	0.80	0.64	0.71	211
accuracy			0.77	478
macro avg	0.78	0.76	0.76	478
weighted avg	0.78	0.77	0.77	478

mandolin

TRAIN

	precision	recall	f1-score	support
False	0.99	0.39	0.56	1185
True	0.47	0.99	0.64	652
accuracy			0.60	1837
macro avg	0.73	0.69	0.60	1837
weighted avg	0.81	0.60	0.59	1837

TEST

	precision	recall	f1-score	support
False	0.99	0.35	0.52	434
True	0.40	0.99	0.57	193
accuracy			0.55	627
macro avg	0.70	0.67	0.55	627
weighted avg	0.81	0.55	0.54	627

organ

TRAIN					
	precision	recall	f1-score	support	
False	0.88	0.85	0.87	977	
True	0.72	0.77	0.75	482	
accuracy			0.83	1459	
macro avg	0.80	0.81	0.81	1459	
weighted avg	0.83	0.83	0.83	1459	
TEST					
	precision	recall	f1-score	support	
False	0.83	0.85	0.84	310	
True	0.59	0.55	0.57	121	
accuracy			0.77	431	
macro avg	0.71	0.70	0.70	431	
weighted avg	0.76	0.77	0.76	431	

piano

TRAIN					
	precision	recall	f1-score	support	
False	0.97	0.95	0.96	420	
True	0.98	0.99	0.98	885	
accuracy			0.97	1305	
macro avg	0.97	0.97	0.97	1305	
weighted avg	0.97	0.97	0.97	1305	
TEST					
	precision	recall	f1-score	support	
False	0.97	0.85	0.91	130	
True	0.94	0.99	0.96	285	
accuracy			0.95	415	
macro avg	0.96	0.92	0.94	415	
weighted avg	0.95	0.95	0.95	415	

saxophone

TRAIN					
	precision	recall	f1-score	support	

False	0.84	0.75	0.79	906
True	0.75	0.84	0.79	830
accuracy			0.79	1736
macro avg	0.80	0.79	0.79	1736
weighted avg	0.80	0.79	0.79	1736

TEST				
	precision	recall	f1-score	support
False	0.86	0.76	0.81	324
True	0.77	0.87	0.82	305
accuracy			0.81	629
macro avg	0.82	0.81	0.81	629
weighted avg	0.82	0.81	0.81	629

synthesizer

TRAIN				
	precision	recall	f1-score	support
False	0.99	0.76	0.86	399
True	0.90	1.00	0.94	823
accuracy			0.92	1222
macro avg	0.94	0.88	0.90	1222
weighted avg	0.93	0.92	0.92	1222

TEST				
	precision	recall	f1-score	support
False	0.96	0.73	0.83	112
True	0.90	0.99	0.94	268
accuracy			0.91	380
macro avg	0.93	0.86	0.89	380
weighted avg	0.92	0.91	0.91	380

trombone

TRAIN				
	precision	recall	f1-score	support
False	0.83	0.92	0.87	1405
True	0.77	0.58	0.66	635
accuracy			0.81	2040

macro avg	0.80	0.75	0.77	2040
weighted avg	0.81	0.81	0.81	2040

TEST

	precision	recall	f1-score	support
False	0.83	0.92	0.87	492
True	0.77	0.59	0.67	228
accuracy			0.81	720
macro avg	0.80	0.75	0.77	720
weighted avg	0.81	0.81	0.81	720

trumpet

TRAIN

	precision	recall	f1-score	support
False	0.91	0.70	0.79	1303
True	0.65	0.89	0.76	828
accuracy			0.78	2131
macro avg	0.78	0.80	0.77	2131
weighted avg	0.81	0.78	0.78	2131

TEST

	precision	recall	f1-score	support
False	0.88	0.64	0.74	467
True	0.62	0.87	0.73	318
accuracy			0.73	785
macro avg	0.75	0.76	0.73	785
weighted avg	0.78	0.73	0.73	785

ukulele

TRAIN

	precision	recall	f1-score	support
False	0.92	0.73	0.81	1279
True	0.58	0.85	0.69	556
accuracy			0.77	1835
macro avg	0.75	0.79	0.75	1835
weighted avg	0.82	0.77	0.78	1835

TEST

	precision	recall	f1-score	support
False	0.89	0.69	0.78	408
True	0.54	0.82	0.65	182
accuracy			0.73	590
macro avg	0.72	0.75	0.71	590
weighted avg	0.79	0.73	0.74	590

violin

TRAIN				
	precision	recall	f1-score	support
False	0.59	0.98	0.74	623
True	0.97	0.45	0.62	779
accuracy			0.69	1402
macro avg	0.78	0.72	0.68	1402
weighted avg	0.80	0.69	0.67	1402

TEST				
	precision	recall	f1-score	support
False	0.48	0.97	0.64	237
True	0.95	0.37	0.53	394
accuracy			0.59	631
macro avg	0.72	0.67	0.59	631
weighted avg	0.78	0.59	0.57	631

voice

TRAIN				
	precision	recall	f1-score	support
False	0.90	0.91	0.91	426
True	0.95	0.94	0.95	764
accuracy			0.93	1190
macro avg	0.93	0.93	0.93	1190
weighted avg	0.93	0.93	0.93	1190

TEST				
	precision	recall	f1-score	support
False	0.84	0.93	0.89	150
True	0.95	0.88	0.92	224

accuracy			0.90	374
macro avg	0.90	0.91	0.90	374
weighted avg	0.91	0.90	0.90	374

0.0.6 Random Forest

```
[77]: for instrument in class_map:

    inst_num = class_map[instrument]

    train_inst = Y_mask_train[:, inst_num]
    test_inst = Y_mask_test[:, inst_num]

    X_train_inst = X_train[train_inst]

    X_train_inst_sklearn = np.mean(X_train_inst, axis=1)

    Y_true_train_inst = Y_true_train[train_inst, inst_num] >= 0.5

    X_test_inst = X_test[test_inst]
    X_test_inst_sklearn = np.mean(X_test_inst, axis=1)
    Y_true_test_inst = Y_true_test[test_inst, inst_num] >= 0.5

    clf = RandomForestClassifier(max_depth=8, n_estimators=250, random_state=0)

    clf.fit(X_train_inst_sklearn, Y_true_train_inst)

    # Evaluate the model on both train and test
    Y_pred_train = clf.predict(X_train_inst_sklearn)
    Y_pred_test = clf.predict(X_test_inst_sklearn)

    print('-' * 52)
    print(instrument)
    print('\tTRAIN')
    print(classification_report(Y_true_train_inst, Y_pred_train))
    print('\tTEST')
    print(classification_report(Y_true_test_inst, Y_pred_test))
    print('\tConfusion Matrix')
    print(confusion_matrix(Y_true_test_inst, Y_pred_test))
```

 accordion

TRAIN				
	precision	recall	f1-score	support
False	0.96	1.00	0.98	1159

True	1.00	0.87	0.93	374
accuracy			0.97	1533
macro avg	0.98	0.93	0.95	1533
weighted avg	0.97	0.97	0.97	1533

TEST				
	precision	recall	f1-score	support
False	0.84	0.97	0.90	423
True	0.78	0.33	0.46	115
accuracy			0.84	538
macro avg	0.81	0.65	0.68	538
weighted avg	0.83	0.84	0.81	538

Confusion Matrix
[[412 11]
[77 38]]

banjo

TRAIN				
	precision	recall	f1-score	support
False	0.98	0.99	0.98	1148
True	0.98	0.96	0.97	592
accuracy			0.98	1740
macro avg	0.98	0.98	0.98	1740
weighted avg	0.98	0.98	0.98	1740

TEST				
	precision	recall	f1-score	support
False	0.83	0.90	0.86	338
True	0.68	0.54	0.61	140
accuracy			0.79	478
macro avg	0.76	0.72	0.73	478
weighted avg	0.78	0.79	0.79	478

Confusion Matrix
[[303 35]
[64 76]]

bass

TRAIN				
	precision	recall	f1-score	support

False	0.98	0.99	0.98	1010
True	0.97	0.94	0.95	415
accuracy			0.97	1425
macro avg	0.97	0.96	0.97	1425
weighted avg	0.97	0.97	0.97	1425

TEST				
	precision	recall	f1-score	support
False	0.83	0.96	0.89	329
True	0.85	0.53	0.65	134
accuracy			0.84	463
macro avg	0.84	0.75	0.77	463
weighted avg	0.84	0.84	0.82	463

Confusion Matrix
[[316 13]
[63 71]]

cello

TRAIN				
	precision	recall	f1-score	support
False	0.99	0.97	0.98	866
True	0.95	0.99	0.97	598
accuracy			0.98	1464
macro avg	0.97	0.98	0.97	1464
weighted avg	0.98	0.98	0.98	1464

TEST				
	precision	recall	f1-score	support
False	0.80	0.84	0.82	259
True	0.80	0.76	0.78	226
accuracy			0.80	485
macro avg	0.80	0.80	0.80	485
weighted avg	0.80	0.80	0.80	485

Confusion Matrix
[[217 42]
[55 171]]

clarinet

TRAIN				
	precision	recall	f1-score	support
False	0.91	1.00	0.96	1349
True	1.00	0.68	0.81	396
accuracy			0.93	1745
macro avg	0.96	0.84	0.88	1745
weighted avg	0.93	0.93	0.92	1745

TEST				
	precision	recall	f1-score	support
False	0.80	0.99	0.88	503
True	0.67	0.07	0.13	137
accuracy			0.79	640
macro avg	0.73	0.53	0.51	640
weighted avg	0.77	0.79	0.72	640

Confusion Matrix
[[498 5]
[127 10]]

cymbals

TRAIN				
	precision	recall	f1-score	support
False	1.00	0.89	0.94	485
True	0.94	1.00	0.97	814
accuracy			0.96	1299
macro avg	0.97	0.95	0.96	1299
weighted avg	0.96	0.96	0.96	1299

TEST				
	precision	recall	f1-score	support
False	0.96	0.85	0.90	139
True	0.93	0.98	0.96	297
accuracy			0.94	436
macro avg	0.95	0.92	0.93	436
weighted avg	0.94	0.94	0.94	436

Confusion Matrix
[[118 21]
[5 292]]

drums

TRAIN					
	precision	recall	f1-score	support	
False	1.00	0.95	0.97	495	
True	0.97	1.00	0.99	828	
accuracy			0.98	1323	
macro avg	0.99	0.97	0.98	1323	
weighted avg	0.98	0.98	0.98	1323	
TEST					
	precision	recall	f1-score	support	
False	0.92	0.79	0.85	146	
True	0.90	0.96	0.93	278	
accuracy			0.91	424	
macro avg	0.91	0.88	0.89	424	
weighted avg	0.91	0.91	0.90	424	

Confusion Matrix
[[116 30]
[10 268]]

flute

TRAIN					
	precision	recall	f1-score	support	
False	0.97	0.99	0.98	1050	
True	0.98	0.94	0.96	472	
accuracy			0.98	1522	
macro avg	0.98	0.97	0.97	1522	
weighted avg	0.98	0.98	0.98	1522	
TEST					
	precision	recall	f1-score	support	
False	0.76	0.92	0.83	387	
True	0.68	0.36	0.47	175	
accuracy			0.75	562	
macro avg	0.72	0.64	0.65	562	
weighted avg	0.74	0.75	0.72	562	

Confusion Matrix

[[357 30]
[112 63]]

guitar

TRAIN	precision	recall	f1-score	support
False	1.00	0.96	0.98	362
True	0.98	1.00	0.99	852
accuracy			0.99	1214
macro avg	0.99	0.98	0.99	1214
weighted avg	0.99	0.99	0.99	1214

TEST	precision	recall	f1-score	support
False	0.97	0.97	0.97	150
True	0.98	0.98	0.98	286
accuracy			0.98	436
macro avg	0.97	0.97	0.97	436
weighted avg	0.98	0.98	0.98	436

Confusion Matrix
[[145 5]
[5 281]]

mallet_percussion

TRAIN	precision	recall	f1-score	support
False	1.00	0.95	0.97	802
True	0.93	1.00	0.96	522
accuracy			0.97	1324
macro avg	0.96	0.97	0.97	1324
weighted avg	0.97	0.97	0.97	1324

TEST	precision	recall	f1-score	support
False	0.79	0.84	0.82	267
True	0.78	0.72	0.75	211
accuracy			0.79	478
macro avg	0.79	0.78	0.78	478
weighted avg	0.79	0.79	0.79	478

Confusion Matrix
[[225 42]
[60 151]]

mandolin

TRAIN				
	precision	recall	f1-score	support
False	0.97	0.97	0.97	1185
True	0.95	0.95	0.95	652
accuracy			0.96	1837
macro avg	0.96	0.96	0.96	1837
weighted avg	0.96	0.96	0.96	1837

TEST				
	precision	recall	f1-score	support
False	0.81	0.83	0.82	434
True	0.60	0.56	0.58	193
accuracy			0.75	627
macro avg	0.71	0.70	0.70	627
weighted avg	0.75	0.75	0.75	627

Confusion Matrix
[[362 72]
[84 109]]

organ

TRAIN				
	precision	recall	f1-score	support
False	0.97	1.00	0.98	977
True	1.00	0.93	0.96	482
accuracy			0.98	1459
macro avg	0.98	0.96	0.97	1459
weighted avg	0.98	0.98	0.98	1459

TEST				
	precision	recall	f1-score	support
False	0.77	0.95	0.85	310
True	0.69	0.27	0.39	121
accuracy			0.76	431

macro avg	0.73	0.61	0.62	431
weighted avg	0.75	0.76	0.72	431

Confusion Matrix
[[295 15]
[88 33]]

piano

TRAIN				
	precision	recall	f1-score	support
False	1.00	0.96	0.98	420
True	0.98	1.00	0.99	885
accuracy			0.99	1305
macro avg	0.99	0.98	0.99	1305
weighted avg	0.99	0.99	0.99	1305

TEST				
	precision	recall	f1-score	support
False	0.96	0.85	0.90	130
True	0.94	0.98	0.96	285
accuracy			0.94	415
macro avg	0.95	0.92	0.93	415
weighted avg	0.94	0.94	0.94	415

Confusion Matrix
[[111 19]
[5 280]]

saxophone

TRAIN				
	precision	recall	f1-score	support
False	1.00	0.94	0.97	906
True	0.94	1.00	0.97	830
accuracy			0.97	1736
macro avg	0.97	0.97	0.97	1736
weighted avg	0.97	0.97	0.97	1736

TEST				
	precision	recall	f1-score	support
False	0.84	0.80	0.82	324
True	0.80	0.84	0.82	305

accuracy			0.82	629
macro avg	0.82	0.82	0.82	629
weighted avg	0.82	0.82	0.82	629

Confusion Matrix
[[259 65]
[48 257]]

synthesizer

TRAIN					
		precision	recall	f1-score	support
False		0.99	0.96	0.97	399
True		0.98	1.00	0.99	823
accuracy				0.98	1222
macro avg		0.99	0.98	0.98	1222
weighted avg		0.98	0.98	0.98	1222

TEST					
		precision	recall	f1-score	support
False		0.93	0.90	0.91	112
True		0.96	0.97	0.96	268
accuracy				0.95	380
macro avg		0.94	0.94	0.94	380
weighted avg		0.95	0.95	0.95	380

Confusion Matrix
[[101 11]
[8 260]]

trombone

TRAIN					
		precision	recall	f1-score	support
False		0.95	0.98	0.97	1405
True		0.96	0.89	0.92	635
accuracy				0.95	2040
macro avg		0.96	0.94	0.95	2040
weighted avg		0.95	0.95	0.95	2040

TEST					
		precision	recall	f1-score	support

False	0.81	0.93	0.87	492
True	0.78	0.53	0.63	228
accuracy			0.80	720
macro avg	0.79	0.73	0.75	720
weighted avg	0.80	0.80	0.79	720

Confusion Matrix
[[457 35]
[107 121]]

trumpet

TRAIN				
	precision	recall	f1-score	support
False	0.96	0.97	0.97	1303
True	0.95	0.94	0.95	828
accuracy			0.96	2131
macro avg	0.96	0.96	0.96	2131
weighted avg	0.96	0.96	0.96	2131

TEST				
	precision	recall	f1-score	support
False	0.78	0.88	0.83	467
True	0.78	0.63	0.70	318
accuracy			0.78	785
macro avg	0.78	0.75	0.76	785
weighted avg	0.78	0.78	0.77	785

Confusion Matrix
[[411 56]
[118 200]]

ukulele

TRAIN				
	precision	recall	f1-score	support
False	0.97	0.99	0.98	1279
True	0.96	0.94	0.95	556
accuracy			0.97	1835
macro avg	0.97	0.96	0.96	1835
weighted avg	0.97	0.97	0.97	1835

TEST

	precision	recall	f1-score	support
False	0.81	0.89	0.85	408
True	0.68	0.52	0.59	182
accuracy			0.78	590
macro avg	0.74	0.71	0.72	590
weighted avg	0.77	0.78	0.77	590

Confusion Matrix
[[363 45]
[87 95]]

violin

TRAIN				
	precision	recall	f1-score	support
False	1.00	0.87	0.93	623
True	0.90	1.00	0.95	779
accuracy			0.94	1402
macro avg	0.95	0.93	0.94	1402
weighted avg	0.95	0.94	0.94	1402

TEST				
	precision	recall	f1-score	support
False	0.86	0.71	0.78	237
True	0.84	0.93	0.88	394
accuracy			0.85	631
macro avg	0.85	0.82	0.83	631
weighted avg	0.85	0.85	0.84	631

Confusion Matrix
[[168 69]
[27 367]]

voice

TRAIN				
	precision	recall	f1-score	support
False	1.00	0.91	0.95	426
True	0.95	1.00	0.98	764
accuracy			0.97	1190
macro avg	0.98	0.96	0.96	1190
weighted avg	0.97	0.97	0.97	1190

	precision	recall	f1-score	support
False	0.94	0.89	0.91	150
True	0.93	0.96	0.94	224
accuracy			0.93	374
macro avg	0.93	0.92	0.93	374
weighted avg	0.93	0.93	0.93	374

Confusion Matrix
[[133 17]
[9 215]]

0.0.7 Logistic Regression

```
[43]: for instrument in class_map:

    inst_num = class_map[instrument]

    train_inst = Y_mask_train[:, inst_num]
    test_inst = Y_mask_test[:, inst_num]

    X_train_inst = X_train[train_inst]

    X_train_inst_sklearn = np.mean(X_train_inst, axis=1)

    Y_true_train_inst = Y_true_train[train_inst, inst_num] >= 0.5

    X_test_inst = X_test[test_inst]
    X_test_inst_sklearn = np.mean(X_test_inst, axis=1)
    Y_true_test_inst = Y_true_test[test_inst, inst_num] >= 0.5

    clf = LogisticRegression(random_state=0, penalty='l1', solver = 'liblinear')

    clf.fit(X_train_inst_sklearn, Y_true_train_inst)

    # Evaluate the model on both train and test
    Y_pred_train = clf.predict(X_train_inst_sklearn)
    Y_pred_test = clf.predict(X_test_inst_sklearn)

    print('-' * 52)
    print(instrument)
    print('\tTRAIN')
    print(classification_report(Y_true_train_inst, Y_pred_train))
    print('\tTEST')
```

```
print(classification_report(Y_true_test_inst, Y_pred_test))
```

accordion

TRAIN		precision	recall	f1-score	support
False		0.88	0.94	0.91	1159
True		0.75	0.61	0.67	374
accuracy				0.86	1533
macro avg		0.82	0.77	0.79	1533
weighted avg		0.85	0.86	0.85	1533

TEST		precision	recall	f1-score	support
False		0.85	0.89	0.87	423
True		0.52	0.43	0.47	115
accuracy				0.79	538
macro avg		0.68	0.66	0.67	538
weighted avg		0.78	0.79	0.78	538

banjo

TRAIN		precision	recall	f1-score	support
False		0.87	0.89	0.88	1148
True		0.77	0.74	0.75	592
accuracy				0.84	1740
macro avg		0.82	0.81	0.81	1740
weighted avg		0.83	0.84	0.83	1740

TEST		precision	recall	f1-score	support
False		0.83	0.83	0.83	338
True		0.58	0.59	0.58	140
accuracy				0.76	478
macro avg		0.70	0.71	0.71	478
weighted avg		0.76	0.76	0.76	478

bass

TRAIN				
	precision	recall	f1-score	support
False	0.86	0.90	0.88	1010
True	0.73	0.65	0.69	415
accuracy			0.83	1425
macro avg	0.80	0.77	0.78	1425
weighted avg	0.82	0.83	0.82	1425
TEST				
	precision	recall	f1-score	support
False	0.86	0.89	0.88	329
True	0.71	0.66	0.68	134
accuracy			0.82	463
macro avg	0.79	0.77	0.78	463
weighted avg	0.82	0.82	0.82	463

cello

TRAIN				
	precision	recall	f1-score	support
False	0.85	0.85	0.85	866
True	0.78	0.78	0.78	598
accuracy			0.82	1464
macro avg	0.81	0.81	0.81	1464
weighted avg	0.82	0.82	0.82	1464
TEST				
	precision	recall	f1-score	support
False	0.78	0.80	0.79	259
True	0.76	0.75	0.75	226
accuracy			0.77	485
macro avg	0.77	0.77	0.77	485
weighted avg	0.77	0.77	0.77	485

clarinet

TRAIN				
	precision	recall	f1-score	support
False	0.83	0.94	0.88	1349

True	0.64	0.36	0.46	396
accuracy			0.81	1745
macro avg	0.74	0.65	0.67	1745
weighted avg	0.79	0.81	0.79	1745

TEST				
	precision	recall	f1-score	support
False	0.83	0.90	0.87	503
True	0.49	0.34	0.40	137
accuracy			0.78	640
macro avg	0.66	0.62	0.63	640
weighted avg	0.76	0.78	0.77	640

cymbals

TRAIN				
	precision	recall	f1-score	support
False	0.93	0.91	0.92	485
True	0.94	0.96	0.95	814
accuracy			0.94	1299
macro avg	0.94	0.93	0.94	1299
weighted avg	0.94	0.94	0.94	1299

TEST				
	precision	recall	f1-score	support
False	0.90	0.86	0.88	139
True	0.93	0.96	0.95	297
accuracy			0.92	436
macro avg	0.92	0.91	0.91	436
weighted avg	0.92	0.92	0.92	436

drums

TRAIN				
	precision	recall	f1-score	support
False	0.96	0.94	0.95	495
True	0.96	0.98	0.97	828
accuracy			0.96	1323
macro avg	0.96	0.96	0.96	1323

weighted avg	0.96	0.96	0.96	1323
TEST				
	precision	recall	f1-score	support
False	0.86	0.79	0.82	146
True	0.89	0.94	0.91	278
accuracy			0.88	424
macro avg	0.88	0.86	0.87	424
weighted avg	0.88	0.88	0.88	424

flute

TRAIN				
	precision	recall	f1-score	support
False	0.83	0.89	0.86	1050
True	0.71	0.59	0.64	472
accuracy			0.80	1522
macro avg	0.77	0.74	0.75	1522
weighted avg	0.79	0.80	0.79	1522
TEST				
	precision	recall	f1-score	support
False	0.80	0.83	0.82	387
True	0.59	0.54	0.57	175
accuracy			0.74	562
macro avg	0.70	0.69	0.69	562
weighted avg	0.74	0.74	0.74	562

guitar

TRAIN				
	precision	recall	f1-score	support
False	0.97	0.96	0.97	362
True	0.98	0.99	0.99	852
accuracy			0.98	1214
macro avg	0.98	0.98	0.98	1214
weighted avg	0.98	0.98	0.98	1214
TEST				
	precision	recall	f1-score	support

False	0.90	0.85	0.87	150
True	0.92	0.95	0.94	286
accuracy			0.92	436
macro avg	0.91	0.90	0.90	436
weighted avg	0.91	0.92	0.91	436

mallet_percussion

TRAIN				
	precision	recall	f1-score	support
False	0.87	0.87	0.87	802
True	0.80	0.80	0.80	522
accuracy			0.84	1324
macro avg	0.83	0.83	0.83	1324
weighted avg	0.84	0.84	0.84	1324

TEST				
	precision	recall	f1-score	support
False	0.79	0.82	0.81	267
True	0.76	0.72	0.74	211
accuracy			0.78	478
macro avg	0.78	0.77	0.77	478
weighted avg	0.78	0.78	0.78	478

mandolin

TRAIN				
	precision	recall	f1-score	support
False	0.83	0.86	0.85	1185
True	0.73	0.68	0.70	652
accuracy			0.80	1837
macro avg	0.78	0.77	0.77	1837
weighted avg	0.79	0.80	0.79	1837

TEST				
	precision	recall	f1-score	support
False	0.83	0.81	0.82	434
True	0.59	0.62	0.60	193

accuracy			0.75	627
macro avg	0.71	0.71	0.71	627
weighted avg	0.75	0.75	0.75	627

organ

TRAIN				
	precision	recall	f1-score	support
False	0.88	0.92	0.90	977
True	0.83	0.74	0.78	482
accuracy			0.86	1459
macro avg	0.85	0.83	0.84	1459
weighted avg	0.86	0.86	0.86	1459
TEST				
	precision	recall	f1-score	support
False	0.79	0.88	0.84	310
True	0.58	0.40	0.48	121
accuracy			0.75	431
macro avg	0.68	0.64	0.66	431
weighted avg	0.73	0.75	0.73	431

piano

TRAIN				
	precision	recall	f1-score	support
False	0.99	0.98	0.99	420
True	0.99	1.00	0.99	885
accuracy			0.99	1305
macro avg	0.99	0.99	0.99	1305
weighted avg	0.99	0.99	0.99	1305
TEST				
	precision	recall	f1-score	support
False	0.86	0.82	0.84	130
True	0.92	0.94	0.93	285
accuracy			0.90	415
macro avg	0.89	0.88	0.89	415
weighted avg	0.90	0.90	0.90	415

```

-----
saxophone
  TRAIN
    precision    recall  f1-score   support

  False         0.83     0.80     0.81     906
  True          0.79     0.82     0.80     830

 accuracy
macro avg       0.81     0.81     0.81    1736
weighted avg    0.81     0.81     0.81    1736

  TEST
    precision    recall  f1-score   support

  False         0.83     0.79     0.81     324
  True          0.79     0.82     0.80     305

 accuracy
macro avg       0.81     0.81     0.81     629
weighted avg    0.81     0.81     0.81     629

```

```

-----
synthesizer
  TRAIN
    precision    recall  f1-score   support

  False         0.96     0.94     0.95     399
  True          0.97     0.98     0.98     823

 accuracy
macro avg       0.96     0.96     0.96    1222
weighted avg    0.97     0.97     0.97    1222

  TEST
    precision    recall  f1-score   support

  False         0.85     0.86     0.85     112
  True          0.94     0.94     0.94     268

 accuracy
macro avg       0.89     0.90     0.90     380
weighted avg    0.91     0.91     0.91     380

```

```

-----
trombone
  TRAIN
    precision    recall  f1-score   support

```


False	0.85	0.91	0.88	1405
True	0.76	0.64	0.69	635
accuracy			0.82	2040
macro avg	0.80	0.77	0.78	2040
weighted avg	0.82	0.82	0.82	2040

TEST				
	precision	recall	f1-score	support
False	0.84	0.86	0.85	492
True	0.69	0.66	0.67	228
accuracy			0.80	720
macro avg	0.77	0.76	0.76	720
weighted avg	0.80	0.80	0.80	720

trumpet

TRAIN				
	precision	recall	f1-score	support
False	0.84	0.86	0.85	1303
True	0.77	0.74	0.76	828
accuracy			0.81	2131
macro avg	0.81	0.80	0.80	2131
weighted avg	0.81	0.81	0.81	2131

TEST				
	precision	recall	f1-score	support
False	0.81	0.84	0.82	467
True	0.75	0.70	0.73	318
accuracy			0.79	785
macro avg	0.78	0.77	0.78	785
weighted avg	0.78	0.79	0.78	785

ukulele

TRAIN				
	precision	recall	f1-score	support
False	0.85	0.90	0.87	1279
True	0.73	0.63	0.68	556

accuracy			0.82	1835
macro avg	0.79	0.76	0.77	1835
weighted avg	0.81	0.82	0.81	1835

TEST

	precision	recall	f1-score	support
False	0.83	0.86	0.84	408
True	0.65	0.59	0.62	182

accuracy			0.78	590
macro avg	0.74	0.73	0.73	590
weighted avg	0.77	0.78	0.77	590

violin

TRAIN

	precision	recall	f1-score	support
False	0.89	0.80	0.84	623
True	0.85	0.92	0.88	779

accuracy			0.87	1402
macro avg	0.87	0.86	0.86	1402
weighted avg	0.87	0.87	0.87	1402

TEST

	precision	recall	f1-score	support
False	0.77	0.79	0.78	237
True	0.87	0.86	0.86	394

accuracy			0.83	631
macro avg	0.82	0.82	0.82	631
weighted avg	0.83	0.83	0.83	631

voice

TRAIN

	precision	recall	f1-score	support
False	0.96	0.93	0.94	426
True	0.96	0.98	0.97	764

accuracy			0.96	1190
macro avg	0.96	0.95	0.96	1190
weighted avg	0.96	0.96	0.96	1190

TEST	precision	recall	f1-score	support
False	0.86	0.89	0.88	150
True	0.93	0.90	0.91	224
accuracy			0.90	374
macro avg	0.89	0.90	0.89	374
weighted avg	0.90	0.90	0.90	374

0.0.8 Neural Network

```
[72]: import warnings
warnings.filterwarnings('ignore')

for instrument in class_map:

    inst_num = class_map[instrument]

    train_inst = Y_mask_train[:, inst_num]
    test_inst = Y_mask_test[:, inst_num]

    X_train_inst = X_train[train_inst]

    X_train_inst_sklearn = np.mean(X_train_inst, axis=1)

    Y_true_train_inst = Y_true_train[train_inst, inst_num] >= 0.5

    X_test_inst = X_test[test_inst]
    X_test_inst_sklearn = np.mean(X_test_inst, axis=1)
    Y_true_test_inst = Y_true_test[test_inst, inst_num] >= 0.5

    clf = MLPClassifier(solver='lbfgs', alpha=1e-5, hidden_layer_sizes=(5,2),
↳max_iter=100, random_state=0)

    clf.fit(X_train_inst_sklearn, Y_true_train_inst)

    # Evaluate the model on both train and test
    Y_pred_train = clf.predict(X_train_inst_sklearn)
    Y_pred_test = clf.predict(X_test_inst_sklearn)

    print('-' * 52)
    print(instrument)
    print('\tTRAIN')
    print(classification_report(Y_true_train_inst, Y_pred_train))
    print('\tTEST')
```

```
print(classification_report(Y_true_test_inst, Y_pred_test))
```

accordion

TRAIN		precision	recall	f1-score	support
False		0.84	0.90	0.87	1159
True		0.62	0.48	0.54	374
accuracy				0.80	1533
macro avg		0.73	0.69	0.71	1533
weighted avg		0.79	0.80	0.79	1533

TEST		precision	recall	f1-score	support
False		0.85	0.90	0.87	423
True		0.53	0.42	0.47	115
accuracy				0.80	538
macro avg		0.69	0.66	0.67	538
weighted avg		0.78	0.80	0.79	538

banjo

TRAIN		precision	recall	f1-score	support
False		0.80	0.86	0.83	1148
True		0.69	0.59	0.64	592
accuracy				0.77	1740
macro avg		0.75	0.73	0.73	1740
weighted avg		0.76	0.77	0.76	1740

TEST		precision	recall	f1-score	support
False		0.83	0.86	0.84	338
True		0.62	0.57	0.60	140
accuracy				0.77	478
macro avg		0.73	0.71	0.72	478
weighted avg		0.77	0.77	0.77	478

bass

TRAIN				
	precision	recall	f1-score	support
False	0.85	0.89	0.87	1010
True	0.70	0.61	0.65	415
accuracy			0.81	1425
macro avg	0.77	0.75	0.76	1425
weighted avg	0.81	0.81	0.81	1425

TEST				
	precision	recall	f1-score	support
False	0.84	0.90	0.87	329
True	0.71	0.59	0.64	134
accuracy			0.81	463
macro avg	0.77	0.74	0.76	463
weighted avg	0.80	0.81	0.80	463

cello

TRAIN				
	precision	recall	f1-score	support
False	0.83	0.83	0.83	866
True	0.75	0.76	0.76	598
accuracy			0.80	1464
macro avg	0.79	0.79	0.79	1464
weighted avg	0.80	0.80	0.80	1464

TEST				
	precision	recall	f1-score	support
False	0.80	0.80	0.80	259
True	0.77	0.78	0.77	226
accuracy			0.79	485
macro avg	0.79	0.79	0.79	485
weighted avg	0.79	0.79	0.79	485

clarinet

TRAIN				
	precision	recall	f1-score	support
False	0.80	0.95	0.87	1349

True	0.52	0.19	0.28	396
accuracy			0.78	1745
macro avg	0.66	0.57	0.57	1745
weighted avg	0.74	0.78	0.73	1745

TEST				
	precision	recall	f1-score	support
False	0.81	0.94	0.87	503
True	0.49	0.20	0.28	137
accuracy			0.78	640
macro avg	0.65	0.57	0.58	640
weighted avg	0.74	0.78	0.75	640

cymbals

TRAIN				
	precision	recall	f1-score	support
False	0.97	0.83	0.90	485
True	0.91	0.99	0.94	814
accuracy			0.93	1299
macro avg	0.94	0.91	0.92	1299
weighted avg	0.93	0.93	0.93	1299

TEST				
	precision	recall	f1-score	support
False	0.97	0.81	0.88	139
True	0.92	0.99	0.95	297
accuracy			0.93	436
macro avg	0.94	0.90	0.91	436
weighted avg	0.93	0.93	0.93	436

drums

TRAIN				
	precision	recall	f1-score	support
False	0.94	0.89	0.91	495
True	0.94	0.96	0.95	828
accuracy			0.94	1323
macro avg	0.94	0.93	0.93	1323

weighted avg	0.94	0.94	0.94	1323
TEST				
	precision	recall	f1-score	support
False	0.89	0.81	0.85	146
True	0.90	0.95	0.93	278
accuracy			0.90	424
macro avg	0.90	0.88	0.89	424
weighted avg	0.90	0.90	0.90	424

flute

TRAIN				
	precision	recall	f1-score	support
False	0.76	0.87	0.81	1050
True	0.56	0.38	0.45	472
accuracy			0.72	1522
macro avg	0.66	0.62	0.63	1522
weighted avg	0.70	0.72	0.70	1522
TEST				
	precision	recall	f1-score	support
False	0.76	0.85	0.80	387
True	0.56	0.42	0.48	175
accuracy			0.72	562
macro avg	0.66	0.63	0.64	562
weighted avg	0.70	0.72	0.70	562

guitar

TRAIN				
	precision	recall	f1-score	support
False	0.95	0.92	0.93	362
True	0.97	0.98	0.97	852
accuracy			0.96	1214
macro avg	0.96	0.95	0.95	1214
weighted avg	0.96	0.96	0.96	1214
TEST				
	precision	recall	f1-score	support

False	0.95	0.95	0.95	150
True	0.98	0.98	0.98	286
accuracy			0.97	436
macro avg	0.96	0.96	0.96	436
weighted avg	0.97	0.97	0.97	436

mallet_percussion

TRAIN				
	precision	recall	f1-score	support
False	0.61	1.00	0.75	802
True	0.00	0.00	0.00	522
accuracy			0.61	1324
macro avg	0.30	0.50	0.38	1324
weighted avg	0.37	0.61	0.46	1324

TEST				
	precision	recall	f1-score	support
False	0.56	1.00	0.72	267
True	0.00	0.00	0.00	211
accuracy			0.56	478
macro avg	0.28	0.50	0.36	478
weighted avg	0.31	0.56	0.40	478

mandolin

TRAIN				
	precision	recall	f1-score	support
False	0.80	0.84	0.82	1185
True	0.68	0.63	0.65	652
accuracy			0.76	1837
macro avg	0.74	0.73	0.74	1837
weighted avg	0.76	0.76	0.76	1837

TEST				
	precision	recall	f1-score	support
False	0.81	0.82	0.81	434
True	0.58	0.58	0.58	193

accuracy			0.74	627
macro avg	0.70	0.70	0.70	627
weighted avg	0.74	0.74	0.74	627

organ

TRAIN				
	precision	recall	f1-score	support
False	0.84	0.91	0.88	977
True	0.79	0.65	0.71	482
accuracy			0.83	1459
macro avg	0.81	0.78	0.79	1459
weighted avg	0.82	0.83	0.82	1459
TEST				
	precision	recall	f1-score	support
False	0.78	0.92	0.85	310
True	0.64	0.35	0.45	121
accuracy			0.76	431
macro avg	0.71	0.63	0.65	431
weighted avg	0.74	0.76	0.74	431

piano

TRAIN				
	precision	recall	f1-score	support
False	0.95	0.93	0.94	420
True	0.97	0.98	0.97	885
accuracy			0.96	1305
macro avg	0.96	0.96	0.96	1305
weighted avg	0.96	0.96	0.96	1305
TEST				
	precision	recall	f1-score	support
False	0.93	0.85	0.89	130
True	0.94	0.97	0.95	285
accuracy			0.93	415
macro avg	0.93	0.91	0.92	415
weighted avg	0.93	0.93	0.93	415

```

-----
saxophone
  TRAIN
    precision    recall  f1-score   support

 False         0.79      0.78      0.79      906
  True         0.76      0.78      0.77      830

 accuracy              0.78      1736
 macro avg         0.78      0.78      0.78      1736
 weighted avg      0.78      0.78      0.78      1736

  TEST
    precision    recall  f1-score   support

 False         0.82      0.80      0.81      324
  True         0.79      0.82      0.81      305

 accuracy              0.81      629
 macro avg         0.81      0.81      0.81      629
 weighted avg      0.81      0.81      0.81      629

```

```

-----
synthesizer
  TRAIN
    precision    recall  f1-score   support

 False         0.94      0.91      0.92      399
  True         0.96      0.97      0.96      823

 accuracy              0.95      1222
 macro avg         0.95      0.94      0.94      1222
 weighted avg      0.95      0.95      0.95      1222

  TEST
    precision    recall  f1-score   support

 False         0.92      0.88      0.90      112
  True         0.95      0.97      0.96      268

 accuracy              0.94      380
 macro avg         0.94      0.92      0.93      380
 weighted avg      0.94      0.94      0.94      380

```

```

-----
trombone
  TRAIN
    precision    recall  f1-score   support

```

False	0.69	1.00	0.82	1405
True	0.93	0.02	0.04	635
accuracy			0.69	2040
macro avg	0.81	0.51	0.43	2040
weighted avg	0.77	0.69	0.58	2040

TEST				
	precision	recall	f1-score	support
False	0.69	1.00	0.82	492
True	1.00	0.02	0.04	228
accuracy			0.69	720
macro avg	0.84	0.51	0.43	720
weighted avg	0.79	0.69	0.57	720

trumpet

TRAIN				
	precision	recall	f1-score	support
False	0.80	0.85	0.83	1303
True	0.74	0.67	0.70	828
accuracy			0.78	2131
macro avg	0.77	0.76	0.76	2131
weighted avg	0.78	0.78	0.78	2131

TEST				
	precision	recall	f1-score	support
False	0.78	0.85	0.81	467
True	0.74	0.64	0.69	318
accuracy			0.77	785
macro avg	0.76	0.75	0.75	785
weighted avg	0.76	0.77	0.76	785

ukulele

TRAIN				
	precision	recall	f1-score	support
False	0.81	0.86	0.83	1279
True	0.62	0.54	0.58	556

accuracy			0.76	1835
macro avg	0.72	0.70	0.71	1835
weighted avg	0.75	0.76	0.76	1835

TEST

	precision	recall	f1-score	support
False	0.81	0.86	0.84	408
True	0.64	0.54	0.59	182

accuracy			0.76	590
macro avg	0.72	0.70	0.71	590
weighted avg	0.76	0.76	0.76	590

----- violin

TRAIN

	precision	recall	f1-score	support
False	0.85	0.74	0.79	623
True	0.81	0.89	0.85	779

accuracy			0.83	1402
macro avg	0.83	0.82	0.82	1402
weighted avg	0.83	0.83	0.83	1402

TEST

	precision	recall	f1-score	support
False	0.77	0.76	0.76	237
True	0.86	0.86	0.86	394

accuracy			0.82	631
macro avg	0.81	0.81	0.81	631
weighted avg	0.82	0.82	0.82	631

----- voice

TRAIN

	precision	recall	f1-score	support
False	0.96	0.86	0.91	426
True	0.93	0.98	0.95	764

accuracy			0.94	1190
macro avg	0.94	0.92	0.93	1190
weighted avg	0.94	0.94	0.94	1190

TEST	precision	recall	f1-score	support
False	0.92	0.88	0.90	150
True	0.92	0.95	0.93	224
accuracy			0.92	374
macro avg	0.92	0.91	0.92	374
weighted avg	0.92	0.92	0.92	374

0.0.9 Support Vector Machine

```
[13]: from sklearn.pipeline import make_pipeline
from sklearn.preprocessing import StandardScaler
from sklearn.datasets import make_classification
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import VotingClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
from itertools import product

# This dictionary will include the classifiers for each model
models = dict()

# We'll iterate over all instrument classes, and fit a model for each one
# After training, we'll print a classification report for each instrument
for instrument in class_map:

    # Map the instrument name to its column number
    inst_num = class_map[instrument]

    # Step 1: sub-sample the data

    # First, we need to select down to the data for which we have annotations
    # This is what the mask arrays are for
    train_inst = Y_mask_train[:, inst_num]
    test_inst = Y_mask_test[:, inst_num]

    # Here, we're using the Y_mask_train array to slice out only the training
    → examples
    # for which we have annotations for the given class
    X_train_inst = X_train[train_inst]

    # Step 3: simplify the data by averaging over time
```

```

# Let's arrange the data for a sklearn Random Forest model
# Instead of having time-varying features, we'll summarize each track by
→ its mean feature vector over time
X_train_inst_sklearn = np.mean(X_train_inst, axis=1)

# Again, we slice the labels to the annotated examples
# We threshold the label likelihoods at 0.5 to get binary labels
Y_true_train_inst = Y_true_train[train_inst, inst_num] >= 0.5

# Repeat the above slicing and dicing but for the test set
X_test_inst = X_test[test_inst]
X_test_inst_sklearn = np.mean(X_test_inst, axis=1)
Y_true_test_inst = Y_true_test[test_inst, inst_num] >= 0.5

# Step 3.
# Initialize a new classifier
clf = make_pipeline(StandardScaler(),
→ SVC(gamma='auto', kernel='poly', degree=2))

# Step 4.
clf.fit(X_train_inst_sklearn, Y_true_train_inst)

# Step 5.
# Finally, we'll evaluate the model on both train and test
Y_pred_train = clf.predict(X_train_inst_sklearn)
Y_pred_test = clf.predict(X_test_inst_sklearn)

print('-' * 52)
print(instrument)
print('\tTRAIN')
print(classification_report(Y_true_train_inst, Y_pred_train))
print('\tTEST')
print(classification_report(Y_true_test_inst, Y_pred_test))

# Store the classifier in our dictionary
models[instrument] = clf

```

accordion

	precision	recall	f1-score	support
TRAIN				
False	0.84	0.99	0.91	1159
True	0.91	0.43	0.58	374
accuracy			0.85	1533

macro avg	0.88	0.71	0.75	1533
weighted avg	0.86	0.85	0.83	1533

TEST

	precision	recall	f1-score	support
False	0.83	0.98	0.90	423
True	0.79	0.27	0.40	115
accuracy			0.83	538
macro avg	0.81	0.63	0.65	538
weighted avg	0.82	0.83	0.79	538

----- banjo

TRAIN

	precision	recall	f1-score	support
False	0.81	0.96	0.88	1148
True	0.89	0.57	0.70	592
accuracy			0.83	1740
macro avg	0.85	0.77	0.79	1740
weighted avg	0.84	0.83	0.82	1740

TEST

	precision	recall	f1-score	support
False	0.79	0.93	0.85	338
True	0.70	0.41	0.52	140
accuracy			0.78	478
macro avg	0.75	0.67	0.69	478
weighted avg	0.77	0.78	0.76	478

----- bass

TRAIN

	precision	recall	f1-score	support
False	0.81	0.98	0.89	1010
True	0.92	0.45	0.60	415
accuracy			0.83	1425
macro avg	0.87	0.71	0.75	1425
weighted avg	0.84	0.83	0.81	1425

TEST

	precision	recall	f1-score	support
False	0.79	0.97	0.87	329
True	0.84	0.36	0.50	134
accuracy			0.79	463
macro avg	0.82	0.67	0.69	463
weighted avg	0.80	0.79	0.76	463

cello

TRAIN				
	precision	recall	f1-score	support
False	0.83	0.90	0.87	866
True	0.84	0.74	0.79	598
accuracy			0.84	1464
macro avg	0.84	0.82	0.83	1464
weighted avg	0.84	0.84	0.83	1464

TEST				
	precision	recall	f1-score	support
False	0.73	0.80	0.76	259
True	0.74	0.65	0.69	226
accuracy			0.73	485
macro avg	0.73	0.73	0.73	485
weighted avg	0.73	0.73	0.73	485

clarinet

TRAIN				
	precision	recall	f1-score	support
False	0.81	1.00	0.89	1349
True	0.96	0.19	0.31	396
accuracy			0.81	1745
macro avg	0.88	0.59	0.60	1745
weighted avg	0.84	0.81	0.76	1745

TEST				
	precision	recall	f1-score	support
False	0.79	0.98	0.88	503
True	0.47	0.07	0.12	137

accuracy			0.78	640
macro avg	0.63	0.52	0.50	640
weighted avg	0.73	0.78	0.71	640

cymbals

TRAIN				
	precision	recall	f1-score	support
False	0.99	0.83	0.90	485
True	0.91	0.99	0.95	814
accuracy			0.93	1299
macro avg	0.95	0.91	0.93	1299
weighted avg	0.94	0.93	0.93	1299
TEST				
	precision	recall	f1-score	support
False	0.97	0.81	0.88	139
True	0.92	0.99	0.95	297
accuracy			0.93	436
macro avg	0.94	0.90	0.92	436
weighted avg	0.93	0.93	0.93	436

drums

TRAIN				
	precision	recall	f1-score	support
False	1.00	0.89	0.94	495
True	0.94	1.00	0.97	828
accuracy			0.96	1323
macro avg	0.97	0.95	0.96	1323
weighted avg	0.96	0.96	0.96	1323
TEST				
	precision	recall	f1-score	support
False	0.93	0.78	0.85	146
True	0.89	0.97	0.93	278
accuracy			0.90	424
macro avg	0.91	0.87	0.89	424
weighted avg	0.91	0.90	0.90	424

```

-----
flute
      TRAIN
      precision    recall  f1-score   support

    False         0.80      0.98      0.88     1050
     True         0.91      0.45      0.60      472

 accuracy              0.82     1522
  macro avg         0.85      0.72      0.74     1522
 weighted avg         0.83      0.82      0.79     1522

      TEST
      precision    recall  f1-score   support

    False         0.74      0.93      0.83      387
     True         0.66      0.29      0.40      175

 accuracy              0.73     562
  macro avg         0.70      0.61      0.61     562
 weighted avg         0.72      0.73      0.69     562

```

```

-----
guitar
      TRAIN
      precision    recall  f1-score   support

    False         0.98      0.93      0.95      362
     True         0.97      0.99      0.98      852

 accuracy              0.97    1214
  macro avg         0.97      0.96      0.97    1214
 weighted avg         0.97      0.97      0.97    1214

      TEST
      precision    recall  f1-score   support

    False         0.96      0.89      0.92      150
     True         0.94      0.98      0.96      286

 accuracy              0.95     436
  macro avg         0.95      0.93      0.94     436
 weighted avg         0.95      0.95      0.95     436

```

```

-----
mallet_percussion
      TRAIN

```

	precision	recall	f1-score	support
False	0.92	0.88	0.90	802
True	0.83	0.89	0.86	522
accuracy			0.88	1324
macro avg	0.87	0.88	0.88	1324
weighted avg	0.88	0.88	0.88	1324

TEST				
	precision	recall	f1-score	support
False	0.80	0.75	0.77	267
True	0.70	0.76	0.73	211
accuracy			0.75	478
macro avg	0.75	0.75	0.75	478
weighted avg	0.75	0.75	0.75	478

mandolin

TRAIN				
	precision	recall	f1-score	support
False	0.77	0.95	0.85	1185
True	0.85	0.49	0.62	652
accuracy			0.79	1837
macro avg	0.81	0.72	0.74	1837
weighted avg	0.80	0.79	0.77	1837

TEST				
	precision	recall	f1-score	support
False	0.77	0.90	0.83	434
True	0.64	0.40	0.49	193
accuracy			0.74	627
macro avg	0.70	0.65	0.66	627
weighted avg	0.73	0.74	0.73	627

organ

TRAIN				
	precision	recall	f1-score	support
False	0.82	0.99	0.89	977
True	0.95	0.56	0.70	482

accuracy			0.84	1459
macro avg	0.88	0.77	0.80	1459
weighted avg	0.86	0.84	0.83	1459

TEST

	precision	recall	f1-score	support
False	0.75	0.97	0.84	310
True	0.69	0.15	0.24	121
accuracy			0.74	431
macro avg	0.72	0.56	0.54	431
weighted avg	0.73	0.74	0.68	431

----- piano

TRAIN

	precision	recall	f1-score	support
False	0.98	0.94	0.96	420
True	0.97	0.99	0.98	885
accuracy			0.98	1305
macro avg	0.98	0.97	0.97	1305
weighted avg	0.98	0.98	0.98	1305

TEST

	precision	recall	f1-score	support
False	0.97	0.82	0.89	130
True	0.92	0.99	0.96	285
accuracy			0.94	415
macro avg	0.95	0.91	0.92	415
weighted avg	0.94	0.94	0.94	415

----- saxophone

TRAIN

	precision	recall	f1-score	support
False	0.92	0.79	0.85	906
True	0.80	0.93	0.86	830
accuracy			0.85	1736
macro avg	0.86	0.86	0.85	1736
weighted avg	0.86	0.85	0.85	1736

TEST				
	precision	recall	f1-score	support
False	0.86	0.69	0.76	324
True	0.73	0.89	0.80	305
accuracy			0.78	629
macro avg	0.79	0.79	0.78	629
weighted avg	0.80	0.78	0.78	629

synthesizer

TRAIN				
	precision	recall	f1-score	support
False	0.97	0.93	0.95	399
True	0.97	0.99	0.98	823
accuracy			0.97	1222
macro avg	0.97	0.96	0.96	1222
weighted avg	0.97	0.97	0.97	1222

TEST				
	precision	recall	f1-score	support
False	0.95	0.88	0.92	112
True	0.95	0.98	0.97	268
accuracy			0.95	380
macro avg	0.95	0.93	0.94	380
weighted avg	0.95	0.95	0.95	380

trombone

TRAIN				
	precision	recall	f1-score	support
False	0.82	0.98	0.89	1405
True	0.91	0.52	0.67	635
accuracy			0.84	2040
macro avg	0.86	0.75	0.78	2040
weighted avg	0.85	0.84	0.82	2040

TEST				
	precision	recall	f1-score	support

False	0.80	0.94	0.87	492
True	0.79	0.51	0.62	228
accuracy			0.80	720
macro avg	0.80	0.72	0.74	720
weighted avg	0.80	0.80	0.79	720

trumpet

TRAIN				
	precision	recall	f1-score	support
False	0.85	0.94	0.89	1303
True	0.88	0.73	0.80	828
accuracy			0.86	2131
macro avg	0.86	0.83	0.84	2131
weighted avg	0.86	0.86	0.85	2131
TEST				
	precision	recall	f1-score	support
False	0.75	0.84	0.79	467
True	0.71	0.58	0.64	318
accuracy			0.73	785
macro avg	0.73	0.71	0.71	785
weighted avg	0.73	0.73	0.73	785

ukulele

TRAIN				
	precision	recall	f1-score	support
False	0.80	0.96	0.87	1279
True	0.84	0.46	0.59	556
accuracy			0.81	1835
macro avg	0.82	0.71	0.73	1835
weighted avg	0.81	0.81	0.79	1835
TEST				
	precision	recall	f1-score	support
False	0.77	0.95	0.85	408
True	0.75	0.37	0.49	182
accuracy			0.77	590

macro avg	0.76	0.66	0.67	590
weighted avg	0.77	0.77	0.74	590

violin

TRAIN				
	precision	recall	f1-score	support
False	0.99	0.66	0.79	623
True	0.79	1.00	0.88	779
accuracy			0.85	1402
macro avg	0.89	0.83	0.84	1402
weighted avg	0.88	0.85	0.84	1402
TEST				
	precision	recall	f1-score	support
False	0.93	0.62	0.75	237
True	0.81	0.97	0.88	394
accuracy			0.84	631
macro avg	0.87	0.80	0.82	631
weighted avg	0.86	0.84	0.83	631

voice

TRAIN				
	precision	recall	f1-score	support
False	0.99	0.85	0.92	426
True	0.92	1.00	0.96	764
accuracy			0.95	1190
macro avg	0.96	0.93	0.94	1190
weighted avg	0.95	0.95	0.94	1190
TEST				
	precision	recall	f1-score	support
False	0.96	0.86	0.91	150
True	0.91	0.98	0.94	224
accuracy			0.93	374
macro avg	0.94	0.92	0.93	374
weighted avg	0.93	0.93	0.93	374

[]: