

openmic-MEL-ML

March 2, 2020

```
[1]: import librosa as lb
import librosa.display
import scipy
import json
import numpy as np
import sklearn
from sklearn.metrics import classification_report
from sklearn.model_selection import train_test_split
import os
import keras
from keras.utils import np_utils
from keras import layers
from keras import models
from keras.models import Sequential
from keras.layers import Dense, Conv2D, MaxPool2D, Flatten, Dropout
from keras.preprocessing.image import ImageDataGenerator
from model_builder import build_example
from plotter import plot_history
import matplotlib.pyplot as plt
```

Using TensorFlow backend.

```
[2]: # CONSTANTS
```

```
DATA_DIR = "openmic-2018/"
CATEGORY_COUNT = 8
LEARNING_RATE = 0.00001
THRESHOLD = 0.5
```

```
[6]: # LOAD DATA
```

```
OPENMIC = np.load(os.path.join(DATA_DIR, 'openmic-mel.npz'), allow_pickle=True)
print('OpenMIC keys: ' + str(list(OPENMIC.keys())))
X, Y_true, Y_mask, sample_key = OPENMIC['MEL'], OPENMIC['Y_true'],
    ↪OPENMIC['Y_mask'], OPENMIC['sample_key']
print('X has shape: ' + str(X.shape))
print('Y_true has shape: ' + str(Y_true.shape))
```

```
print('Y_mask has shape: ' + str(Y_mask.shape))
print('sample_key has shape: ' + str(sample_key.shape))
```

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OpenMIC keys: ['MEL', 'Y_true', 'Y_mask', 'sample_key']
X has shape: (20000, 128, 430)
Y_true has shape: (20000, 20)
Y_mask has shape: (20000, 20)
sample_key has shape: (20000,)
```

[8]: *# LOAD LABELS*

```
with open(os.path.join(DATA_DIR, 'class-map.json'), 'r') as f:
    INSTRUMENTS = json.load(f)
print('OpenMIC instruments: ' + str(INSTRUMENTS))
```

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OpenMIC instruments: {'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}
```

[9]: *# SPLIT DATA (TRAIN - TEST - VAL)*

```
# CHANGE X TO MEL
split_train, split_test, X_train, X_test, Y_true_train, Y_true_test,
→Y_mask_train, Y_mask_test = train_test_split(sample_key, X, Y_true, Y_mask)
split_val, split_test, X_val, X_test, Y_true_val, Y_true_test, Y_mask_val,
→Y_mask_test = train_test_split(split_test, X_test, Y_true_test, Y_mask_test,
→test_size=0.5)
train_set = np.asarray(set(split_train))
test_set = np.asarray(set(split_test))
print('# Train: {}, # Val: {}, # Test: {}'.format(len(split_train),
→len(split_test), len(split_val)))
```

```
# Train: 15000, # Val: 2500, # Test: 2500
```

[10]: *# DUPLICATE OF THE MODEL PREPROCESS*

```
print(X_train.shape)
print(X_test.shape)

for instrument in INSTRUMENTS:

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

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print(instrument)

# TRAIN
train_inst = Y_mask_train[:, inst_num]
X_train_inst = X_train[train_inst]
X_train_inst = X_train_inst.astype('float16')
shape = X_train_inst.shape
X_train_inst = X_train_inst.reshape(shape[0],1, shape[1], shape[2])
Y_true_train_inst = Y_true_train[train_inst, inst_num] >= THRESHOLD
i = 0
for val in Y_true_train_inst:
    i += val

print('TRAIN: ' + str(i) + ' true of ' + str(len(Y_true_train_inst)) + ' (' +
→ str(round(i / len(Y_true_train_inst) * 100,2)) + ' %' )

# TEST
test_inst = Y_mask_test[:, inst_num]
X_test_inst = X_test[test_inst]
X_test_inst = X_test_inst.astype('float16')
shape = X_test_inst.shape
X_test_inst = X_test_inst.reshape(shape[0],1, shape[1], shape[2])
Y_true_test_inst = Y_true_test[test_inst, inst_num] >= THRESHOLD

i = 0
for val in Y_true_test_inst:
    i += val

print('TEST: ' + str(i) + ' true of ' + str(len(Y_true_test_inst)) + ' (' +
→ str(round(i / len(Y_true_test_inst) * 100,2)) + ' %' )

# VALIDATION
val_inst = Y_mask_val[:, inst_num]
X_val_inst = X_val[val_inst]
X_val_inst = X_val_inst.astype('float16')
shape = X_val_inst.shape
X_val_inst = X_val_inst.reshape(shape[0],1, shape[1], shape[2])
Y_true_val_inst = Y_true_val[val_inst, inst_num] >= THRESHOLD

i = 0
for val in Y_true_val_inst:
    i += val

print('VALIDATION: ' + str(i) + ' true of ' + str(len(Y_true_val_inst)) + ' (' +
→ str(round(i / len(Y_true_val_inst) * 100,2)) + ' %' )

```

(15000, 128, 430)
 (2500, 128, 430)
 accordion
 TRAIN: 366 true of 1535 (23.84 %)
 TEST: 66 true of 269 (24.54 %)
 VALIDATION: 57 true of 267 (21.35 %)
 banjo
 TRAIN: 541 true of 1661 (32.57 %)
 TEST: 99 true of 287 (34.49 %)
 VALIDATION: 92 true of 270 (34.07 %)
 bass
 TRAIN: 400 true of 1417 (28.23 %)
 TEST: 75 true of 227 (33.04 %)
 VALIDATION: 74 true of 244 (30.33 %)
 cello
 TRAIN: 608 true of 1458 (41.7 %)
 TEST: 110 true of 255 (43.14 %)
 VALIDATION: 106 true of 236 (44.92 %)
 clarinet
 TRAIN: 400 true of 1790 (22.35 %)
 TEST: 68 true of 291 (23.37 %)
 VALIDATION: 65 true of 304 (21.38 %)
 cymbals
 TRAIN: 824 true of 1296 (63.58 %)
 TEST: 156 true of 241 (64.73 %)
 VALIDATION: 131 true of 198 (66.16 %)
 drums
 TRAIN: 835 true of 1332 (62.69 %)
 TEST: 142 true of 215 (66.05 %)
 VALIDATION: 129 true of 200 (64.5 %)
 flute
 TRAIN: 492 true of 1565 (31.44 %)
 TEST: 74 true of 249 (29.72 %)
 VALIDATION: 81 true of 270 (30.0 %)
 guitar
 TRAIN: 826 true of 1215 (67.98 %)
 TEST: 150 true of 214 (70.09 %)
 VALIDATION: 162 true of 221 (73.3 %)
 mallet_percussion
 TRAIN: 533 true of 1348 (39.54 %)
 TEST: 101 true of 225 (44.89 %)
 VALIDATION: 99 true of 229 (43.23 %)
 mandolin
 TRAIN: 648 true of 1868 (34.69 %)
 TEST: 103 true of 301 (34.22 %)
 VALIDATION: 94 true of 295 (31.86 %)
 organ
 TRAIN: 452 true of 1438 (31.43 %)

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TEST: 70 true of 234 (29.91 %)
VALIDATION: 81 true of 218 (37.16 %)
piano
TRAIN: 879 true of 1292 (68.03 %)
TEST: 154 true of 220 (70.0 %)
VALIDATION: 137 true of 208 (65.87 %)
saxophone
TRAIN: 846 true of 1750 (48.34 %)
TEST: 133 true of 293 (45.39 %)
VALIDATION: 156 true of 322 (48.45 %)
synthesizer
TRAIN: 819 true of 1202 (68.14 %)
TEST: 140 true of 199 (70.35 %)
VALIDATION: 132 true of 201 (65.67 %)
trombone
TRAIN: 657 true of 2060 (31.89 %)
TEST: 105 true of 348 (30.17 %)
VALIDATION: 101 true of 352 (28.69 %)
trumpet
TRAIN: 849 true of 2200 (38.59 %)
TEST: 142 true of 348 (40.8 %)
VALIDATION: 155 true of 368 (42.12 %)
ukulele
TRAIN: 559 true of 1819 (30.73 %)
TEST: 95 true of 314 (30.25 %)
VALIDATION: 84 true of 292 (28.77 %)
violin
TRAIN: 881 true of 1535 (57.39 %)
TEST: 141 true of 229 (61.57 %)
VALIDATION: 151 true of 269 (56.13 %)
voice
TRAIN: 744 true of 1181 (63.0 %)
TEST: 121 true of 191 (63.35 %)
VALIDATION: 123 true of 192 (64.06 %)

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[15]: # VALAMI FANCY ADATKIÍRÁS
      len(Y_true_val_inst)

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[15]: 193

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

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

          # Map the istrument name to its column number

```

```

inst_num = INSTRUMENTS[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 = RandomForestClassifier(max_depth=8, n_estimators=100, 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))

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print(Y_true_train_inst[3])
print(Y_pred_train[3])
print('\tTEST')
print(classification_report(Y_true_test_inst, Y_pred_test))

print(Y_true_test_inst.shape)
print(Y_pred_test.shape)

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

```

accordion

	precision	recall	f1-score	support
TRAIN				
False	0.82	1.00	0.90	1169
True	1.00	0.31	0.48	366
accuracy			0.84	1535
macro avg	0.91	0.66	0.69	1535
weighted avg	0.87	0.84	0.80	1535

False

False

	precision	recall	f1-score	support
TEST				
False	0.76	1.00	0.86	203
True	1.00	0.02	0.03	66
accuracy			0.76	269
macro avg	0.88	0.51	0.45	269
weighted avg	0.82	0.76	0.66	269

(269,)

(269,)

banjo

	precision	recall	f1-score	support
TRAIN				
False	0.87	1.00	0.93	1120
True	1.00	0.70	0.82	541
accuracy			0.90	1661
macro avg	0.94	0.85	0.88	1661

weighted avg	0.91	0.90	0.90	1661
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True
False

	TEST				
		precision	recall	f1-score	support
	False	0.65	0.98	0.78	188
	True	0.00	0.00	0.00	99
	accuracy			0.64	287
	macro avg	0.33	0.49	0.39	287
	weighted avg	0.43	0.64	0.51	287

(287,)
(287,)

bass

	TRAIN				
		precision	recall	f1-score	support
	False	0.87	1.00	0.93	1017
	True	1.00	0.62	0.76	400
	accuracy			0.89	1417
	macro avg	0.93	0.81	0.85	1417
	weighted avg	0.91	0.89	0.88	1417

False
False

	TEST				
		precision	recall	f1-score	support
	False	0.67	0.97	0.79	152
	True	0.33	0.03	0.05	75
	accuracy			0.66	227
	macro avg	0.50	0.50	0.42	227
	weighted avg	0.56	0.66	0.55	227

(227,)
(227,)

cello

	TRAIN				
		precision	recall	f1-score	support
	False	0.97	0.80	0.88	850

True	0.78	0.96	0.86	608
accuracy			0.87	1458
macro avg	0.87	0.88	0.87	1458
weighted avg	0.89	0.87	0.87	1458

False
False

TEST				
	precision	recall	f1-score	support
False	0.69	0.64	0.67	145
True	0.57	0.63	0.60	110
accuracy			0.64	255
macro avg	0.63	0.63	0.63	255
weighted avg	0.64	0.64	0.64	255

(255,)

(255,)

clarinet

TRAIN				
	precision	recall	f1-score	support
False	0.84	1.00	0.91	1390
True	1.00	0.32	0.48	400
accuracy			0.85	1790
macro avg	0.92	0.66	0.70	1790
weighted avg	0.87	0.85	0.82	1790

False
False

TEST				
	precision	recall	f1-score	support
False	0.77	1.00	0.87	223
True	0.00	0.00	0.00	68
accuracy			0.77	291
macro avg	0.38	0.50	0.43	291
weighted avg	0.59	0.77	0.66	291

(291,)

(291,)

C:\Users\hjani\Documents\Conda\lib\site-

packages\sklearn\metrics\classification.py:1437: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples.

'precision', 'predicted', average, warn_for)

cymbals

TRAIN		precision	recall	f1-score	support
False		0.94	0.96	0.95	472
True		0.98	0.97	0.97	824
accuracy				0.97	1296
macro avg		0.96	0.97	0.96	1296
weighted avg		0.97	0.97	0.97	1296

True

True

TEST		precision	recall	f1-score	support
False		0.78	0.71	0.74	85
True		0.85	0.89	0.87	156
accuracy				0.83	241
macro avg		0.81	0.80	0.80	241
weighted avg		0.82	0.83	0.82	241

(241,)

(241,)

drums

TRAIN		precision	recall	f1-score	support
False		0.93	0.91	0.92	497
True		0.95	0.96	0.95	835
accuracy				0.94	1332
macro avg		0.94	0.94	0.94	1332
weighted avg		0.94	0.94	0.94	1332

True

True

TEST		precision	recall	f1-score	support
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False	0.79	0.73	0.76	73
True	0.86	0.90	0.88	142
accuracy			0.84	215
macro avg	0.83	0.81	0.82	215
weighted avg	0.84	0.84	0.84	215

(215,)

(215,)

flute

TRAIN				
	precision	recall	f1-score	support
False	0.80	1.00	0.89	1073
True	1.00	0.44	0.61	492
accuracy			0.82	1565
macro avg	0.90	0.72	0.75	1565
weighted avg	0.86	0.82	0.80	1565

False

False

TEST				
	precision	recall	f1-score	support
False	0.70	1.00	0.83	175
True	0.00	0.00	0.00	74
accuracy			0.70	249
macro avg	0.35	0.50	0.41	249
weighted avg	0.49	0.70	0.58	249

(249,)

(249,)

C:\Users\hjani\Documents\Conda\lib\site-packages\sklearn\metrics\classification.py:1437: UndefinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples.

'precision', 'predicted', average, warn_for)

guitar

TRAIN				
	precision	recall	f1-score	support
False	1.00	0.57	0.73	389

True	0.83	1.00	0.91	826
accuracy			0.86	1215
macro avg	0.92	0.79	0.82	1215
weighted avg	0.89	0.86	0.85	1215

True
True

TEST				
	precision	recall	f1-score	support
False	0.45	0.08	0.13	64
True	0.71	0.96	0.82	150
accuracy			0.70	214
macro avg	0.58	0.52	0.47	214
weighted avg	0.63	0.70	0.61	214

(214,)

(214,)

mallet_percussion

TRAIN				
	precision	recall	f1-score	support
False	0.93	0.99	0.96	815
True	0.99	0.89	0.94	533
accuracy			0.95	1348
macro avg	0.96	0.94	0.95	1348
weighted avg	0.95	0.95	0.95	1348

True
False

TEST				
	precision	recall	f1-score	support
False	0.58	0.82	0.68	124
True	0.55	0.27	0.36	101
accuracy			0.57	225
macro avg	0.57	0.54	0.52	225
weighted avg	0.57	0.57	0.54	225

(225,)

(225,)

mandolin

TRAIN				
	precision	recall	f1-score	support
False	0.81	1.00	0.89	1220
True	1.00	0.55	0.71	648
accuracy			0.84	1868
macro avg	0.90	0.77	0.80	1868
weighted avg	0.87	0.84	0.83	1868

False
False

TEST				
	precision	recall	f1-score	support
False	0.65	0.98	0.79	198
True	0.00	0.00	0.00	103
accuracy			0.65	301
macro avg	0.33	0.49	0.39	301
weighted avg	0.43	0.65	0.52	301

(301,)

(301,)

organ

TRAIN				
	precision	recall	f1-score	support
False	0.88	0.99	0.93	986
True	0.96	0.70	0.81	452
accuracy			0.90	1438
macro avg	0.92	0.84	0.87	1438
weighted avg	0.90	0.90	0.89	1438

True
False

TEST				
	precision	recall	f1-score	support
False	0.74	0.96	0.84	164
True	0.70	0.23	0.34	70
accuracy			0.74	234
macro avg	0.72	0.59	0.59	234
weighted avg	0.73	0.74	0.69	234

(234,)

(234,)

piano

TRAIN	precision	recall	f1-score	support
False	1.00	0.90	0.95	413
True	0.96	1.00	0.98	879
accuracy			0.97	1292
macro avg	0.98	0.95	0.96	1292
weighted avg	0.97	0.97	0.97	1292

True

True

TEST	precision	recall	f1-score	support
False	0.84	0.71	0.77	66
True	0.88	0.94	0.91	154
accuracy			0.87	220
macro avg	0.86	0.83	0.84	220
weighted avg	0.87	0.87	0.87	220

(220,)

(220,)

saxophone

TRAIN	precision	recall	f1-score	support
False	0.99	0.89	0.94	904
True	0.90	0.99	0.94	846
accuracy			0.94	1750
macro avg	0.94	0.94	0.94	1750
weighted avg	0.95	0.94	0.94	1750

True

True

TEST	precision	recall	f1-score	support
False	0.66	0.53	0.59	160
True	0.54	0.68	0.60	133

accuracy			0.59	293
macro avg	0.60	0.60	0.59	293
weighted avg	0.61	0.59	0.59	293

(293,)

(293,)

synthesizer

TRAIN

	precision	recall	f1-score	support
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False	0.98	0.96	0.97	383
-------	------	------	------	-----

True	0.98	0.99	0.98	819
------	------	------	------	-----

accuracy			0.98	1202
macro avg	0.98	0.97	0.97	1202
weighted avg	0.98	0.98	0.98	1202

True

True

TEST

	precision	recall	f1-score	support
--	-----------	--------	----------	---------

False	0.35	0.19	0.24	59
-------	------	------	------	----

True	0.71	0.86	0.78	140
------	------	------	------	-----

accuracy			0.66	199
macro avg	0.53	0.52	0.51	199
weighted avg	0.61	0.66	0.62	199

(199,)

(199,)

trombone

TRAIN

	precision	recall	f1-score	support
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False	0.82	1.00	0.90	1403
-------	------	------	------	------

True	1.00	0.52	0.69	657
------	------	------	------	-----

accuracy			0.85	2060
macro avg	0.91	0.76	0.79	2060
weighted avg	0.88	0.85	0.83	2060

False

False

TEST

	precision	recall	f1-score	support
--	-----------	--------	----------	---------

False	0.71	0.99	0.83	243
True	0.75	0.06	0.11	105
accuracy			0.71	348
macro avg	0.73	0.52	0.47	348
weighted avg	0.72	0.71	0.61	348

(348,)

(348,)

trumpet

TRAIN				
	precision	recall	f1-score	support
False	0.88	1.00	0.93	1351
True	1.00	0.78	0.87	849
accuracy			0.91	2200
macro avg	0.94	0.89	0.90	2200
weighted avg	0.92	0.91	0.91	2200

False

False

TEST				
	precision	recall	f1-score	support
False	0.65	0.94	0.77	206
True	0.75	0.27	0.40	142
accuracy			0.67	348
macro avg	0.70	0.61	0.59	348
weighted avg	0.69	0.67	0.62	348

(348,)

(348,)

ukulele

TRAIN				
	precision	recall	f1-score	support
False	0.80	1.00	0.89	1260
True	1.00	0.45	0.62	559
accuracy			0.83	1819
macro avg	0.90	0.72	0.75	1819
weighted avg	0.86	0.83	0.81	1819


```

False
False
      TEST
      precision    recall  f1-score   support

False      0.70      1.00      0.82      219
True       1.00      0.02      0.04       95

accuracy          0.70      314
macro avg      0.85      0.51      0.43      314
weighted avg   0.79      0.70      0.59      314

```

(314,)

(314,)

violin

```

      TRAIN
      precision    recall  f1-score   support

False      1.00      0.58      0.74      654
True       0.76      1.00      0.87      881

accuracy          0.82     1535
macro avg      0.88      0.79      0.80     1535
weighted avg   0.86      0.82      0.81     1535

```

False

True

```

      TEST
      precision    recall  f1-score   support

False      0.57      0.30      0.39       88
True       0.66      0.86      0.75      141

accuracy          0.64      229
macro avg      0.61      0.58      0.57      229
weighted avg   0.62      0.64      0.61      229

```

(229,)

(229,)

voice

```

      TRAIN
      precision    recall  f1-score   support

False      1.00      0.76      0.87      437
True       0.88      1.00      0.93      744

```

accuracy			0.91	1181
macro avg	0.94	0.88	0.90	1181
weighted avg	0.92	0.91	0.91	1181

True

True

TEST

	precision	recall	f1-score	support
--	-----------	--------	----------	---------

False	0.85	0.67	0.75	70
-------	------	------	------	----

True	0.83	0.93	0.88	121
------	------	------	------	-----

accuracy			0.84	191
macro avg	0.84	0.80	0.82	191
weighted avg	0.84	0.84	0.83	191

(191,)

(191,)

```
[8]: import matplotlib.pyplot as plt
from pylab import plot, show, figure, imshow, xlim, ylim, title

def plot_history():
    plt.figure(figsize=(9,4))
    plt.subplot(1,2,1)
    plt.plot(history.history['acc'])
    plt.plot(history.history['val_acc'])
    plt.title('Model accuracy')
    plt.ylabel('Accuracy')
    plt.xlabel('Epoch')
    plt.legend(['Train accuracy', 'Validation accuracy'], loc='upper left')
    plt.subplot(1,2,2)
    plt.plot(history.history['loss'])
    plt.plot(history.history['val_loss'])
    plt.title('Model loss')
    plt.ylabel('Loss')
    plt.xlabel('Epoch')
    plt.legend(['Train loss', 'Validation loss'], loc='upper left')
    plt.show()
```

```
[ ]: """
    # Step 3: simplify the data by averaging over time
    # 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)
    X_test_inst_sklearn = np.mean(X_test_inst, axis=1)
    X_train_inst_sklearn = X_train_inst_sklearn.astype('float32')
```

```
        X_train_inst_sklern = lb.util.normalize(X_train_inst_sklern)
    """

np.savez('models.npz',model=)
```