openmic

December 17, 2019

[1]:
```
import librosa as lb
import librosa.display
import pandas as pd
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
from pylab import plot, show, figure, imshow, xlim, ylim, title
import matplotlib.pyplot as plt
import keras
from keras.utils import np_utils
from keras import layers
from keras import models
```

```
Using TensorFlow backend.
```

[2]:
```
#CONSTANTS

DATA_DIR = "openmic-2018/"
CATEGORY_COUNT = 8
```

[3]:
```
df = pd.read_csv('openmic-2018/openmic-2018-aggregated-labels.csv')
del df['relevance']
del df['num_responses']
```

[4]:
```
labels = df.values
labels
```

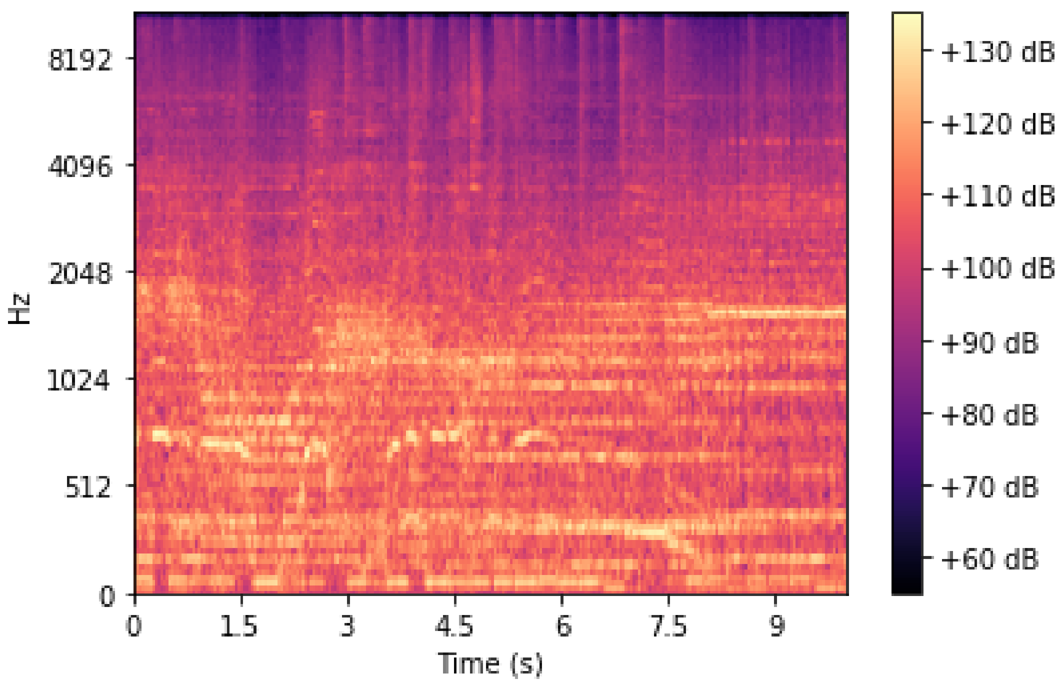
[4]:
```
array([['000046_3840', 'clarinet'],
       ['000046_3840', 'flute'],
       ['000046_3840', 'trumpet'],
       ...,
       ['155311_453120', 'saxophone'],
       ['155311_453120', 'trumpet'],
       ['155311_453120', 'trombone']], dtype=object)
```

[5]:
```
y, sr = lb.load(DATA_DIR + 'audio/000/000135_483840.ogg')
S = lb.feature.melspectrogram(y=y, sr=sr)

S_dB = lb.power_to_db(S, ref=0) # 10 * log10(S / ref)


print(y.shape)
print(sr)
print(S.shape)
print(S_dB.shape)
```

```
(220544,)
22050
(128, 431)
(128, 431)
```

[6]:
```
librosa.display.specshow(S_dB, x_axis='s', y_axis='mel')
plt.colorbar(format='%+2.0f dB')
```

[6]:
```
<matplotlib.colorbar.Colorbar at 0x234e4671278>
```



[7]:
```
OPENMIC = np.load(os.path.join(DATA_DIR, 'openmic-2018.npz'), allow_pickle=True)
print(list(OPENMIC.keys()))
```

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

[8]:
```
X, Y_true, Y_mask, sample_key = OPENMIC['X'], OPENMIC['Y_true'],␣
↪OPENMIC['Y_mask'], OPENMIC['sample_key']
#print(X.shape)
#X = []
#print(len(sample_key))
#for key in sample_key:
#    key_dir = key[:3]
#    y, sr = lb.load(DATA_DIR + 'audio/'+ key_dir + '/' + key + '.ogg')
#    X.append(lb.feature.melspectrogram(y=y, sr=sr))
#    print(len(X))
```

[9]:
```
with open(os.path.join(DATA_DIR, 'class-map.json'), 'r') as f:
    class_map = json.load(f)
```

[21]:
```
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
```

[23]:
```
print(X_train.shape)
print(X_val.shape)
print(X_test.shape)
```

```
(15000, 10, 128)
(2500, 10, 128)
(2500, 10, 128)
```

[29]:
```
THRESHOLD = 0.3

# This dictionary will include the classifiers for each model
mymodels = 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 instrument
for instrument in class_map:

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

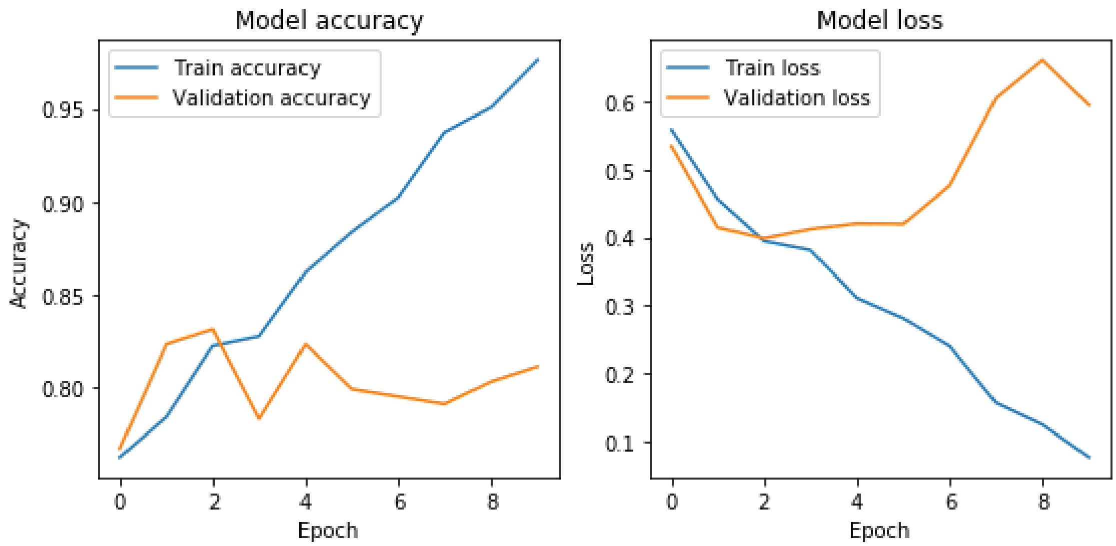
```
    # Step 1: sub-sample the data

    # 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]
    val_inst = Y_mask_val[:, 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]
    X_val_inst = X_val[val_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 thresold the label likelihoods at 0.5 to get binary labels
    Y_true_train_inst = Y_true_train[train_inst, inst_num] >= THRESHOLD
    Y_true_val_inst = Y_true_val[val_inst, inst_num] >= THRESHOLD


    # 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] >= THRESHOLD


    X_train_inst = X_train_inst.astype('float32')
    X_val_inst = X_val_inst.astype('float32')
    X_train_inst_sklearn = X_train_inst_sklearn.astype('float32')
    X_train_inst_sklearn = lb.util.normalize(X_train_inst_sklearn)
   # X_train_inst = S_dB
    print(X_train_inst.shape)
    shape = X_train_inst.shape
    X_train_inst = X_train_inst.reshape(shape[0],1, shape[1], shape[2])
    shape = X_val_inst.shape
    X_val_inst = X_val_inst.reshape(shape[0],1, shape[1], shape[2])
    shape = X_test_inst.shape
    X_test_inst = X_test_inst.reshape(shape[0],1, shape[1], shape[2])
    #X_train_inst = X_train_inst.reshape(1,1,431,128)
    print(X_train_inst.shape)
```

```
print(Y_true_train_inst[0])
# Step 3.
# Initialize a new classifier
import keras,os
from keras.models import Sequential
from keras.layers import Dense, Conv2D, MaxPool2D , Flatten
from keras.preprocessing.image import ImageDataGenerator
import numpy as np
model = models.Sequential()

# model.add(layers.Conv2D(filters=8,kernel_size=(3,3),activation='relu',␣
↪input_shape=(10,128,1,)))
model.
↪add(Conv2D(input_shape=(1,10,128),data_format="channels_first",filters=64,kernel_size=(3,3)
↪activation="relu"))
model.add(Conv2D(filters=32,kernel_size=(3,3),padding="same",␣
↪activation="relu"))
model.add(MaxPool2D(pool_size=(3,3),strides=(2,2)))
model.add(Conv2D(filters=128, kernel_size=(3,3), padding="same",␣
↪activation="relu"))
model.add(Conv2D(filters=128, kernel_size=(3,3), padding="same",␣
↪activation="relu"))
model.add(MaxPool2D(pool_size=(2,2),strides=(2,2)))
model.add(Conv2D(filters=256, kernel_size=(3,3), padding="same",␣
↪activation="relu"))
model.add(Conv2D(filters=256, kernel_size=(3,3), padding="same",␣
↪activation="relu"))
model.add(Conv2D(filters=256, kernel_size=(3,3), padding="same",␣
↪activation="relu"))
model.add(MaxPool2D(pool_size=(2,2),strides=(2,2)))
model.add(Conv2D(filters=512, kernel_size=(3,3), padding="same",␣
↪activation="relu"))
model.add(Conv2D(filters=512, kernel_size=(3,3), padding="same",␣
↪activation="relu"))
model.add(Conv2D(filters=512, kernel_size=(3,3), padding="same",␣
↪activation="relu"))
model.add(layers.Flatten())
model.add(layers.Dense(units=4096, activation='relu'))
model.add(layers.Dense(units=4096, activation='relu'))
model.add(layers.Dense(units=1, activation='sigmoid'))

model.compile(loss='binary_crossentropy',
              optimizer=keras.optimizers.Adam(lr=0.0001),
               metrics = ['accuracy'])

# model.summary()
```

```
    # Step 4.
    history = model.fit(X_train_inst,Y_true_train_inst , epochs=10,␣
↪batch_size=64, validation_data=(X_val_inst,Y_true_val_inst))

    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()

    loss, acc = model.evaluate(X_test_inst, Y_true_test_inst)
    print('Test loss: {}'.format(loss))
    print('Test accuracy: {:.2%}'.format(acc))

    # Step 5.
    # Finally, we'll evaluate the model on both train and test
    Y_pred_train = model.predict(X_train_inst)
    Y_pred_test = model.predict(X_test_inst)
    Y_pred_train_bool = Y_pred_train > THRESHOLD - 0.2 #THRESHOLD (should be␣
↪lower than 0.5)
    Y_pred_test_bool = Y_pred_test > THRESHOLD - 0.2 #THRESHOLD (should be␣
↪lower than 0.5)
    print(Y_pred_train[0])
    print('-' * 52)
    print(instrument)
    print('\tTRAIN')
    print(classification_report(Y_true_train_inst, Y_pred_train_bool))

    print(Y_true_train_inst[3])
    print(Y_pred_train[3])
    print('\tTEST')
    print(classification_report(Y_true_test_inst, Y_pred_test_bool))
    sum = 0
  #  for i, prob in enumerate(Y_pred_train):
```

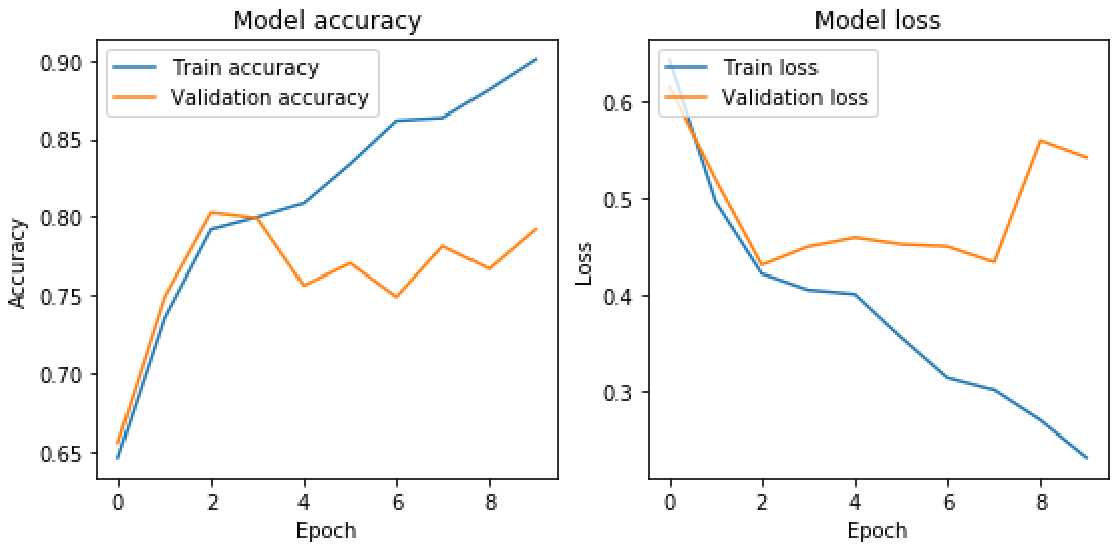
```
#      print (i)
#      print (prob)
#      sum += prob
#  print(sum)
  # Store the classifier in our dictionary
  mymodels[instrument] = model
```

```
(1566, 10, 128)
(1566, 1, 10, 128)
False
Train on 1566 samples, validate on 249 samples
Epoch 1/10
1566/1566 [==============================] - 92s 58ms/step - loss: 0.5582 - acc:
0.7625 - val_loss: 0.5340 - val_acc: 0.7671
Epoch 2/10
1566/1566 [==============================] - 95s 60ms/step - loss: 0.4559 - acc:
0.7842 - val_loss: 0.4145 - val_acc: 0.8233
Epoch 3/10
1566/1566 [==============================] - 90s 58ms/step - loss: 0.3943 - acc:
0.8225 - val_loss: 0.3986 - val_acc: 0.8313
Epoch 4/10
1566/1566 [==============================] - 89s 57ms/step - loss: 0.3811 - acc:
0.8276 - val_loss: 0.4120 - val_acc: 0.7831
Epoch 5/10
1566/1566 [==============================] - 89s 57ms/step - loss: 0.3109 - acc:
0.8621 - val_loss: 0.4202 - val_acc: 0.8233
Epoch 6/10
1566/1566 [==============================] - 88s 56ms/step - loss: 0.2811 - acc:
0.8838 - val_loss: 0.4195 - val_acc: 0.7992
Epoch 7/10
1566/1566 [==============================] - 87s 56ms/step - loss: 0.2400 - acc:
0.9023 - val_loss: 0.4760 - val_acc: 0.7952
Epoch 8/10
1566/1566 [==============================] - 89s 57ms/step - loss: 0.1566 - acc:
0.9374 - val_loss: 0.6051 - val_acc: 0.7912
Epoch 9/10
1566/1566 [==============================] - 89s 57ms/step - loss: 0.1246 - acc:
0.9508 - val_loss: 0.6610 - val_acc: 0.8032
Epoch 10/10
1566/1566 [==============================] - 88s 56ms/step - loss: 0.0765 - acc:
0.9764 - val_loss: 0.5946 - val_acc: 0.8112
```




```
256/256 [==============================] - 2s 9ms/step
Test loss: 0.7445437833666801
Test accuracy: 75.00%
[0.03150272]
----------------------------------------------------
accordion
        TRAIN
              precision    recall  f1-score   support

       False       1.00      0.98      0.99      1194
        True       0.94      0.99      0.97       372

    accuracy                           0.98      1566
   macro avg       0.97      0.99      0.98      1566
weighted avg       0.98      0.98      0.98      1566

False
[0.01145008]
        TEST
              precision    recall  f1-score   support

       False       0.89      0.77      0.82       197
        True       0.47      0.68      0.55        59

    accuracy                           0.75       256
   macro avg       0.68      0.72      0.69       256
weighted avg       0.79      0.75      0.76       256

(1669, 10, 128)
```

```
(1669, 1, 10, 128)
True
Train on 1669 samples, validate on 279 samples
Epoch 1/10
1669/1669 [==============================] - 100s 60ms/step - loss: 0.6433 -
acc: 0.6465 - val_loss: 0.6155 - val_acc: 0.6559
Epoch 2/10
1669/1669 [==============================] - 96s 57ms/step - loss: 0.4962 - acc:
0.7358 - val_loss: 0.5193 - val_acc: 0.7491
Epoch 3/10
1669/1669 [==============================] - 94s 57ms/step - loss: 0.4215 - acc:
0.7921 - val_loss: 0.4306 - val_acc: 0.8029
Epoch 4/10
1669/1669 [==============================] - 95s 57ms/step - loss: 0.4049 - acc:
0.7999 - val_loss: 0.4494 - val_acc: 0.7993
Epoch 5/10
1669/1669 [==============================] - 95s 57ms/step - loss: 0.4005 - acc:
0.8089 - val_loss: 0.4588 - val_acc: 0.7563
Epoch 6/10
1669/1669 [==============================] - 94s 56ms/step - loss: 0.3557 - acc:
0.8340 - val_loss: 0.4518 - val_acc: 0.7706
Epoch 7/10
1669/1669 [==============================] - 94s 56ms/step - loss: 0.3137 - acc:
0.8616 - val_loss: 0.4496 - val_acc: 0.7491
Epoch 8/10
1669/1669 [==============================] - 98s 59ms/step - loss: 0.3010 - acc:
0.8634 - val_loss: 0.4336 - val_acc: 0.7814
Epoch 9/10
1669/1669 [==============================] - 101s 61ms/step - loss: 0.2698 -
acc: 0.8814 - val_loss: 0.5598 - val_acc: 0.7670
Epoch 10/10
1669/1669 [==============================] - 93s 56ms/step - loss: 0.2312 - acc:
0.9005 - val_loss: 0.5422 - val_acc: 0.7921
```




```
270/270 [==============================] - 3s 10ms/step
Test loss: 0.5628210295129705
Test accuracy: 79.63%
[0.93295425]
-----------------------------------------------------
banjo
        TRAIN
              precision    recall  f1-score   support

       False       0.97      0.85      0.91      1123
        True       0.76      0.95      0.84       546

    accuracy                           0.89      1669
   macro avg       0.87      0.90      0.88      1669
weighted avg       0.90      0.89      0.89      1669

False
[0.00056961]
        TEST
              precision    recall  f1-score   support

       False       0.87      0.73      0.80       180
        True       0.59      0.78      0.67        90

    accuracy                           0.75       270
   macro avg       0.73      0.76      0.73       270
weighted avg       0.78      0.75      0.75       270

(1401, 10, 128)
```

```
(1401, 1, 10, 128)
False
Train on 1401 samples, validate on 258 samples
Epoch 1/10
1401/1401 [==============================] - 87s 62ms/step - loss: 0.6153 - acc:
0.7059 - val_loss: 0.5531 - val_acc: 0.7364
Epoch 2/10
1401/1401 [==============================] - 78s 56ms/step - loss: 0.5357 - acc:
0.7281 - val_loss: 0.4700 - val_acc: 0.7674
Epoch 3/10
1401/1401 [==============================] - 83s 59ms/step - loss: 0.4440 - acc:
0.7844 - val_loss: 0.4689 - val_acc: 0.7791
Epoch 4/10
 960/1401 [===================>...] - ETA: 25s - loss: 0.3998 - acc:
```

```
      ␣
 ↪---------------------------------------------------------------------------

       KeyboardInterrupt                         Traceback (most recent call␣
 ↪last)

       <ipython-input-29-b6a7d116500e> in <module>
        91    # model.summary()
        92     # Step 4.
   ---> 93     history = model.fit(X_train_inst,Y_true_train_inst , epochs=10,␣
 ↪batch_size=64, validation_data=(X_val_inst,Y_true_val_inst))
        94
        95     plt.figure(figsize=(9,4))


       ~\Documents\Conda\lib\site-packages\keras\engine\training.py in␣
 ↪fit(self, x, y, batch_size, epochs, verbose, callbacks, validation_split,␣
 ↪validation_data, shuffle, class_weight, sample_weight, initial_epoch,␣
 ↪steps_per_epoch, validation_steps, **kwargs)
      1037                                         initial_epoch=initial_epoch,
      1038                                         ␣
 ↪steps_per_epoch=steps_per_epoch,
   -> 1039                                         ␣
 ↪validation_steps=validation_steps)
      1040
      1041     def evaluate(self, x=None, y=None,


       ~\Documents\Conda\lib\site-packages\keras\engine\training_arrays.py in␣
 ↪fit_loop(model, f, ins, out_labels, batch_size, epochs, verbose, callbacks,␣
 ↪val_f, val_ins, shuffle, callback_metrics, initial_epoch, steps_per_epoch,␣
 ↪validation_steps)
```

```
    197                         ins_batch[i] = ins_batch[i].toarray()
    198
--> 199                     outs = f(ins_batch)
    200                     outs = to_list(outs)
    201                     for l, o in zip(out_labels, outs):


    ~\Documents\Conda\lib\site-packages\keras\backend\tensorflow_backend.py␣
↪in __call__(self, inputs)
   2713                     return self._legacy_call(inputs)
   2714
-> 2715                 return self._call(inputs)
   2716             else:
   2717                 if py_any(is_tensor(x) for x in inputs):


    ~\Documents\Conda\lib\site-packages\keras\backend\tensorflow_backend.py␣
↪in _call(self, inputs)
   2673                 fetched = self._callable_fn(*array_vals,␣
↪run_metadata=self.run_metadata)
   2674             else:
-> 2675                 fetched = self._callable_fn(*array_vals)
   2676             return fetched[:len(self.outputs)]
   2677


    ~\Documents\Conda\lib\site-packages\tensorflow\python\client\session.py␣
↪in __call__(self, *args, **kwargs)
   1437           ret = tf_session.TF_SessionRunCallable(
   1438               self._session._session, self._handle, args, status,
-> 1439               run_metadata_ptr)
   1440         if run_metadata:
   1441           proto_data = tf_session.TF_GetBuffer(run_metadata_ptr)


    KeyboardInterrupt:
```

[ ]:
```python
print(X_train_inst_sklearn)
print(Y_pred_train)
```

[ ]:
```python

```