main_1104

November 4, 2020

1 Part 0 Python Environment Set-up

This project is completed using Python. There are two ways of setting up the Python environment.

1. Colab (on virtual machine)

- Set up Google Colaboratory on Google drive, upload the notebook and open it with Colab.
- If you choose to run our notebook on Colab, there is no need to install any library.
- Before training the model, please upload `fiducial_pt_full.pkl` and `label_full.pkl` from output folder.

2. Jupyter Notebook (on local machine)

- Download Anaconda from https://www.anaconda.com/products/individual
- Open the notebook with Jupyter Notebook
- Install libraries that do not come with Anaconda: `!pip install tensorflow`, `!pip install scikit-learn`, `!pip install tensorflow_hub`. (or any other required libraries)

2 Part I Data Pre-Processing

2.1 1. Read fiducial point and save as pickle files

[1]:
```python
import scipy.io
import os
import numpy as np
import pandas as pd
import pickle
import tensorflow as tf
import warnings
warnings.filterwarnings('ignore')
```

[2]:
```python
def get_points(file):
    '''load matlab style file'''
    mat = scipy.io.loadmat(file)
    return mat[list(mat.keys())[3]]

def pickle_save(filename, content):
    '''save the file into python pickle object under output folder'''
    with open(filename, 'wb') as f:
```

```
        pickle.dump(content, f)

def pickle_open(filename):
    '''load the pickle file'''
    with open(filename, 'rb') as f:
        content = pickle.load(f)
    return content
```

[ ]:
```
## No need to run this cell if pickle files are uploaded

from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

[ ]:
```
## No need to run this cell if pickle files are uploaded

# read mat format file into pickle
dir_list = os.listdir('drive/My Drive/points')
dir_list.sort()

fiducial_pt_full = np.stack((get_points('drive/My Drive/points/'+filename) for␣
 ↪filename in dir_list))
label_full = pd.read_csv('label.csv')['label']

# save the data into pickle files, so that we don't need to read raw data␣
 ↪everytime
pickle_save('fiducial_pt_full', fiducial_pt_full)
pickle_save('label_full', label_full)
```

2.2 2. Train-test split

[3]:
```
from sklearn.model_selection import train_test_split

# load data from pickle oject
fiducial_pt_full = pickle_open('fiducial_pt_full.pkl')
label_full = pickle_open('label_full.pkl')

## Note: randomly split into training & test set with seed 42
X_train, X_test, y_train, y_test = train_test_split(fiducial_pt_full,␣
 ↪label_full, test_size=0.2, random_state=42)
```

[4]:
```
X_train.shape, y_test.shape
```

[4]:
```
((2400, 78, 2), (600,))
```

2.3 3. Feature Construction

Keep the fiducial points on eyes, eyebrows,and lips. Compute the pairwise distances.

[10]:
```
from sklearn.metrics import pairwise_distances
import time

# extract pairwise distance as features (78*77/2=3003 features)
# nrow=number of records of the dataset; ncol=3003
# keep 48 points on lips, eyes, and eyebrows, 48*47

start_time = time.time()
feature_train = np.stack((pairwise_distances(X_train[i])[np.triu_indices(78, k␣
↪= 1)] for i in range(X_train.shape[0])))
print('Baseline training feature extraction takes %s seconds.'%round((time.
↪time()-start_time),3))

start_time = time.time()
feature_test = np.stack((pairwise_distances(X_test[i])[np.triu_indices(78, k =␣
↪1)] for i in range(X_test.shape[0])))
print('Baseline training feature extraction takes %s seconds.'%round((time.
↪time()-start_time),3))
```

```
Baseline training feature extraction takes 1.049 seconds.
Baseline training feature extraction takes 0.263 seconds.
```

3 Part II Baseline Model: GBT

We optimized the baseline model with tuned parameters. Referencing main_draft.ipynb for more information.

[11]:
```
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.metrics import precision_score, recall_score, roc_auc_score,␣
↪accuracy_score
import time

# define function to report metrics for baseline model
def clf_metrics(y_true, y_pred, y_score):
    accuracy = accuracy_score(y_true, y_pred)

    # reweight dataset in order to estimate the accuracy of "balanced" data set
    weight_data = np.zeros(len(y_true))
    for v in np.unique(y_true):
        weight_data[y_true==v] = 0.5*len(y_true)/np.sum(y_true==v)
    weighted_acc = np.sum(weight_data * (y_pred==y_true)/np.sum(weight_data))

    precision = precision_score(y_true, y_pred)
    recall = recall_score(y_true, y_pred)
```

```
    auc = roc_auc_score(y_true, y_score, average='weighted')

    df = pd.DataFrame({'accuracy':[accuracy],'weighted acc':[weighted_acc],
                       'precision': [precision], 'recall': [recall], 'auc':
 ↪[auc]})
    print(df)
```

[34]:
```
# assign weights for data to remedy the imbalanced training data
weights2 = np.zeros(len(y_train))
weights2[y_train == 0] = 1
weights2[y_train == 1] = 10

gbt_baseline = GradientBoostingClassifier(learning_rate=0.1, n_estimators=150,
                                          max_depth=4, min_samples_split=2,␣
 ↪min_samples_leaf=1,
                                          subsample=0.8,max_features='sqrt',␣
 ↪random_state=242)
start_baseline = time.time()
gbt_baseline.fit(feature_train, y_train, sample_weight = weights2)
end_baseline = time.time()
print('Training time cost {:.2f} s'.format(end_baseline-start_baseline))
```

```
Training time cost 7.13 s
```

[36]:
```
# store the trained model
pickle_save('gbt_baseline.pkl', gbt_baseline)
```

[37]:
```
# load the trained model from file
gbt_baseline = pickle_open('gbt_baseline.pkl')
```

[18]:
```
gbt_baseline.get_params()
```

[18]:
```
{'ccp_alpha': 0.0,
 'criterion': 'friedman_mse',
 'init': None,
 'learning_rate': 0.1,
 'loss': 'deviance',
 'max_depth': 4,
 'max_features': 'sqrt',
 'max_leaf_nodes': None,
 'min_impurity_decrease': 0.0,
 'min_impurity_split': None,
 'min_samples_leaf': 1,
 'min_samples_split': 2,
 'min_weight_fraction_leaf': 0.0,
 'n_estimators': 150,
 'n_iter_no_change': None,
```

```
 'presort': 'deprecated',
 'random_state': 299,
 'subsample': 0.8,
 'tol': 0.0001,
 'validation_fraction': 0.1,
 'verbose': 0,
 'warm_start': False}
```

[90]:

```
# Gradient boosting baseline model performance
pred_train = gbt_baseline.predict(feature_train)
score_train = gbt_baseline.decision_function(feature_train)
print('Training set:')
clf_metrics(y_train, pred_train, score_train)
print('\n')

test_start_baseline = time.time()
pred_test = gbt_baseline.predict(feature_test)
score_test = gbt_baseline.decision_function(feature_test)
test_end_baseline = time.time()
print('Test set:')
clf_metrics(y_test, pred_test, score_test)
print('\n')
print('Testing takes {:.2f} seconds'.
 ↪format(test_end_baseline-test_start_baseline))
```

```
Training set:
   accuracy  weighted acc  precision  recall       auc
0  0.964167      0.977846   0.842202     1.0  0.999891


Test set:
   accuracy  weighted acc  precision    recall       auc
0  0.778333      0.704997   0.519737  0.568345  0.789447


Testing takes 0.02 seconds
```

4 Part III Our Model: Densely Connected Neural Network

4.1 1. Feature engineering

[39]:

```
import warnings
warnings.filterwarnings('ignore')
start_time = time.time()
feature_train = np.stack((pairwise_distances(X_train[i])[np.triu_indices(78, k␣
 ↪= 1)] for i in range(X_train.shape[0])))
```

```
print('Training feature extraction takes %s seconds.'%round((time.
 ↪time()-start_time),3))

start_time = time.time()
feature_test = np.stack((pairwise_distances(X_test[i])[np.triu_indices(78, k =␣
 ↪1)] for i in range(X_test.shape[0])))
print('Test feature extraction takes %s seconds.'%round((time.
 ↪time()-start_time),3))
```

```
Training feature extraction takes 1.059 seconds.
Test feature extraction takes 0.295 seconds.
```

4.2 2. Oversampling the minority class

[40]:
```
y_train = np.array(y_train)
y_test = np.array(y_test)

bool_train_labels = y_train != 0
pos_features = feature_train[bool_train_labels]
neg_features = feature_train[~bool_train_labels]

pos_labels = y_train[bool_train_labels]
neg_labels = y_train[~bool_train_labels]
```

[41]:
```
pos_labels.shape, neg_labels.shape
```

[41]:
```
((459,), (1941,))
```

[78]:
```
# Balance the dataset manually by choosing the right number of random indices␣
 ↪from the positive examples
RANDOM_SEED = 111
np.random.seed(RANDOM_SEED)

ids = np.arange(len(pos_features))
choices = np.random.choice(ids, len(neg_features))

res_pos_features = pos_features[choices]
res_pos_labels = pos_labels[choices]

res_pos_features.shape
```

[78]:
```
(1941, 3003)
```

[79]:
```
resampled_features = np.concatenate([res_pos_features, neg_features], axis=0)
resampled_labels = np.concatenate([res_pos_labels, neg_labels], axis=0)

order = np.arange(len(resampled_labels))
```

```
np.random.shuffle(order)
resampled_features = resampled_features[order]
resampled_labels = resampled_labels[order]

resampled_features.shape, resampled_labels.shape
```

[79]: ((3882, 3003), (3882,))

4.3 3. Model Training

[80]:
```
from tensorflow import keras

METRICS = [
           keras.metrics.BinaryAccuracy(name='accuracy'),
           keras.metrics.AUC(name='auc'),
           keras.metrics.Precision(name='precision'),
           keras.metrics.Recall(name='recall')
]
INPUT_SHAPE=[3003]
model1 = keras.Sequential([
                           keras.layers.
 ↪BatchNormalization(input_shape=INPUT_SHAPE,
                                                                momentum=0.80),
                           keras.layers.Dense(1024, activation='relu',
                                              kernel_initializer=keras.
 ↪initializers.glorot_normal(seed=99)),
                           keras.layers.Dropout(0.3, seed=4),
                           keras.layers.Dense(512, activation='relu',
                                              kernel_initializer=keras.
 ↪initializers.glorot_normal(seed=99)),
                           keras.layers.Dropout(0.3, seed=4),
                           keras.layers.Dense(256, activation='relu',
                                              kernel_initializer=keras.
 ↪initializers.glorot_normal(seed=99)),
                           keras.layers.Dense(128, activation='relu',
                                              kernel_initializer=keras.
 ↪initializers.glorot_normal(seed=99)),
                           keras.layers.Dropout(0.3, seed=4),
                           keras.layers.Dense(64, activation='relu',
                                              kernel_initializer=keras.
 ↪initializers.glorot_normal(seed=99)),
                           keras.layers.Dropout(0.25, seed=4),
                           keras.layers.Dense(32, activation='relu',
                                              kernel_initializer=keras.
 ↪initializers.glorot_normal(seed=99)),
                           keras.layers.Dropout(0.1, seed=4),
```

```
                            keras.layers.Dense(16, activation='relu',
                                               kernel_initializer=keras.
↪initializers.glorot_normal(seed=99)),
                            keras.layers.Dense(1, activation='sigmoid')
])

model1.compile(
      #optimizer=keras.optimizers.RMSprop(),
      optimizer=keras.optimizers.Adam(lr=0.001),
      loss=keras.losses.BinaryCrossentropy(),
      metrics=METRICS)

early_stopping = tf.keras.callbacks.EarlyStopping(
    monitor='val_auc',
    verbose=1,
    patience=5,
    mode='max',
    restore_best_weights=True)

model1.summary()
```

```
Model: "sequential_7"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
batch_normalization_7 (Batch (None, 3003)              12012
_________________________________________________________________
dense_56 (Dense)             (None, 1024)              3076096
_________________________________________________________________
dropout_35 (Dropout)         (None, 1024)              0
_________________________________________________________________
dense_57 (Dense)             (None, 512)               524800
_________________________________________________________________
dropout_36 (Dropout)         (None, 512)               0
_________________________________________________________________
dense_58 (Dense)             (None, 256)               131328
_________________________________________________________________
dense_59 (Dense)             (None, 128)               32896
_________________________________________________________________
dropout_37 (Dropout)         (None, 128)               0
_________________________________________________________________
dense_60 (Dense)             (None, 64)                8256
_________________________________________________________________
dropout_38 (Dropout)         (None, 64)                0
_________________________________________________________________
dense_61 (Dense)             (None, 32)                2080
_________________________________________________________________
```

```
dropout_39 (Dropout)         (None, 32)                0
_________________________________________________________________
dense_62 (Dense)             (None, 16)                528
_________________________________________________________________
dense_63 (Dense)             (None, 1)                 17
=================================================================
Total params: 3,788,013
Trainable params: 3,782,007
Non-trainable params: 6,006
_________________________________________________________________
```

[81]:
```
start_NN = time.time()

EPOCHS=100
resampled_history = model1.fit(
    resampled_features, resampled_labels,
    epochs=EPOCHS,
    batch_size=64,
    callbacks = [early_stopping],
    validation_split=0.2
    )

end_NN = time.time()
print("training  model takes %s seconds" % round((end_NN-start_NN),3))
```

```
Epoch 1/100
49/49 [==============================] - 3s 71ms/step - loss: 0.8279 - accuracy:
0.4979 - auc: 0.4973 - precision: 0.4945 - recall: 0.4333 - val_loss: 0.6949 -
val_accuracy: 0.5084 - val_auc: 0.5181 - val_precision: 0.5097 - val_recall:
0.9924
Epoch 2/100
49/49 [==============================] - 3s 68ms/step - loss: 0.7238 - accuracy:
0.5089 - auc: 0.5164 - precision: 0.5058 - recall: 0.5376 - val_loss: 0.6904 -
val_accuracy: 0.5508 - val_auc: 0.5670 - val_precision: 0.5373 - val_recall:
0.8715
Epoch 3/100
49/49 [==============================] - 3s 68ms/step - loss: 0.7157 - accuracy:
0.4957 - auc: 0.5006 - precision: 0.4937 - recall: 0.5544 - val_loss: 0.6913 -
val_accuracy: 0.5187 - val_auc: 0.5410 - val_precision: 0.5228 - val_recall:
0.6650
Epoch 4/100
49/49 [==============================] - 3s 68ms/step - loss: 0.7082 - accuracy:
0.5192 - auc: 0.5149 - precision: 0.5147 - recall: 0.5784 - val_loss: 0.6911 -
val_accuracy: 0.5135 - val_auc: 0.5684 - val_precision: 0.5629 - val_recall:
0.2141
Epoch 5/100
49/49 [==============================] - 3s 68ms/step - loss: 0.7004 - accuracy:
0.5069 - auc: 0.5004 - precision: 0.5039 - recall: 0.5389 - val_loss: 0.6919 -
```

```
val_accuracy: 0.5354 - val_auc: 0.5555 - val_precision: 0.5308 - val_recall:
0.7809
Epoch 6/100
49/49 [==============================] - 3s 70ms/step - loss: 0.6962 - accuracy:
0.5176 - auc: 0.5260 - precision: 0.5145 - recall: 0.5278 - val_loss: 0.6947 -
val_accuracy: 0.5225 - val_auc: 0.5110 - val_precision: 0.5489 - val_recall:
0.3678
Epoch 7/100
49/49 [==============================] - 3s 69ms/step - loss: 0.6937 - accuracy:
0.5488 - auc: 0.5683 - precision: 0.5467 - recall: 0.5421 - val_loss: 0.6682 -
val_accuracy: 0.6165 - val_auc: 0.6574 - val_precision: 0.6410 - val_recall:
0.5668
Epoch 8/100
49/49 [==============================] - 3s 69ms/step - loss: 0.6789 - accuracy:
0.5820 - auc: 0.6086 - precision: 0.5712 - recall: 0.6392 - val_loss: 0.6428 -
val_accuracy: 0.6281 - val_auc: 0.6757 - val_precision: 0.6280 - val_recall:
0.6675
Epoch 9/100
49/49 [==============================] - 3s 68ms/step - loss: 0.6507 - accuracy:
0.6006 - auc: 0.6450 - precision: 0.5836 - recall: 0.6872 - val_loss: 0.6228 -
val_accuracy: 0.6757 - val_auc: 0.7364 - val_precision: 0.6436 - val_recall:
0.8186
Epoch 10/100
49/49 [==============================] - 3s 69ms/step - loss: 0.6237 - accuracy:
0.6319 - auc: 0.6931 - precision: 0.6206 - recall: 0.6684 - val_loss: 0.5970 -
val_accuracy: 0.6834 - val_auc: 0.7505 - val_precision: 0.6332 - val_recall:
0.9043
Epoch 11/100
49/49 [==============================] - 3s 69ms/step - loss: 0.6018 - accuracy:
0.6631 - auc: 0.7374 - precision: 0.6479 - recall: 0.7066 - val_loss: 0.5691 -
val_accuracy: 0.6602 - val_auc: 0.7758 - val_precision: 0.6157 - val_recall:
0.8917
Epoch 12/100
49/49 [==============================] - 3s 68ms/step - loss: 0.5616 - accuracy:
0.6953 - auc: 0.7781 - precision: 0.6728 - recall: 0.7539 - val_loss: 0.5432 -
val_accuracy: 0.7079 - val_auc: 0.8079 - val_precision: 0.7607 - val_recall:
0.6247
Epoch 13/100
49/49 [==============================] - 3s 69ms/step - loss: 0.5282 - accuracy:
0.7192 - auc: 0.8069 - precision: 0.7005 - recall: 0.7604 - val_loss: 0.5991 -
val_accuracy: 0.7143 - val_auc: 0.7621 - val_precision: 0.6606 - val_recall:
0.9068
Epoch 14/100
49/49 [==============================] - 3s 70ms/step - loss: 0.4969 - accuracy:
0.7456 - auc: 0.8329 - precision: 0.7116 - recall: 0.8212 - val_loss: 0.4748 -
val_accuracy: 0.7838 - val_auc: 0.8576 - val_precision: 0.7657 - val_recall:
0.8312
Epoch 15/100
```

```
49/49 [==============================] - 3s 68ms/step - loss: 0.4696 - accuracy:
0.7778 - auc: 0.8582 - precision: 0.7485 - recall: 0.8329 - val_loss: 0.4545 -
val_accuracy: 0.8018 - val_auc: 0.8613 - val_precision: 0.7845 - val_recall:
0.8438
Epoch 16/100
49/49 [==============================] - 3s 69ms/step - loss: 0.4723 - accuracy:
0.7646 - auc: 0.8551 - precision: 0.7634 - recall: 0.7630 - val_loss: 0.4309 -
val_accuracy: 0.8069 - val_auc: 0.8805 - val_precision: 0.7826 - val_recall:
0.8615
Epoch 17/100
49/49 [==============================] - 3s 68ms/step - loss: 0.4494 - accuracy:
0.7942 - auc: 0.8732 - precision: 0.7698 - recall: 0.8361 - val_loss: 0.4209 -
val_accuracy: 0.8198 - val_auc: 0.8827 - val_precision: 0.7800 - val_recall:
0.9018
Epoch 18/100
49/49 [==============================] - 3s 68ms/step - loss: 0.4163 - accuracy:
0.8068 - auc: 0.8865 - precision: 0.7763 - recall: 0.8588 - val_loss: 0.3918 -
val_accuracy: 0.8366 - val_auc: 0.8980 - val_precision: 0.8111 - val_recall:
0.8866
Epoch 19/100
49/49 [==============================] - 3s 67ms/step - loss: 0.4010 - accuracy:
0.8161 - auc: 0.8946 - precision: 0.7901 - recall: 0.8582 - val_loss: 0.4333 -
val_accuracy: 0.7773 - val_auc: 0.8922 - val_precision: 0.8237 - val_recall:
0.7179
Epoch 20/100
49/49 [==============================] - 3s 68ms/step - loss: 0.4033 - accuracy:
0.8148 - auc: 0.8951 - precision: 0.7739 - recall: 0.8867 - val_loss: 0.4041 -
val_accuracy: 0.8069 - val_auc: 0.8934 - val_precision: 0.7947 - val_recall:
0.8388
Epoch 21/100
49/49 [==============================] - 3s 67ms/step - loss: 0.3890 - accuracy:
0.8209 - auc: 0.9025 - precision: 0.7930 - recall: 0.8659 - val_loss: 0.4003 -
val_accuracy: 0.8237 - val_auc: 0.9038 - val_precision: 0.7664 - val_recall:
0.9421
Epoch 22/100
49/49 [==============================] - 3s 68ms/step - loss: 0.3613 - accuracy:
0.8309 - auc: 0.9184 - precision: 0.8097 - recall: 0.8627 - val_loss: 0.3636 -
val_accuracy: 0.8430 - val_auc: 0.9131 - val_precision: 0.8146 - val_recall:
0.8967
Epoch 23/100
49/49 [==============================] - 3s 67ms/step - loss: 0.3459 - accuracy:
0.8409 - auc: 0.9214 - precision: 0.8121 - recall: 0.8847 - val_loss: 0.3595 -
val_accuracy: 0.8507 - val_auc: 0.9247 - val_precision: 0.8022 - val_recall:
0.9395
Epoch 24/100
49/49 [==============================] - 3s 69ms/step - loss: 0.3443 - accuracy:
0.8464 - auc: 0.9260 - precision: 0.8166 - recall: 0.8912 - val_loss: 0.4439 -
val_accuracy: 0.7928 - val_auc: 0.8605 - val_precision: 0.7389 - val_recall:
```

```
0.9194
Epoch 25/100
49/49 [==============================] - 3s 70ms/step - loss: 0.3540 - accuracy:
0.8303 - auc: 0.9187 - precision: 0.8065 - recall: 0.8666 - val_loss: 0.3627 -
val_accuracy: 0.8237 - val_auc: 0.9156 - val_precision: 0.8009 - val_recall:
0.8715
Epoch 26/100
49/49 [==============================] - 3s 69ms/step - loss: 0.3199 - accuracy:
0.8548 - auc: 0.9334 - precision: 0.8314 - recall: 0.8880 - val_loss: 0.3590 -
val_accuracy: 0.8288 - val_auc: 0.9162 - val_precision: 0.7661 - val_recall:
0.9572
Epoch 27/100
49/49 [==============================] - 3s 69ms/step - loss: 0.3082 - accuracy:
0.8612 - auc: 0.9389 - precision: 0.8322 - recall: 0.9028 - val_loss: 0.3082 -
val_accuracy: 0.8674 - val_auc: 0.9416 - val_precision: 0.8789 - val_recall:
0.8589
Epoch 28/100
49/49 [==============================] - 3s 66ms/step - loss: 0.3053 - accuracy:
0.8567 - auc: 0.9407 - precision: 0.8332 - recall: 0.8899 - val_loss: 0.3589 -
val_accuracy: 0.8546 - val_auc: 0.9123 - val_precision: 0.8034 - val_recall:
0.9471
Epoch 29/100
49/49 [==============================] - 3s 67ms/step - loss: 0.3077 - accuracy:
0.8576 - auc: 0.9398 - precision: 0.8352 - recall: 0.8892 - val_loss: 0.3262 -
val_accuracy: 0.8739 - val_auc: 0.9363 - val_precision: 0.8453 - val_recall:
0.9219
Epoch 30/100
49/49 [==============================] - 3s 66ms/step - loss: 0.2815 - accuracy:
0.8776 - auc: 0.9508 - precision: 0.8665 - recall: 0.8912 - val_loss: 0.3431 -
val_accuracy: 0.8468 - val_auc: 0.9267 - val_precision: 0.8697 - val_recall:
0.8237
Epoch 31/100
49/49 [==============================] - 3s 66ms/step - loss: 0.2816 - accuracy:
0.8741 - auc: 0.9504 - precision: 0.8556 - recall: 0.8983 - val_loss: 0.3289 -
val_accuracy: 0.8430 - val_auc: 0.9389 - val_precision: 0.8917 - val_recall:
0.7884
Epoch 32/100
49/49 [==============================] - ETA: 0s - loss: 0.2933 - accuracy:
0.8680 - auc: 0.9464 - precision: 0.8607 - recall: 0.8763Restoring model weights
from the end of the best epoch.
49/49 [==============================] - 3s 67ms/step - loss: 0.2933 - accuracy:
0.8680 - auc: 0.9464 - precision: 0.8607 - recall: 0.8763 - val_loss: 0.3452 -
val_accuracy: 0.8237 - val_auc: 0.9185 - val_precision: 0.8186 - val_recall:
0.8413
Epoch 00032: early stopping
training  model takes 110.419 seconds
```

[82]:
```
# calculate weighted accuracy on test data
pred_prob = model1.predict(feature_test).reshape(len(y_test))
pred_test = np.zeros(len(y_test))
pred_test[pred_prob>0.5] = 1

weight_test = np.zeros(len(y_test))
for v in np.unique(y_test):
    weight_test[y_test==v] = 0.5*len(y_test)/np.sum(y_test==v)
weighted_acc = np.sum(weight_test * (pred_test==y_test)/np.sum(weight_test))
```

[94]:
```
test_start = time.time()
eval = model1.evaluate(feature_test, y_test)
test_end = time.time()
print('Test accuracy: {:.2f}'.format(eval[1]))
print('Test weighted accuracy: {:.3f}'.format(weighted_acc))
print('Test auc: {:.3f}'.format(eval[2]))
print('Testing takes {:.2f} seconds'.format(test_end-test_start))
```

```
19/19 [==============================] - 0s 11ms/step - loss: 0.4495 - accuracy:
0.8050 - auc: 0.8306 - precision: 0.5764 - recall: 0.5971
Test accuracy: 0.81
Test weighted accuracy: 0.732
Test auc: 0.831
Testing takes 0.30 seconds
```

4.4 4. Visualization

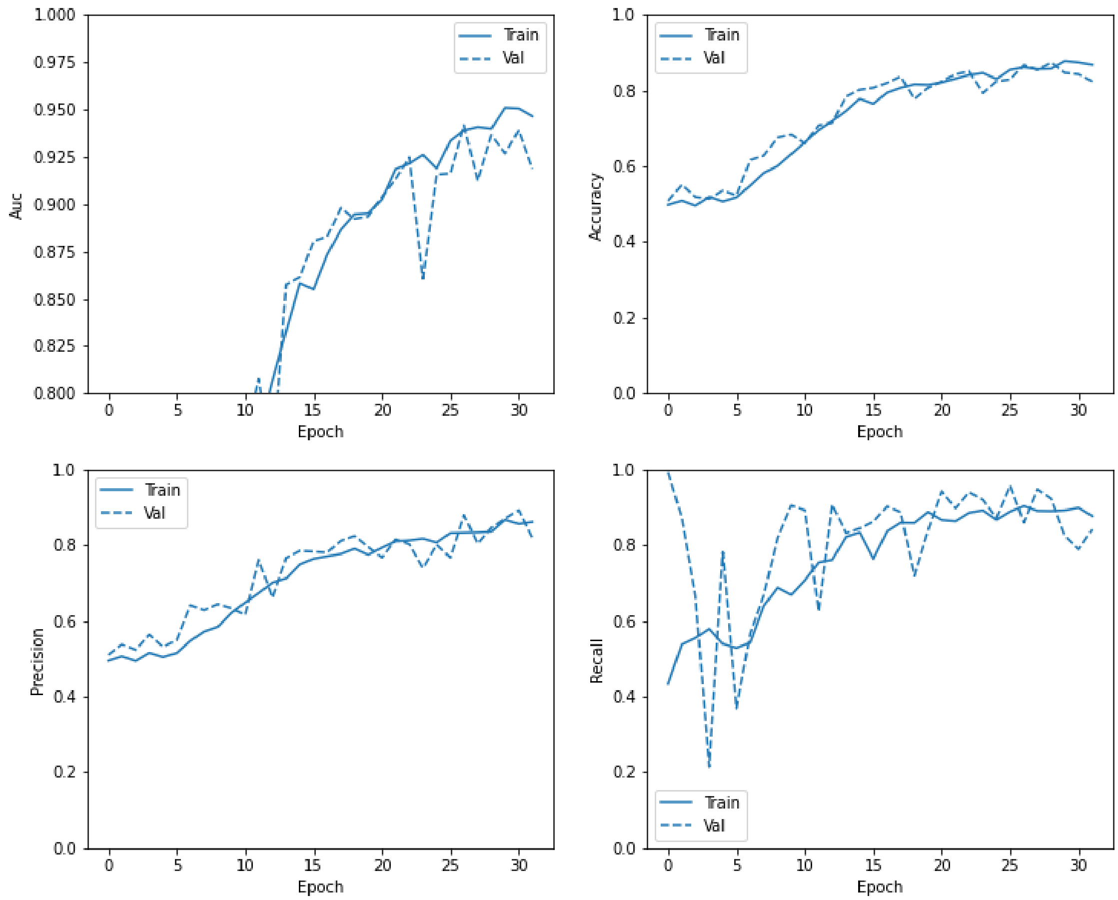
[48]:
```
import matplotlib as mpl
from matplotlib import pyplot as plt
mpl.rcParams['figure.figsize'] = (12, 10)
colors = plt.rcParams['axes.prop_cycle'].by_key()['color']

def plot_metrics(history):
  metrics =  ['auc', 'accuracy', 'precision', 'recall']
  for n, metric in enumerate(metrics):
    name = metric.replace("_"," ").capitalize()
    plt.subplot(2,2,n+1)
    plt.plot(history.epoch,  history.history[metric], color=colors[0],␣
 ↪label='Train')
    plt.plot(history.epoch, history.history['val_'+metric],
             color=colors[0], linestyle="--", label='Val')
    plt.xlabel('Epoch')
    plt.ylabel(name)
    if metric == 'loss':
      plt.ylim([0, plt.ylim()[1]])
    elif metric == 'auc':
      plt.ylim([0.8,1])
```

```
    else:
      plt.ylim([0,1])

    plt.legend()
```

[84]:
```
plot_metrics(resampled_history)
```



4.5 5. Export the model

[96]:
```
export_path_keras = "NNmodel.h5"
model1.save(export_path_keras)

# load the exported model

# NN_model = tf.keras.models.load_model(
#    export_path_keras,
#    custom_objects={'KerasLayer': hub.KerasLayer})
```

5 Part IV Comparison

The densely connected neural network is chosen from all the models we experimented for its running time and performance on accuracy and auc. The results and the links for other models we tried are shown below.

Model	Accuracy	Weighted Accuracy	AUC	Train Time	Test time	Link
Baseline Model (GBT)	0.78	0.70	0.79	7.13 s	0.02 s	GBT
XGBoost	0.81	0.72	0.83	37.21 s	0.06 s	XGBoost
Random Forest	0.80	0.58	0.81	8.38 s	0.23 s	Random Forest
SVM	0.66	0.71	0.79	51.37 s	7.87 s	SVM
Neural Networks	0.81	0.73	0.83	110.419 s	0.3 s	NN
CNN	0.52	0.52	0.51	278 s	25 s	CNN
KNN	0.76	0.50	0.51	73.33 s	15.2 s	KNN
LDA	0.70	0.53	0.68	20.34 s		LDA
LDA with PCA	0.72	0.59	0.8	0.02s		LDA with PCA