ImplementMLProjectPlan

August 11, 2023

1 Lab 8: Implement Your Machine Learning Project Plan

In this lab assignment, you will implement the machine learning project plan you created in the written assignment. You will:

1. Load your data set and save it to a Pandas DataFrame.
2. Perform exploratory data analysis on your data to determine which feature engineering and data preparation techniques you will use.
3. Prepare your data for your model and create features and a label.
4. Fit your model to the training data and evaluate your model.
5. Improve your model by performing model selection and/or feature selection techniques to find best model for your problem.

1.0.1 Import Packages

Before you get started, import a few packages.

[2]:
```
import pandas as pd
import numpy as np
import os
import matplotlib.pyplot as plt
import seaborn as sns
```

Task: In the code cell below, import additional packages that you have used in this course that you will need for this task.

[3]:
```
# YOUR CODE HERE
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.metrics import plot_roc_curve, accuracy_score, roc_auc_score
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.metrics import roc_curve, auc
import tensorflow.keras as keras
import time
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import RandomizedSearchCV
from sklearn.ensemble import StackingClassifier
```

1.1 Part 1: Load the Data Set

You have chosen to work with one of four data sets. The data sets are located in a folder named "data." The file names of the three data sets are as follows:

- The "adult" data set that contains Census information from 1994 is located in file `adultData.csv`
- The airbnb NYC "listings" data set is located in file `airbnbListingsData.csv`
- The World Happiness Report (WHR) data set is located in file `WHR2018Chapter2OnlineData.csv`
- The book review data set is located in file `bookReviewsData.csv`

Task: In the code cell below, use the same method you have been using to load your data using `pd.read_csv()` and save it to DataFrame `df`.

[4]:
```
# YOUR CODE HERE
bookReviewDataSet_filename = os.path.join(os.getcwd(), "data", "bookReviewsData.
↪csv")
df = pd.read_csv(bookReviewDataSet_filename, header = 0)
df.head()
```

[4]:
```
                                              Review  Positive Review
0  This was perhaps the best of Johannes Steinhof...             True
1  This very fascinating book is a story written ...             True
2  The four tales in this collection are beautifu...             True
3  The book contained more profanity than I expec...            False
4  We have now entered a second time of deep conc...             True
```

1.2 Part 2: Exploratory Data Analysis

The next step is to inspect and analyze your data set with your machine learning problem and project plan in mind.

This step will help you determine data preparation and feature engineering techniques you will need to apply to your data to build a balanced modeling data set for your problem and model. These data preparation techniques may include: * addressing missingness, such as replacing missing values with means * renaming features and labels * finding and replacing outliers * performing winsorization if needed * performing one-hot encoding on categorical features * performing vectorization for an NLP problem * addressing class imbalance in your data sample to promote fair AI

Think of the different techniques you have used to inspect and analyze your data in this course. These include using Pandas to apply data filters, using the Pandas `describe()` method to get insight into key statistics for each column, using the Pandas `dtypes` property to inspect the data type of each column, and using Matplotlib and Seaborn to detect outliers and visualize relationships between features and labels. If you are working on a classification problem, use techniques you have learned to determine if there is class imbalance.

Task: Use the techniques you have learned in this course to inspect and analyze your data.

Note: You can add code cells if needed by going to the Insert menu and clicking on Insert Cell Below in the drop-drown menu.

[5]:
```
# YOUR CODE HERE

#addressing missingness
print(df.isnull().sum())

#addressing class imbalance
positive_reviews = df['Positive Review'].value_counts('True')
negative_reviews = df['Positive Review'].value_counts('False')

print('negative reviews: ', negative_reviews,'positive reviews: ',␣
↪positive_reviews)

print(df.describe())

print(df.dtypes)
```

```
Review             0
Positive Review    0
dtype: int64
negative reviews:  False    0.503294
True     0.496706
Name: Positive Review, dtype: float64 positive reviews:  False    0.503294
True     0.496706
Name: Positive Review, dtype: float64
                                                   Review Positive Review
count                                                1973            1973
unique                                               1865               2
top     I have read several of Hiaasen's books and lov...           False
freq                                                    3             993
Review             object
Positive Review      bool
dtype: object
```

1.3 Part 3: Implement Your Project Plan

Task: Use the rest of this notebook to carry out your project plan. You will:

1. Prepare your data for your model and create features and a label.
2. Fit your model to the training data and evaluate your model.
3. Improve your model by performing model selection and/or feature selection techniques to find best model for your problem.

Add code cells below and populate the notebook with commentary, code, analyses, results, and figures as you see fit.

[6]:
```
#creating x and y
y = df['Positive Review']
X = df['Review']
```

```
#splitting data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.20,␣
 ↪random_state = 1234)

#performing vectorization
tfidf_vectorizer = TfidfVectorizer()

tfidf_vectorizer.fit(X_train)

X_train_tfidf = tfidf_vectorizer.transform(X_train)
X_test_tfidf = tfidf_vectorizer.transform(X_test)

vocabulary_size = len(tfidf_vectorizer.vocabulary_)

print(vocabulary_size)
```

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[6]:
```
#Decision Tree
def train_test_DT(X_train, X_test, y_train, y_test, leaf, depth,␣
 ↪crit='entropy'):

     # 1. Create the  Scikit-learn DecisionTreeClassifier model object below␣
 ↪and assign to variable 'model'
    dt_model = DecisionTreeClassifier(criterion = crit, max_depth = depth,␣
 ↪min_samples_leaf = leaf)

    # 2. Fit the model to the training data below
    dt_model.fit(X_train, y_train)

    # 3. Make predictions on the test data below and assign the result to the␣
 ↪variable 'class_label_predictions'
    class_label_predictions_dt = dt_model.predict(X_test)

    # 4. Compute the accuracy here and save the result to the variable␣
 ↪'acc_score'
    acc_score = accuracy_score(y_test, class_label_predictions_dt)


    return acc_score
```

[7]:
```
depth1 = 2
depth2 = 50
leaf = 1

max_depth_range = [17,18,19,20,21,22,23,46,47,48,49,depth2]
acc = []
```

```
for md in max_depth_range:
    score = train_test_DT(X_train_tfidf.toarray(), X_test_tfidf.toarray(),␣
 ↪y_train, y_test, 1, md)
    print('Depth=' + str(md) + ', accuracy score: ' + str(score))
    acc.append(float(score))

print(acc)
```

```
Depth=17, accuracy score: 0.6227848101265823
Depth=18, accuracy score: 0.6329113924050633
Depth=19, accuracy score: 0.640506329113924
Depth=20, accuracy score: 0.6531645569620254
Depth=21, accuracy score: 0.6227848101265823
Depth=22, accuracy score: 0.6455696202531646
Depth=23, accuracy score: 0.6455696202531646
Depth=46, accuracy score: 0.640506329113924
Depth=47, accuracy score: 0.6379746835443038
Depth=48, accuracy score: 0.6303797468354431
Depth=49, accuracy score: 0.6379746835443038
Depth=50, accuracy score: 0.6455696202531646
[0.6227848101265823, 0.6329113924050633, 0.640506329113924, 0.6531645569620254,
0.6227848101265823, 0.6455696202531646, 0.6455696202531646, 0.640506329113924,
0.6379746835443038, 0.6303797468354431, 0.6379746835443038, 0.6455696202531646]
```

[8]:
```
# Create a range of hyperparameter values for 'max_depth'.
#Note these are the same values as those used above
hyperparams_depth = [2*n for n in range(2,15)]

# Create a range of hyperparameter values for 'min_samples_leaf'.
hyperparams_leaf = [25*2**n for n in range(0,3)]

# Create parameter grid.
param_grid={'max_depth':hyperparams_depth, 'min_samples_leaf':hyperparams_leaf}
param_grid
```

[8]:
```
{'max_depth': [4, 6, 8, 10, 12, 14, 16, 18, 20, 22, 24, 26, 28],
 'min_samples_leaf': [25, 50, 100]}
```

[9]:
```
print('Running Grid Search...')

DT_model = DecisionTreeClassifier()

# Run a Grid Search with 5-fold cross-validation using the model.
grid = GridSearchCV(DT_model, param_grid, cv=5)

# Fit the model on the training data and assign the fitted model to the
#    variable grid_search
```

```
grid_search = grid.fit(X_train_tfidf.toarray(), y_train)

print('Done')

# Print best-performing hyperparameter configuration
print('Optimal hyperparameters: {0}'.format(grid_search.best_params_))

# print best accuracy score resulting from this configuration
print('Accuracy score: {0}'.format(grid_search.best_score_))
```

```
Running Grid Search...
Done
Optimal hyperparameters: {'max_depth': 8, 'min_samples_leaf': 25}
Accuracy score: 0.6698191681735985
```

Best Hyperparameters: - max_depth = 8 - min_samples_leaf = 25
AUC: 0.706850579427751

[10]:
```
dt_model = DecisionTreeClassifier(max_depth = 8, min_samples_leaf = 25)
dt_model.fit(X_train_tfidf.toarray(), y_train)
predictions_proba = dt_model.predict_proba(X_test_tfidf.toarray())[:, 1]
auc = roc_auc_score(y_test, predictions_proba)
print("AUC:", auc)
```

```
AUC: 0.7051840836837248
```

[11]:
```
# Random Forest
print('Begin Random Forest Implementation...')
# 1. Create the RandomForestClassifier model object below and assign to␣
 ↪variable 'rf_20_model'
rf_20_model = RandomForestClassifier(criterion='entropy', n_estimators=20)

# 2. Fit the model to the training data below
rf_20_model.fit(X_train_tfidf.toarray(), y_train)

# 3. Make predictions on the test data using the predict_proba() method and␣
 ↪assign the result to a
# list named 'rf_20_predictions' below
rf_20_predictions = rf_20_model.predict_proba(X_test_tfidf.toarray())[:,1].
 ↪tolist()

# 4. Create the RandomForestClassifier model object below and assign to␣
 ↪variable 'rf_100_model'
rf_100_model = RandomForestClassifier(criterion='entropy', n_estimators=100)

# 5. Fit the model to the training data below
rf_100_model.fit(X_train_tfidf.toarray(), y_train)
```

```
# 6. Make predictions on the test data using the predict_proba() method and␣
↪assign the result to a
# list named 'rf_100_predictions' below
rf_100_predictions = rf_100_model.predict_proba(X_test_tfidf.toarray())[:,1].
↪tolist()

print('End')
```

```
Begin Random Forest Implementation...
End
```

[12]:
```
print('Computing ROC Curve...')

#1. Use roc_curve to record fpr and tpr for rf_20_model
fpr_20, tpr_20, thresholds_20 = roc_curve(y_test, rf_20_predictions)

#2. Use roc_curve to record fpr and tpr for rf_100_model
fpr_100, tpr_100, thresholds_100 = roc_curve(y_test, rf_100_predictions)

print('End')
```

```
Computing ROC Curve...
End
```

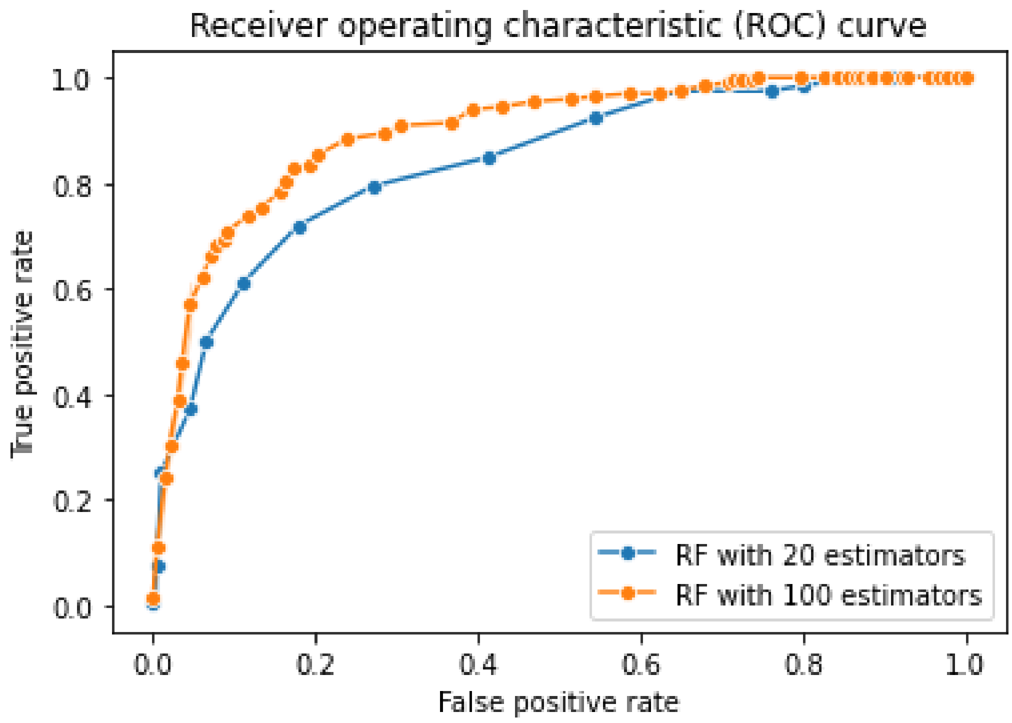
[13]:
```
auc_20 = roc_auc_score(y_test, rf_20_predictions)

print("AUC of the RF model with 20 estimators is {:.3f}".format(auc_20))

# 2. AUC for rf_100_model
auc_100 = roc_auc_score(y_test, rf_100_predictions)

print("AUC of the RF model with 100 estimators is {:.3f}".format(auc_100))
```

```
AUC of the RF model with 20 estimators is 0.840
AUC of the RF model with 100 estimators is 0.898
```

[14]:
```
print('Plotting ROC Curve...')

fig = plt.figure()
ax = fig.add_subplot(111)


sns.lineplot(x=fpr_20, y=tpr_20, marker = 'o')
sns.lineplot(x=fpr_100, y=tpr_100, marker = 'o')

plt.title("Receiver operating characteristic (ROC) curve")
```

```
plt.xlabel("False positive rate")
plt.ylabel("True positive rate")
plt.legend(['RF with 20 estimators', 'RF with 100 estimators'])
plt.show()
```

```
Plotting ROC Curve...
```



Best parameters: - rf model with 200 estimators, min_samples_leaf:4, max_depth:20
auc = 0.907

[15]:
```
# Random Forest Model
rf_model = RandomForestClassifier(criterion='entropy')

# using grid search to find best parameters
rf_param_grid = {
    'n_estimators': [50, 100, 150, 200],
    'max_depth': [None, 10, 20, 30],
    'min_samples_leaf': [1, 2, 4, 6, 8],
}

rf_randomized_search = RandomizedSearchCV(rf_model, rf_param_grid, cv=3,␣
 ↪scoring='accuracy')
rf_randomized_search.fit(X_train_tfidf.toarray(), y_train)

best_params = rf_randomized_search.best_params_
```

```python
print("Best parameters:", best_params)
```

```
Best parameters: {'n_estimators': 200, 'min_samples_leaf': 4, 'max_depth': 20}
```

[16]:
```python
#Best random forest model

rf_best_model = RandomForestClassifier(criterion='entropy', n_estimators=150,␣
    ↪min_samples_leaf=2,max_depth=30)
rf_best_model.fit(X_train_tfidf.toarray(), y_train)
rf_best_predictions = rf_best_model.predict_proba(X_test_tfidf.toarray())[:,1].
    ↪tolist()

print('Computing ROC Curve...')

#Use roc_curve to record fpr and tpr for rf_best_model
fpr_best, tpr_best, thresholds_best = roc_curve(y_test, rf_best_predictions)

print('End')

auc_best = roc_auc_score(y_test, rf_best_predictions)

print("AUC of the RF model with 150 estimators is {:.3f}".format(auc_best))
```

```
Computing ROC Curve...
End
AUC of the RF model with 150 estimators is 0.907
```

[17]:
```python
# GBDT BEST
print('Begin Best GBDT Implementation...')

# 1. Create the GradientBoostingClassifier model object
gbdt_best_model = GradientBoostingClassifier(n_estimators = 200, max_depth = 2)

# 2. Fit the model to the training data below
gbdt_best_model.fit(X_train_tfidf.toarray(), y_train)

# 3. Make predictions on the test data using the predict_proba() method
gbdt_best_predictions = gbdt_best_model.predict_proba(X_test_tfidf.toarray())[:
    ↪,1].tolist()

print('End')
```

```
Begin Best GBDT Implementation...
End
```

[20]:
```
# AUC for gbdt_best_model
auc_gbdt_best = roc_auc_score(y_test, gbdt_best_predictions)

print("AUC of the GBDT model with a max depth of 2 is {:.3f}".
 ↪format(auc_gbdt_best))
```

```
AUC of the GBDT model with a max depth of 2 is 0.878
```

n_estimators = 50 - AUC of the GBDT model with a max depth of 2 is 0.838 - AUC of the GBDT model with a max depth of 10 is 0.855

n_estimators = 100 - AUC of the GBDT model with a max depth of 10 is 0.873 - AUC of the GBDT model with a max depth of 2 is 0.866

n_estimators = 200 - AUC of the GBDT model with a max depth of 2 is 0.879 - AUC of the GBDT model with a max depth of 10 is 0.877

[ ]:
```
print('Plotting ROC Curve...')

fig = plt.figure()
ax = fig.add_subplot(111)

sns.lineplot(x=fpr_gbdt_best, y=tpr_gbdt_best, marker = 'o')

plt.title("Receiver operating characteristic (ROC) curve")
plt.xlabel("False positive rate")
plt.ylabel("True positive rate")
plt.legend(['BEST GBDT MODEL'])
plt.show()
```

With best parameters, make the optimal model

[21]:
```
# 1. Create model object
nn_model = keras.Sequential()

# 2. Create the input layer and add it to the model object:

# Create input layer:
input_layer = keras.layers.InputLayer(input_shape=(vocabulary_size,))

# Add input_layer to the model object:
nn_model.add(input_layer)


# 3. Create the first hidden layer and add it to the model object:

# Create input layer:
hidden_layer_1 = keras.layers.Dense(units=64, activation = 'relu')

# Add hidden_layer_1 to the model object:
nn_model.add(hidden_layer_1)
nn_model.add(keras.layers.Dropout(.25))
```

```python
# 4. Create the second layer and add it to the model object:

# Create input layer:
hidden_layer_2 = keras.layers.Dense(units=32, activation = 'relu')

# Add hidden_layer_2 to the model object:
nn_model.add(hidden_layer_2)
nn_model.add(keras.layers.Dropout(.25))

# 5. Create the third layer and add it to the model object:

# Create input layer:
hidden_layer_3 = keras.layers.Dense(units=16, activation='relu')

# Add hidden_layer_3 to the model object:
nn_model.add(hidden_layer_3)
nn_model.add(keras.layers.Dropout(.25))

# 6. Create the output layer and add it to the model object:

# Create input layer:
output_layer = keras.layers.Dense(units = 1, activation='sigmoid')

# Add output_layer to the model object:
nn_model.add(output_layer)


# Print summary of neural network model structure
nn_model.summary()
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense (Dense)                (None, 64)                1217920
_________________________________________________________________
dropout (Dropout)            (None, 64)                0
_________________________________________________________________
dense_1 (Dense)              (None, 32)                2080
_________________________________________________________________
dropout_1 (Dropout)          (None, 32)                0
_________________________________________________________________
dense_2 (Dense)              (None, 16)                528
_________________________________________________________________
dropout_2 (Dropout)          (None, 16)                0
_________________________________________________________________
```

```
dense_3 (Dense)             (None, 1)                 17
=================================================================
Total params: 1,220,545
Trainable params: 1,220,545
Non-trainable params: 0
_________________________________________________________________
```

[22]:
```
sgd_optimizer = keras.optimizers.SGD(learning_rate = 0.1)

loss_fn = keras.losses.BinaryCrossentropy(from_logits=False)

nn_model.compile(optimizer=sgd_optimizer, loss=loss_fn, metrics=['accuracy'])
```

[23]:
```
class ProgBarLoggerNEpochs(keras.callbacks.Callback):

    def __init__(self, num_epochs: int, every_n: int = 50):
        self.num_epochs = num_epochs
        self.every_n = every_n

    def on_epoch_end(self, epoch, logs=None):
        if (epoch + 1) % self.every_n == 0:
            s = 'Epoch [{}/ {}]'.format(epoch + 1, self.num_epochs)
            logs_s = ['{}: {:.4f}'.format(k.capitalize(), v)
                      for k, v in logs.items()]
            s_list = [s] + logs_s
            print(', '.join(s_list))
```

[24]:
```
t0 = time.time() # start time

#epochs

num_epochs = 50  # You can adjust this value based on your experimentation

# Train the model using batches of training data
history = nn_model.fit(X_train_tfidf.toarray(), y_train, epochs = num_epochs,␣
↪verbose = 0, callbacks = [ProgBarLoggerNEpochs(num_epochs, every_n = 50)],␣
↪validation_split = 0.2)


t1 = time.time() # stop time
#
print('Elapsed time: %.2fs' % (t1-t0))

loss, accuracy = nn_model.evaluate(X_test_tfidf.toarray(), y_test)
loss_train, accuracy_train = nn_model.evaluate(X_train_tfidf.toarray(), y_train)

print('Loss: ', str(loss) , 'Accuracy: ', str(accuracy))
print('Loss: ', str(loss_train) , 'Accuracy: ', str(accuracy_train))
```

```
Epoch [50/ 50], Loss: 0.3780, Accuracy: 0.9049, Val_loss: 0.4397, Val_accuracy:
0.7880
Elapsed time: 38.93s
13/13 [==============================] - 0s 10ms/step - loss: 0.4121 - accuracy:
0.8253
50/50 [==============================] - 0s 7ms/step - loss: 0.1400 - accuracy:
0.9575
Loss:  0.4121495187282562 Accuracy:  0.8253164291381836
Loss:  0.13998398184776306 Accuracy:  0.9575411677360535
```

[25]:
```
nn_predictions = nn_model.predict(X_test_tfidf.toarray())
auc_score = roc_auc_score(y_test, nn_predictions)
auc_score
```

[25]:
```
0.9025228181724951
```

Try to find best parameters for neural network model
compare each one's auc
Ranking based on auc score: 1. Random Forest model - 0.906 2. Neural Network model - 0.903 3. Gradient Boosting Decision Tree model - 0.878 4. Decision Tree model - 0.705

1.4 On different runs, neural network performs better. Interchangeable!

couldn't perform grid search cross validation on gradient boosting as it took too long and did it manually

try stacking model with all these models combined

[ ]:
```
#TAKES TOO LONG TO RUN - tried simplifying the stack by taking decision tree␣
↪and neural network but won't work

estimators = [("RF", RandomForestClassifier()),
              ("GBDT", GradientBoostingClassifier()),
             ]

stacking_model = StackingClassifier(estimators = estimators, cv = 3,␣
↪passthrough = False)

print('Performing Cross-Validation...')

# Choose an appropriate classification scoring metric (e.g., accuracy)
accuracy_avg = np.mean(cross_val_score(stacking_model, X_train_tfidf.toarray(),␣
↪y_train, cv=3, scoring='accuracy'))

print('End')
print('average accuracy: {}'.format(accuracy_avg))

stacking_model.fit(X_train_tfidf.toarray(), y_train)

stacking_predictions = stacking_model.predict(X_test_tfidf.toarray())
```

```
auc_stacking = roc_auc_score(y_test, stacking_predictions)
```

[ ]:

```

```