ML Models and Prediction

May 21, 2020

ENGR350

Introduction Data Science with Python Term - Project

Hotel Booking ML Models and Predictions

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[1]:
```
# importing data libraries

import numpy as np
import pandas as pd

# importing visualization libraries

import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

[2]:
```
# importing models from sklearn and tensorflow.keras

# sklearn classification algorithms
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.svm import SVC
from sklearn.model_selection import cross_val_score, StratifiedKFold
from sklearn.metrics import confusion_matrix

# tensorflow.keras Sequential model
from tensorflow.keras import Sequential
from tensorflow.keras.layers import Dense
from tensorflow.keras.backend import clear_session
```

0.0.1 Read Data:

[3]:
```
data = pd.read_csv('../Data/hotel_bookings_cleaned-2.csv')
```

[4]:
```
data.shape
```

[4]:
```
(118894, 269)
```

[5]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 118894 entries, 0 to 118893
Columns: 269 entries, is_canceled to customer_type_Transient-Party
dtypes: float64(4), int64(265)
memory usage: 244.0 MB
```

[6]:
```
data.columns[data.isnull().any()]
```

[6]:
```
Index([], dtype='object')
```

[7]:
```
data.isnull().values.any()
```

[7]:
```
False
```

[8]:
```
data.describe()

# we have different range of values.
# most of our columns consist dummy variables
```

[8]:

	is_canceled	lead_time	arrival_date_week_number	\
count	118894.000000	118894.000000	118894.000000	
mean	0.371348	104.313784	27.166737	
std	0.483167	106.904302	13.589887	
min	0.000000	0.000000	1.000000	
25%	0.000000	18.000000	16.000000	
50%	0.000000	69.000000	28.000000	
75%	1.000000	161.000000	38.000000	
max	1.000000	737.000000	53.000000	

	stays_in_weekend_nights	stays_in_week_nights	adults	\
count	118894.000000	118894.000000	118894.000000	
mean	0.928878	2.502111	1.855745	
std	0.996181	1.900065	0.488923	
min	0.000000	0.000000	0.000000	
25%	0.000000	1.000000	2.000000	
50%	1.000000	2.000000	2.000000	
75%	2.000000	3.000000	2.000000	
max	16.000000	41.000000	5.000000	

```
            children         babies  is_repeated_guest  booking_changes  …  \
count  118894.000000  118894.000000      118894.000000    118894.000000  …
mean        0.104126       0.007788           0.032012         0.221147  …
std         0.398146       0.089238           0.176032         0.652764  …
min         0.000000       0.000000           0.000000         0.000000  …
25%         0.000000       0.000000           0.000000         0.000000  …
50%         0.000000       0.000000           0.000000         0.000000  …
75%         0.000000       0.000000           0.000000         0.000000  …
max         3.000000       2.000000           1.000000        21.000000  …

       assigned_room_type_K  assigned_room_type_L  assigned_room_type_P  \
count         118894.000000         118894.000000         118894.000000
mean               0.002347              0.000008              0.000017
std                0.048385              0.002900              0.004101
min                0.000000              0.000000              0.000000
25%                0.000000              0.000000              0.000000
50%                0.000000              0.000000              0.000000
75%                0.000000              0.000000              0.000000
max                1.000000              1.000000              1.000000

       deposit_type_No Deposit  deposit_type_Non Refund  \
count            118894.000000            118894.000000
mean                  0.876074                 0.122563
std                   0.329498                 0.327936
min                   0.000000                 0.000000
25%                   1.000000                 0.000000
50%                   1.000000                 0.000000
75%                   1.000000                 0.000000
max                   1.000000                 1.000000

       deposit_type_Refundable  customer_type_Contract  customer_type_Group  \
count            118894.000000           118894.000000        118894.000000
mean                  0.001363                0.034274             0.004794
std                   0.036888                0.181933             0.069074
min                   0.000000                0.000000             0.000000
25%                   0.000000                0.000000             0.000000
50%                   0.000000                0.000000             0.000000
75%                   0.000000                0.000000             0.000000
max                   1.000000                1.000000             1.000000

       customer_type_Transient  customer_type_Transient-Party
count            118894.000000                 118894.000000
mean                  0.750013                      0.210919
std                   0.433007                      0.407963
min                   0.000000                      0.000000
25%                   1.000000                      0.000000
```

```
50%                    1.000000                       0.000000
75%                    1.000000                       0.000000
max                    1.000000                       1.000000

[8 rows x 269 columns]
```

[9]:
```
X = data.drop(['is_canceled'], axis=1).values
y = data['is_canceled'].values
```

[10]:
```
X.shape, y.shape
```

[10]:
```
((118894, 268), (118894,))
```

[11]:
```
train_data_length = X.shape[0]
```

[12]:
```
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X[:train_data_length], y[:
↪train_data_length], test_size=0.1)
```

[13]:
```
X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

[13]:
```
((107004, 268), (11890, 268), (107004,), (11890,))
```

0.0.2 Standardize Data:

[14]:
```
from sklearn.preprocessing import StandardScaler

std = StandardScaler()

X_train = std.fit_transform(X_train)
X_test = std.transform(X_test)
```

[15]:
```
pd.DataFrame(X_train).describe() # result of standardization
```

[15]:
```
                0             1             2             3             4    \
count  1.070040e+05  1.070040e+05  1.070040e+05  1.070040e+05  1.070040e+05
mean   4.294639e-17  3.685388e-17  8.350225e-18  3.354201e-17  3.047915e-17
std    1.000005e+00  1.000005e+00  1.000005e+00  1.000005e+00  1.000005e+00
min   -9.767182e-01 -1.926124e+00 -9.307626e-01 -1.314286e+00 -3.796049e+00
25%   -8.082092e-01 -8.226712e-01 -9.307626e-01 -7.891880e-01  2.956217e-01
50%   -3.307672e-01  6.009089e-02  7.155533e-02 -2.640899e-01  2.956217e-01
75%    5.305009e-01  7.957260e-01  1.073873e+00  2.610082e-01  2.956217e-01
max    5.922788e+00  1.899179e+00  1.510633e+01  2.021474e+01  6.433128e+00

                5             6             7             8             9    \
count  1.070040e+05  1.070040e+05  1.070040e+05  1.070040e+05  1.070040e+05
```

```
mean   3.008073e-17 -2.908468e-17  2.792262e-17  2.747440e-18 -5.046657e-18
std    1.000005e+00  1.000005e+00  1.000005e+00  1.000005e+00  1.000005e+00
min   -2.617225e-01 -8.741091e-02 -1.820614e-01 -3.374246e-01 -1.327995e-01
25%   -2.617225e-01 -8.741091e-02 -1.820614e-01 -3.374246e-01 -1.327995e-01
50%   -2.617225e-01 -8.741091e-02 -1.820614e-01 -3.374246e-01 -1.327995e-01
75%   -2.617225e-01 -8.741091e-02 -1.820614e-01 -3.374246e-01 -1.327995e-01
max    7.266599e+00  2.247789e+01  5.492653e+00  3.173217e+01  2.218791e+01

       …           258           259           260           261  \
count  …  1.070040e+05  1.070040e+05  1.070040e+05  1.070040e+05
mean   … -7.702792e-18  1.531428e-18  1.676685e-18  5.586184e-17
std    …  1.000005e+00  1.000005e+00  1.000005e+00  1.000005e+00
min    … -4.906691e-02 -3.057046e-03 -4.323337e-03 -2.657058e+00
25%    … -4.906691e-02 -3.057046e-03 -4.323337e-03  3.763561e-01
50%    … -4.906691e-02 -3.057046e-03 -4.323337e-03  3.763561e-01
75%    … -4.906691e-02 -3.057046e-03 -4.323337e-03  3.763561e-01
max    …  2.038033e+01  3.271131e+02  2.313028e+02  3.763561e-01

                262           263           264           265           266  \
count  1.070040e+05  1.070040e+05  1.070040e+05  1.070040e+05  1.070040e+05
mean  -3.393213e-17  2.045224e-17  2.008702e-18  1.181980e-17 -6.729983e-17
std    1.000005e+00  1.000005e+00  1.000005e+00  1.000005e+00  1.000005e+00
min   -3.739573e-01 -3.721615e-02 -1.887223e-01 -6.933883e-02 -1.732526e+00
25%   -3.739573e-01 -3.721615e-02 -1.887223e-01 -6.933883e-02  5.771920e-01
50%   -3.739573e-01 -3.721615e-02 -1.887223e-01 -6.933883e-02  5.771920e-01
75%   -3.739573e-01 -3.721615e-02 -1.887223e-01 -6.933883e-02  5.771920e-01
max    2.674102e+00  2.687006e+01  5.298790e+00  1.442193e+01  5.771920e-01

                267
count  1.070040e+05
mean  -1.308147e-17
std    1.000005e+00
min   -5.167004e-01
25%   -5.167004e-01
50%   -5.167004e-01
75%   -5.167004e-01
max    1.935358e+00

[8 rows x 268 columns]
```

[16]:
```python
# PCA Dimension Reduction

from sklearn.decomposition import PCA

pca = PCA(n_components = 0.95)

X_train = pca.fit_transform(X_train)
```

```
X_test = pca.transform(X_test)
```

[17]:
```
X_train.shape, X_test.shape
```

[17]:
```
((107004, 220), (11890, 220))
```

0.0.3 Create Models and Fit with KFold

[18]:
```
import warnings
from tqdm.notebook import tqdm
warnings.filterwarnings('ignore')

kfold = StratifiedKFold(n_splits=10)

# Modeling with different algorithms

state = 42
classifiers = list()

# algorithms = ["SVC","DecisionTree", "RandomForest","GradientBoosting",␣
 ↪"KNeighboors","LogisticRegression",
#               "LinearDiscriminantAnalysis", "Keras"]

algorithms = ["LogisticRegression", "LinearDiscriminantAnalysis", "Keras"]

tree_algorithms = {"DecisionTree": 1, "RandomForest": 2, "GradientBoosting": 3}

# classifiers.append(SVC(random_state=state, kernel='rbf'))
# classifiers.append(DecisionTreeClassifier(random_state=state))
# classifiers.append(RandomForestClassifier(random_state=state))
# classifiers.append(GradientBoostingClassifier(random_state=state))
# classifiers.append(KNeighborsClassifier())
classifiers.append(LogisticRegression(random_state = state))
classifiers.append(LinearDiscriminantAnalysis())

cv_results = dict()

for i in tqdm(range(len(classifiers))):
    cv_results[algorithms[i]] = cross_val_score(classifiers[i], X_train,␣
 ↪y_train, scoring='accuracy', cv = kfold, verbose=1, n_jobs=-1)
```

```
HBox(children=(FloatProgress(value=0.0, max=2.0), HTML(value='')))


[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  10 out of  10 | elapsed:   36.2s finished
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
```

```
[Parallel(n_jobs=-1)]: Done  10 out of  10 | elapsed:   39.0s finished
```

0.0.4 Keras Sequential Model:

[19]:
```
model = Sequential()

model.add(Dense(128, input_shape=(X_train.shape[1],), activation="relu"))
model.add(Dense(256, activation="relu"))
model.add(Dense(128, activation="relu"))
model.add(Dense(1, activation='sigmoid'))

model.compile(loss='binary_crossentropy', optimizer='adam',␣
 ↪metrics=['accuracy'])

model.fit(X_train, y_train, epochs=32, batch_size=128, verbose=1,␣
 ↪validation_split=0.2)
score = model.evaluate(X_test, y_test, verbose=0)

print(score)
```

```
Train on 85603 samples, validate on 21401 samples
Epoch 1/32
85603/85603 [==============================] - 10s 120us/sample - loss: 0.4110 -
accuracy: 0.8046 - val_loss: 0.3619 - val_accuracy: 0.8283
Epoch 2/32
85603/85603 [==============================] - 8s 94us/sample - loss: 0.3475 -
accuracy: 0.8362 - val_loss: 0.3404 - val_accuracy: 0.8393
Epoch 3/32
85603/85603 [==============================] - 8s 94us/sample - loss: 0.3284 -
accuracy: 0.8459 - val_loss: 0.3328 - val_accuracy: 0.8469
Epoch 4/32
85603/85603 [==============================] - 8s 93us/sample - loss: 0.3143 -
accuracy: 0.8524 - val_loss: 0.3261 - val_accuracy: 0.8485
Epoch 5/32
85603/85603 [==============================] - 8s 93us/sample - loss: 0.3041 -
accuracy: 0.8576 - val_loss: 0.3212 - val_accuracy: 0.8541
Epoch 6/32
85603/85603 [==============================] - 9s 105us/sample - loss: 0.2931 -
accuracy: 0.8640 - val_loss: 0.3221 - val_accuracy: 0.8530
Epoch 7/32
85603/85603 [==============================] - 9s 101us/sample - loss: 0.2845 -
accuracy: 0.8676 - val_loss: 0.3207 - val_accuracy: 0.8573
Epoch 8/32
85603/85603 [==============================] - 9s 101us/sample - loss: 0.2740 -
accuracy: 0.8716 - val_loss: 0.3280 - val_accuracy: 0.8537
Epoch 9/32
```

```
85603/85603 [==============================] - 11s 131us/sample - loss: 0.2651 -
accuracy: 0.8779 - val_loss: 0.3251 - val_accuracy: 0.8594
Epoch 10/32
85603/85603 [==============================] - 9s 106us/sample - loss: 0.2556 -
accuracy: 0.8833 - val_loss: 0.3310 - val_accuracy: 0.8564
Epoch 11/32
85603/85603 [==============================] - 8s 95us/sample - loss: 0.2464 -
accuracy: 0.8875 - val_loss: 0.3337 - val_accuracy: 0.8584
Epoch 12/32
85603/85603 [==============================] - 8s 95us/sample - loss: 0.2368 -
accuracy: 0.8918 - val_loss: 0.3355 - val_accuracy: 0.8574
Epoch 13/32
85603/85603 [==============================] - 8s 96us/sample - loss: 0.2259 -
accuracy: 0.8963 - val_loss: 0.3526 - val_accuracy: 0.8558
Epoch 14/32
85603/85603 [==============================] - 8s 98us/sample - loss: 0.2180 -
accuracy: 0.9032 - val_loss: 0.3553 - val_accuracy: 0.8551
Epoch 15/32
85603/85603 [==============================] - 8s 96us/sample - loss: 0.2054 -
accuracy: 0.9084 - val_loss: 0.3674 - val_accuracy: 0.8575
Epoch 16/32
85603/85603 [==============================] - 8s 95us/sample - loss: 0.1975 -
accuracy: 0.9120 - val_loss: 0.3852 - val_accuracy: 0.8566
Epoch 17/32
85603/85603 [==============================] - 8s 97us/sample - loss: 0.1877 -
accuracy: 0.9165 - val_loss: 0.3957 - val_accuracy: 0.8587
Epoch 18/32
85603/85603 [==============================] - 8s 97us/sample - loss: 0.1753 -
accuracy: 0.9219 - val_loss: 0.4267 - val_accuracy: 0.8596
Epoch 19/32
85603/85603 [==============================] - 8s 99us/sample - loss: 0.1675 -
accuracy: 0.9263 - val_loss: 0.4183 - val_accuracy: 0.8549
Epoch 20/32
85603/85603 [==============================] - 8s 99us/sample - loss: 0.1579 -
accuracy: 0.9310 - val_loss: 0.4364 - val_accuracy: 0.8586
Epoch 21/32
85603/85603 [==============================] - 9s 102us/sample - loss: 0.1492 -
accuracy: 0.9364 - val_loss: 0.4510 - val_accuracy: 0.8574
Epoch 22/32
85603/85603 [==============================] - 9s 100us/sample - loss: 0.1431 -
accuracy: 0.9393 - val_loss: 0.4668 - val_accuracy: 0.8574
Epoch 23/32
85603/85603 [==============================] - 8s 97us/sample - loss: 0.1361 -
accuracy: 0.9430 - val_loss: 0.4914 - val_accuracy: 0.8509
Epoch 24/32
85603/85603 [==============================] - 8s 98us/sample - loss: 0.1298 -
accuracy: 0.9446 - val_loss: 0.5024 - val_accuracy: 0.8515
Epoch 25/32
```

```
85603/85603 [==============================] - 8s 96us/sample - loss: 0.1240 -
accuracy: 0.9487 - val_loss: 0.5253 - val_accuracy: 0.8536
Epoch 26/32
85603/85603 [==============================] - 8s 96us/sample - loss: 0.1201 -
accuracy: 0.9510 - val_loss: 0.5587 - val_accuracy: 0.8528
Epoch 27/32
85603/85603 [==============================] - 8s 97us/sample - loss: 0.1131 -
accuracy: 0.9538 - val_loss: 0.5583 - val_accuracy: 0.8535
Epoch 28/32
85603/85603 [==============================] - 9s 100us/sample - loss: 0.1052 -
accuracy: 0.9573 - val_loss: 0.5704 - val_accuracy: 0.8558
Epoch 29/32
85603/85603 [==============================] - 12s 135us/sample - loss: 0.1023 -
accuracy: 0.9585 - val_loss: 0.5752 - val_accuracy: 0.8529
Epoch 30/32
85603/85603 [==============================] - 8s 95us/sample - loss: 0.0986 -
accuracy: 0.9604 - val_loss: 0.5858 - val_accuracy: 0.8532
Epoch 31/32
85603/85603 [==============================] - 6s 69us/sample - loss: 0.0939 -
accuracy: 0.9624 - val_loss: 0.6518 - val_accuracy: 0.8530
Epoch 32/32
85603/85603 [==============================] - 7s 76us/sample - loss: 0.0923 -
accuracy: 0.9626 - val_loss: 0.6147 - val_accuracy: 0.8506
[0.651026355959569, 0.8460891]
```

[20]:
```
cv_results['Keras'] = np.array([score[1]])
```

[21]:
```
cv_means = {}
cv_std = {}

for algorithm in cv_results.keys():
    cv_means[algorithm] = [cv_results[algorithm].mean(), cv_results[algorithm].
 ↪std()]

cv_means = {k: v for k, v in sorted(cv_means.items(), key=lambda item: item[1],␣
 ↪reverse=True)}
cv = np.array(list(cv_means.values()))

cv_df = pd.DataFrame({"Algorithm": list(cv_means.keys()), "CVMean": cv[:, 0],␣
 ↪"CVStd": cv[:, 1]})
```

[22]:
```
cv_df
```

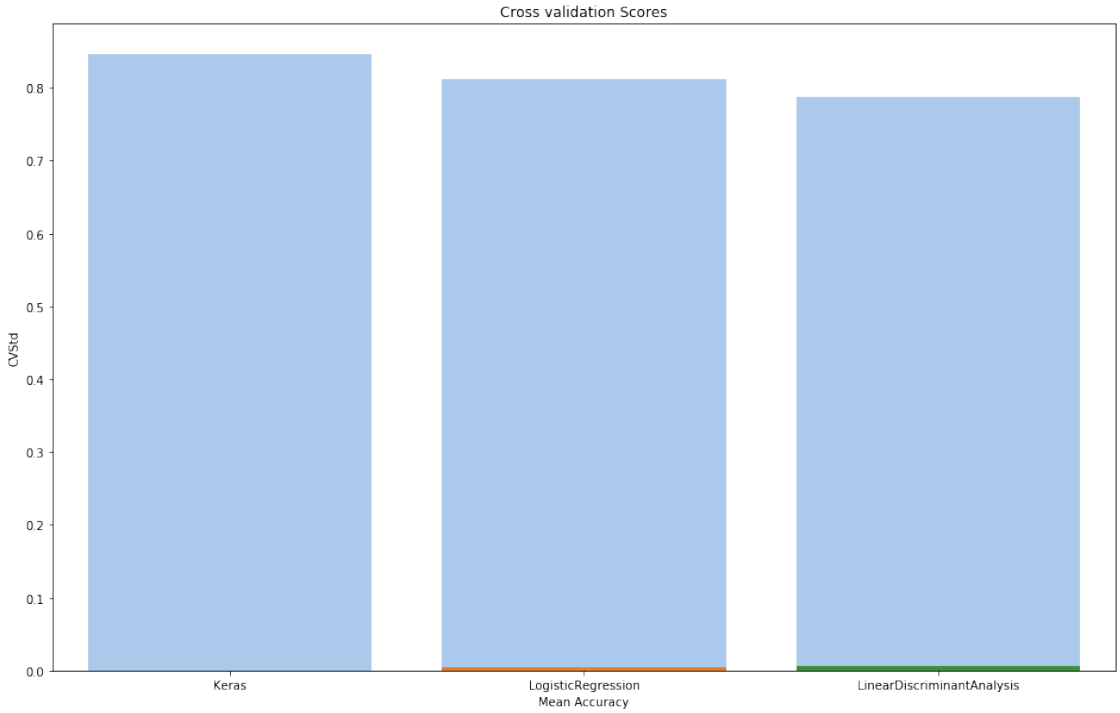
[22]:

	Algorithm	CVMean	CVStd
0	Keras	0.846089	0.000000
1	LogisticRegression	0.811185	0.004038
2	LinearDiscriminantAnalysis	0.787569	0.006361

[23]:
```
plt.figure(figsize=(16, 10))

sns.set_color_codes("pastel")
g = sns.barplot(x='Algorithm', y='CVMean', data=cv_df, color='b')
sns.set_color_codes("muted")
g = sns.barplot(x='Algorithm', y='CVStd', data=cv_df)

g.set_xlabel("Mean Accuracy")
g = g.set_title("Cross validation Scores")
```



[24]:
```
def plot_feature_importance(classifier, name):

    plt.figure(figsize=(16, 8))

    indices = np.argsort(classifier.feature_importances_)[::-1][:20]

    importances = classifier.feature_importances_[indices]
    columns = data.drop(['is_canceled'], axis=1).columns[indices]

    g = sns.barplot(x=importances, y=columns)

    plt.title(name)
    plt.show(g)
```

[26]:
```
# for tree in tree_algorithms.keys():
#     classifiers[tree_algorithms[tree]].fit(X_train, y_train)
#     plot_feature_importance( classifiers[tree_algorithms[tree]], tree)
```

0.0.5 Test Data:

[27]:
```
test_results = dict()

for i in tqdm(range(len(classifiers))):
    classifiers[i].fit(X_train, y_train)
    test_results[algorithms[i]] = classifiers[i].score(X_test, y_test)

test_results['Keras'] = model.evaluate(X_test, y_test, verbose=0)[1]
```

```
HBox(children=(FloatProgress(value=0.0, max=2.0), HTML(value='')))
```

[28]:
```
test_scores = {}

for algorithm in test_results.keys():
    test_scores[algorithm] = test_results[algorithm]

test_results = {k: v for k, v in sorted(test_scores.items(), key=lambda item:␣
↪item[1], reverse=True)}

test_df = pd.DataFrame({"Algorithm": list(cv_means.keys()), "TestScore":␣
↪list(test_results.values())})
```

[29]:
```
test_df
```

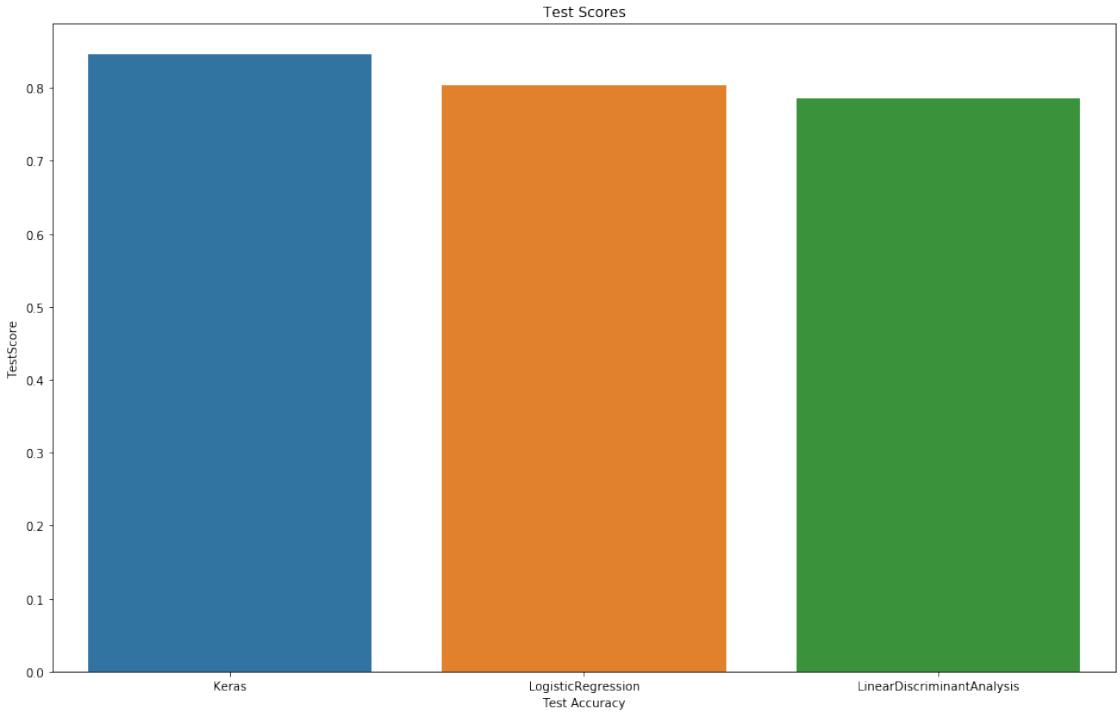
[29]:

	Algorithm	TestScore
0	Keras	0.846089
1	LogisticRegression	0.803701
2	LinearDiscriminantAnalysis	0.785366

[30]:
```
plt.figure(figsize=(16, 10))

g = sns.barplot(x='Algorithm', y='TestScore', data=test_df)

g.set_xlabel("Test Accuracy")
g = g.set_title("Test Scores")
```


Test Scores
TestScore
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
Keras
LogisticRegression
LinearDiscriminantAnalysis
Test Accuracy

[ ]: