PredictFlightOntimePerformance

November 6, 2019

[1]:
```
import pandas as pd
# Read flight data from spreadsheet to 'pandas' model
# read_csv returns a DataFrame (two-D data structure with labeled axes)
flight_data = pd.read_csv('ONTIME_FLIGHT_DATA.csv')
flight_data.head()
```

[1]:
```
   YEAR  MONTH  DAY_OF_MONTH  DAY_OF_WEEK  ORIGIN_AIRPORT_ID  \
0  2019      1            19            6              13487
1  2019      1            20            7              13487
2  2019      1            21            1              13487
3  2019      1            22            2              13487
4  2019      1            23            3              13487

   ORIGIN_AIRPORT_SEQ_ID  ORIGIN_CITY_MARKET_ID ORIGIN  DEST_AIRPORT_ID  \
0                1348702                  31650    MSP            11193
1                1348702                  31650    MSP            11193
2                1348702                  31650    MSP            11193
3                1348702                  31650    MSP            11193
4                1348702                  31650    MSP            11193

   DEST_AIRPORT_SEQ_ID  DEST_CITY_MARKET_ID DEST  CRS_DEP_TIME  ARR_DELAY_NEW  \
0              1119302                33105  CVG          1556            0.0
1              1119302                33105  CVG          1556            0.0
2              1119302                33105  CVG          1556            0.0
3              1119302                33105  CVG          1556            0.0
4              1119302                33105  CVG          1556            0.0

   ARR_DEL15  Unnamed: 15
0        0.0          NaN
1        0.0          NaN
2        0.0          NaN
3        0.0          NaN
4        0.0          NaN
```

[2]:
```
print(type(flight_data))
```

```
<class 'pandas.core.frame.DataFrame'>
```

1 Clean Data

[3]:
```
# before construct a model, need to clean data to remove null values
flight_data.isnull().values.any()
```

[3]:
```
True
```

[4]:
```
flight_data.isnull().sum()
```

[4]:
```
YEAR                          0
MONTH                         0
DAY_OF_MONTH                  0
DAY_OF_WEEK                   0
ORIGIN_AIRPORT_ID             0
ORIGIN_AIRPORT_SEQ_ID         0
ORIGIN_CITY_MARKET_ID         0
ORIGIN                        0
DEST_AIRPORT_ID               0
DEST_AIRPORT_SEQ_ID           0
DEST_CITY_MARKET_ID           0
DEST                          0
CRS_DEP_TIME                  0
ARR_DELAY_NEW             21000
ARR_DEL15                 21000
Unnamed: 15              638649
dtype: int64
```

[5]:
```
flight_data = flight_data.drop('Unnamed: 15', axis=1)
```

[6]:
```
flight_data.isnull().sum()
```

[6]:
```
YEAR                         0
MONTH                        0
DAY_OF_MONTH                 0
DAY_OF_WEEK                  0
ORIGIN_AIRPORT_ID            0
ORIGIN_AIRPORT_SEQ_ID        0
ORIGIN_CITY_MARKET_ID        0
ORIGIN                       0
DEST_AIRPORT_ID              0
DEST_AIRPORT_SEQ_ID          0
DEST_CITY_MARKET_ID          0
DEST                         0
CRS_DEP_TIME                 0
ARR_DELAY_NEW            21000
ARR_DEL15                21000
dtype: int64
```

[7]:
```
# CRS_ARR_TIME        Scheduled arrival time; ARR_DEL15        0=Arrived less␣
↪than 15 minutes late, 1=Arrived 15 minutes or more late
```

```
flight_data = flight_data[['MONTH', 'DAY_OF_MONTH', 'DAY_OF_WEEK', 'ORIGIN',␣
 ↪'DEST', 'CRS_DEP_TIME', 'ARR_DEL15']]
```

[8]:
```
flight_data.isnull().sum()
```

[8]:
```
MONTH              0
DAY_OF_MONTH       0
DAY_OF_WEEK        0
ORIGIN             0
DEST               0
CRS_DEP_TIME       0
ARR_DEL15      21000
dtype: int64
```

[9]:
```
flight_data.shape
```

[9]:
```
(638649, 7)
```

[10]:
```
flight_data = flight_data.fillna({'ARR_DEL15': 1}) # fill NA values with '1' in␣
 ↪ARR_DEL15 column
```

[11]:
```
import numpy as np
# In order to avoid overfitting, divide CRS_DEP_TIME:scheduled arrival time by␣
 ↪100 because it matters more if flight is delayed by hours rather than by a␣
 ↪minutes
flight_data['CRS_DEP_TIME'] = flight_data['CRS_DEP_TIME'].div(100).apply(np.
 ↪floor)
```

[12]:
```
flight_data.head()
```

[12]:
```
   MONTH  DAY_OF_MONTH  DAY_OF_WEEK ORIGIN DEST  CRS_DEP_TIME  ARR_DEL15
0      1            19            6    MSP  CVG          15.0        0.0
1      1            20            7    MSP  CVG          15.0        0.0
2      1            21            1    MSP  CVG          15.0        0.0
3      1            22            2    MSP  CVG          15.0        0.0
4      1            23            3    MSP  CVG          15.0        0.0
```

[13]:
```
# Create dummies for 'ORIGIN' and 'DEST' columns
# These columns need to be converted into discrete columns containing indicator␣
 ↪variables, sometimes known as "dummy" variables.
# With each column containing 1s and 0s indicating whether a flight originated␣
 ↪at the airport that the column represents.
flight_data = pd.get_dummies(flight_data, columns=['ORIGIN', 'DEST'])
flight_data.head()
```

[13]:
```
   MONTH  DAY_OF_MONTH  DAY_OF_WEEK  CRS_DEP_TIME  ARR_DEL15  ORIGIN_ABE  \
0      1            19            6          15.0        0.0           0
1      1            20            7          15.0        0.0           0
2      1            21            1          15.0        0.0           0
3      1            22            2          15.0        0.0           0
4      1            23            3          15.0        0.0           0
```

```
   ORIGIN_ABI  ORIGIN_ABQ  ORIGIN_ABR  ORIGIN_ABY  ...  DEST_UIN  \
0           0           0           0           0  ...         0
1           0           0           0           0  ...         0
2           0           0           0           0  ...         0
3           0           0           0           0  ...         0
4           0           0           0           0  ...         0

   DEST_USA  DEST_VEL  DEST_VLD  DEST_VPS  DEST_WRG  DEST_XNA  DEST_YAK  \
0         0         0         0         0         0         0         0
1         0         0         0         0         0         0         0
2         0         0         0         0         0         0         0
3         0         0         0         0         0         0         0
4         0         0         0         0         0         0         0

   DEST_YKM  DEST_YUM
0         0         0
1         0         0
2         0         0
3         0         0
4         0         0

[5 rows x 725 columns]
```

2 Build Machine Learning Model

[14]:
```
import math
flight_data_first_quarter = flight_data[: math.floor(len(flight_data.index)/4)]
flight_data_first_quarter.shape
```

[14]:
```
(159662, 725)
```

[15]:
```
from sklearn.model_selection import train_test_split
# Split DataFrame: flight data into a training set containing 80% of the␣
↪original data, and a test set containing the remaining 20%
# The random_state parameter seeds the random-number generator used to do the␣
↪splitting, while the first and second parameters are DataFrames containing the␣
↪feature columns and the label column.
train_x, test_x, train_y, test_y = train_test_split(flight_data_first_quarter.
↪drop('ARR_DEL15', axis=1), flight_data_first_quarter['ARR_DEL15'], test_size=0.
↪2, random_state=42)
```

[16]:
```
train_x.shape
```

[16]:
```
(127729, 724)
```

[17]:
```
train_y.shape
```

[17]:
```
(127729,)
```

[18]:
```python
test_x.shape
```

[18]: (31933, 724)

[19]:
```python
test_y.shape
```

[19]: (31933,)

3 Train a classification model

[20]:
```python
# In this project predicting the probability of a flight will deplay, model will␣
↪be a binary classification model that predicts
# whether a flight will arrive on-time or late ("binary" because there are only␣
↪two possible outputs).
# Use RandomForestClassifier which fits multiple decision trees to the data and␣
↪uses averaging to boost the overall accuracy and limit overfitting.
from sklearn.ensemble import RandomForestClassifier
```

[21]:
```python
from sklearn.metrics import mean_absolute_error
def get_mae(max_leaf_nodes, n_estimators, train_x, test_x, train_y, test_y):
    model = RandomForestClassifier(max_leaf_nodes=max_leaf_nodes,␣
↪n_estimators=n_estimators, random_state=3)
    model.fit(train_x, train_y)
    preds_val = model.predict(test_x)
    mae = mean_absolute_error(test_y, preds_val)
    return(mae)
```

[31]:
```python
# compare MAE with differing values of max_leaf_nodes
scores = {leaf_size: get_mae(leaf_size, 10, train_x, test_x, train_y, test_y)␣
↪for leaf_size in [500, 1000, 2000, 2500, 5000, 10000, 20000, 30000, 50000]}
```

[32]:
```python
best_tree_size = min(scores, key=scores.get)
print(best_tree_size)
```

10000

[38]:
```python
tree_scores = {num_of_trees: get_mae(best_tree_size, num_of_trees, train_x,␣
↪test_x, train_y, test_y) for num_of_trees in [10, 20, 30, 50, 60, 100]}
```

[39]:
```python
best_tree_num = min(tree_scores, key=tree_scores.get)
print(best_tree_num)
```

50

[40]:
```python
# 'n_estimators' is the number of trees in the forest
model = RandomForestClassifier(random_state=3, max_leaf_nodes=best_tree_size,␣
↪n_estimators=best_tree_num)
model.fit(train_x, train_y)
```

[40]:
```
RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
             max_depth=None, max_features='auto', max_leaf_nodes=10000,
             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=50, n_jobs=None,
             oob_score=False, random_state=3, verbose=0, warm_start=False)
```

[41]:
```
predicted = model.predict(test_x)
model.score(test_x, test_y)
```

[41]:
```
0.8210628503429055
```

[42]:
```
# One of the best overall measures for a binary classification model is Area␣
 ↪Under Receiver Operating Characteristic Curve
# (sometimes referred to as "ROC AUC"), which essentially quantifies how often␣
 ↪the model will make a correct prediction
# regardless of the outcome.
# Compute an ROC AUC score for the model

from sklearn.metrics import roc_auc_score
probabilities = model.predict_proba(test_x)
```

[43]:
```
roc_auc_score(test_y, probabilities[:, 1])
```

[43]:
```
0.7638784856474098
```

[44]:
```
# The output from the score method reflects how many of the items in the test␣
 ↪set the model predicted correctly.
# This score is skewed by the fact that the dataset the model was trained and␣
 ↪tested with contains
# many more rows representing on-time arrivals than rows representing late␣
 ↪arrivals.
# Because of this imbalance in the data, it's more likely to be correct if you␣
 ↪predict that a flight will be on time than if you predict that a flight will␣
 ↪be late.
# ROC AUC takes this into account and provides a more accurate indication of how␣
 ↪likely it is that a prediction of on-time or late will be correct.
```

4 Confusion Matrix

[45]:
```
# The confusion matrix quantifies the number of times each answer
# was classified correctly or incorrectly. Specifically, it quantifies the
# number of false positives, false negatives, true positives, and true negatives.
```

[46]:
```
from sklearn.metrics import confusion_matrix
confusion_matrix(test_y, predicted)
```

[46]:
```
array([[24424,   476],
       [ 5238,  1795]])
```

5 Precison and Recall

[47]:
```
from sklearn.metrics import precision_score

train_predictions = model.predict(train_x)
precision_score(train_y, train_predictions)
```

[47]: 0.972072952287901

[48]:
```
from sklearn.metrics import recall_score

recall_score(train_y, train_predictions)
```

[48]: 0.42060947683635724

6 Visualize Output of Model

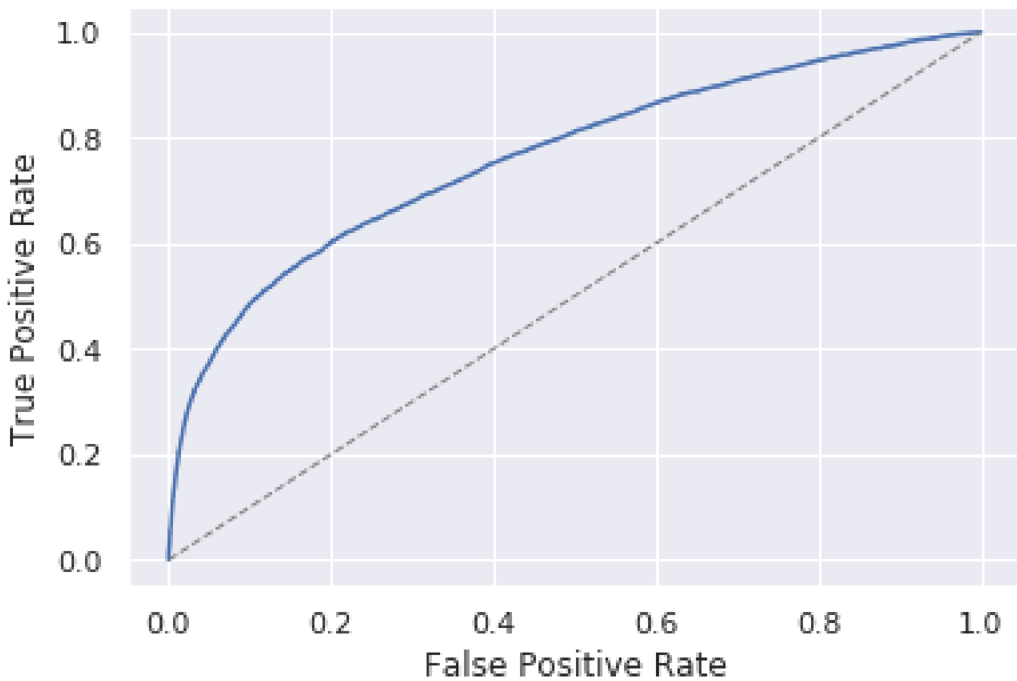
[49]:
```
%matplotlib inline
import matplotlib.pyplot as plt
import seaborn as sns

sns.set()
```

[50]:
```
from sklearn.metrics import roc_curve

fpr, tpr, _ = roc_curve(test_y, probabilities[:, 1])
plt.plot(fpr, tpr)
plt.plot([0, 1], [0, 1], color='grey', lw=1, linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
```

[50]: Text(0, 0.5, 'True Positive Rate')



[51]:
```
def insertCode(origin, destinatation):
    origin = 'ORIGIN_' + origin
    destinatation = 'DEST_' + destinatation
    # Create a dict of airports with initial value 0
    airportDict = {}
    for code in train_x.columns.tolist()[4:]:
        airportDict[code] = 0
    airportDict[origin] = 1
    airportDict[destinatation] = 1
    return airportDict
```

[52]:
```
def predict_delay(departure_date_time, origin, destination):
    from datetime import datetime

    try:
        departure_date_time_parsed = datetime.strptime(departure_date_time, '%d/
 ↪%m %H:%M')
    except ValueError as e:
        return 'Error parsing date/time - {}'.format(e)

    month = departure_date_time_parsed.month
    day = departure_date_time_parsed.day
    day_of_week = departure_date_time_parsed.isoweekday()
    hour = departure_date_time_parsed.hour
```

```
    origin = origin.upper()
    destination = destination.upper()

    input = {'MONTH': month,
             'DAY_OF_MONTH': day,
             'DAY_OF_WEEK': day_of_week,
             'CRS_DEP_TIME': hour}
    input = [{**input, **insertCode(origin, destination)}]

    return model.predict_proba(pd.DataFrame(input))[0][0]
```

[53]:
```
predict_delay('1/10 15:45', 'EWR', 'SEA')
```

[53]: 0.8414408368109711

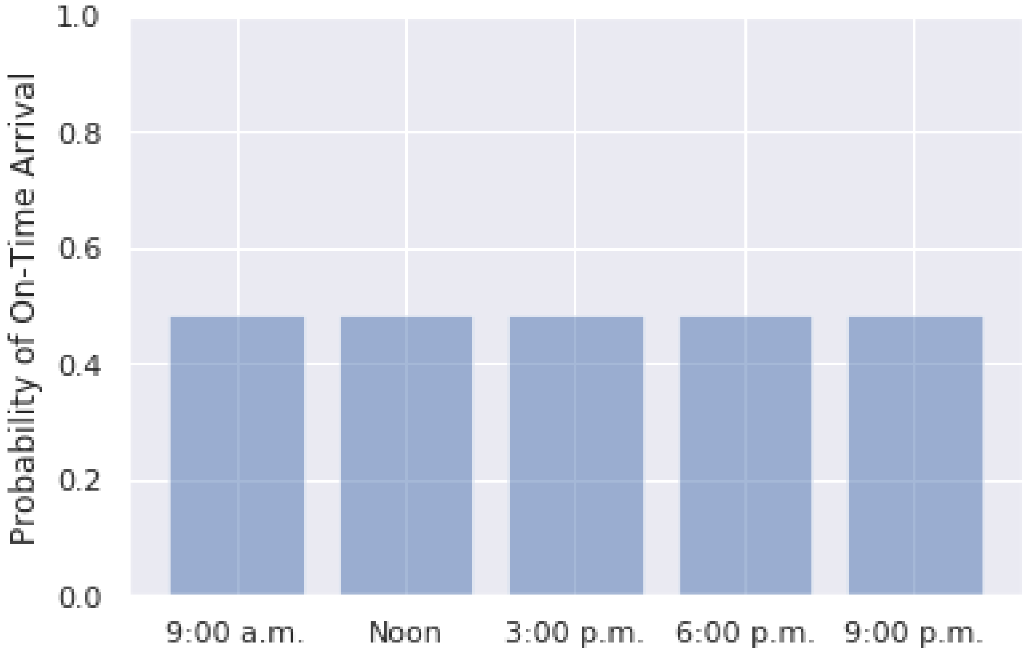
[54]:
```
predict_delay('24/12 09:00', 'LAX', 'EWR')
```

[54]: 0.8827298060829265

[ ]:
```
# flights leaving SEA for ATL at 9:00 a.m., noon, 3:00 p.m., 6:00 p.m., and 9:00␣
 ↪p.m. on January 30 will arrive on time
labels = ('9:00 a.m.', 'Noon', '3:00 p.m.', '6:00 p.m.', '9:00 p.m.')
values = (predict_delay('23/12 09:00', 'EWR', 'LAX'),
          predict_delay('23/12 12:00', 'EWR', 'LAX'),
          predict_delay('23/12 15:45', 'EWR', 'LAX'),
          predict_delay('23/12 18:00', 'EWR', 'LAX'),
          predict_delay('23/12 21:00', 'EWR', 'LAX'))
alabels = np.arange(len(labels))

plt.bar(alabels, values, align='center', alpha=0.5)
plt.xticks(alabels, labels)
plt.ylabel('Probability of On-Time Arrival')
plt.ylim((0.0, 1.0))
```

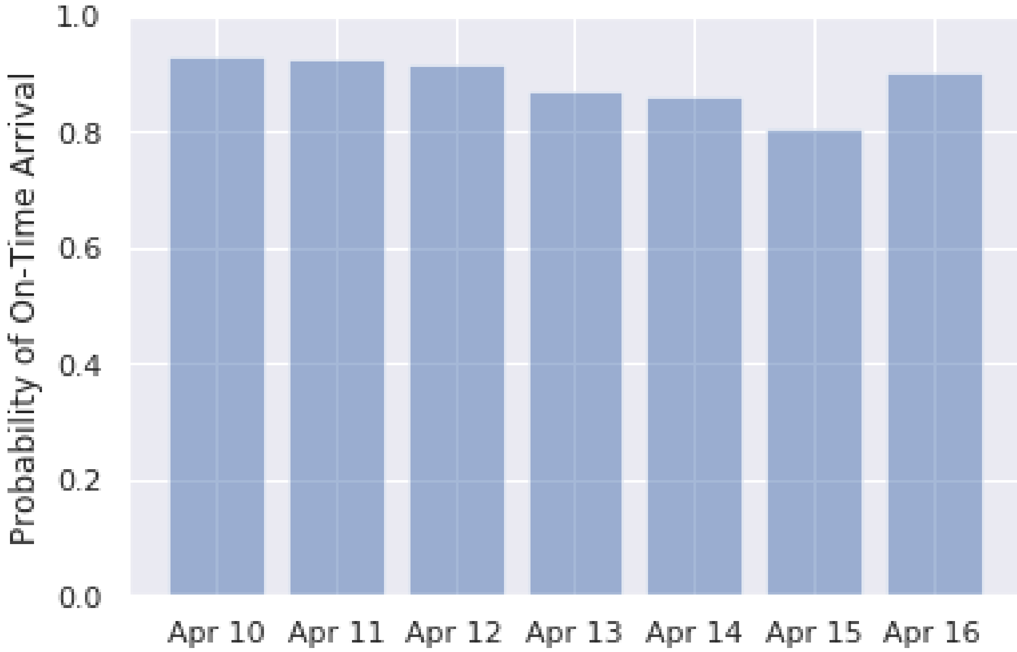
[ ]: (0.0, 1.0)



[ ]:
```python
labels = ('Apr 10', 'Apr 11', 'Apr 12', 'Apr 13', 'Apr 14', 'Apr 15', 'Apr 16')
values = (predict_delay('10/04 13:00', 'JFK', 'MSP'),
          predict_delay('11/04 13:00', 'JFK', 'MSP'),
          predict_delay('12/04 13:00', 'JFK', 'MSP'),
          predict_delay('13/04 13:00', 'JFK', 'MSP'),
          predict_delay('14/04 13:00', 'JFK', 'MSP'),
          predict_delay('15/04 13:00', 'JFK', 'MSP'),
          predict_delay('16/04 13:00', 'JFK', 'MSP'))
alabels = np.arange(len(labels))

plt.bar(alabels, values, align='center', alpha=0.5)
plt.xticks(alabels, labels)
plt.ylabel('Probability of On-Time Arrival')
plt.ylim((0.0, 1.0))
```

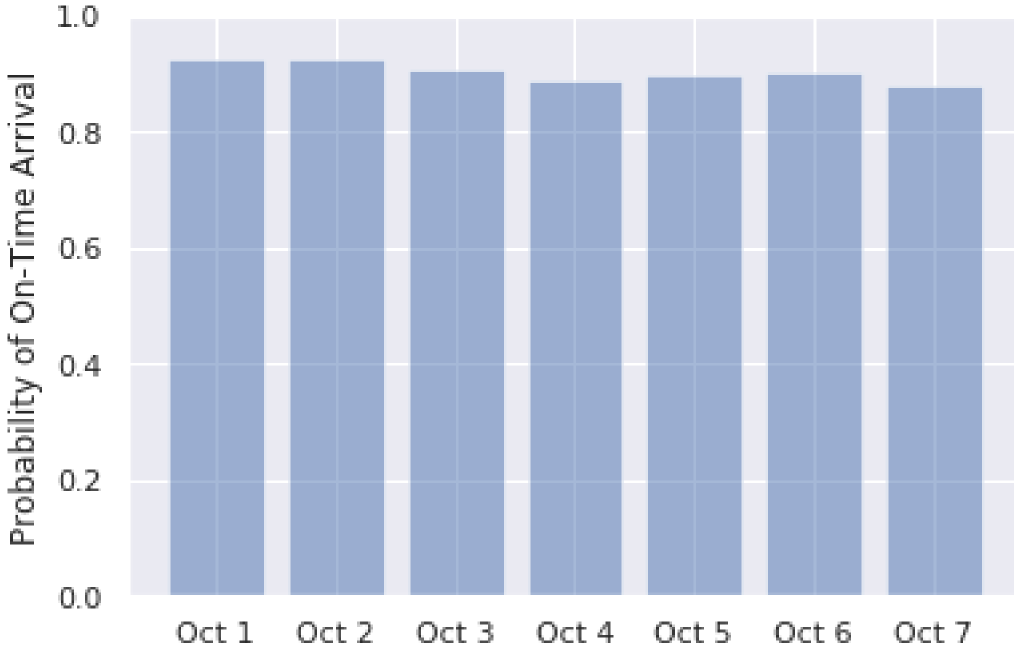
[ ]: (0.0, 1.0)



[ ]:
```
labels = ('Oct 1', 'Oct 2', 'Oct 3', 'Oct 4', 'Oct 5', 'Oct 6', 'Oct 7')
values = (predict_delay('1/10 21:45', 'JFK', 'ATL'),
          predict_delay('2/10 21:45', 'JFK', 'ATL'),
          predict_delay('3/10 21:45', 'JFK', 'ATL'),
          predict_delay('4/10 21:45', 'JFK', 'ATL'),
          predict_delay('5/10 21:45', 'JFK', 'ATL'),
          predict_delay('6/10 21:45', 'JFK', 'ATL'),
          predict_delay('7/10 21:45', 'JFK', 'ATL'))
alabels = np.arange(len(labels))

plt.bar(alabels, values, align='center', alpha=0.5)
plt.xticks(alabels, labels)
plt.ylabel('Probability of On-Time Arrival')
plt.ylim((0.0, 1.0))
```

[ ]:
```
(0.0, 1.0)
```


1.0
0.8
0.6
0.4
0.2
0.0
Probability of On-Time Arrival
Oct 1
Oct 2
Oct 3
Oct 4
Oct 5
Oct 6
Oct 7