kaggle new york city taxi fare prediction challenge

September 25, 2018

```
In [1]: # Initial Python environment setup...
        import numpy as np # linear algebra
        import pandas as pd # CSV file I/O (e.g. pd.read_csv)
        import os # reading the input files we have access to
        print(os.listdir('../input'))
['GCP-Coupons-Instructions.rtf', 'sample_submission.csv', 'test.csv', 'train.csv']
In [2]: train_df = pd.read_csv('../input/train.csv',nrows=10_000_000)
        train_df.dtypes
Out [2]: key
                              object
       fare_amount
                             float64
        pickup_datetime
                              object
       pickup_longitude
                             float64
       pickup_latitude
                             float64
        dropoff_longitude
                             float64
        dropoff_latitude
                             float64
        passenger_count
                               int64
        dtype: object
In [3]: #get a sense how training data looks like
        train_df[:5]
Out [3]:
                                          fare_amount
                                                               pickup_datetime \
                                     key
             2009-06-15 17:26:21.0000001
                                                  4.5 2009-06-15 17:26:21 UTC
        1
            2010-01-05 16:52:16.0000002
                                                 16.9 2010-01-05 16:52:16 UTC
           2011-08-18 00:35:00.00000049
                                                  5.7 2011-08-18 00:35:00 UTC
            2012-04-21 04:30:42.0000001
                                                  7.7 2012-04-21 04:30:42 UTC
        4 2010-03-09 07:51:00.000000135
                                                  5.3 2010-03-09 07:51:00 UTC
           pickup_longitude pickup_latitude dropoff_longitude dropoff_latitude \
        0
                 -73.844311
                                   40.721319
                                                     -73.841610
                                                                        40.712278
        1
                 -74.016048
                                   40.711303
                                                     -73.979268
                                                                        40.782004
        2
                 -73.982738
                                   40.761270
                                                     -73.991242
                                                                        40.750562
        3
                -73.987130
                                   40.733143
                                                     -73.991567
                                                                        40.758092
```

```
4
                 -73.968095
                                    40.768008
                                                      -73.956655
                                                                          40.783762
           passenger_count
        0
        1
                         1
        2
                         2
        3
                         1
        4
                          1
In [4]: plot = train_df.plot.scatter('passenger_count', 'fare_amount')
In [5]: train_df.describe()
Out[5]:
                fare_amount
                             pickup_longitude
                                               pickup_latitude
                                                                  dropoff_longitude
                                  1.000000e+07
        count
              1.000000e+07
                                                   1.000000e+07
                                                                       9.999931e+06
        mean
               1.133854e+01
                                 -7.250775e+01
                                                   3.991934e+01
                                                                      -7.250897e+01
               9.799930e+00
                                 1.299421e+01
                                                   9.322539e+00
                                                                      1.287532e+01
        std
              -1.077500e+02
                                 -3.439245e+03
                                                  -3.492264e+03
                                                                      -3.426601e+03
        min
        25%
                                                                      -7.399139e+01
               6.000000e+00
                                 -7.399207e+01
                                                   4.073491e+01
        50%
               8.500000e+00
                                -7.398181e+01
                                                   4.075263e+01
                                                                      -7.398016e+01
        75%
               1.250000e+01
                                -7.396710e+01
                                                   4.076712e+01
                                                                      -7.396367e+01
                                                   3.344459e+03
        max
               1.273310e+03
                                  3.457626e+03
                                                                       3.457622e+03
               dropoff_latitude
                                 passenger_count
                   9.999931e+06
                                     1.000000e+07
        count
                   3.991913e+01
                                     1.684793e+00
        mean
                   9.237280e+00
                                     1.323423e+00
        std
                                     0.000000e+00
                  -3.488080e+03
        min
        25%
                   4.073403e+01
                                     1.000000e+00
        50%
                   4.075316e+01
                                     1.000000e+00
        75%
                   4.076810e+01
                                     2.000000e+00
                   3.351403e+03
                                     2.080000e+02
        max
In [6]: # Given a dataframe, add two new features 'abs diff longitude' and
        # 'abs_diff_latitude' representing the "Manhattan vector" from
        # the pickup location to the dropoff location.
        def add_travel_vector_features(df):
            df['abs_diff_longitude'] = (df.dropoff_longitude - df.pickup_longitude).abs()
            df['abs_diff_latitude'] = (df.dropoff_latitude - df.pickup_latitude).abs()
        add_travel_vector_features(train_df)
In [7]: #Clean NA values
        print('Old size: %d' % len(train_df))
        train_df = train_df.dropna(how = 'any', axis = 'rows')
        print('New size: %d' % len(train_df))
Old size: 10000000
New size: 9999931
```

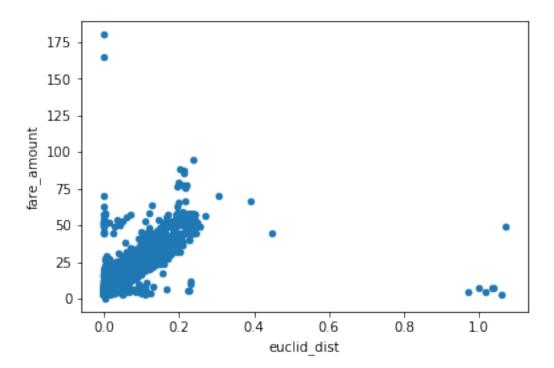
```
In [8]: print('Old size: %d' % len(train_df))
                  train_df = train_df[(train_df.abs_diff_longitude < 5.0) & (train_df.abs_diff_latitude </pre>
                  print('New size: %d' % len(train_df))
Old size: 9999931
New size: 9979187
In [9]: print('Old size: %d' % len(train_df))
                  train_df = train_df[(train_df.fare_amount > 0)]
                  print('New size: %d' % len(train_df))
Old size: 9979187
New size: 9978549
In [10]: print('Old size: %d' % len(train_df))
                    train_df = train_df[(train_df.pickup_longitude != 0) & (train_df.pickup_latitude!=0)]
                    print('New size: %d' % len(train_df))
Old size: 9978549
New size: 9797235
In [11]: print('Old size: %d' % len(train_df))
                    \label{train_df} \verb|train_df| = train_df[(train_df.dropoff_longitude != 0) & (train_df.dropoff_latitude != 0) & (train_d
                    print('New size: %d' % len(train_df))
Old size: 9797235
New size: 9797221
In [12]: # Given a dataframe, add two new features 'abs_diff_longitude' and
                     \# 'abs_diff_latitude' representing the "Manhattan vector" from
                     # the pickup location to the dropoff location.
                     def add_euclid_distance_feature(df):
                              abs_diff_longitude = (df.dropoff_longitude - df.pickup_longitude)
                              abs_diff_latitude = (df.dropoff_latitude - df.pickup_latitude)
                              abs_diff_longitude_square = abs_diff_longitude ** 2
                              abs_diff_latitude_square = abs_diff_latitude ** 2
                              df['euclid_dist'] = (abs_diff_longitude_square + abs_diff_latitude_square) ** (1/2)
                     add_euclid_distance_feature(train_df)
In [13]: train_df.corr()
Out[13]:
                                                                   fare_amount pickup_longitude pickup_latitude \
                    fare_amount
                                                                          1.000000
                                                                                                                    0.005782
                                                                                                                                                         -0.004231
                    pickup_longitude
                                                                          0.005782
```

1.000000

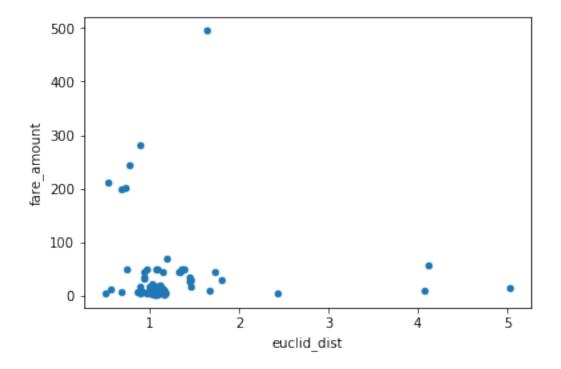
-0.353907

```
pickup_latitude
                       -0.004231
                                         -0.353907
                                                            1.000000
dropoff_longitude
                        0.004879
                                          0.999945
                                                           -0.353907
dropoff_latitude
                       -0.004082
                                         -0.353901
                                                            0.999954
passenger_count
                        0.013833
                                          0.005445
                                                           -0.005951
                                          0.002789
abs diff longitude
                                                           -0.000495
                        0.710765
abs_diff_latitude
                        0.536288
                                          0.003477
                                                           -0.003181
euclid dist
                        0.726546
                                          0.003378
                                                           -0.001911
                     dropoff_longitude
                                        dropoff_latitude
                                                           passenger_count
fare_amount
                              0.004879
                                                -0.004082
                                                                   0.013833
pickup_longitude
                              0.999945
                                                -0.353901
                                                                   0.005445
pickup_latitude
                             -0.353907
                                                 0.999954
                                                                 -0.005951
dropoff_longitude
                              1.000000
                                                -0.353897
                                                                   0.005428
dropoff_latitude
                             -0.353897
                                                 1.000000
                                                                 -0.005928
passenger_count
                              0.005428
                                                -0.005928
                                                                   1.000000
abs_diff_longitude
                              0.002041
                                                -0.000392
                                                                   0.007301
abs_diff_latitude
                              0.002850
                                                -0.003186
                                                                   0.006233
euclid_dist
                              0.002674
                                                -0.001905
                                                                   0.007672
                    abs diff longitude
                                         abs diff latitude
                                                             euclid dist
fare amount
                                                   0.536288
                                                                0.726546
                               0.710765
pickup longitude
                               0.002789
                                                                0.003378
                                                   0.003477
pickup_latitude
                              -0.000495
                                                  -0.003181
                                                               -0.001911
dropoff_longitude
                               0.002041
                                                   0.002850
                                                                0.002674
dropoff_latitude
                              -0.000392
                                                  -0.003186
                                                               -0.001905
passenger_count
                               0.007301
                                                   0.006233
                                                                0.007672
abs_diff_longitude
                               1.000000
                                                   0.507669
                                                                0.904494
abs_diff_latitude
                               0.507669
                                                   1.000000
                                                                0.808833
euclid_dist
                               0.904494
                                                   0.808833
                                                                1.000000
```

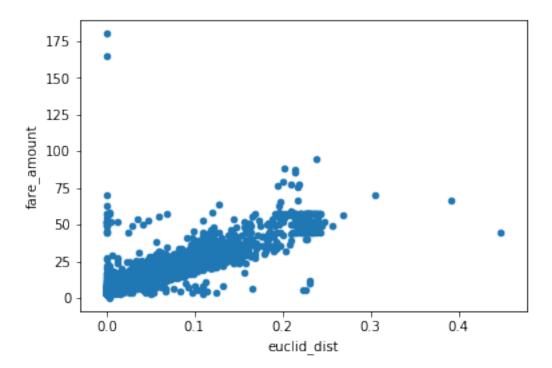
In [14]: plot = train_df.iloc[:10000].plot.scatter('euclid_dist', 'fare_amount')



In [15]: #When euclid distance is more than 0.5, you can still fit a line but most of the data
 x = train_df[train_df.euclid_dist>0.5]
 plot = x.iloc[:100].plot.scatter('euclid_dist','fare_amount')



In [16]: #When euclid distance is less than 0.5, one can fit a line such that most data points
 x = train_df[train_df.euclid_dist<0.5]
 plot = x.iloc[:10000].plot.scatter('euclid_dist','fare_amount')</pre>



In [17]: #Convert pickup date time string to a pandas datetime object

from datetime import timedelta, datetime
from pandas import DataFrame, Series

lines = train_df['pickup_datetime']

dt_lst = []

for date_str in lines:
 dt = datetime.strptime(date_str, '%Y-%m-%d %H:%M:%S UTC')
 seconds_since_midnight = int((dt - dt.replace(hour=0, minute=0, second=0, microsedt_lst.append(seconds_since_midnight)

Create a Series named "Request_Time"
sr_dt = Series(dt_lst, name='Second_Of_Day')

Create a DataFrame using the Request_Time Series

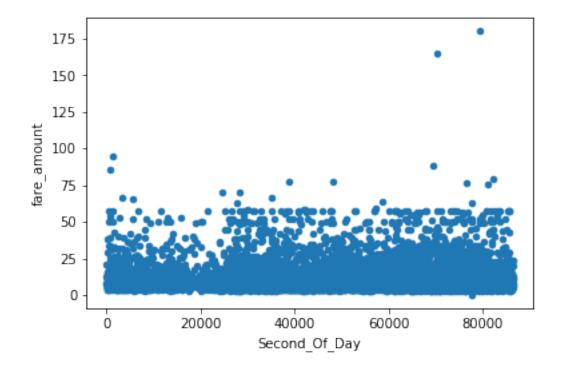
```
df = DataFrame(sr_dt)
    df['fare_amount'] = train_df['fare_amount']
    df['euclid_dist'] = train_df['euclid_dist']

In [18]: df.corr()

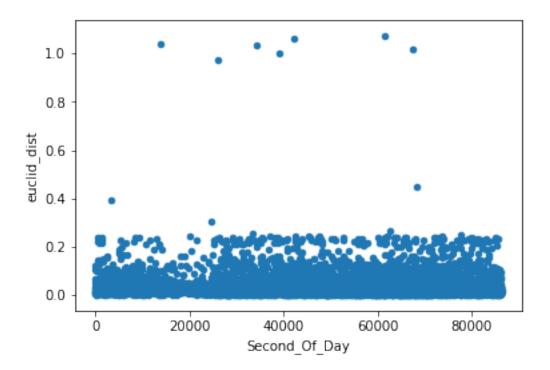
Out[18]: Second Of Day fare amount eucli
```

Out[18]: Second_Of_Day fare_amount euclid_dist -0.000365 1.000000 -0.000165 Second_Of_Day 0.725529 fare_amount -0.000365 1.000000 euclid_dist -0.000165 0.725529 1.000000

In [19]: plot = df.iloc[:10000].plot.scatter('Second_Of_Day','fare_amount')



In [20]: plot = df.iloc[:10000].plot.scatter('Second_Of_Day','euclid_dist')



In [21]: # Model 1 : A simple linear regression model that uses the feature euclidean distance import matplotlib.pyplot as plt from scipy import stats xi = train_df['euclid_dist'] y = train_df['fare_amount'] #Train the model on train data slope, intercept, r_value, p_value, std_err = stats.linregress(xi,y) print ('r value', r_value) print ('p_value', p_value) print ('standard deviation', std_err) print ('slope is:', slope) print ("r-squared:", r_value**2) #Check the model fit #plt.plot(xi, y, 'o', label='original data') #plt.plot(xi, intercept + slope*xi, 'r', label='fitted line') #plt.legend() #plt.show() r value 0.7265459653520138 p_value 0.0 standard deviation 0.04594354813355792

```
slope is: 152.05748221076286
r-squared: 0.5278690397692896
In [22]: #Test the model on test data
         test_df = pd.read_csv('../input/test.csv')
         add_euclid_distance_feature(test_df)
         xi = test_df['euclid_dist']
         test_y_predictions=[]
         for x in xi:
             y = round(slope*x + intercept, 2)
             test_y_predictions.append(y)
         # Write the predictions to a CSV file which we can submit to the competition.
         submission = pd.DataFrame(
             {'key': test_df.key, 'fare_amount': test_y_predictions},
             columns = ['key', 'fare_amount'])
         submission.to_csv('submission.csv', index = False)
         print(os.listdir('.'))
['.git', '.ipynb_checkpoints', 'kaggle new york city taxi fare prediction challenge.ipynb', 'mo
In [23]: # Model 2: Use random forest regressor model that uses the feature euclidean distanc
         from sklearn.ensemble import RandomForestRegressor as rfr
         from sklearn.model_selection import cross_val_score
         # build the model with the desired parameters...
         numFeatures = 1 # the number of features to inlcude
         train_df_mini = train_df[:1000000]
         trees = 10 # trees in the forest
         included_features = ['euclid_dist']
         # define the training data X...
         X = train_df_mini[included_features]
         Y = train_df_mini[['fare_amount']]
         yt = [i for i in Y['fare_amount']]
         np.random.seed(11111)
         model = rfr(n_estimators=trees,max_depth=None)
         scores_rfr = cross_val_score(model,X,yt,cv=10,scoring='explained_variance')
         print('explained variance scores for k=10 fold validation:',scores_rfr)
         print("Est. explained variance: %0.2f (+/- %0.2f)" % (scores_rfr.mean(), scores_rfr.s
         # fit the model
         model.fit(X,yt)
explained variance scores for k=10 fold validation: [0.66106363 0.68731691 0.64530205 0.668022
0.70530754 0.69416429 0.69226933 0.6774113 ]
```

```
Est. explained variance: 0.68 (+/-0.03)
Out [23]: RandomForestRegressor(bootstrap=True, criterion='mse', max_depth=None,
                    max_features='auto', 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=10, n_jobs=1,
                    oob_score=False, random_state=None, verbose=0, warm_start=False)
In [24]: # apply the model to the test data and get the output...
         X_test = test_df[included_features]
         y_output = model.predict(X_test.fillna(0)) # get the results and fill nan's with 0
         print(y_output)
         test_y_predictions=[]
         for elem in y_output:
             test_y_predictions.append(round(elem,2))
[ 8.44973482  9.0342475
                        4.74166667 ... 42.648
                                                     21.472
  6.152843771
In [25]: # Write the predictions to a CSV file which we can submit to the competition.
         submission = pd.DataFrame(
             {'key': test_df.key, 'fare_amount': test_y_predictions},
             columns = ['key', 'fare_amount'])
         submission.to_csv('submission.csv', index = False)
         print(os.listdir('.'))
['.git', '.ipynb_checkpoints', 'kaggle new york city taxi fare prediction challenge.ipynb', 'mo
In [26]: # Model 3: Use LightGBM decision tree model that uses multiple features to predict t
         import lightgbm as lgb
         # load or create your dataset
         print('Load data...')
         included_features = ['euclid_dist', 'passenger_count', 'pickup_latitude', 'pickup_longit']
         train_X = train_df[included_features]
         train_y = train_df['fare_amount']
         params = {
                 'nthread': -1,
         #Default Parameters
         train_set = lgb.Dataset(train_X, train_y, silent=True)
         model3 = lgb.train(params, train_set = train_set, num_boost_round=300)
```

```
Load data...
In [27]: model3.save_model('modellgbm.txt')
         print('Start predicting...')
        X_test = test_df[included_features]
         # predict
         y_pred = model3.predict(X_test, num_iteration=model3.best_iteration)
Start predicting...
In [28]: test_y_predictions=[]
         for elem in y_pred:
             test_y_predictions.append(round(elem,2))
         # Write the predictions to a CSV file which we can submit to the competition.
         submission = pd.DataFrame(
             {'key': test_df.key, 'fare_amount': test_y_predictions},
             columns = ['key', 'fare_amount'])
         submission.to_csv('submission.csv', index = False)
         print(os.listdir('.'))
['.git', '.ipynb_checkpoints', 'kaggle new york city taxi fare prediction challenge.ipynb', 'me
```