UNTER NY TAXI TRIP PREDICTION

May 28, 2018

```
In [1]: import pandas as pd
        import numpy as np
        from sklearn.model_selection import cross_val_score
```

```
In [2]: train_df = pd.read_csv("data/train.csv")
```

1 Data exploration and preprocessnig

```
In [3]: train_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1458644 entries, 0 to 1458643
Data columns (total 11 columns):
id                    1458644 non-null object
vendor_id             1458644 non-null int64
pickup_datetime       1458644 non-null object
dropoff_datetime      1458644 non-null object
passenger_count       1458644 non-null int64
pickup_longitude      1458644 non-null float64
pickup_latitude       1458644 non-null float64
dropoff_longitude     1458644 non-null float64
dropoff_latitude      1458644 non-null float64
store_and_fwd_flag    1458644 non-null object
trip_duration         1458644 non-null int64
dtypes: float64(4), int64(3), object(4)
memory usage: 122.4+ MB
```

Define two functions for later use.

```
In [4]: def euklidian_dist(a_x,a_y,b_x,b_y):
            return np.sqrt((a_x - b_x)**2 + (a_y - b_y)**2)

        def manhattan_dist(a_x,a_y,b_x,b_y):
            return np.absolute(a_x - b_x) + np.absolute(a_y - b_y)
```

Here we define our custom fields: 1. Transform field pickup_datetime to extract information about: month, day of the month, day of the week and hour.

2. Euklidian distance between pickup place and dropoff place.

3. Mahattan distance between pickup place and dropoff place, because we operate in NYC.

4. We also transform trip_duration field with log function.

In [5]:
```python
train_df['datetime'] = pd.to_datetime(train_df.pickup_datetime)
train_df['day_of_week'] = train_df.datetime.dt.dayofweek
train_df['hour'] = train_df.datetime.dt.hour
train_df['day_of_month'] = train_df.datetime.dt.day
train_df['month'] = train_df.datetime.dt.month
train_df['euklidian_distance'] = euklidian_dist(train_df.dropoff_latitude,  train_df.dro
train_df['manhattan_distance'] = manhattan_dist(train_df.dropoff_latitude,  train_df.dro
train_df['log_trip_duration'] = np.log(train_df.trip_duration)
```

In [6]:
```python
#actual data frame
train_df[:11]
```

Out[6]:
```
           id  vendor_id      pickup_datetime     dropoff_datetime  \
0   id2875421          2  2016-03-14 17:24:55  2016-03-14 17:32:30
1   id2377394          1  2016-06-12 00:43:35  2016-06-12 00:54:38
2   id3858529          2  2016-01-19 11:35:24  2016-01-19 12:10:48
3   id3504673          2  2016-04-06 19:32:31  2016-04-06 19:39:40
4   id2181028          2  2016-03-26 13:30:55  2016-03-26 13:38:10
5   id0801584          2  2016-01-30 22:01:40  2016-01-30 22:09:03
6   id1813257          1  2016-06-17 22:34:59  2016-06-17 22:40:40
7   id1324603          2  2016-05-21 07:54:58  2016-05-21 08:20:49
8   id1301050          1  2016-05-27 23:12:23  2016-05-27 23:16:38
9   id0012891          2  2016-03-10 21:45:01  2016-03-10 22:05:26
10  id1436371          2  2016-05-10 22:08:41  2016-05-10 22:29:55

    passenger_count  pickup_longitude  pickup_latitude  dropoff_longitude  \
0                 1        -73.982155        40.767937         -73.964630
1                 1        -73.980415        40.738564         -73.999481
2                 1        -73.979027        40.763939         -74.005333
3                 1        -74.010040        40.719971         -74.012268
4                 1        -73.973053        40.793209         -73.972923
5                 6        -73.982857        40.742195         -73.992081
6                 4        -73.969017        40.757839         -73.957405
7                 1        -73.969276        40.797779         -73.922470
8                 1        -73.999481        40.738400         -73.985786
9                 1        -73.981049        40.744339         -73.973000
10                1        -73.982651        40.763840         -74.002228

    dropoff_latitude store_and_fwd_flag  trip_duration            datetime  \
0          40.765602                  N            455 2016-03-14 17:24:55
1          40.731152                  N            663 2016-06-12 00:43:35
2          40.710087                  N           2124 2016-01-19 11:35:24
```

```
3           40.706718                   N             429 2016-04-06 19:32:31
4           40.782520                   N             435 2016-03-26 13:30:55
5           40.749184                   N             443 2016-01-30 22:01:40
6           40.765896                   N             341 2016-06-17 22:34:59
7           40.760559                   N            1551 2016-05-21 07:54:58
8           40.732815                   N             255 2016-05-27 23:12:23
9           40.789989                   N            1225 2016-03-10 21:45:01
10          40.732990                   N            1274 2016-05-10 22:08:41

    day_of_week  hour  day_of_month  month  euklidian_distance  \
0             0    17            14      3            0.017680
1             6     0            12      6            0.020456
2             1    11            19      1            0.059934
3             2    19             6      4            0.013438
4             5    13            26      3            0.010690
5             5    22            30      1            0.011572
6             4    22            17      6            0.014133
7             5     7            21      5            0.059801
8             4    23            27      5            0.014790
9             3    21            10      3            0.046355
10            1    22            10      5            0.036537

    manhattan_distance  log_trip_duration
0             0.019859           6.120297
1             0.026478           6.496775
2             0.080158           7.661056
3             0.015480           6.061457
4             0.010818           6.075346
5             0.016212           6.093570
6             0.019669           5.831882
7             0.084026           7.346655
8             0.019279           5.541264
9             0.053699           7.110696
10            0.050426           7.149917
```

We tranform use log function on trip_duration, because it is supposed reduce skeewnes.

More on that here https://becominghuman.ai/how-to-deal-with-skewed-dataset-in-machine-learning-afd2928011cc

All I know is that can help with regression in some cases, and it was true in ours.

Here is what is correlation between given fields and a trip_duration, it gives us information how each field influences the output:

```
In [7]: corr = train_df.corr()
        print(corr["trip_duration"].sort_values(ascending = False))
```

```
trip_duration         1.000000
log_trip_duration     0.252624
euklidian_distance    0.095368
```

```
manhattan_distance    0.094738
pickup_longitude      0.026542
vendor_id             0.020304
dropoff_longitude     0.014678
passenger_count       0.008471
month                 0.006607
hour                  0.003690
day_of_month          0.000566
day_of_week          -0.000708
dropoff_latitude     -0.020677
pickup_latitude      -0.029204
Name: trip_duration, dtype: float64
```

And here is correlation betwen given fields and log_trip_duration:

```
In [8]: print(corr["log_trip_duration"].sort_values(ascending = False))
```

```
log_trip_duration     1.000000
euklidian_distance    0.567401
manhattan_distance    0.561209
trip_duration         0.252624
pickup_longitude      0.110344
dropoff_longitude     0.071411
month                 0.046488
hour                  0.039107
passenger_count       0.021124
vendor_id             0.019833
day_of_month          0.010385
day_of_week          -0.027817
dropoff_latitude     -0.123265
pickup_latitude      -0.144149
Name: log_trip_duration, dtype: float64
```

```
In [9]: #column names
        train_df.columns
```

```
Out[9]: Index(['id', 'vendor_id', 'pickup_datetime', 'dropoff_datetime',
               'passenger_count', 'pickup_longitude', 'pickup_latitude',
               'dropoff_longitude', 'dropoff_latitude', 'store_and_fwd_flag',
               'trip_duration', 'datetime', 'day_of_week', 'hour', 'day_of_month',
               'month', 'euklidian_distance', 'manhattan_distance',
               'log_trip_duration'],
              dtype='object')
```

```
In [10]: train_X = train_df[[
                'pickup_longitude', 'pickup_latitude',
                'dropoff_longitude', 'dropoff_latitude',
```

```
                'hour', 'month',
                'euklidian_distance', 'manhattan_distance',
                ]].values


        train_y = train_df['log_trip_duration'].values
```

In [11]:

```
Out[11]: array([ -7.39804153e+01,   4.07385635e+01,  -7.39994812e+01,
                  4.07311516e+01,   0.00000000e+00,   6.00000000e+00,
                  2.04559039e-02,   2.64778137e-02])
```

In [11]: train_X

```
Out[11]: array([[ -7.39821548e+01,   4.07679367e+01,  -7.39646301e+01, ...,
                   3.00000000e+00,   1.76795395e-02,   1.98593140e-02],
                [ -7.39804153e+01,   4.07385635e+01,  -7.39994812e+01, ...,
                   6.00000000e+00,   2.04559039e-02,   2.64778137e-02],
                [ -7.39790268e+01,   4.07639389e+01,  -7.40053329e+01, ...,
                   1.00000000e+00,   5.99337994e-02,   8.01582336e-02],
                ...,
                [ -7.39591293e+01,   4.07687988e+01,  -7.40044327e+01, ...,
                   4.00000000e+00,   7.63269339e-02,   1.06731415e-01],
                [ -7.39820786e+01,   4.07490616e+01,  -7.39746323e+01, ...,
                   1.00000000e+00,   1.09623176e-02,   1.54914856e-02],
                [ -7.39795380e+01,   4.07817497e+01,  -7.39728088e+01, ...,
                   4.00000000e+00,   1.11056524e-02,   1.55639648e-02]])
```

We scale our input. By calculating mean of each column, and then dividing each element by mean of column it is in. After that operation all input fields should be moreover the same.

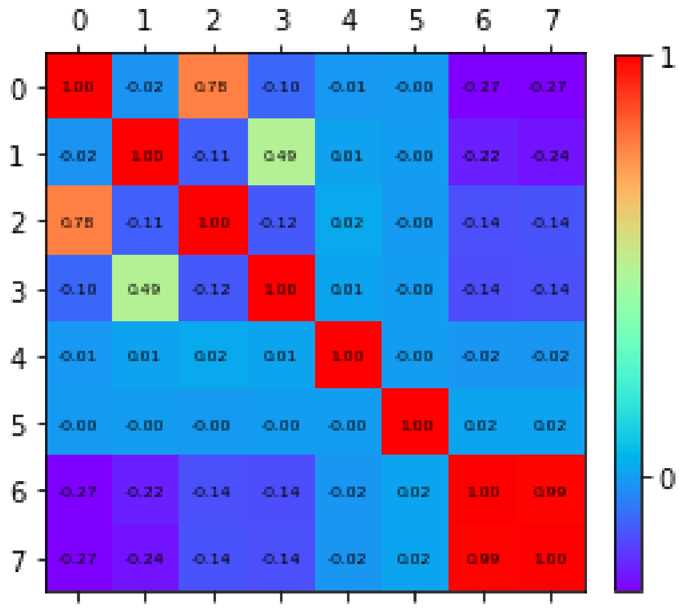
```
In [12]: means = np.array([np.mean(train_X[:,i]) for i in range(len(train_X[0]))])
         train_X = train_X / means
```

```
In [13]: train_X[1]
```

```
Out[13]: array([ 1.00009367,  0.99969676,  1.00035236,  0.99949332,  0.        ,
                 1.70608788,  0.57650972,  0.57684401])
```

We now can check correlation betwen input fields. We visualize that with matrix.

```
In [13]: import matplotlib.pyplot as plt
         cov_data = np.corrcoef(train_X.T)
         img = plt.matshow(cov_data, cmap=plt.cm.rainbow)
         plt.colorbar(img, ticks=[-1, 0, 1],fraction=0.045)
         for x in range(cov_data.shape[0]):
             for y in range(cov_data.shape[1]):
                 plt.text(x,y, "%0.2f" % cov_data[x,y],
                          size=6, color='black', ha="center", va="center")
         plt.show()
```



We do not see very strong correlation betwen features apart from **euklidian_distance** and **manhattan_distance** which is not that big of surprise. However have decided to use both euklidian and manhattan distance, because this configuration gave us the best results

We select 8 features for model training:

1. euklidian_distance (calculated from coordinates)
2. manhattan_distance (calculated from coordinates)
3. pickup_latitude
4. pickup_longitude
5. dropoff_latitude
6. dropoff_longitude
7. month
8. hour

2 Model testing

To test performance of models we use cross validation. Given data is randomly splited, with first part of dataset model is trained, and other part is used for testing. This process is repeated two times.

We use **NEGATIVE MEAN SQUARED ERROR** as a scoring function.

After that we calculate mean and standard error of all tests.

1. Support vector machine with liear kernel

```
In [22]: from sklearn.svm import SVR

         model = SVR(kernel='linear',C=1)
         score = cross_val_score(model, train_X[:100000], train_y[:100000], scoring='neg_mean_sq
         print("average: {} std: {}".format(score.mean(), score.std()*2))
```

```
average: -0.4029606009563827 std: 0.0035690115845566917
```

2. Svm with radian based function kernel

```
In [31]: from sklearn.svm import SVR
         model =  SVR(kernel='rbf', C=1)
         score = cross_val_score(model, train_X[:100000], train_y[:100000], scoring='neg_mean_ab
         print("average: {} std: {}".format(score.mean(), score.std()*2))
```

```
average: -0.5718316168537649 std: 0.009856788742861333
```

3. Extra Trees regressor

```
In [51]: from sklearn.ensemble import ExtraTreesRegressor
         model = ExtraTreesRegressor(n_estimators=30, criterion='mse',n_jobs=-1)
         score = cross_val_score(model, train_X[:100000], train_y[:100000], scoring='neg_mean_sq
         print("average: {} std: {}".format(score.mean(), score.std()*2))
```

```
average: -0.2112642692752844 std: 0.001417616736263505
```

4 .Gradient Boosted Trees

```
In [20]: from sklearn.ensemble import GradientBoostingRegressor
         model = GradientBoostingRegressor(criterion='mae')
         score = cross_val_score(model, train_X[:100000], train_y[:100000], scoring='neg_mean_sq
         print("average: {} std: {}".format(score.mean(), score.std()*2))
```

```
average: -0.20860082611219993 std: 0.005568361927162313
```

5. NN

```
In [54]: #Input data dimention
         len(train_X[0])
```

```
Out[54]: 12
```

We created three diferent neural network models for testing.

```
In [0]: from keras.layers import Dense
        from keras.models import Sequential
        from keras.wrappers.scikit_learn import KerasRegressor


        #One deep layer with twelve units

        def baseline_model():
```

```
    model = Sequential()
    model.add(Dense(12, input_dim=12, kernel_initializer='normal', activation='relu'))
    model.add(Dense(1, kernel_initializer='normal'))

    model.compile(loss='mean_squared_error', optimizer='adam')
    return model



def deep_model():
    model = Sequential()
    model.add(Dense(12, input_dim=12, kernel_initializer='normal', activation='relu'))
    model.add(Dense(6, kernel_initializer='normal', activation='relu'))
    model.add(Dense(1, kernel_initializer='normal'))

    model.compile(loss='mean_squared_error', optimizer='adam')
    return model



def wide_model():
    model = Sequential()
    model.add(Dense(20 ,input_dim=12,kernel_initializer='normal', activation='relu'))
    model.add(Dense(1, kernel_initializer='normal'))

    model.compile(loss='mean_squared_error', optimizer='adam')
    return model




def super_model():
    model = Sequential()
    model.add(Dense(20 ,input_dim=12,kernel_initializer='normal', activation='linear'))
    model.add(Dense(30 ,input_dim=12,kernel_initializer='normal', activation='linear'))
    model.add(Dense(20 ,input_dim=12,kernel_initializer='normal', activation='linear'))
    model.add(Dense(1, kernel_initializer='normal'))

    model.compile(loss='mean_squared_error', optimizer='adam')
    return model
```

baseline model is neural network with one deep layer containing 12 units.

In [49]:
```
#baseline model
model = KerasRegressor(build_fn=baseline_model, epochs=10, batch_size=5, verbose=0)
```

```
score = cross_val_score(model, train_X[:100000], train_y[:100000], scoring='neg_mean_sq
print("average: {} std: {}".format(score.mean(), score.std()*2))
```

```
average: -0.41262410003476846 std: 0.005083226723735235
```

deep model is neural network with two deep layers, first with twelve units and second with six

```
In [50]: #deep model
         model = KerasRegressor(build_fn=deep_model, epochs=10, batch_size=5, verbose=0)

         score = cross_val_score(model, train_X[:100000], train_y[:100000], scoring='neg_mean_sq
         print("average: {} std: {}".format(score.mean(), score.std()*2))
```

```
average: -0.4086664039889718 std: 0.0022726769349029063
```

wide model is neural network with one deep layer containing 20 cells

```
In [52]: #wide model
         model = KerasRegressor(build_fn=wide_model, epochs=10, batch_size=5, verbose=0)

         score = cross_val_score(model, train_X[:100000], train_y[:100000], scoring='neg_mean_sq
         print("average: {} std: {}".format(score.mean(), score.std()*2))
```

```
average: -0.4288367635620518 std: 0.008279389463369868
```

super model is putting the saying "The more the better" to test. It is neural network with three deep layers: * First with 20 units * Second with 30 units * Third with 20 units

```
In [72]: #super model
         model = KerasRegressor(build_fn=super_model, epochs=5, batch_size=5, verbose=0)

         score = cross_val_score(model, train_X[:100000], train_y[:100000], scoring='neg_mean_sq
         print("average: {} std: {}".format(score.mean(), score.std()*2))
```

```
average: -0.43262690728540126 std: 0.024165916882937455
```

All networks has average mse around 0.4 which translates into 1.49 seconds of error.

3 Summary

After testing 8 different models we get following results.

Model ranked by performance in cross validation scored by mean mean squarred error:

1 . Gradient Boosted Trees **0.208**

2 . Random Trees Regressor **0.211**
3 . Support Vector Machine with linear kernel **0.402**
4 . The "deep model" Neural Network **0.408**
5 . The "baseline model" Neural Network **0.412**
6 . The "wide model" Neural Network **0.428**
7 . The "super model" Neural Network **0.432**
8 . Support Vector Machine with rbf kernel **0.571**

For further development we choose **Gradient Boosted Trees** model, which scored the lowest error of all model. The Downside is relatively long time of training which can be a bit painfull with using the whole database containing over 1 milion records.

A: danpisq @ UNTER