Class Final Project: NYC Taxi duration - visuals

In [2]:
```
# imports

import numpy as np
import pandas as pd

from sklearn.metrics import accuracy_score
from sklearn.cross_validation import train_test_split
from sklearn.cross_validation import cross_val_score
from sklearn import metrics
from matplotlib import pyplot as plt
```

```
/Users/thp/anaconda3/lib/python3.6/site-packages/sklearn/cross_validati
on.py:41: DeprecationWarning: This module was deprecated in version 0.1
8 in favor of the model_selection module into which all the refactored
classes and functions are moved. Also note that the interface of the ne
w CV iterators are different from that of this module. This module will
be removed in 0.20.
  "This module will be removed in 0.20.", DeprecationWarning)
```

Import the training dataset and start preprocessing the data

In [64]:
```
# import the dataset and check
taxi = pd.read_csv('/Users/thp/Documents/CSULA/5661 Data Science/Projec
t/train.csv')
print(taxi.shape)
taxi.head()
```

```
(1458644, 11)
```

Out[64]:

	id	vendor_id	pickup_datetime	dropoff_datetime	passenger_count	pickup_lo
0	id2875421	2	2016-03-14 17:24:55	2016-03-14 17:32:30	1	-73.98215
1	id2377394	1	2016-06-12 00:43:35	2016-06-12 00:54:38	1	-73.98041
2	id3858529	2	2016-01-19 11:35:24	2016-01-19 12:10:48	1	-73.97902
3	id3504673	2	2016-04-06 19:32:31	2016-04-06 19:39:40	1	-74.01004
4	id2181028	2	2016-03-26 13:30:55	2016-03-26 13:38:10	1	-73.97305

in this data set, we found out that some columns are not necessary for the prediction.

For example, "id" and "vendor_id" and "store_and_fwd_flag" column, so we first drop those.

In [65]:

```
taxi_new = taxi.drop(['id','vendor_id','store_and_fwd_flag'],axis=1)
taxi_new.head()
```

Out[65]:

	pickup_datetime	dropoff_datetime	passenger_count	pickup_longitude	pickup_latituc
0	2016-03-14 17:24:55	2016-03-14 17:32:30	1	-73.982155	40.767937
1	2016-06-12 00:43:35	2016-06-12 00:54:38	1	-73.980415	40.738564
2	2016-01-19 11:35:24	2016-01-19 12:10:48	1	-73.979027	40.763939
3	2016-04-06 19:32:31	2016-04-06 19:39:40	1	-74.010040	40.719971
4	2016-03-26 13:30:55	2016-03-26 13:38:10	1	-73.973053	40.793209

In further observation, we found that Pick-up time - Drop-off time = trip duration,

so if we just need to find out what time the taxi pick people up, we can omit the drop-off column.

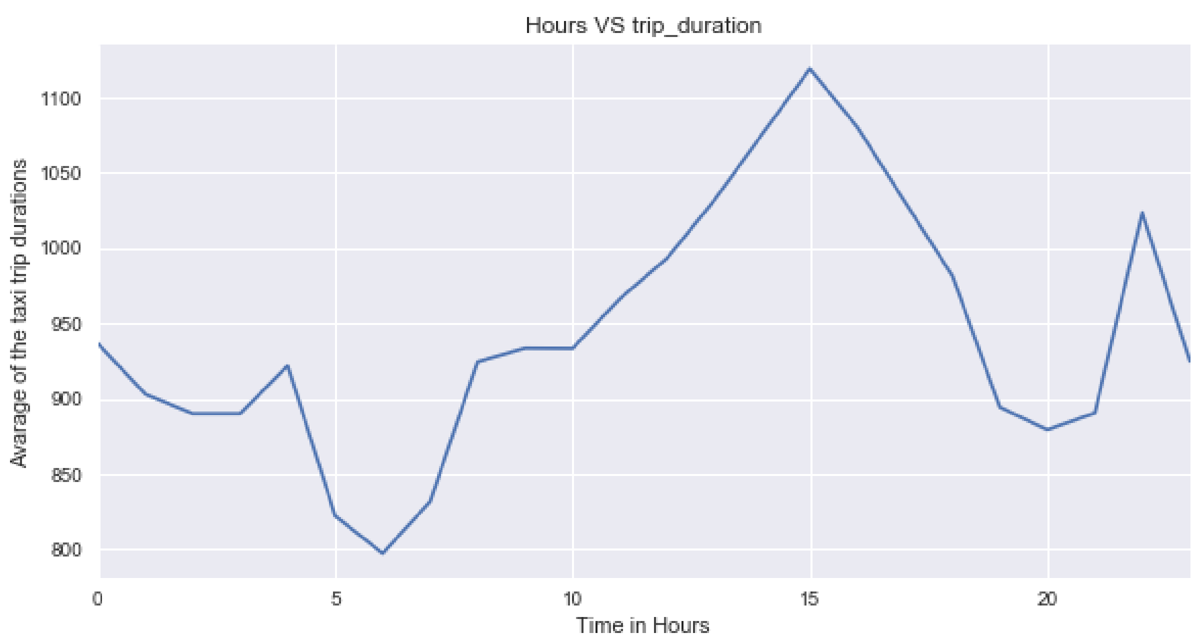
To easily capture the hour results, use the following code:

In [66]:
```
taxi_new_h = pd.to_datetime(taxi_new["pickup_datetime"])
taxi_new['hour'] = taxi_new_h.map(lambda x: x.hour)
taxi_new.head()
```

Out[66]:

	pickup_datetime	dropoff_datetime	passenger_count	pickup_longitude	pickup_latituc
0	2016-03-14 17:24:55	2016-03-14 17:32:30	1	-73.982155	40.767937
1	2016-06-12 00:43:35	2016-06-12 00:54:38	1	-73.980415	40.738564
2	2016-01-19 11:35:24	2016-01-19 12:10:48	1	-73.979027	40.763939
3	2016-04-06 19:32:31	2016-04-06 19:39:40	1	-74.010040	40.719971
4	2016-03-26 13:30:55	2016-03-26 13:38:10	1	-73.973053	40.793209

In [195]:
```
figure,axes = plt.subplots(figsize = (10, 5))
hours = taxi_new.groupby(["hour"]).agg(('mean'))["trip_duration"]
hours.plot(kind="line", ax=axes)
plt.title('Hours VS trip_duration')
axes.set_xlabel('Time in Hours')
axes.set_ylabel('Avarage of the taxi trip durations')
plt.show()
```



we can see that we have a column 'hour' that captures the hour of the day when the taxi picks up the customer.

we believe that this timing of the ride is very important.

To avoid numeric relationship, we categorize the hour of a day by 5 differnt time zones:

In [29]:
```
def cateHours(x):
    if 0 <= x <= 5:
        return "EM"    # Early Morning, mono decrease
    elif 6 <= x <= 15:
        return "MP"    # Morning Peak, mono increase
    elif 16 <= x <= 19:
        return "AF"    # Afternoon to night time, mono decrease
    elif 20 <= x <= 22:
        return "AP"   # Night peak, mono increase
    elif 23 <= x <= 24:
        return "LN"   # Late Night, mono decrase
```

Then we apply this function to the dataset to change the 'hour' column to discrete values:

In [67]:
```
taxi_new['hour'] = taxi_new['hour'].apply(cateHours)
taxi_new.head()
```

Out[67]:

	pickup_datetime	dropoff_datetime	passenger_count	pickup_longitude	pickup_latituc
0	2016-03-14 17:24:55	2016-03-14 17:32:30	1	-73.982155	40.767937
1	2016-06-12 00:43:35	2016-06-12 00:54:38	1	-73.980415	40.738564
2	2016-01-19 11:35:24	2016-01-19 12:10:48	1	-73.979027	40.763939
3	2016-04-06 19:32:31	2016-04-06 19:39:40	1	-74.010040	40.719971
4	2016-03-26 13:30:55	2016-03-26 13:38:10	1	-73.973053	40.793209

In [68]:
```
# One hot encoding

taxi_new_onehotHour = pd.get_dummies(taxi_new['hour'])
taxi_new_onehotHour.head()
```

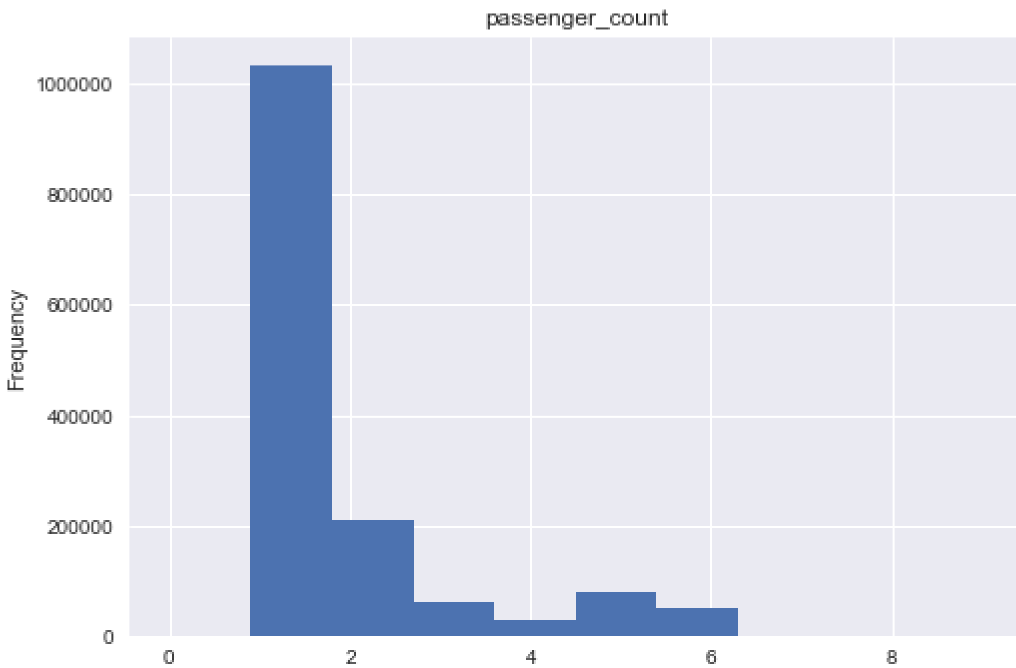
Out[68]:

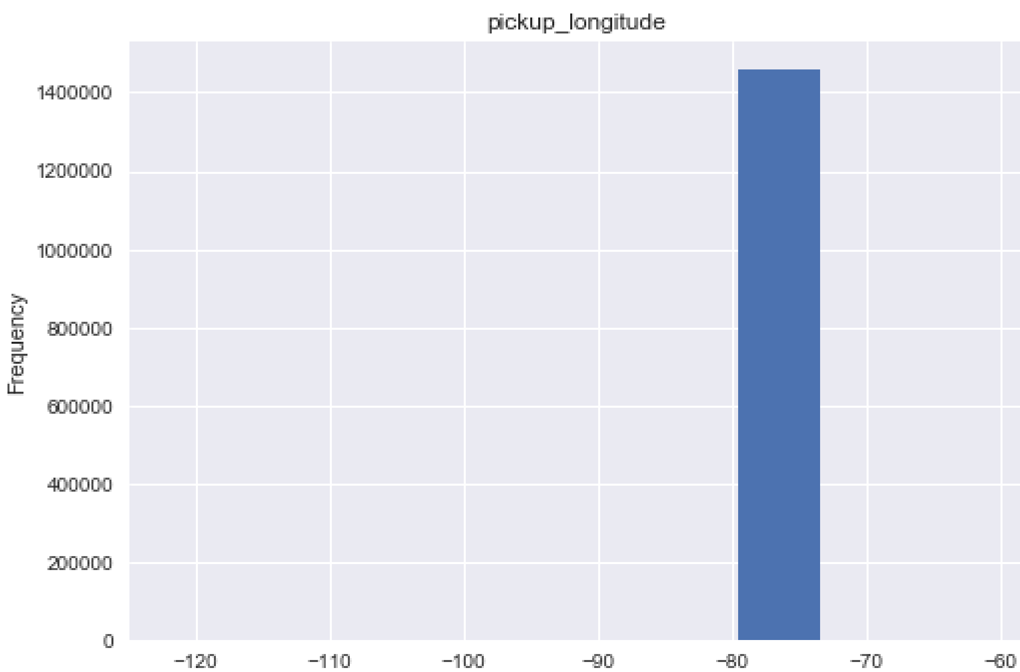
	AF	AP	EM	LN	MP
0	1	0	0	0	0
1	0	0	1	0	0
2	0	0	0	0	1
3	1	0	0	0	0
4	0	0	0	0	1

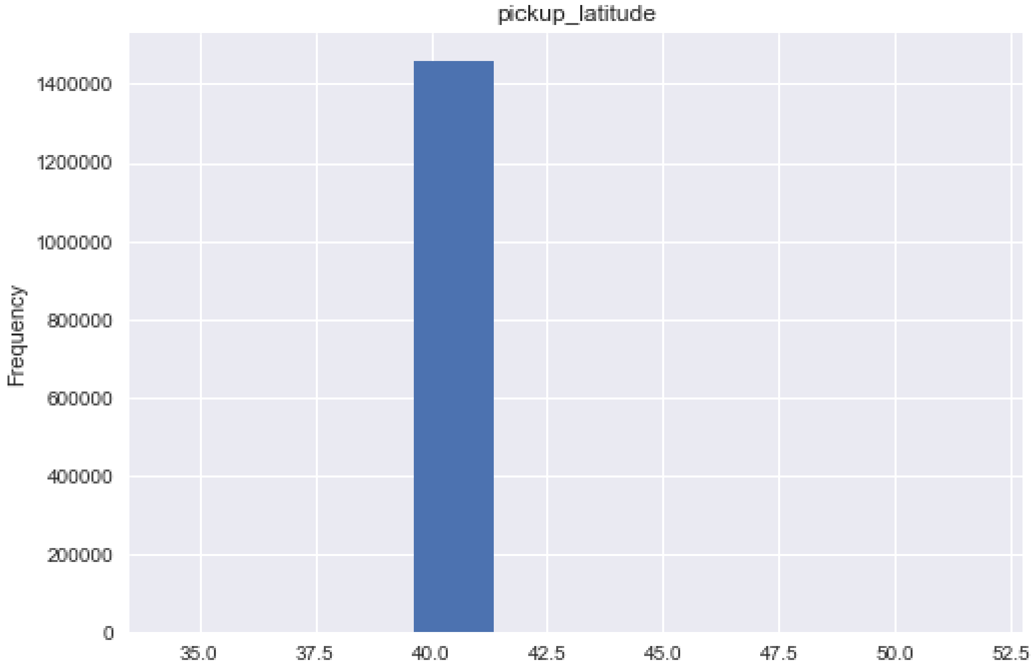
In [199]:
```
time = taxi_new.set_index('trip_duration')
```

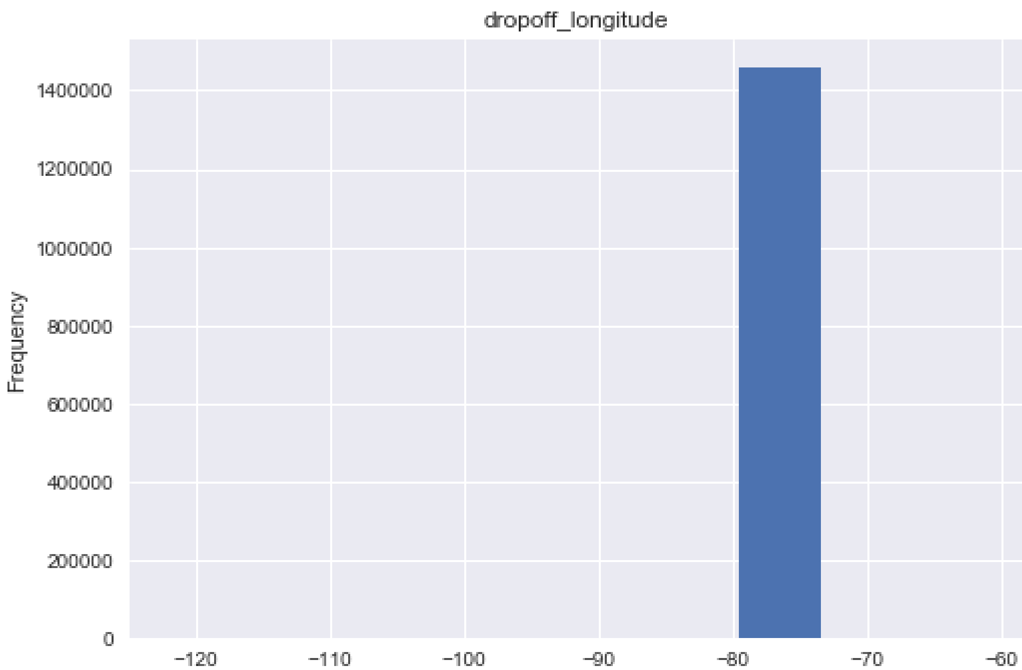
In [200]:

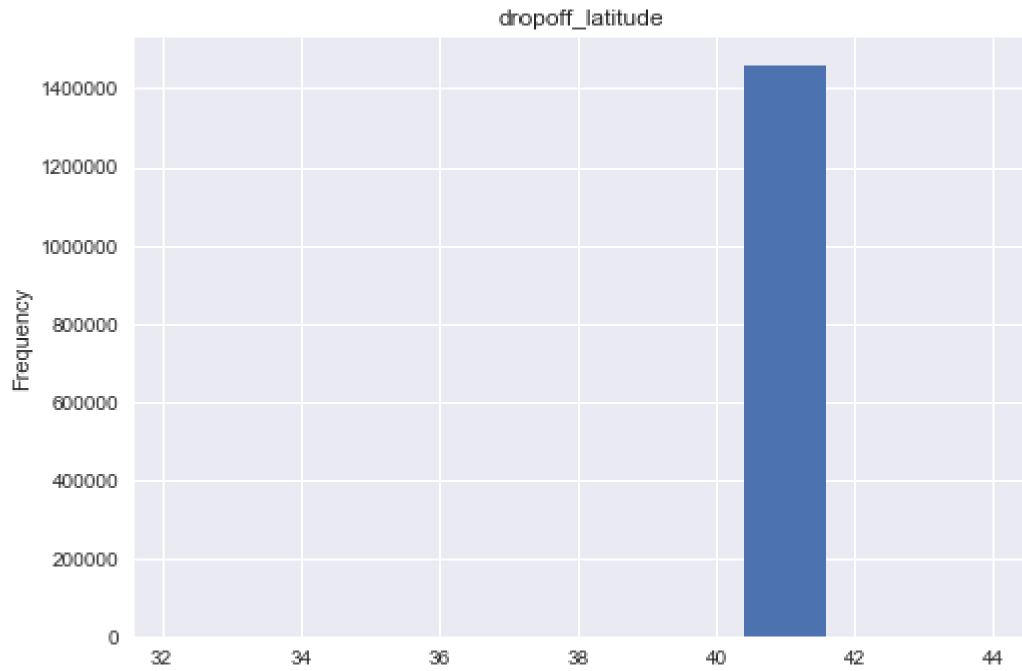
```
feature_cols = ['passenger_count','pickup_longitude','pickup_latitude',
'dropoff_longitude','dropoff_latitude']

for f in feature_cols:
    plt.figure()
    plt.title(f)
    time[f].plot(kind='hist')
    plt.show()
```


passenger_count
Frequency
1000000
800000
600000
400000
200000
0
0
2
4
6
8


pickup_longitude
Frequency
1400000
1200000
1000000
800000
600000
400000
200000
0
−120
−110
−100
−90
−80
−70
−60


pickup_latitude
Frequency
1400000
1200000
1000000
800000
600000
400000
200000
0
35.0
37.5
40.0
42.5
45.0
47.5
50.0
52.5


dropoff_longitude
Frequency
1400000
1200000
1000000
800000
600000
400000
200000
0
−120
−110
−100
−90
−80
−70
−60



Then we use OneHot Encoding for column 'hour'

In [75]:
```
# put this into the dataset

taxi_new = pd.concat([taxi_new,taxi_new_onehotHour], axis=1)
taxi_new.head()
```

Out[75]:

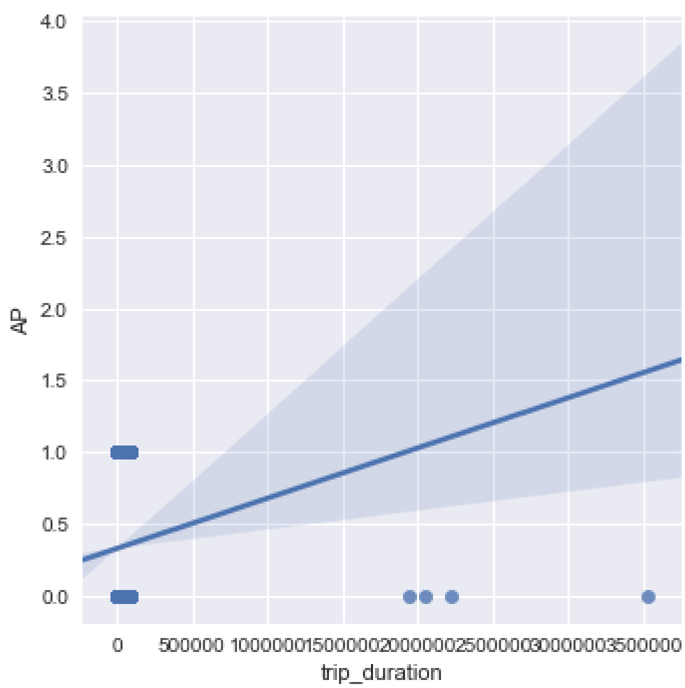
	pickup_datetime	dropoff_datetime	passenger_count	pickup_longitude	pickup_latituc
0	2016-03-14 17:24:55	2016-03-14 17:32:30	1	-73.982155	40.767937
1	2016-06-12 00:43:35	2016-06-12 00:54:38	1	-73.980415	40.738564
2	2016-01-19 11:35:24	2016-01-19 12:10:48	1	-73.979027	40.763939
3	2016-04-06 19:32:31	2016-04-06 19:39:40	1	-74.010040	40.719971
4	2016-03-26 13:30:55	2016-03-26 13:38:10	1	-73.973053	40.793209

In [76]:
```
taxi_new.head()
```

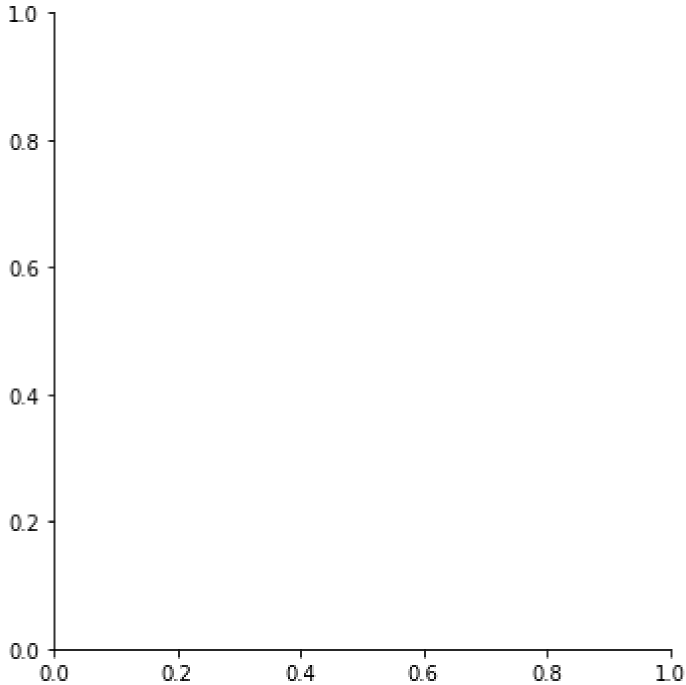
Out[76]:

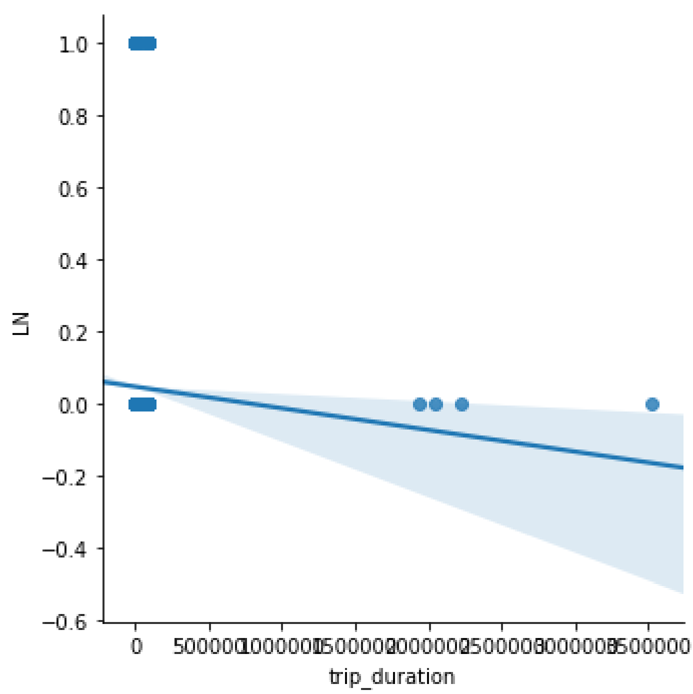
	pickup_datetime	dropoff_datetime	passenger_count	pickup_longitude	pickup_latituc
0	2016-03-14 17:24:55	2016-03-14 17:32:30	1	-73.982155	40.767937
1	2016-06-12 00:43:35	2016-06-12 00:54:38	1	-73.980415	40.738564
2	2016-01-19 11:35:24	2016-01-19 12:10:48	1	-73.979027	40.763939
3	2016-04-06 19:32:31	2016-04-06 19:39:40	1	-74.010040	40.719971
4	2016-03-26 13:30:55	2016-03-26 13:38:10	1	-73.973053	40.793209

In [202]:
```python
import seaborn as sns
sns.lmplot(x='trip_duration', y='AP', data=taxi_new)
plt.show()
```



```
In [77]: import seaborn as sns
         sns.lmplot(x='trip_duration', y='LN', data= taxi_new)
         plt.show()
```





After getting the pick-up time zone, we can drop the pickup_datetime and dropoff_datetime

but before we do that, let make the Label first.

```
In [10]: label = taxi_new['trip_duration']
         label.shape
```

```
Out[10]: (1458644,)
```

Direct Distance from Andrew

```
In [33]: from math import cos, asin, sqrt, sin, atan2, radians
         def getDistanceFromLatLon(lat1,lon1,lat2,lon2):
             R = 3959 # Radius of the earth in miles
             dLat = radians(lat2-lat1)  #deg2rad below
             dLon = radians(lon2-lon1)
             a = sin(dLat/2) * sin(dLat/2) + cos(radians(lat1)) * cos(radians(lat
         2)) * sin(dLon/2) * sin(dLon/2)
             c = 2 * atan2(sqrt(a), sqrt(1-a))
             d = R * c; #Distance in km
             #print(d)
             return d

         def f(x):
             return getDistanceFromLatLon(x[0], x[1], x[2], x[3])
```

```
In [79]: taxi_new['distance'] = taxi_new[['pickup_latitude','pickup_longitude','d
         ropoff_latitude','dropoff_longitude']].apply(f, axis =1)
         taxi_new['distance'].head()
```

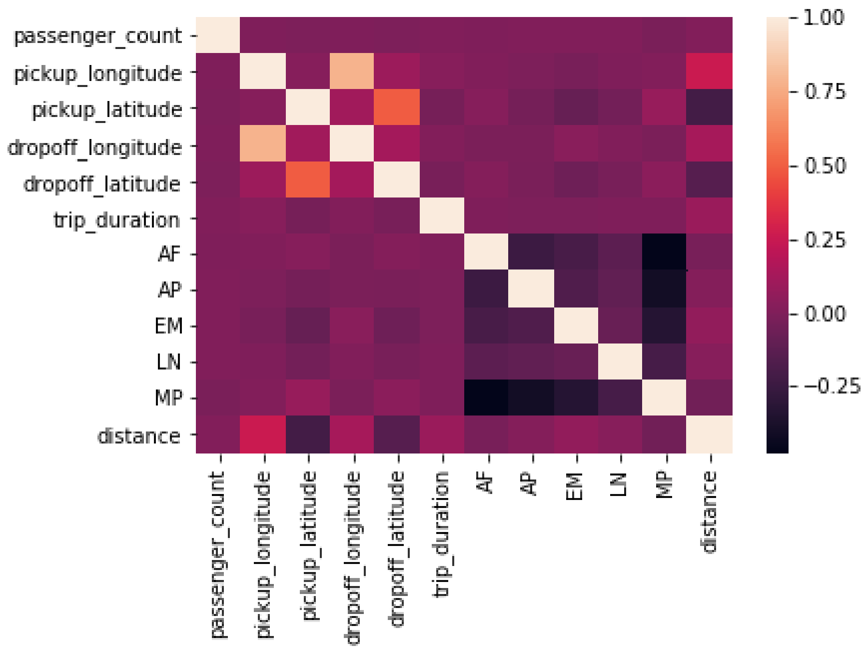
```
Out[79]: 0    0.931195
         1    1.121959
         2    3.967761
         3    0.923103
         4    0.738600
         Name: distance, dtype: float64
```

```
In [80]: taxi_new.head()
```

Out[80]:

	pickup_datetime	dropoff_datetime	passenger_count	pickup_longitude	pickup_latituc
0	2016-03-14 17:24:55	2016-03-14 17:32:30	1	-73.982155	40.767937
1	2016-06-12 00:43:35	2016-06-12 00:54:38	1	-73.980415	40.738564
2	2016-01-19 11:35:24	2016-01-19 12:10:48	1	-73.979027	40.763939
3	2016-04-06 19:32:31	2016-04-06 19:39:40	1	-74.010040	40.719971
4	2016-03-26 13:30:55	2016-03-26 13:38:10	1	-73.973053	40.793209

In [36]:
```
# Calculate correlations
corr = taxi_new.corr()

# Heatmap
sns.heatmap(corr)
plt.show()
```



In [ ]:
```
.agg(('mean'))
```

In [ ]:
```
figure,axes = plt.subplots(figsize = (10, 5))
distance = taxi_new.groupby(["distance"])["trip_duration"]
distance.plot(kind="line", ax=axes)
plt.title('Distance VS trip_duration')
axes.set_xlabel('Distance')
axes.set_ylabel('Trip durations')
plt.show()
```

then drop all unnecessary columns, and make the feature matrix

In [37]:
```
taxi_new = taxi_new.drop(['pickup_datetime','dropoff_datetime','hour','t
rip_duration'],axis=1)
taxi_new.head()
```

Out[37]:

	passenger_count	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitud
0	1	-73.982155	40.767937	-73.964630	40.765602
1	1	-73.980415	40.738564	-73.999481	40.731152
2	1	-73.979027	40.763939	-74.005333	40.710087
3	1	-74.010040	40.719971	-74.012268	40.706718
4	1	-73.973053	40.793209	-73.972923	40.782520

In [23]:
```
taxi_new = taxi_beforeScalled
```

Scaling may help to normalize the data:

In [59]:
```
from sklearn import preprocessing

taxi_beforeScalled = taxi_new   ## back up before scalling

taxi_scaled = preprocessing.scale(taxi_new)
taxi_new = pd.DataFrame(taxi_scaled)
taxi_new.head()
```

Out[59]:

	0	1	2	3	4	5	6	7
0	-0.505637	-0.122261	0.517494	0.124369	0.384575	1.879925	-0.453426	-0.364997
1	-0.505637	-0.097727	-0.375819	-0.368970	-0.575303	-0.531936	-0.453426	2.739745
2	-0.505637	-0.078143	0.395910	-0.451805	-1.162220	-0.531936	-0.453426	-0.364997
3	-0.505637	-0.515558	-0.941274	-0.549976	-1.256071	1.879925	-0.453426	-0.364997
4	-0.505637	0.006112	1.286091	0.006974	0.855957	-0.531936	-0.453426	-0.364997

Algorithm selection:

We select Linear Regression, Lasso, ElasticNet, and Ridge to perform regression, and compare them together

In [38]:
```
# Frist define the RMSE method.

def RMSE(y_test,y_predict):
    # Calculating "Mean Square Error" (MSE):
    mse = metrics.mean_squared_error(y_test, y_predict)
    # Using numpy sqrt function to take the square root and calculate "R
oot Mean Square Error" (RMSE)
    rmse = np.sqrt(mse)
    return(rmse)
```

In [61]:
```
# Define a method to run all 4 regression at the same time:

def Regressions(feature,label):

    # split the dataset into training and testing sets by 80-20 ratio
    X_train, X_test, y_train, y_test = train_test_split(feature, label,
test_size=0.2, random_state=3)


    #linear
    from sklearn.linear_model import LinearRegression
    myLinearReg = LinearRegression()
    myLinearReg.fit(X_train,y_train)
    y_predict = myLinearReg.predict(X_test)
    print('Linear ',RMSE(y_test,y_predict))

    y_predict = myLinearReg.predict(X_train)
    print('Linear Train',RMSE(y_train,y_predict),'\n')    ## Output the
 RMSE on the Training set.

    #Ridge
    from sklearn.linear_model import Ridge
    myRidge = Ridge()
    myRidge.fit(X_train,y_train)
    y_predict = myRidge.predict(X_test)
    print('Ridge ', RMSE(y_test,y_predict))

    y_predict = myRidge.predict(X_train)
    print('Ridge Train', RMSE(y_train,y_predict),'\n')    ## Output the
 RMSE on the Training set.

    #ElasticNet
    from sklearn.linear_model import ElasticNet
    myENet = ElasticNet()
    myENet.fit(X_train,y_train)
    y_predict = myENet.predict(X_test)
    print('ElasticNet ', RMSE(y_test,y_predict))

    y_predict = myENet.predict(X_train)
    print('ElasticNet Train', RMSE(y_train,y_predict),'\n')

    #Lasso
    from sklearn.linear_model import Lasso
    myLasso = Lasso()
    myLasso.fit(X_train,y_train)
    y_predict = myLasso.predict(X_test)
    print('Lasso ', RMSE(y_test,y_predict))

    y_predict = myLasso.predict(X_train)
    print('Lasso Train', RMSE(y_train,y_predict),'\n')


    # 10-fold Cross validation:
    rmse_list = cross_val_score(myLasso, X_train, y_train, cv=10, scorin
g='neg_mean_squared_error')
    #print(rmse_list)
```

```
    # Notice that "cross_val_score" by default provides "negative" value
s for "mse" to clarify that mse is error.
    # in order to calculate root mean square error (rmse), we have to ma
ke them positive!
    mse_list_positive = -rmse_list

    # using numpy sqrt function to calculate rmse:
    rmse_list = np.sqrt(mse_list_positive)
    #print(rmse_list)

    print('cross-validation',rmse_list.mean())
```

Also, in order to reduce work load and compare result, we create a method to split the dataset

In [40]:
```
def shrinkDataSet (train,label,times, splitSize):   #times= how many tim
es to split the original dataset
    X_train = train
    y_train = label
    for i in range (0,times):
        X_train, X_test, y_train, y_test = train_test_split(X_train, y_t
rain, test_size=splitSize, random_state=3)
    return X_train, y_train
```

Split the dataset to make it smaller:

In [41]:
```
# use spliting 5 times as example.

taxi_reduced, label_reduced = shrinkDataSet (taxi_new,label,5,0.5)    #
 split 5 times, into half

print('original: ',taxi_new.shape)
print('After: ',taxi_reduced.shape)
```

```
original:  (1458644, 11)
After:  (45582, 11)
```

In [62]:
```
def Run_compare(k):        # K = how many times to split

    taxi_reduced, label_reduced = shrinkDataSet (taxi_new,label, k ,0.5)
# split k times, into half
    print('Original shape: ',taxi_new.shape)
    print('After shape: ',taxi_reduced.shape,'\n')

    Regressions(taxi_reduced,label_reduced)
```

In [214]:

```

```

```
Original shape:  (1458644, 10)
After shape:  (5697, 10)

Linear  1780.31324731
Linear Train 2877.55620639

Ridge  1780.14500926
Ridge Train 2877.51993951

ElasticNet  1807.14705691
ElasticNet Train 2882.81447578

Lasso  1780.44201904
Lasso Train 2877.52232499

cross-validation 2126.98030196
```

start predicting:

First, Define a method for easy comparing:

In [63]:

```
# with k=8

k=8

Run_compare(k)
```

```
Original shape:  (1458644, 11)
After shape:  (5697, 11)

Linear  1677.38367183
Linear Train 2850.67764143

Ridge  1677.4026249
Ridge Train 2850.6776485

ElasticNet  1716.15264197
ElasticNet Train 2856.9494962

Lasso  1677.07258237
Lasso Train 2850.68223431

cross-validation 2021.76111409
```

In [44]:
```
# with k=5

k=5

Run_compare(k)
```

```
Original shape:  (1458644, 11)
After shape:  (45582, 11)

Linear  2360.00212068
Linear Train 3139.21822558

Ridge  2359.9389808
Ridge Train 3139.21934679

ElasticNet  2360.50990752
ElasticNet Train 3141.12840396

Lasso  2359.43538113
Lasso Train 3139.65687642

cross-validation 3120.46497092
```

In [55]:
```
# with k=3

k=3

Run_compare(k)
```

```
Original shape:  (1458644, 11)
After shape:  (182330, 11)

Linear  3122.76943374
Linear Train 2993.6234682

Ridge  3122.77069386
Ridge Train 2993.62347391

ElasticNet  3123.88277372
ElasticNet Train 2994.63109028

Lasso  3123.09736192
Lasso Train 2993.82103544

cross-validation 2980.58463961

-----------------------------------------------------------------------
----
NameError                                 Traceback (most recent call l
ast)
<ipython-input-55-cfa522c26e9a> in <module>()
      3 k=3
      4
----> 5 Run_compare(k)

<ipython-input-53-abf3f31d4d2b> in Run_compare(k)
      5     print('After shape: ',taxi_reduced.shape,'\n')
      6
----> 7     final_submit = Regressions(taxi_reduced,label_reduced)
      8
      9

<ipython-input-54-6118307aec98> in Regressions(feature, label)
     64     print('cross-validation',rmse_list.mean())
     65
---> 66     final_submit['trip_duration'] = np.round(y_predict)
     67
     68     return final_submit

NameError: name 'final_submit' is not defined
```

In [46]:
```
# with k=1

k=1

Run_compare(k)
```

```
Original shape:  (1458644, 11)
After shape:  (729322, 11)

Linear  3130.13732036
Linear Train 6827.78006402

Ridge  3130.13736018
Ridge Train 6827.7800642

ElasticNet  3130.92467467
ElasticNet Train 6828.24569576

Lasso  3130.33679291
Lasso Train 6827.85985898

cross-validation 5276.14189853
```

In [49]:
```
# with k=0 , not spliting at all

k=0

Run_compare(k)
```

```
Original shape:  (1458644, 11)
After shape:  (1458644, 11)

Linear  4774.16988657
Linear Train 5317.03045721

Ridge  4774.16895939
Ridge Train 5317.03045751

ElasticNet  4772.98346594
ElasticNet Train 5317.98241472

Lasso  4773.79623661
Lasso Train 5317.15883643

cross-validation 4455.35744246

-----------------------------------------------------------------------
----
NameError                                 Traceback (most recent call l
ast)
<ipython-input-49-a9017d89ae2a> in <module>()
      3 k=0
      4
----> 5 Run_compare(k)

<ipython-input-48-bc8904a9fb9f> in Run_compare(k)
      7     Regressions(taxi_reduced,label_reduced)
      8
----> 9     final_submit['trip_duration'] = np.round(y_predict)

NameError: name 'y_predict' is not defined
```

From article, if we compare the RMSE from the Predicted RMSE and the Training RMSE, and if they are similar, it's good.

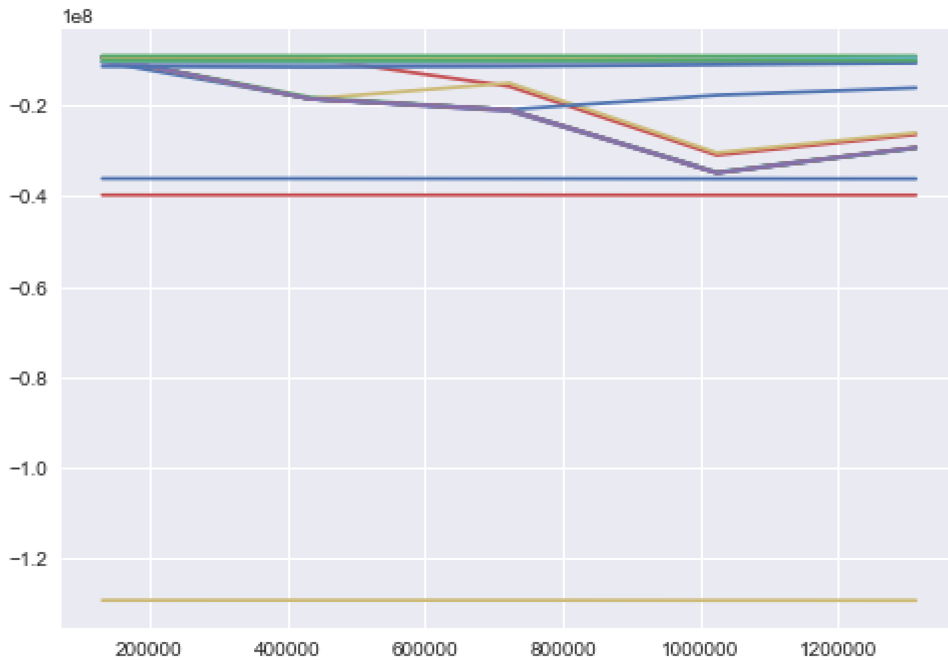
RMSE doesn't have a specific threadhold to say "below xxx is good".

Therefore, we can see that at k=8, the RMSE of predicted and training are the closest.

In this case, I can say that when we split the dataset into 3 times, providing about 180k rows of data, the model is trained to the best fit.

In [220]:

```
#Plot learning curve
from sklearn.model_selection import learning_curve
train_sizes_abs, train_scores, test_scores = learning_curve(my_linreg ,X
, y, n_jobs=-1,cv=10, verbose=0, scoring='neg_mean_squared_error',train_
sizes=np.array([ 0.1, 0.33, 0.55, 0.78, 1. ]))
plt.plot(train_sizes_abs, train_scores)
plt.plot(train_sizes_abs, test_scores)
plt.show()
```



In [221]:

```
#Mean learning curves for different cross validation folds
train_score_mean = np.mean(train_scores,axis=1)
test_score_mean = np.mean(test_scores,axis=1)
plt.plot(train_sizes_abs,train_score_mean)
plt.plot(train_sizes_abs, test_score_mean)
plt.show()
```