NYC_Taxifare_Prediction

September 25, 2018

```
In [83]: import pandas as pd
         import warnings

         warnings.simplefilter('ignore')

         df_train = pd.read_csv("/Users/manideepattanti/Acads/SEM1/DSF/hw2/train.csv", nrows=50
                                parse_dates=["pickup_datetime"])
         df_test = pd.read_csv("/Users/manideepattanti/Acads/SEM1/DSF/hw2/test.csv", parse_date
         print("Shape at the time of loading:", df_train.shape)
         print("Data types:")
         print(df_train.dtypes)
```

```
Shape at the time of loading: (500000, 8)
Data types:
key                           object
fare_amount                  float64
pickup_datetime       datetime64[ns]
pickup_longitude             float64
pickup_latitude              float64
dropoff_longitude            float64
dropoff_latitude             float64
passenger_count                int64
dtype: object
```

Imported 500,000 lines from the csv into df_train.

```
In [84]: # Cleaning the data
         def check_longitude(longitude):
             return (longitude <= -72.986532) & (longitude >= -74.263242)


         def check_latitude(latitude):
             return (latitude >= 40.568973) & (latitude <= 41.709555)


         def check_fare(fare):
             return (fare > 0) & (fare < 500)
```

```python
def check_passenger_count(count):
    return (count > 0) & (count < 8)


def cleaning_conditions(fare_amount, p_lon, p_lat, d_lon, d_lat, p_count):
    conditions = check_fare(fare_amount)
    conditions = conditions & check_longitude(p_lon)
    conditions = conditions & check_latitude(p_lat)
    conditions = conditions & check_longitude(d_lon)
    conditions = conditions & check_latitude(d_lat)
    conditions = conditions & check_passenger_count(p_count)
    return conditions


def clean_data(df):
    df = df[cleaning_conditions(df.fare_amount, df.pickup_longitude, df.pickup_latitu
                                df.dropoff_longitude, df.dropoff_latitude,
                                df.passenger_count)]
    df = df.dropna()
    return df


df_train = clean_data(df_train)
print("Shape after cleaning data:", df_train.shape)
print(df_train.head())
```

```
Shape after cleaning data: (487599, 8)
                             key  fare_amount     pickup_datetime  \
0    2009-06-15 17:26:21.0000001          4.5 2009-06-15 17:26:21
1    2010-01-05 16:52:16.0000002         16.9 2010-01-05 16:52:16
2   2011-08-18 00:35:00.00000049          5.7 2011-08-18 00:35:00
3    2012-04-21 04:30:42.0000001          7.7 2012-04-21 04:30:42
4  2010-03-09 07:51:00.000000135          5.3 2010-03-09 07:51:00

   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                1
2                2
3                1
```

4 1

For Data Cleaning I chose the following criteria: * The fare amount should be greater than 0 and less than 500. Rest of the data seems like noise. * Same with passenger count. It should be greater than 0 and less than 8. * For latitude and longitude, I wanted to train in the boundaries of the test data. Hence those coordinates. * Finally dropped the nan values since few timestamps were nan.

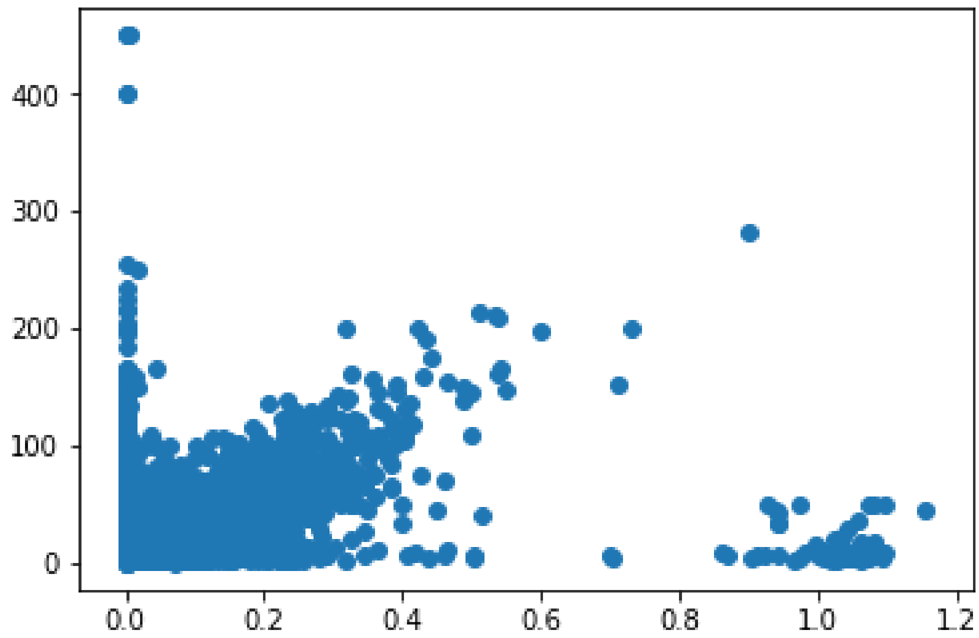
```
In [85]: # Adding Euclidean Distance and Day to the data to find the correlation
         df_train['distance'] = (((df_train.pickup_longitude - df_train.dropoff_longitude) ** 2
                                  (df_train.pickup_latitude - df_train.dropoff_latitude) ** 2) ** .5

         df_train['hour'] = df_train.pickup_datetime.apply(lambda x: x.hour)

         print("Shape after adding features:", df_train.shape)
```

```
Shape after adding features: (487599, 10)
```

```
In [87]: # Finding Distance and Fare Correlation
         distance_fare_correlation = df_train['distance'].corr(df_train['fare_amount'], method=
         print(distance_fare_correlation)

         # Scatter Plot of Distance and Fare
         import matplotlib.pyplot as plt

         plt.scatter(df_train['distance'], df_train['fare_amount'])
         plt.plot()
```

```
0.8189413154105973
```

```
Out[87]: []
```

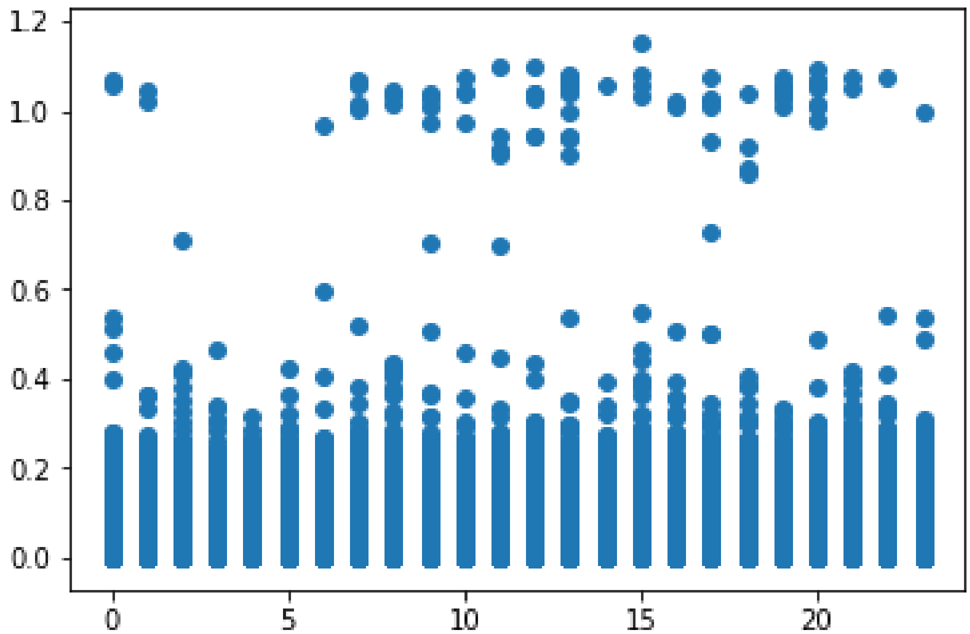


This scatter plot shows a high positive correlation between the distance travelled and fare_amount whis is 0.819. There seems to be a linear relation between fare and distance. It makes sense as fare increases with increasing distance linearly.

In [88]:
```
# Finding Time of Day(hour) and distance correlation
hour_distance_correlation = df_train['hour'].corr(df_train['distance'], method='pearso
print(hour_distance_correlation)

# Scatter Plot of Hour and Distance
plt.scatter(df_train['hour'], df_train['distance'])
plt.plot()
```

```
-0.031012930775137785
```

Out[88]: []

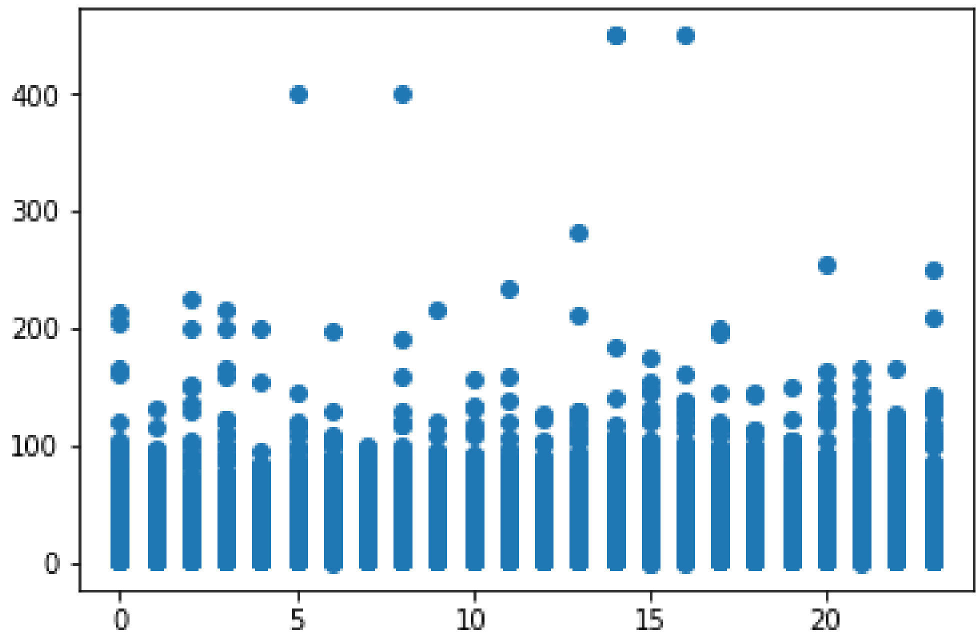


This scatter plot shows that distance and time(hour of day) has very less negative correlation of -0.031. This may be because the density is different during different week days. Hour and distance also have non linear relation.

```
In [89]: # Finding Hour and Fare Correlation
         hour_fare_correlation = df_train['hour'].corr(df_train['fare_amount'], method='pearson
         print(hour_fare_correlation)

         # Scatter Plot of Hour and Fare
         plt.scatter(df_train['hour'], df_train['fare_amount'])
         plt.plot()
```

```
-0.019615850595663627
```

```
Out[89]: []
```



This scatter plot shows that time and fare have very less negative correlation of -0.0196. This may be because fares don't change with time or may be because different weekdays have different distribution of time fare relation. There is a non-linear relation between fare and hour as can be seen in the plots done below.

From the above three plots, it can be seen that distance and fare have highest correlation.

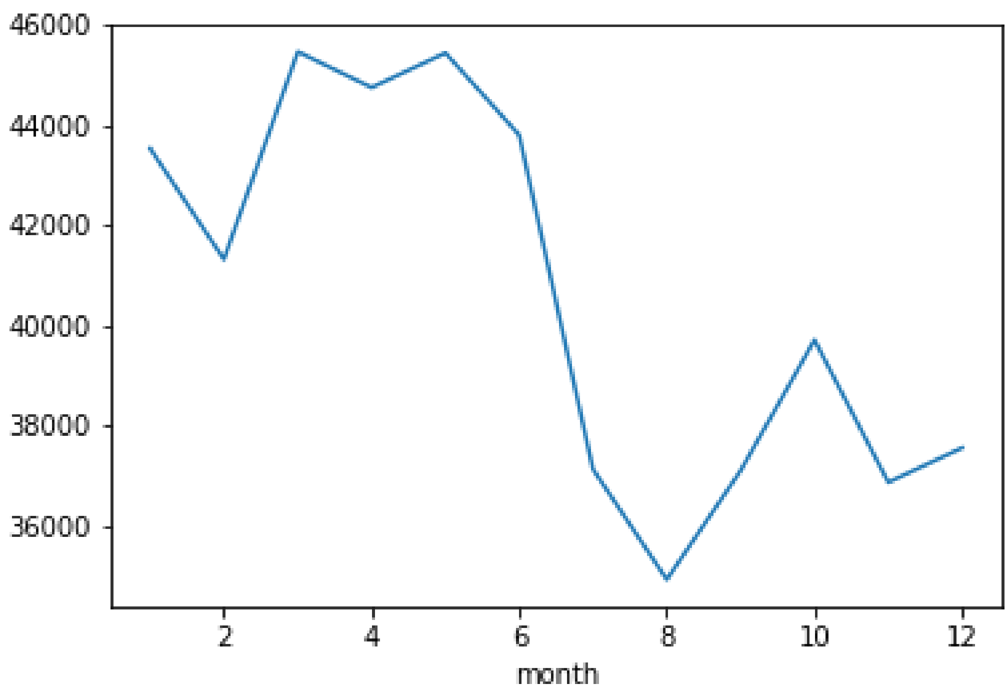
In [90]:
```
# Adding additional features to the data
def add_features(df):
    df['year'] = df.pickup_datetime.apply(lambda x: x.year)
    df['month'] = df.pickup_datetime.apply(lambda x: x.month)
    df['day'] = df.pickup_datetime.apply(lambda x: x.day)
    df['weekday'] = df.pickup_datetime.apply(lambda x: x.weekday())

    from pandas.tseries.holiday import USFederalHolidayCalendar

    cal = USFederalHolidayCalendar()
    holidays = cal.holidays(start='2009-01-01', end='2015-12-31').to_pydatetime()
    df['is_holiday'] = df['pickup_datetime'].apply(lambda x: 1 if x in holidays else (

    return df


df_train = add_features(df_train)
df_test = add_features(df_test)
print("Data Types after adding Features:")
print(df_train.dtypes)
```

```
Data Types after adding Features:
key                           object
fare_amount                  float64
pickup_datetime       datetime64[ns]
pickup_longitude             float64
pickup_latitude              float64
dropoff_longitude            float64
dropoff_latitude             float64
passenger_count                int64
distance                     float64
hour                           int64
year                           int64
month                          int64
day                            int64
weekday                        int64
is_holiday                     int64
dtype: object
```

Chose additional features of YEAR, MONTH, DAY, WEEKDAY, and IS_HOLIDAY, which were the first things to come in mind from the above scatter plots as well as looking at the different densities. Holiday was chosen as it seemed to be a distinguishing factor when people may go out more than in normal non-holiday day. So imported the data source of US Federal Holidays has been used from pandas package and each dataset is labelled 1 for holiday and 0 for non-holiday.

```
In [94]: df_train.groupby('month')['key'].count().plot()
```

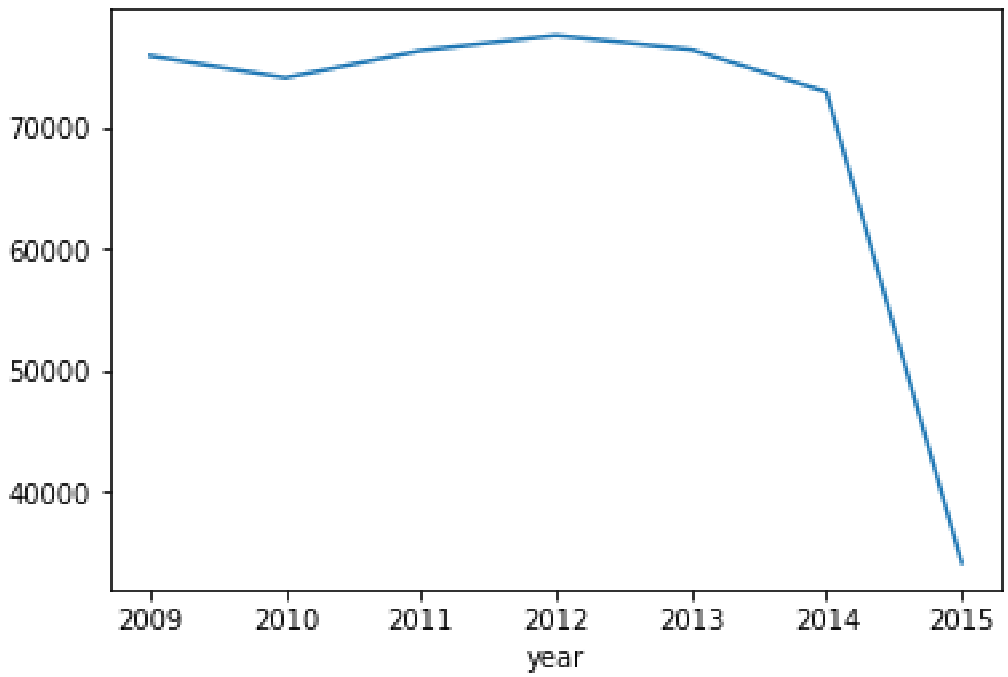
```
Out[94]: <matplotlib.axes._subplots.AxesSubplot at 0x10ff0c240>
```



The above plot between month and number of rides show a minimum in August and comparable variation between months.

```
In [95]: df_train.groupby('year')['key'].count().plot()
```

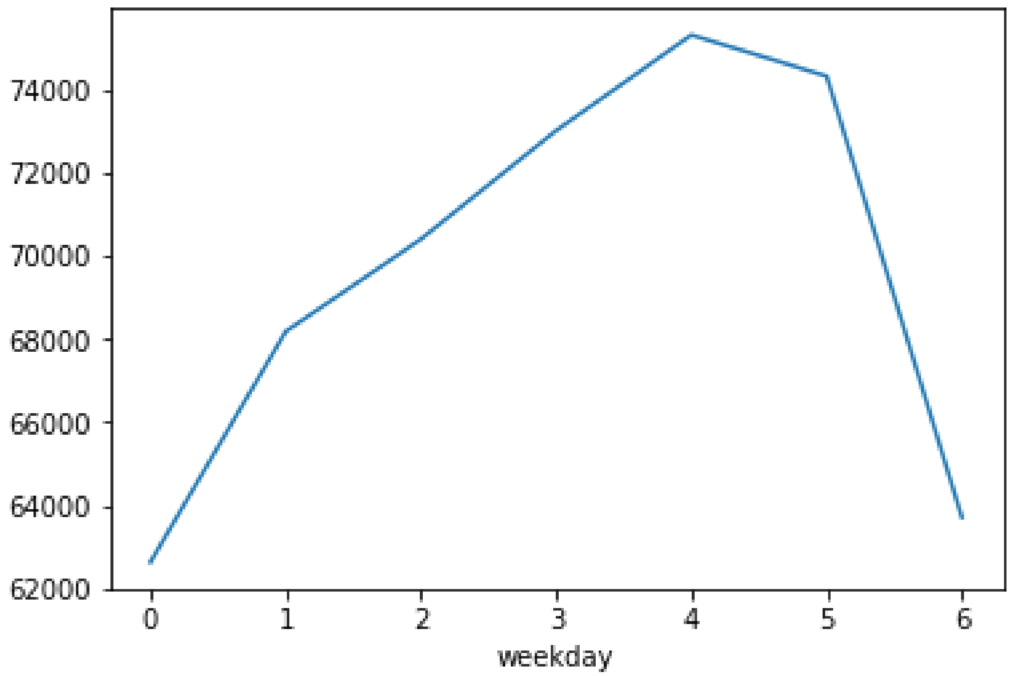
```
Out[95]: <matplotlib.axes._subplots.AxesSubplot at 0x111f44710>
```



The above plot shows the data is pretty evenly distributed between the years and we don't have entire data of 2015 which is the reason for dip.

```
In [96]: df_train.groupby('weekday')['key'].count().plot()
```

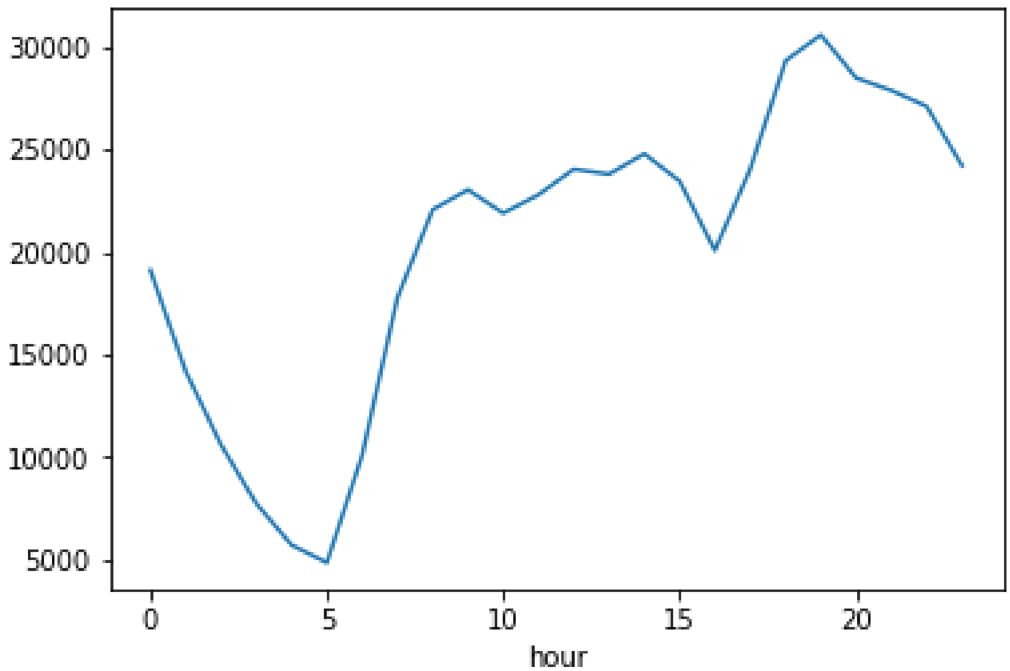
```
Out[96]: <matplotlib.axes._subplots.AxesSubplot at 0x1a2b917208>
```



The above plot shows that friday and saturday are the days with most taxi usage and sunday and monday being the least. This may be because people are free from work on friday and go out a lot on these days.

```
In [97]: df_train.groupby('hour')['key'].count().plot()
```

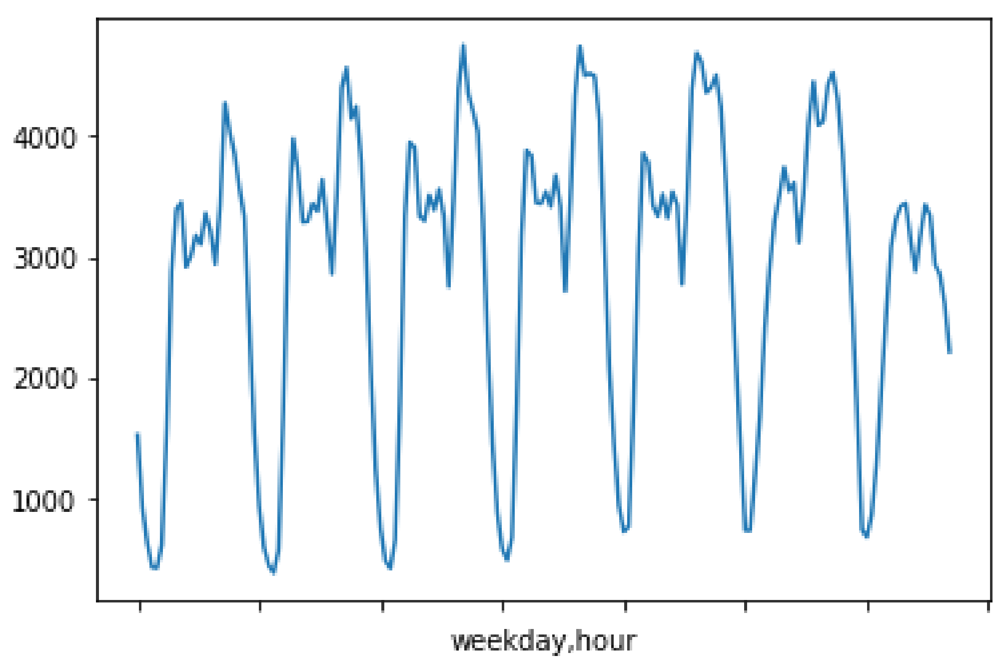
```
Out[97]: <matplotlib.axes._subplots.AxesSubplot at 0x1a29da79b0>
```



This graph shows peak hour around 1900 hrs every day, may be the time when people get back from work or go out. It's minimum is at 0500 hrs.

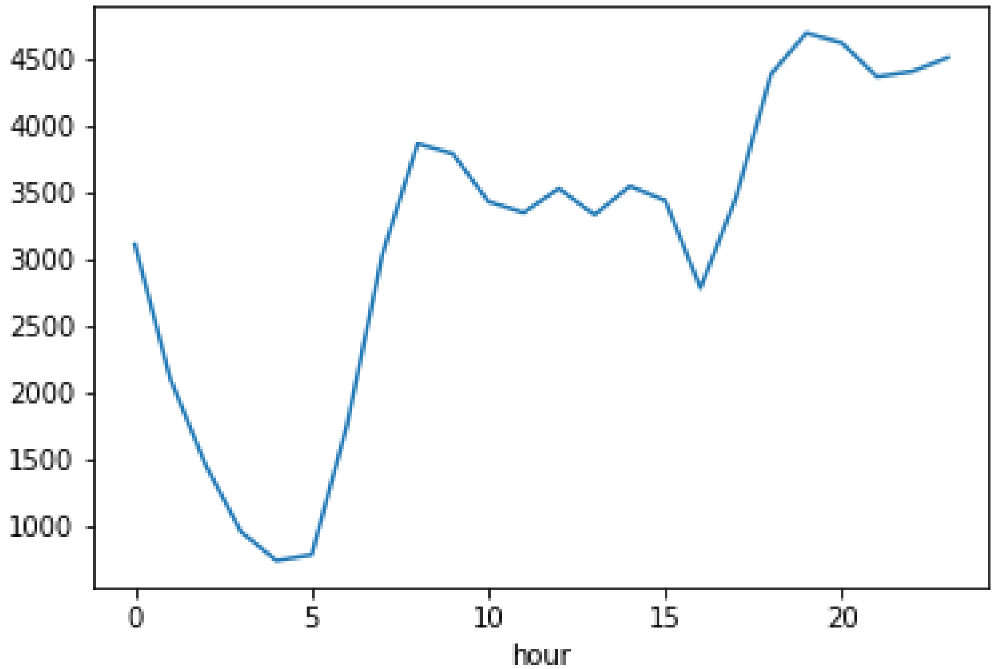
```
In [100]: df_train.groupby(['weekday', 'hour'])['key'].count().plot()
```

```
Out[100]: <matplotlib.axes._subplots.AxesSubplot at 0x123ff6cf8>
```



```
In [116]: df_train[df_train['weekday'] == 4].groupby(['hour'])['key'].count().plot()
```

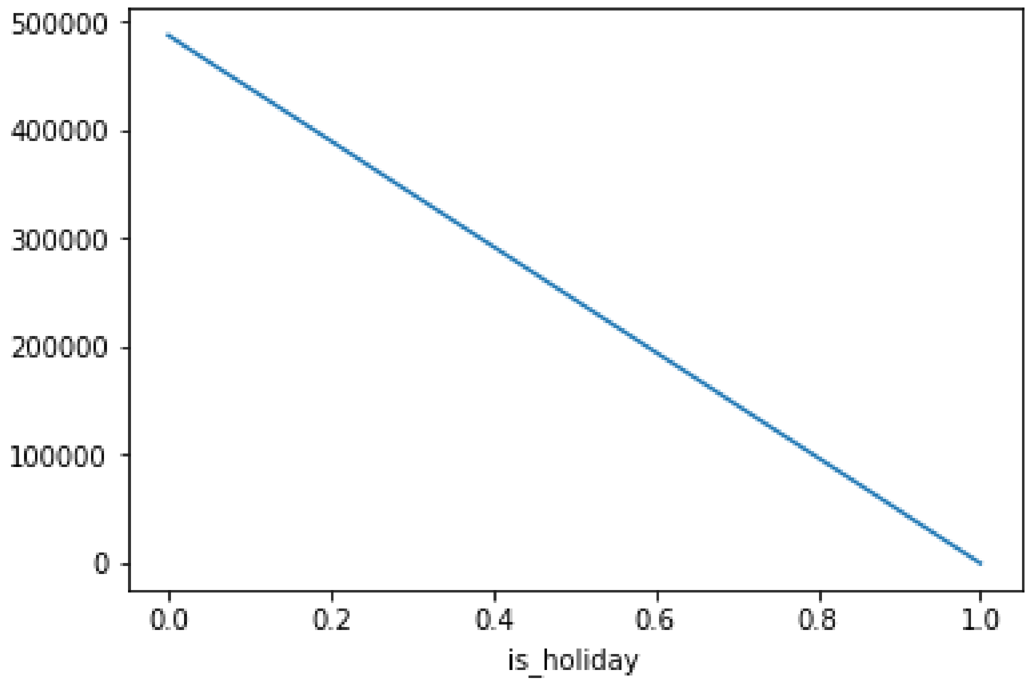
```
Out[116]: <matplotlib.axes._subplots.AxesSubplot at 0x1a2b8a6748>
```



Plots like this on all week days show high taxi usage on friday night, saturday night. Rest all days have peak at around 1900 hrs and not much usage in the night after that. This helps us to take variable representing friday or saturday night as this is differentiating from other week days. We will try to incorporate this variable in our final improvement phase.

```
In [117]: df_train.groupby('is_holiday')['key'].count().plot()
```

```
Out[117]: <matplotlib.axes._subplots.AxesSubplot at 0x1a298f4128>
```



The number of rides is very less on holidays. This feature plays a part in training since we have days whose rides are very less and this feature proves why.

```
In [79]: def feature_set(df):
             columns = ['distance', 'year', 'month', 'day', 'hour', 'weekday', 'is_holiday']
             df = df[columns]

             return df

         df_target_set = df_train[['fare_amount']]
         df_training_set = feature_set(df_train)
         print("Data Types of final training set:")
         print(df_training_set.dtypes)
```

```
Data Types of final training set:
distance      float64
year            int64
month           int64
day             int64
hour            int64
weekday         int64
is_holiday      int64
dtype: object
```

Choosing the features to train the final model on.

In [80]:
```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
import numpy as np
from sklearn.metrics import mean_squared_error

# Linear Regression Model
def linear_regression(train, target, normalize=False):
    train, train_test, target, target_test = train_test_split(train, target)

    linear_regression = LinearRegression(normalize=normalize)
    linear_regression.fit(train, target)
    print(linear_regression.intercept_, linear_regression.coef_)

    target_prediction = linear_regression.predict(train_test)
    rms = np.sqrt(mean_squared_error(target_test, target_prediction))
    print(rms)

    return linear_regression

linear_regression(df_training_set, df_target_set)
```

```
[-1078.8569968] [[ 1.97021982e+02  5.38330542e-01  7.50986327e-02  1.61208368e-03
   7.05998739e-03 -3.41771903e-02 -2.72672082e+00]]
5.546056554236399
```

Out[80]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=1, normalize=False)
```

Training the linear regression model and predicting on the test data which is split from the chosen training data without normalization and choosing the above features gives rmse of 5.54. The coefficients are printed and it can be seen that distance has highest weight of 197. So it's the most important feature. Holiday is the second important feature with a weight of -2.726 followed by year with 0.538. Other features contribute less comparatively. * Distance : 197.021982 * Year : 0.538330542 * Month : 0.0750986327 * Day : 0.00161208368 * Hour : 0.00705998739 * Weekday : -0.0341771903 * Holiday : -2.72672082

In [81]:
```
from sklearn.ensemble import RandomForestRegressor

# Random Forest Regressor
def random_forest_regressor(train, target):
    train, train_test, target, target_test = train_test_split(train, target)
    random_forest_regressor = RandomForestRegressor(n_estimators=25, max_features=None
                                                    min_samples_split=3, min_samples_
    random_forest_regressor.fit(train, target)
    target_prediction = random_forest_regressor.predict(train_test)
    rms = np.sqrt(mean_squared_error(target_test, target_prediction))
    print(rms)

    return random_forest_regressor
```

```
random_forest_regressor(df_training_set, df_target_set)
```

```
4.902812414231889
```

```
Out[81]: RandomForestRegressor(bootstrap=True, criterion='mse', max_depth=25,
                    max_features=None, max_leaf_nodes=None,
                    min_impurity_decrease=0.0, min_impurity_split=None,
                    min_samples_leaf=2, min_samples_split=3,
                    min_weight_fraction_leaf=0.0, n_estimators=25, n_jobs=1,
                    oob_score=False, random_state=0, verbose=0, warm_start=False)
```

To improve on the Linear regression model, used random forest to predict fare on same features. It performs well and gives an RMSE of 4.902 on test data split from training set. It is an improvement on the Linear Regression model done previously.

```
In [82]: import xgboost as xgb

         # XGBoost
         def xg_boost(train, target):
             train, train_test, target, target_test = train_test_split(train, target)
             matrix_train = xgb.DMatrix(train, label=target)
             matrix_test = xgb.DMatrix(train_test, label=target_test)
             xgboost_model = xgb.train(params={'objective': 'reg:linear', 'eval_metric': 'rmse
                                   dtrain=matrix_train, num_boost_round=100,
                                   early_stopping_rounds=25, evals=[(matrix_test, 'test')])

             return xgboost_model

         xg_boost(df_training_set, df_target_set)
```

```
[20:25:36] src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 124 extra nodes, 0 pruned n
[0]        test-rmse:10.6296
Will train until test-rmse hasn't improved in 25 rounds.
[20:25:36] src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 126 extra nodes, 0 pruned n
[1]        test-rmse:8.08862
[20:25:36] src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 126 extra nodes, 0 pruned n
[2]        test-rmse:6.48381
[20:25:36] src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 126 extra nodes, 0 pruned n
[3]        test-rmse:5.5143
[20:25:37] src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 122 extra nodes, 0 pruned n
[4]        test-rmse:4.9639
[20:25:37] src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 124 extra nodes, 0 pruned n
[5]        test-rmse:4.67076
[20:25:37] src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 122 extra nodes, 0 pruned n
[6]        test-rmse:4.51562
[20:25:38] src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 124 extra nodes, 0 pruned n
[7]        test-rmse:4.42969
```

```
[20:25:38] src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 126 extra nodes, 0 pruned n
[8]	test-rmse:4.3864
[20:25:38] src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 126 extra nodes, 0 pruned n
[9]	test-rmse:4.36312
[20:25:39] src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 120 extra nodes, 0 pruned n
[10]	test-rmse:4.34896
[20:25:39] src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 122 extra nodes, 0 pruned n
[11]	test-rmse:4.34121
[20:25:39] src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 124 extra nodes, 0 pruned n
[12]	test-rmse:4.33834
[20:25:40] src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 110 extra nodes, 0 pruned n
[13]	test-rmse:4.33101
[20:25:40] src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 106 extra nodes, 0 pruned n
[14]	test-rmse:4.33025
[20:25:40] src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 120 extra nodes, 0 pruned n
[15]	test-rmse:4.33425
[20:25:40] src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 88 extra nodes, 0 pruned no
[16]	test-rmse:4.33822
[20:25:41] src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 122 extra nodes, 0 pruned n
[17]	test-rmse:4.34113
[20:25:41] src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 92 extra nodes, 0 pruned no
[18]	test-rmse:4.34094
[20:25:41] src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 118 extra nodes, 0 pruned n
[19]	test-rmse:4.34338
[20:25:42] src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 118 extra nodes, 0 pruned n
[20]	test-rmse:4.34855
[20:25:42] src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 90 extra nodes, 0 pruned no
[21]	test-rmse:4.34689
[20:25:42] src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 112 extra nodes, 0 pruned n
[22]	test-rmse:4.3471
[20:25:42] src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 108 extra nodes, 0 pruned n
[23]	test-rmse:4.36442
[20:25:43] src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 86 extra nodes, 0 pruned no
[24]	test-rmse:4.36609
[20:25:43] src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 62 extra nodes, 0 pruned no
[25]	test-rmse:4.3648
[20:25:43] src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 82 extra nodes, 0 pruned no
[26]	test-rmse:4.36582
[20:25:44] src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 104 extra nodes, 0 pruned n
[27]	test-rmse:4.36501
[20:25:44] src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 70 extra nodes, 0 pruned no
[28]	test-rmse:4.37179
[20:25:44] src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 124 extra nodes, 0 pruned n
[29]	test-rmse:4.37162
[20:25:44] src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 120 extra nodes, 0 pruned n
[30]	test-rmse:4.37225
[20:25:45] src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 96 extra nodes, 0 pruned no
[31]	test-rmse:4.37331
```

```
[20:25:45] src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 22 extra nodes, 0 pruned no
[32]       test-rmse:4.37349
[20:25:45] src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 102 extra nodes, 0 pruned n
[33]       test-rmse:4.37477
[20:25:45] src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 102 extra nodes, 0 pruned n
[34]       test-rmse:4.37225
[20:25:46] src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 88 extra nodes, 0 pruned no
[35]       test-rmse:4.37268
[20:25:46] src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 108 extra nodes, 0 pruned n
[36]       test-rmse:4.38138
[20:25:46] src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 40 extra nodes, 0 pruned no
[37]       test-rmse:4.38162
[20:25:47] src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 86 extra nodes, 0 pruned no
[38]       test-rmse:4.38297
[20:25:47] src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 62 extra nodes, 0 pruned no
[39]       test-rmse:4.38055
Stopping. Best iteration:
[14]       test-rmse:4.33025
```

```
Out[82]: <xgboost.core.Booster at 0x1105f4f28>
```

Then chose XGBoost model to get the RMSE which comes to be around 4.33 for 100 iterations. It is an improvement on the Random Forest as well as Linear Regression models.

External Datasets: * Used holiday dataset of pandas as explained above. * Weather dataset can make a decent contribution as the prices will definitely depend on the weather as the traffic and other reasons for waiting may be more on few days.

Improvements: * As discussed in the above plots we can take a feature weekend_night which includes times between 2000 and 0400 on friday and saturday. * Location specific data will be helpful as it would help divide the regions so that we can more precisely predict the prices. This is because different regions experience different congestion and prices may adjust accordingly. Other impacts can be the distance of the trips since malls and other places may be far from some regions. * Long distance travel, which is common when visiting famous places in New York and other from Air Ports. The price for such high distance travel may be less than the ususl short-distance travels. This can be seen in the distance scatter plot where fares of long distance travels are comparatively lower or discounted and seem fixed * Weather dataset can be helpful since the congestion and other criteria for pricing may depend on that. * Using better distance function like haversine distance function.

Based on the above the following features may be added: * weekend_night: True if it's friday or saturday and time is 2000 - 0000 or if saturday or sunday between 0000 - 0400 * cluster the locations. * distance from different airports

Note: Inspiration of clustering and airports has been taken from the following kernels. https://www.kaggle.com/justjun0321/exploratory-geoclustering-to-modeling https://www.kaggle.com/dimitreoliveira/taxi-fare-prediction-with-keras-deep-learning

Improving Model: * Normalization can be used to improve the Linear regression model. * Scaling Features using standard scaler

In [ ]:
```
def haversine_distance(p_lat, p_lon, d_lat, d_lon):
    p_lon, p_lat, d_lon, d_lat = map(np.radians, [p_lon, p_lat, d_lon, d_lat])
    a = np.sin((d_lat - p_lat) / 2.0) ** 2 + np.cos(p_lat) * np.cos(d_lat) * np.sin((d_
    return 6367 * 2 * np.arcsin(np.sqrt(a)) * 0.62137


def is_weekend_night(row):
    if ((row['weekday'] == 4 or row['weekday'] == 5) and (row['hour'] >= 20)) or \
            ((row['weekday'] == 5 or row['weekday'] == 6) and (row['hour'] <= 4)):
        return 1
    else:
        return 0


# Adding additional features discussed above
def add_additional_features(df):
    df['distance'] = haversine_distance(df.pickup_latitude, df.pickup_longitude,
                                        df.dropoff_latitude, df.dropoff_longitude)
    ny = (-74.0063889, 40.7141667)
    jfk = (-73.7822222222, 40.6441666667)
    ewr = (-74.175, 40.69)
    lgr = (-73.87, 40.77)

    df['downtown_pickup_distance'] = haversine_distance(ny[1], ny[0], df.pickup_latitud
    df['downtown_dropoff_distance'] = haversine_distance(ny[1], ny[0], df.dropoff_lati
    df['jfk_pickup_distance'] = haversine_distance(jfk[1], jfk[0], df.pickup_latitude,
    df['jfk_dropoff_distance'] = haversine_distance(jfk[1], jfk[0], df.dropoff_latitude
    df['ewr_pickup_distance'] = haversine_distance(ewr[1], ewr[0], df.pickup_latitude,
    df['ewr_dropoff_distance'] = haversine_distance(ewr[1], ewr[0], df.dropoff_latitude
    df['lgr_pickup_distance'] = haversine_distance(lgr[1], lgr[0], df.pickup_latitude,
    df['lgr_dropoff_distance'] = haversine_distance(lgr[1], lgr[0], df.dropoff_latitude

    # df['weekend_night'] = df.apply(lambda x: is_weekend_night)
    return df


def cluster_locations(df):
    pickup_locations = df[['pickup_longitude', 'pickup_latitude']]
    model = KMeans(n_clusters=6)
    model.fit(pickup_locations)
    pickup_labels = model.predict(pickup_locations)
    df['pickup_cluster'] = pickup_labels

    dropoff_locations = df[['dropoff_longitude', 'dropoff_latitude']]
    model = KMeans(n_clusters=6)
    model.fit(dropoff_locations)
    dropoff_labels = model.predict(dropoff_locations)
    df['dropoff_cluster'] = dropoff_labels
```

```
    pickup_clusters = pd.get_dummies(df['pickup_cluster'], prefix='pickup_cluster', dr
    dropoff_clusters = pd.get_dummies(df['dropoff_cluster'], prefix='dropoff_cluster',

    df = pd.concat([df, pickup_clusters], axis=1).drop('pickup_cluster', axis=1)
    df = pd.concat([df, dropoff_clusters], axis=1).drop('dropoff_cluster', axis=1)
    return df


df_train = add_additional_features(df_train)
df_test = add_additional_features(df_test)
df_train = cluster_locations(df_train)
df_test = cluster_locations(df_test)

df_train = df_train.dropna()
print(df_train.shape)
print(df_train.dtypes)
```

In [ ]:
```
# Final Training Set
def final_feature_set(df):
    columns = ['distance', 'year', 'month', 'day', 'hour', 'weekday', 'is_holiday', 'd
               'downtown_dropoff_distance', 'jfk_pickup_distance', 'jfk_dropoff_distan
               'ewr_dropoff_distance', 'lgr_pickup_distance', 'lgr_dropoff_distance',
               'pickup_cluster_1', 'pickup_cluster_2', 'pickup_cluster_3', 'pickup_clu
               'dropoff_cluster_0', 'dropoff_cluster_1', 'dropoff_cluster_2', 'dropoff_
               'dropoff_cluster_5']
    df = df[columns]
    return df


df_target_set = df_train[['fare_amount']]
df_train_set = final_feature_set(df_train)
df_test_set = final_feature_set(df_test)
```

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

# Scaling the training data using standard scaler
scaler = StandardScaler()
scaler.fit(df_train_set)
df_train_set = scaler.transform(df_train_set)
df_test_set = scaler.transform(df_test_set)
```

In [ ]:
```
# Final Prediction
lr = linear_regression(df_train_set, df_target_set, normalize=True)
# rf = random_forest_regressor(df_train_set, df_target_set)
# xm = xg_boost(df_train_set, df_target_set)

df_target_prediction_lr = lr.predict(df_test_set)
```

```python
# df_target_prediction_rf = rf.predict(df_test_set)
# df_target_prediction_xg = xm.predict(xgb.DMatrix(df_test_set), ntree_limit=model.bes

file_csv = pd.read_csv('sample_submission.csv')
file_csv['key'] = df_test['key']
file_csv['fare_amount'] = df_target_prediction_lr
file_csv.to_csv("submission_lr.csv", index=False)
```