```
!wget https://repo.anaconda.com/archive/Anaconda3-5.2.0-Linux-x86_64.sh
        && bash Anaconda3-5.2.0-Linux-x86_64.sh -bfp /usr/local
```

```
import sys
sys.path.append('/usr/local/lib/python3.6/site-packages')
```

```
import warnings
warnings.filterwarnings('ignore')
```

```
import pandas as pd
import numpy as np
import random as rnd

# visualization
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
```

```
from google.colab import drive
drive.mount('/content/gdrive')
```

Step 1:

Data explore and Data processing

```
test_df = pd.read_csv('gdrive/Shared drives/ISE529/NY taxi/data/test.csv',
                      parse_dates = ['pickup_datetime'])
```

```
train_df = pd.read_csv('gdrive/Shared drives/ISE529/NY taxi/data/train.csv',
                       nrows = 5_000_000, parse_dates = ['pickup_datetime']).drop(columns = 'key')
```

```
train_df.head()
```

	fare_amount	pickup_datetime	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_
0	4.5	2009-06-15 17:26:21+00:00	-73.844311	40.721319	-73.841610	
1	16.9	2010-01-05 16:52:16+00:00	-74.016048	40.711303	-73.979268	
2	5.7	2011-08-18 00:35:00+00:00	-73.982738	40.761270	-73.991242	
3	7.7	2012-04-21 04:30:42+00:00	-73.987130	40.733143	-73.991567	
4	5.3	2010-03-09 07:51:00+00:00	-73.968095	40.768008	-73.956655	

```
test_df.dtypes
```

```
key                                 object
pickup_datetime      datetime64[ns, UTC]
pickup_longitude                 float64
pickup_latitude                  float64
dropoff_longitude                float64
dropoff_latitude                 float64
passenger_count                    int64
dtype: object
```

```
train_df.dtypes
```

```
fare_amount                      float64
pickup_datetime      datetime64[ns, UTC]
pickup_longitude                 float64
pickup_latitude                  float64
dropoff_longitude                float64
dropoff_latitude                 float64
passenger_count                    int64
dtype: object
```

```
corr = train_df.corr()
corr.style.background_gradient().set_precision(2)
```

	fare_amount	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passenger_count
fare_amount	1	0.0086	−0.0067	0.0093	−0.0067	0.013
pickup_longitude	0.0086	1	−0.55	0.71	−0.51	0.00095
pickup_latitude	−0.0067	−0.55	1	−0.56	0.55	−0.0018
dropoff_longitude	0.0093	0.71	−0.56	1	−0.47	0.00011
dropoff_latitude	−0.0067	−0.51	0.55	−0.47	1	−0.0015
passenger_count	0.013	0.00095	−0.0018	0.00011	−0.0015	1

```
train_df.describe()
```

	fare_amount	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passenger_
count	5.000000e+06	5.000000e+06	5.000000e+06	4.999964e+06	4.999964e+06	5.00000
mean	1.134080e+01	−7.250678e+01	3.991974e+01	−7.250652e+01	3.991725e+01	1.68469
std	9.820175e+00	1.280970e+01	8.963509e+00	1.284777e+01	9.486767e+00	1.33185
min	−1.000000e+02	−3.426609e+03	−3.488080e+03	−3.412653e+03	−3.488080e+03	0.00000
25%	6.000000e+00	−7.399206e+01	4.073491e+01	−7.399139e+01	4.073404e+01	1.00000
50%	8.500000e+00	−7.398181e+01	4.075263e+01	−7.398016e+01	4.075315e+01	1.00000
75%	1.250000e+01	−7.396711e+01	4.076712e+01	−7.396367e+01	4.076811e+01	2.00000
max	1.273310e+03	3.439426e+03	3.310364e+03	3.457622e+03	3.345917e+03	2.08000

1. The minimum fare amount should not be < 0.
2. Minimum and Maximum longitude and latitude look not in New York City.
3. Minimum passenger count should not have 0.

Solution:

1. After google, taxi fare initial charge in new york is $2.5, so we are removing fare amount smaller than this amount.
2. Remove 0 passenger count.
3. New York city longitudes are around (-74.5 ~ -72.8) and latitudes are around (40.5 ~ 41.8)

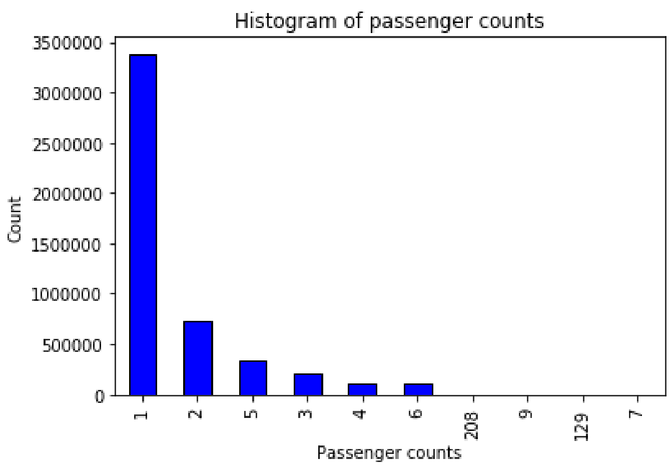
```
train_taxi = train_df[((train_df['pickup_longitude'] > -74.5) & (train_df['pickup_longitude'] < -72.8)) &
                ((train_df['dropoff_longitude'] > -74.5) & (train_df['dropoff_longitude'] < -72.8)) &
                ((train_df['pickup_latitude'] > 40.5) & (train_df['pickup_latitude'] < 41.8)) &
                ((train_df['dropoff_latitude'] > 40.5) & (train_df['dropoff_latitude'] < 41.8)) &
                (train_df['passenger_count'] > 0) & (train_df['fare_amount'] >= 2.5)]
```

```
train_taxi.describe()
```

	fare_amount	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passenger_c
count	4.876330e+06	4.876330e+06	4.876330e+06	4.876330e+06	4.876330e+06	4.87633(
mean	1.132928e+01	−7.397514e+01	4.075108e+01	−7.397429e+01	4.075146e+01	1.69052(
std	9.698604e+00	3.853421e−02	2.957983e−02	3.767663e−02	3.277582e−02	1.31404
min	2.500000e+00	−7.449650e+01	4.050005e+01	−7.449991e+01	4.050005e+01	1.00000(
25%	6.000000e+00	−7.399227e+01	4.073655e+01	−7.399158e+01	4.073560e+01	1.00000(
50%	8.500000e+00	−7.398210e+01	4.075335e+01	−7.398061e+01	4.075386e+01	1.00000(
75%	1.250000e+01	−7.396833e+01	4.076754e+01	−7.396535e+01	4.076841e+01	2.00000(
max	9.520000e+02	−7.281258e+01	4.169685e+01	−7.281783e+01	4.171463e+01	2.08000(

Passenger count:

```
train_taxi['passenger_count'].value_counts().plot.bar(color = 'b', edgecolor = 'k');
plt.title('Histogram of passenger counts');
plt.xlabel('Passenger counts');
plt.ylabel('Count');
```



Solution:

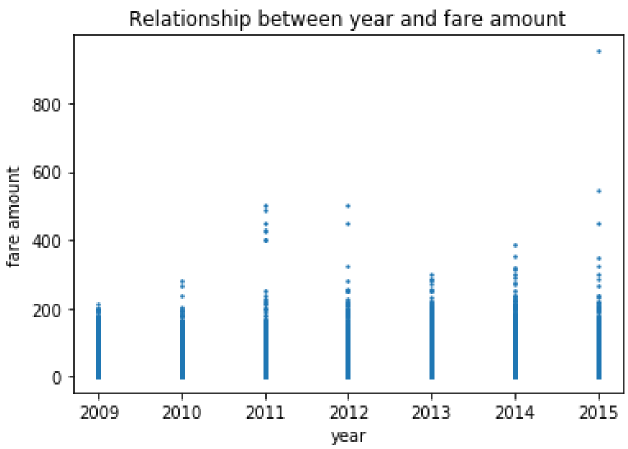
1. From the graph we can tell that the max passenger count is 6, so remove the passenger > 6.

```
taxi2 = train_taxi.loc[train_taxi['passenger_count'] <= 6]
```

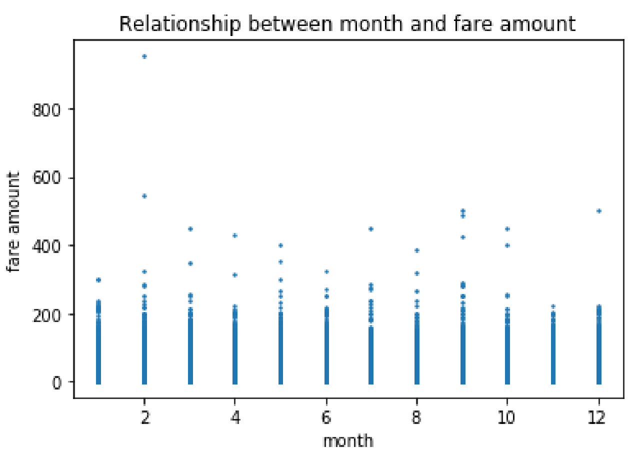
Set Data_time:

```
taxi2['year'] = taxi2.pickup_datetime.dt.year
taxi2['month'] = taxi2.pickup_datetime.dt.month
taxi2['day'] = taxi2.pickup_datetime.dt.day
taxi2['weekday'] = taxi2.pickup_datetime.dt.weekday
taxi2['hour'] = taxi2.pickup_datetime.dt.hour
```

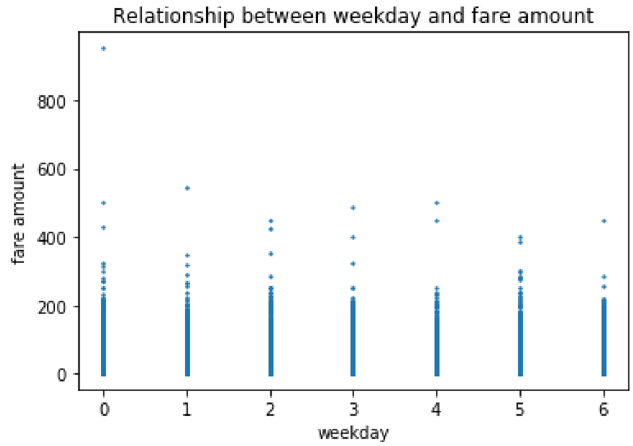
```
#year
plt.scatter(taxi2['year'],taxi2['fare_amount'],s=2)
plt.title('Relationship between year and fare amount')
plt.xlabel('year')
plt.ylabel('fare amount')
plt.show()
```



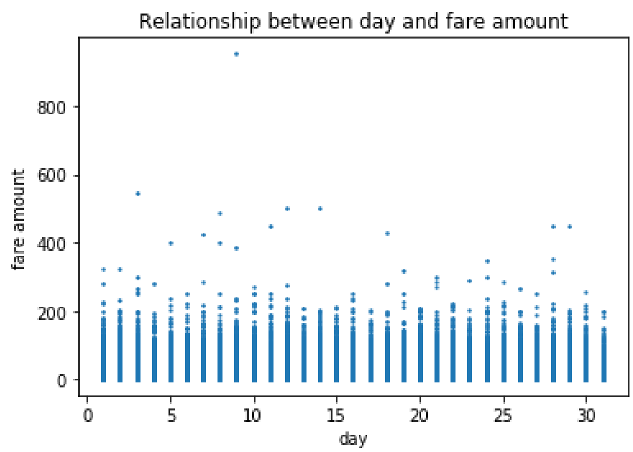

```
#month
plt.scatter(taxi2['month'],taxi2['fare_amount'],s=2)
plt.title('Relationship between month and fare amount')
plt.xlabel('month')
plt.ylabel('fare amount')
plt.show()
```



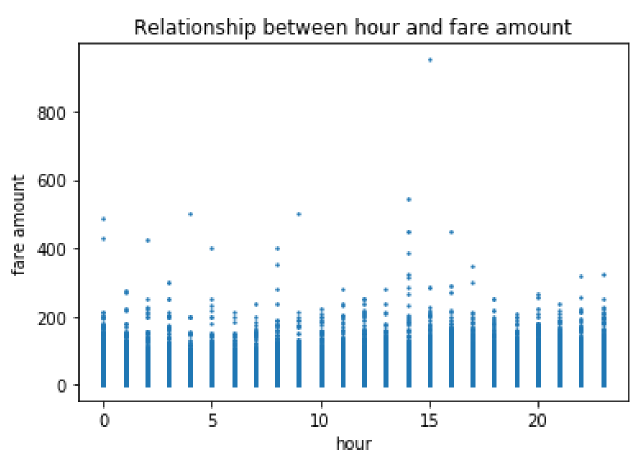

```
#weekday
plt.scatter(taxi2['weekday'],taxi2['fare_amount'],s=2)
plt.title('Relationship between weekday and fare amount')
plt.xlabel('weekday')
plt.ylabel('fare amount')
plt.show()
```




```
#day
plt.scatter(taxi2['day'],taxi2['fare_amount'],s=2)
plt.title('Relationship between day and fare amount')
plt.xlabel('day')
plt.ylabel('fare amount')
plt.show()
```



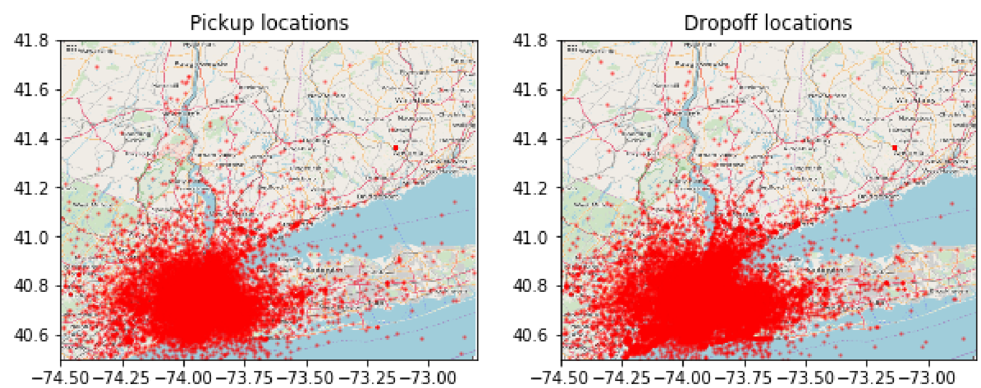

```
#hour
plt.scatter(taxi2['hour'],taxi2['fare_amount'],s=2)
plt.title('Relationship between hour and fare amount')
plt.xlabel('hour')
plt.ylabel('fare amount')
plt.show()
```



```
aa = (-74.5, -72.8, 40.5, 41.8)
nyc_map = plt.imread('https://aiblog.nl/download/nyc_-74.5_-72.8_40.5_41.8.png')

aa_zoom = (-74.3, -73.7, 40.5, 40.9)
nyc_map_zoom = plt.imread('https://aiblog.nl/download/nyc_-74.3_-73.7_40.5_40.9.png')
```

```
def plot_map(df, aa, nyc_map, s=10, alpha=0.2):
    fig, (ax1,ax2) = plt.subplots(1, 2, figsize=(10,8))
    ax1.scatter(df.pickup_longitude, df.pickup_latitude, zorder=1, alpha=alpha, c='r', s=s)
    ax1.set_xlim((aa[0], aa[1]))
    ax1.set_ylim((aa[2], aa[3]))
    ax1.set_title('Pickup locations')
    ax1.imshow(nyc_map, zorder=0, extent=aa)
    ax2.scatter(df.dropoff_longitude, df.dropoff_latitude, zorder=1, alpha=alpha, c='r', s=s)
    ax2.set_xlim((aa[0], aa[1]))
    ax2.set_ylim((aa[2], aa[3]))
    ax2.set_title('Dropoff locations')
    ax2.imshow(nyc_map, zorder=0, extent=aa)
    fig = plt.figure(figsize=(10, 8))
```

```
plot_map(taxi2,aa,nyc_map,s=2,alpha=0.4)
```




```
<Figure size 720x576 with 0 Axes>
```

```
del taxi2['pickup_datetime']
```

```
taxi2.isnull().sum()
```

```
fare_amount          0
pickup_longitude     0
pickup_latitude      0
dropoff_longitude    0
dropoff_latitude     0
passenger_count      0
year                 0
month                0
day                  0
weekday              0
hour                 0
dtype: int64
```

Step 2:

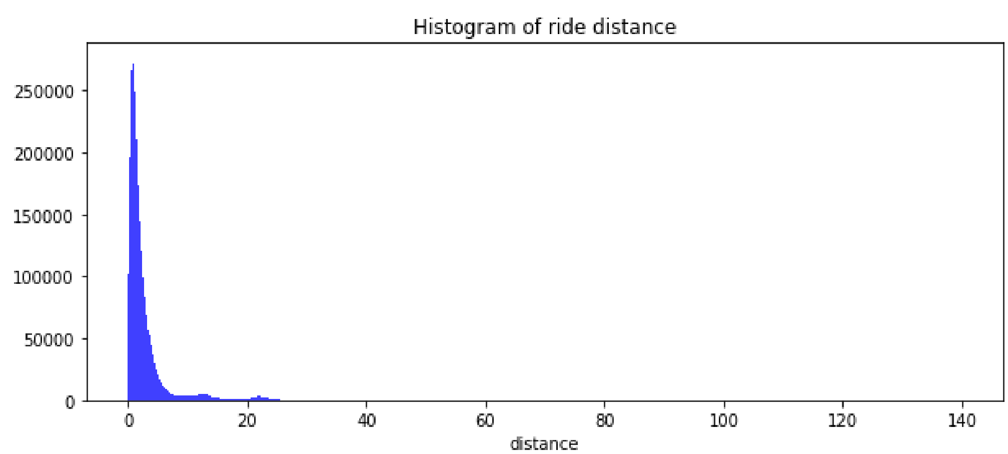
Add new features

1. distance:

Getting distance between two points based on latitude and longitude using haversine formula.
https://stackoverflow.com/questions/29545704/fast-haversine-approximation-python-pandas/29546836#29546836

```
from math import radians, cos, sin, asin, sqrt

def haversine(lon1, lat1, lon2, lat2):
    """
    Calculate the great circle distance between two points
    on the earth (specified in decimal degrees)

    All args must be of equal length.

    """
    lon1, lat1, lon2, lat2 = map(np.radians, [lon1, lat1, lon2, lat2])

    dlon = lon2 - lon1
    dlat = lat2 - lat1

    a = np.sin(dlat/2.0)**2 + np.cos(lat1) * np.cos(lat2) * np.sin(dlon/2.0)**2

    c = 2 * np.arcsin(np.sqrt(a))
    km = 6371 * c  # 6371 is Radius of earth in kilometers. Use 3956 for miles
    return km

taxi2['distance'] = haversine(taxi2['pickup_latitude'], taxi2['pickup_longitude'], taxi2['dropoff_latitude'
```

```
plt.figure(figsize = (10, 4))
n, bins, patches = plt.hist(taxi2.distance, 1000, facecolor='blue', alpha=0.75)
plt.xlabel('distance')
plt.title('Histogram of ride distance')
plt.show();
```



```
taxi2['distance'].describe()
```

```
count    4.876324e+06
mean     2.705057e+00
std      3.930991e+00
min      0.000000e+00
25%      8.530633e-01
50%      1.551455e+00
75%      2.829630e+00
max      1.399139e+02
Name: distance, dtype: float64
```

```
taxi2.groupby(['passenger_count'])['distance','fare_amount'].mean()
```

	distance	fare_amount
passenger_count		
1	2.659048	11.189439
2	2.880164	11.802383
3	2.741211	11.553098
4	2.776115	11.761346
5	2.716048	11.195626
6	2.802337	12.142420

```
#average usd per mile
ave=taxi2.fare_amount.sum()/taxi2.distance.sum()
ave
```

```
4.188177604497326
```

Sol: Distance should not be 0, thus remove 0

```
taxi2 = taxi2.loc[taxi2['distance'] > 0]
```

2. Hotspot coordinate:

distance from pickup or dropoff coordinates to JFK, EWR, LGA

```
jfk_coord = (40.639722, -73.778889)
ewr_coord = (40.6925, -74.168611)
lga_coord = (40.77725, -73.872611)

pickup_JFK = haversine(taxi2['pickup_latitude'], taxi2['pickup_longitude'], jfk_coord[0], jfk_coord[1])
dropoff_JFK = haversine(jfk_coord[0], jfk_coord[1], taxi2['dropoff_latitude'], taxi2['dropoff_longitude'])
pickup_EWR = haversine(taxi2['pickup_latitude'], taxi2['pickup_longitude'], ewr_coord[0], ewr_coord[1])
dropoff_EWR = haversine(ewr_coord[0], ewr_coord[1], taxi2['dropoff_latitude'], taxi2['dropoff_longitude'])
pickup_LGA = haversine(taxi2['pickup_latitude'], taxi2['pickup_longitude'], lga_coord[0], lga_coord[1])
dropoff_LGA = haversine(lga_coord[0], lga_coord[1], taxi2['dropoff_latitude'], taxi2['dropoff_longitude'])

taxi2['JFK_coord'] = pd.concat([pickup_JFK, dropoff_JFK], axis=1).min(axis=1)
taxi2['EWR_coord'] = pd.concat([pickup_EWR, dropoff_EWR], axis=1).min(axis=1)
taxi2['LGA_coord'] = pd.concat([pickup_LGA, dropoff_LGA], axis=1).min(axis=1)
```

```
taxi2.head()
```

	fare_amount	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passenger_count
0	4.5	−73.844311	40.721319	−73.841610	40.712278	
1	16.9	−74.016048	40.711303	−73.979268	40.782004	
2	5.7	−73.982738	40.761270	−73.991242	40.750562	2
3	7.7	−73.987130	40.733143	−73.991567	40.758092	
4	5.3	−73.968095	40.768008	−73.956655	40.783762	

Step 3:

Tune and Do model training

```
from sklearn.model_selection import train_test_split
y = taxi2['fare_amount']
X = taxi2.drop(columns=['fare_amount'])
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)
```

```
from sklearn.metrics import mean_squared_error
```

Models

```
from sklearn.model_selection import GridSearchCV
```

```
# machine learning

from sklearn.ensemble import RandomForestRegressor
from sklearn.neighbors import KNeighborsRegressor
from sklearn.tree import DecisionTreeRegressor
from sklearn.linear_model import LinearRegression
```

```
param_grid = [{'max_depth':[3, 4, 5,6,7,8]}]
```

```
grid_dt = GridSearchCV( DecisionTreeRegressor(random_state =1),param_grid,cv=10,return_train_score = True)
grid_dt.fit(X_train,y_train)
grid_dt.best_params_
```

```
{'max_depth': 8}
```

```
# Decision Tree
decision_tree = DecisionTreeRegressor(max_depth =8, random_state =1)
decision_tree.fit(X_train, y_train)
y_d = decision_tree.predict(X_test)
decision_tree_rmse = mean_squared_error(y_test, y_d) ** 0.5
```

```
DecisionTreeRegressor(criterion='mse', max_depth=8, max_features=None,
                      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,
                      presort=False, random_state=1, splitter='best')
```

```
decision_tree_rmse
```

```
4.401412475249888
```

```
param_grid = [{'max_depth':[3, 4, 5,6,7,8]}]
```

```
grid_rf = GridSearchCV(RandomForestRegressor(random_state=1),param_grid, return_train_score = True)
grid_rf.fit(X_train,y_train)
grid_rf.best_params_
```

```
{'max_depth': 8}
```

```
# Random Forest
random_forest = RandomForestRegressor(n_estimators=100, max_depth=8, random_state=1)
random_forest.fit(X_train, y_train)
y_r= random_forest.predict(X_test)
random_forest_rmse = mean_squared_error(y_test, y_r) ** 0.5
```

```
random_forest_rmse
```

```
4.311196839238369
```

```
param_grid = [{'n_neighbors':[2,3,4]}]
```

```
grid_p = GridSearchCV(KNeighborsRegressor(),param_grid, return_train_score = True)
grid_p.fit(X_train,y_train)
grid_p.best_params_
```

```
{'n_neighbors': 5}
```

```
# KNN
knn = KNeighborsRegressor(n_neighbors = 5)
knn.fit(X_train, y_train)
y_k= knn.predict(X_test)
knn_rmse = mean_squared_error(y_test, y_k) ** 0.5
knn_rmse
```

```
5.023844397500042
```

```
from xgboost import XGBRegressor
```

```
param_grid = [{'learning_rate':[0.001,0.01,0.1]}]
```

```
grid_xgb2 = GridSearchCV(XGBRegressor(),param_grid)
grid_xgb2.fit(X_train,y_train)
grid_xgb2.best_params_
```

```
[15:03:17] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprecated in fa
[15:09:16] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprecated in fa
[15:15:19] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprecated in fa
[15:21:21] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprecated in fa
[15:27:29] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprecated in fa
[15:33:38] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprecated in fa
[15:39:43] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprecated in fa
[15:45:52] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprecated in fa
[15:52:06] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprecated in fa
[15:58:18] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprecated in fa
{'learning_rate': 0.1}
```

```
#xgbregressor
xgb = XGBRegressor(n_estimators = 100,learning_rate = 0.1,random_state=1)
xgb.fit(X_train,y_train)
y_xgb= xgb.predict(X_test)
xgb_rmse= mean_squared_error(y_test, y_xgb) ** 0.5
xgb_rmse
```

```
[16:47:36] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprecated in fa
4.082996940563017
```

```
# Light GBM
import lightgbm as lgb

params = {
        'learning_rate': 0.75,
        'application': 'regression',
        'max_depth': 3,
        'num_leaves': 100,
        'verbosity': -1,
        'metric': 'RMSE',
    }
train_set = lgb.Dataset(X_train, y_train, silent=True)
lb = lgb.train(params, train_set = train_set, num_boost_round=300)
y_pred = lb.predict(X_test, num_iteration = lb.best_iteration)
lgb_rmse = mean_squared_error(y_test, y_pred) ** 0.5
print("Test RMSE: %.3f" % mean_squared_error(y_test, y_pred) ** 0.5)
```

```
Test RMSE: 3.622
```

RMSE comparison: KNN: 5.023; Random Forest: 4.311; XGB: 4.083; Decision Tree: 4.4014; Light GBM: 3.622

Use Neural Network:

```
from keras.models import Sequential
from keras.layers import Dense
from keras.wrappers.scikit_learn import KerasRegressor
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import KFold
```

```
Using TensorFlow backend.
```

```
%tensorflow_version 1.x
import tensorflow as tf
print(tf.__version__)
```

```
1.15.0
```

```
import os
os.environ['TF_CPP_MIN_LOG_LEVEL'] = '3'
import tensorflow as tf
tf.compat.v1.logging.set_verbosity(tf.compat.v1.logging.ERROR)

from keras.callbacks import ModelCheckpoint

from sklearn.preprocessing import StandardScaler
from sklearn.pipeline import Pipeline

from keras import backend

def rmse(y_true, y_pred):
  return backend.sqrt(backend.mean(backend.square(y_pred - y_true), axis=-1))

def baseline_model():
    # create model
    model = Sequential()
    model.add(Dense(12, input_dim=14, kernel_initializer='normal', activation='relu'))
    model.add(Dense(1, kernel_initializer='normal'))
    # Compile model
    model.compile(loss='mean_squared_error', optimizer='adam', metrics=[rmse])
    return model

estimator = KerasRegressor(build_fn=baseline_model, nb_epoch=100, batch_size=5, verbose=0,
                           validation_split=0.25)

filepath="gdrive/Shared drives/ISE529/NY taxi/data/weights.t3m1.hdf5"
checkpoint = ModelCheckpoint(filepath, monitor='val_rmse', save_best_only=True, mode='min', verbose=0)
callbacks_list = [checkpoint]

seed = 7
np.random.seed(seed)
kfold = KFold(n_splits=10, random_state=seed)
results = cross_val_score(estimator, X.values, y.values, cv=kfold,
                          fit_params=dict(callbacks=callbacks_list))
print("Results: %.2f (%.2f) MSE" % (results.mean(), results.std()))
```

```
Results: -27.65 (2.86) MSE
```

```
estimator.fit(X_train, y_train)
y_pred = estimator.predict(X_test)
print("Test RMSE: %.3f" % mean_squared_error(y_test, y_pred) ** 0.5)
```

```
Test RMSE: 5.151
```

Try to standardize the features.

```
def baseline_model2():
    # create model
    model = Sequential()
    model.add(Dense(12, input_dim=14, kernel_initializer='normal', activation='relu'))
    model.add(Dense(1, kernel_initializer='normal'))
    # Compile model
    model.compile(loss='mean_squared_error', optimizer='adam', metrics=[rmse])
    return model
```

```
from sklearn.preprocessing import StandardScaler
from sklearn.pipeline import Pipeline

seed = 7
filepath="gdrive/Shared drives/ISE529/NY taxi/data/weights.t3m2.hdf5"
checkpoint = ModelCheckpoint(filepath, monitor='val_rmse', verbose=0, save_best_only=True, mode='min')
callbacks_list = [checkpoint]
# evaluate model with standardized dataset
np.random.seed(seed)
estimators = []
estimators.append(('standardize', StandardScaler()))
estimators.append(('mlp', KerasRegressor(build_fn=baseline_model2, nb_epoch=100, batch_size=5, verbose=0,
                                         validation_split=0.25)))
pipeline = Pipeline(estimators)
kfold = KFold(n_splits=10, random_state=seed)
results = cross_val_score(pipeline, X, y, cv=kfold,
                          fit_params={'mlp__callbacks':callbacks_list})

print("Standardized: %.2f (%.2f) MSE" % (results.mean(), results.std()))
```

```
Standardized: -17.25 (0.88) MSE
```

Try to add layer of model.

```
def baseline_model3():
    # create model
    model = Sequential()
    model.add(Dense(12, input_dim=14, kernel_initializer='normal', activation='relu'))
    model.add(Dense(6, kernel_initializer='normal'))
    model.add(Dense(1, kernel_initializer='normal'))
    # Compile model
    model.compile(loss='mean_squared_error', optimizer='adam', metrics=[rmse])
    return model
```

```
from sklearn.preprocessing import StandardScaler
from sklearn.pipeline import Pipeline

seed = 7

filepath="gdrive/Shared drives/ISE529/NY taxi/data/weights.t3m3.hdf5"
checkpoint = ModelCheckpoint(filepath, monitor='val_rmse', verbose=0, save_best_only=True, mode='min')
callbacks_list = [checkpoint]
# evaluate model with standardized dataset
np.random.seed(seed)
estimators = []
estimators.append(('standardize', StandardScaler()))
estimators.append(('mlp', KerasRegressor(build_fn=baseline_model3, nb_epoch=100, batch_size=5,
                                         verbose=0, validation_split=0.25)))
pipeline = Pipeline(estimators)
kfold = KFold(n_splits=10, random_state=seed)
results = cross_val_score(pipeline, X, y, cv=kfold,
                          fit_params={'mlp__callbacks':callbacks_list})

print("Standardized: %.2f (%.2f) MSE" % (results.mean(), results.std()))
```

Try to make expand width of model.

```
def baseline_model4():
    # create model
    model = Sequential()
    model.add(Dense(20, input_dim=14, kernel_initializer='normal', activation='relu'))
    model.add(Dense(1, kernel_initializer='normal'))
    # Compile model
    model.compile(loss='mean_squared_error', optimizer='adam', metrics=[rmse])
    return model
```

```
from sklearn.preprocessing import StandardScaler
from sklearn.pipeline import Pipeline

seed = 7

filepath="gdrive/Shared drives/ISE529/NY taxi/data/weights.t3m4.hdf5"
checkpoint = ModelCheckpoint(filepath, monitor='val_rmse', verbose=0, save_best_only=True, mode='min')
callbacks_list = [checkpoint]
# evaluate model with standardized dataset
np.random.seed(seed)
estimators = []
estimators.append(('standardize', StandardScaler()))
estimators.append(('mlp', KerasRegressor(build_fn=baseline_model4, nb_epoch=100, batch_size=5,
                                         verbose=0, validation_split=0.25)))
pipeline = Pipeline(estimators)
kfold = KFold(n_splits=10, random_state=seed)
results = cross_val_score(pipeline, X, y, cv=kfold, fit_params={'mlp__callbacks':callbacks_list})

print("Standardized: %.2f (%.2f) MSE" % (results.mean(), results.std()))
```

```
Standardized: -16.43 (0.74) MSE
```

Step 4:

Process test data and make prediction

```
test_df['year'] = test_df.pickup_datetime.dt.year
test_df['month'] = test_df.pickup_datetime.dt.month
test_df['day'] = test_df.pickup_datetime.dt.day
test_df['weekday'] = test_df.pickup_datetime.dt.weekday
test_df['hour'] = test_df.pickup_datetime.dt.hour


test_df['distance'] = haversine(test_df['pickup_latitude'], test_df['pickup_longitude'],
                                test_df['dropoff_latitude'] , test_df['dropoff_longitude'])


pickup_JFK = haversine(test_df['pickup_latitude'], test_df['pickup_longitude'],
                       jfk_coord[0], jfk_coord[1])
dropoff_JFK = haversine(jfk_coord[0], jfk_coord[1],
                        test_df['dropoff_latitude'], test_df['dropoff_longitude'])
pickup_EWR = haversine(test_df['pickup_latitude'], test_df['pickup_longitude'],
                       ewr_coord[0], ewr_coord[1])
dropoff_EWR = haversine(ewr_coord[0], ewr_coord[1],
                        test_df['dropoff_latitude'], test_df['dropoff_longitude'])
```

```
pickup_LGA = haversine(test_df['pickup_latitude'], test_df['pickup_longitude'],
                       lga_coord[0], lga_coord[1])
dropoff_LGA = haversine(lga_coord[0], lga_coord[1],
                        test_df['dropoff_latitude'], test_df['dropoff_longitude'])

test_df['JFK_coord'] = pd.concat([pickup_JFK, dropoff_JFK], axis=1).min(axis=1)
test_df['EWR_coord'] = pd.concat([pickup_EWR, dropoff_EWR], axis=1).min(axis=1)
test_df['LGA_coord'] = pd.concat([pickup_LGA, dropoff_LGA], axis=1).min(axis=1)

del test_df['pickup_datetime']

test_df.head()
```

	key	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passenger_cc
0	2015-01-27 13:08:24.0000002	-73.973320	40.763805	-73.981430	40.743835	
1	2015-01-27 13:08:24.0000003	-73.986862	40.719383	-73.998886	40.739201	
2	2011-10-08 11:53:44.0000002	-73.982524	40.751260	-73.979654	40.746139	
3	2012-12-01 21:12:12.0000002	-73.981160	40.767807	-73.990448	40.751635	
4	2012-12-01 21:12:12.0000003	-73.966046	40.789775	-73.988565	40.744427	

```
def pred_model():
    # create model
    model = Sequential()
    model.add(Dense(12, input_dim=14, kernel_initializer='normal', activation='relu'))
    model.add(Dense(1, kernel_initializer='normal'))
    model.load_weights("gdrive/Shared drives/ISE529/NY taxi/data/weights.t3m2.hdf5")
    # Compile model
    model.compile(loss='mean_squared_error', optimizer='adam', metrics=[rmse])
    return model

p_estimators = []
p_estimators.append(('standardize', StandardScaler()))
p_estimators.append(('mlp', KerasRegressor(build_fn=pred_model)))
pipeline_p = Pipeline(p_estimators)

pipeline_p.fit(X, y)
y_pred = pipeline_p.predict(test_df.drop(columns=['key']))
```

```
Epoch 1/1
4824505/4824505 [==============================] - 219s 45us/step - loss: 15.8893 - rmse: 1.8418
```

```
y_pred = lb.predict(test_df.drop(columns=['key']), num_iteration = lb.best_iteration)

submission = pd.DataFrame({
    "key": test_df.key,
    "Fare_amount": y_pred
})

submission.to_csv('gdrive/Shared drives/ISE529/NY taxi/data/result/s2.csv', index=False)
```