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CSE

CS 550 ASSIGNMENT_1_PARTB

In [172]:

```
# !pip install -q kaggle
```

In [173]:

```
# from google.colab import files
# files.upload()
```

In [174]:

```
# !mkdir ~/.kaggle
# !cp kaggle.json ~/.kaggle/
# !chmod 600 ~/.kaggle/kaggle.json
```

In [175]:

```
# !kaggle competitions download -c new-york-city-taxi-fare-prediction
```

In [176]:

```
# !unzip new-york-city-taxi-fare-prediction
```

In [2]:

```
# This Python 3 environment comes with many helpful analytics libraries installed
# It is defined by the kaggle/python docker image: https://github.com/kaggle/docker-python
# For example, here's several helpful packages to load in
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
import haversine as hs

import math
from math import sqrt

from numpy import absolute
from numpy import mean
from numpy import std

from sklearn import metrics
from sklearn.feature_selection import f_regression
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import PolynomialFeatures
from sklearn.preprocessing import scale
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import KFold
from sklearn.tree import DecisionTreeRegressor
from sklearn.neighbors import KNeighborsRegressor
from sklearn.preprocessing import MinMaxScaler
from sklearn.linear_model import Ridge
from sklearn.linear_model import RidgeCV
from sklearn.model_selection import RepeatedKFold
from sklearn import neighbors

!pip install tensorflow
import tensorflow as tf
from tensorflow.keras import Model
from tensorflow.keras import Sequential
from tensorflow.keras.optimizers import Adam
from sklearn.preprocessing import StandardScaler
from tensorflow.keras.layers import Dense, Dropout
from tensorflow.keras.losses import MeanSquaredError
from keras.layers import BatchNormalization
from keras.models import Sequential
from keras.layers import Dense
from keras.layers import Dropout
from tensorflow.keras.optimizers import Adam
from keras.callbacks import EarlyStopping
!pip install haversine
from tensorflow.random import set_seed
!pip install xgboost
import xgboost as xgb
```

```
Requirement already satisfied: tensorflow in c:\programdata\anaconda3\lib\site-packages (2.9.1)
Requirement already satisfied: grpcio<2.0,>=1.24.3 in c:\programdata\anaconda3\lib\site-packages (from tensorflow) (1.47.0)
Requirement already satisfied: astunparse>=1.6.0 in c:\programdata\anaconda3\lib\site-packages (from tensorflow) (1.6.3)
Requirement already satisfied: numpy>=1.20 in c:\programdata\anaconda3\lib\site-packages (from tensorflow) (1.20.3)
Requirement already satisfied: typing-extensions>=3.6.6 in c:\programdata\anaconda3\lib\site-packages (from tensorflow) (3.10.0.2)
Requirement already satisfied: absl-py>=1.0.0 in c:\programdata\anaconda3\lib\site-packages (from tensorflow) (1.2.0)
Requirement already satisfied: tensorflow-estimator<2.10.0,>=2.9.0rc0 in c:\programdata\anaconda3\lib\site-packages (from tensorflow) (2.9.0)
Requirement already satisfied: wrapt>=1.11.0 in c:\programdata\anaconda3\lib\site-packages (from tensorflow) (1.12.1)
Requirement already satisfied: six>=1.12.0 in c:\programdata\anaconda3\lib\site-packages (from tensorflow) (1.16.0)
Requirement already satisfied: gast<=0.4.0,>=0.2.1 in c:\programdata\anaconda3\lib\site-packages (from tensorflow) (0.4.0)
Requirement already satisfied: protobuf<3.20,>=3.9.2 in c:\programdata\anaconda3\lib\site-packages (from tensorflow) (3.19.4)
Requirement already satisfied: keras<2.10.0,>=2.9.0rc0 in c:\programdata\anaconda3\lib\site-packages (from tensorflow) (2.9.0)
Requirement already satisfied: flatbuffers<2,>=1.12 in c:\programdata\anaconda3\lib\site-packages (from tensorflow) (1.12)
Requirement already satisfied: opt-einsum>=2.3.2 in c:\programdata\anaconda3\lib\site-packages (from tensorflow) (3.3.0)
Requirement already satisfied: tensorflow-io-gcs-filesystem>=0.23.1 in c:\programdata\anaconda3\lib\site-packages (from tensorflow) (0.26.0)
Requirement already satisfied: packaging in c:\programdata\anaconda3\lib\site-packages (from tensorflow) (21.0)
Requirement already satisfied: tensorboard<2.10,>=2.9 in c:\programdata\anaconda3\lib\site-packages (from tensorflow) (2.9.1)
Requirement already satisfied: termcolor>=1.1.0 in c:\programdata\anaconda3\lib\site-packages (from tensorflow) (1.1.0)
Requirement already satisfied: libclang>=13.0.0 in c:\programdata\anaconda3\lib\site-packages (from tensorflow) (14.0.6)
Requirement already satisfied: h5py>=2.9.0 in c:\programdata\anaconda3\lib\site-packages (from tensorflow) (3.2.1)
Requirement already satisfied: keras-preprocessing>=1.1.1 in c:\programdata\anaconda3\lib\site-packages (from tensorflow) (1.1.2)
Requirement already satisfied: google-pasta>=0.1.1 in c:\programdata\anaconda3\lib\site-packages (from tensorflow) (0.2.0)
Requirement already satisfied: setuptools in c:\programdata\anaconda3\lib\site-packages (from tensorflow) (58.0.4)
Requirement already satisfied: wheel<1.0,>=0.23.0 in c:\programdata\anaconda3\lib\site-packages (from astunparse>=1.6.0->tensorflow) (0.37.0)
Requirement already satisfied: markdown>=2.6.8 in c:\programdata\anaconda3\lib\site-packages (from tensorboard<2.10,>=2.9->tensorflow) (3.4.1)
Requirement already satisfied: werkzeug>=1.0.1 in c:\programdata\anaconda3\lib\site-packages (from tensorboard<2.10,>=2.9->tensorflow) (2.0.2)
Requirement already satisfied: google-auth-oauthlib<0.5,>=0.4.1 in c:\programdata\anaconda3\lib\site-packages (from tensorboard<2.10,>=2.9->tensorflow) (0.4.6)
Requirement already satisfied: tensorboard-plugin-wit>=1.6.0 in c:\programdata\anaconda3\lib\site-packages (from tensorboard<2.10,>=2.9->tensorflow) (1.8.1)
Requirement already satisfied: tensorboard-data-server<0.7.0,>=0.6.0 in c:\programdata\anaconda3\lib\site-packages (from tensorboard<2.10,>=2.9->tensorflow) (0.6.1)
Requirement already satisfied: google-auth<3,>=1.6.3 in c:\programdata\anaconda3\lib\site-packages (from tensorboard<2.10,>=2.9->tensorflow) (2.11.0)
Requirement already satisfied: requests<3,>=2.21.0 in c:\programdata\anaconda3\lib\site-packages (from tensorboard<2.10,>=2.9->tensorflow) (2.26.0)
Requirement already satisfied: rsa<5,>=3.1.4 in c:\programdata\anaconda3\lib\site-packages (from google-auth<3,>=1.6.3->tensorboard<2.10,>=2.9->tensorflow) (4.9)
Requirement already satisfied: cachetools<6.0,>=2.0.0 in c:\programdata\anaconda3\lib\site-packages (from google-auth<3,>=1.6.3->tensorboard<2.10,>=2.9->tensorflow) (5.2.0)
Requirement already satisfied: pyasn1-modules>=0.2.1 in c:\programdata\anaconda3\lib\site-packages (from google-auth<3,>=1.6.3->tensorboard<2.10,>=2.9->tensorflow) (0.2.8)
Requirement already satisfied: requests-oauthlib>=0.7.0 in c:\programdata\anaconda3\lib\site-packages (from google-auth-oauthlib<0.5,>=0.4.1->tensorboard<2.10,>=2.9->tensorflow) (1.3.1)
Requirement already satisfied: importlib-metadata>=4.4 in c:\programdata\anaconda3\lib\site-packages (from markdown>=2.6.8->tensorboard<2.10,>=2.9->tensorflow) (4.8.1)
Requirement already satisfied: zipp>=0.5 in c:\programdata\anaconda3\lib\site-packages (from importlib-metadata>=4.4->markdown>=2.6.8->tensorboard<2.10,>=2.9->tensorflow) (3.6.0)
Requirement already satisfied: pyasn1<0.5.0,>=0.4.6 in c:\programdata\anaconda3\lib\site-packages (from pyasn1-modules>=0.2.1->google-auth<3,>=1.6.3->tensorboard<2.10,>=2.9->tensorflow) (0.
4.8)
Requirement already satisfied: certifi>=2017.4.17 in c:\programdata\anaconda3\lib\site-packages (from requests<3,>=2.21.0->tensorboard<2.10,>=2.9->tensorflow) (2021.10.8)
Requirement already satisfied: urllib3<1.27,>=1.21.1 in c:\programdata\anaconda3\lib\site-packages (from requests<3,>=2.21.0->tensorboard<2.10,>=2.9->tensorflow) (1.26.7)
Requirement already satisfied: charset-normalizer~=2.0.0 in c:\programdata\anaconda3\lib\site-packages (from requests<3,>=2.21.0->tensorboard<2.10,>=2.9->tensorflow) (2.0.4)
Requirement already satisfied: idna<4,>=2.5 in c:\programdata\anaconda3\lib\site-packages (from requests<3,>=2.21.0->tensorboard<2.10,>=2.9->tensorflow) (3.2)
Requirement already satisfied: oauthlib>=3.0.0 in c:\programdata\anaconda3\lib\site-packages (from requests-oauthlib>=0.7.0->google-auth-oauthlib<0.5,>=0.4.1->tensorboard<2.10,>=2.9->tensor
flow) (3.2.0)
Requirement already satisfied: pyparsing>=2.0.2 in c:\programdata\anaconda3\lib\site-packages (from packaging->tensorflow) (3.0.4)
Requirement already satisfied: haversine in c:\programdata\anaconda3\lib\site-packages (2.6.0)
Requirement already satisfied: xgboost in c:\programdata\anaconda3\lib\site-packages (1.6.1)
Requirement already satisfied: numpy in c:\programdata\anaconda3\lib\site-packages (from xgboost) (1.20.3)
Requirement already satisfied: scipy in c:\programdata\anaconda3\lib\site-packages (from xgboost) (1.7.1)
```

There is a lot of data, which will require a lot of computing resources, so I took only a part of it

In [3]:

```
# Read data in pandas dataframe,

train = pd.read_csv("content/train.csv", nrows = 1000000)
test = pd.read_csv("content/test.csv")
```

In [4]:

```
print(train.shape)
print(test.shape)
```

```
(1000000, 8)
(9914, 7)
```

In [5]:

```
train.head()
```

Out[5]:

	key	fare_amount	pickup_datetime	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passenger_count
0	2009-06-15 17:26:21.0000001	4.5	2009-06-15 17:26:21 UTC	-73.844311	40.721319	-73.841610	40.712278	1
1	2010-01-05 16:52:16.0000002	16.9	2010-01-05 16:52:16 UTC	-74.016048	40.711303	-73.979268	40.782004	1
2	2011-08-18 00:35:00.00000049	5.7	2011-08-18 00:35:00 UTC	-73.982738	40.761270	-73.991242	40.750562	2
3	2012-04-21 04:30:42.0000001	7.7	2012-04-21 04:30:42 UTC	-73.987130	40.733143	-73.991567	40.758092	1
4	2010-03-09 07:51:00.000000135	5.3	2010-03-09 07:51:00 UTC	-73.968095	40.768008	-73.956655	40.783762	1

In [6]:

```
train.dtypes   # Cheking Data Type of train
```

Out[6]:

```
key                   object
fare_amount          float64
pickup_datetime       object
pickup_longitude     float64
pickup_latitude      float64
dropoff_longitude    float64
dropoff_latitude     float64
passenger_count        int64
dtype: object
```

In [7]:

```
train.describe()
```

Out[7]:

	fare_amount	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passenger_count
count	1000000.000000	1000000.000000	1000000.000000	999990.000000	999990.000000	1000000.000000
mean	11.348079	-72.526640	39.929008	-72.527860	39.919954	1.684924
std	9.822090	12.057937	7.626154	11.324494	8.201418	1.323911
min	-44.900000	-3377.680935	-3116.285383	-3383.296608	-3114.338567	0.000000
25%	6.000000	-73.992060	40.734965	-73.991385	40.734046	1.000000
50%	8.500000	-73.981792	40.752695	-73.980135	40.753166	1.000000
75%	12.500000	-73.967094	40.767154	-73.963654	40.768129	2.000000
max	500.000000	2522.271325	2621.628430	45.581619	1651.553433	208.000000

From this we learn that

- The minimum fare is negative, which is impossible
- Some travel points are missing the city
- The maximum number of passengers is equal to 208, which is impossible
- The maximum fare also unreal

A Data Cleaning & Feature Engineering

Find, if we have data that has no value

In [8]:

```
print(train.isnull().sum())
```

```
key                   0
fare_amount           0
pickup_datetime       0
pickup_longitude      0
pickup_latitude       0
dropoff_longitude    10
dropoff_latitude     10
passenger_count       0
dtype: int64
```

longitude and latitude

found NaN values in columns dropoff_longitude and dropoff_latitude
We found NaN values in columns

i) dropoff_longitude and

ii) dropoff_latitude

which is not much as comapared to our trainset. So we will Drop it.

In [9]:

```
train = train.dropna(how = 'any', axis = 'rows')  # dropping NULL value
```

In [10]:

```
print('Old size: %d' % len(train))
```

```
Old size: 999990
```

There will be no negative tax and you may not be able to pay more than a certain limit depending on the circumstances, let's say this limit is 200 $

Also, I came to know from google that the minimum fare for a New York taxi is 2,50 $

In [11]:

```
train = train.drop(train[train.fare_amount<2.5].index, axis = 0)     #Droping fare_amount <$2.5
train = train.drop(train[train.fare_amount>300].index, axis = 0)     #Droping fare_amount >$300
```

Delete the data whose passenger_count exceeded 7, because it cannot physically fit more in the taxi and it is not allowed. Taxi can also move without passenger and carry cargo, so lets permit passenger_count == 0 data

In [12]:

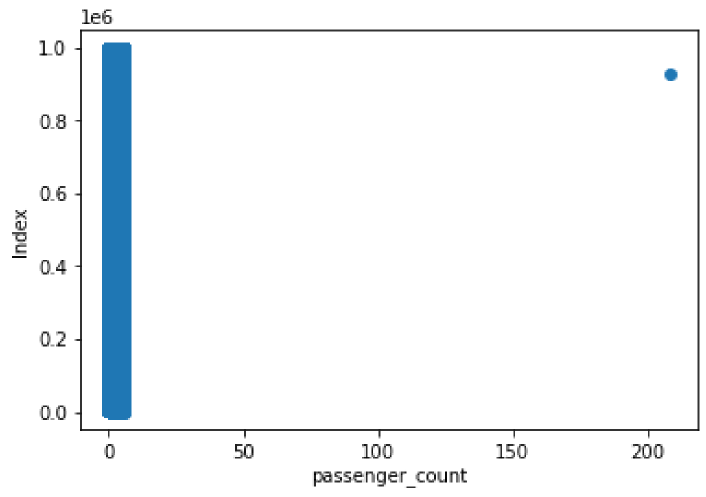
```
train['passenger_count'][train.passenger_count==0].count()
```

Out[12]:

3555

In [13]:

```
plt.scatter(x=train.passenger_count,y=train.index)
plt.ylabel('Index')
plt.xlabel('passenger_count')
plt.show()
```



In [14]:

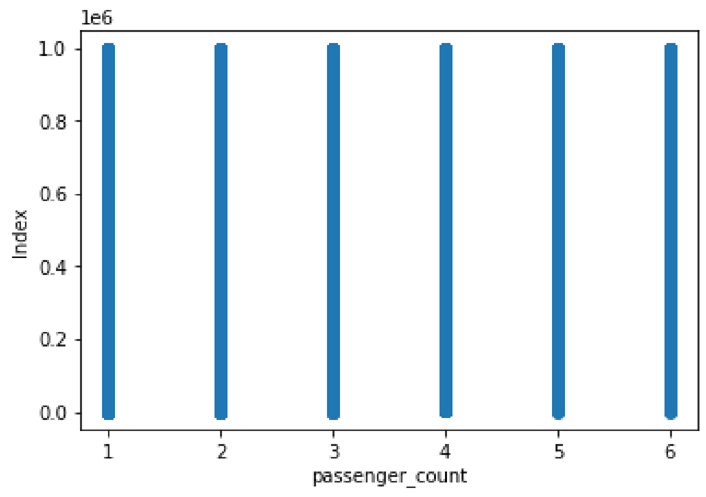
```
train.drop(train[train.passenger_count==0].index,axis=0,inplace=True)    # passenger count ==0 hav e been removed
```

In [15]:

```
train = train.drop(train[train['passenger_count']>7].index, axis = 0)   # we have Assumed that maximum Number of passenger can sit in taxi will be 7
train = train.drop(train[train['passenger_count']<=0].index, axis = 0)   # Droping taxi taking fare without passengers
```

In [16]:

```
plt.scatter(x=train.passenger_count,y=train.index)
plt.ylabel('Index')
plt.xlabel('passenger_count')
plt.show()
```



Remove the pickup_latitude data whose values are greater than 90 and less than -90, because latitudes are between -90 and 90 degrees

In [192]:

```
train = train.drop(train[train['pickup_latitude']<-90].index, axis = 0)
train = train.drop(train[train['pickup_latitude']>90].index, axis = 0)
```

Remove the pickup_longitude data whose values are greater than 180 and less than -180, because longitudes are between -180 and 180 degrees

In [193]:

```
train = train.drop(train[train['pickup_longitude']<-180].index, axis = 0)
train = train.drop(train[train['pickup_longitude']>180].index, axis = 0)
```

Repeat the same for dropoff_latitude and dropoff_longitude

In [194]:

```
train = train.drop(train[train['dropoff_latitude']<-90].index, axis = 0)
train = train.drop(train[train['dropoff_latitude']>90].index, axis = 0)

train = train.drop(train[train['dropoff_longitude']<-180].index, axis = 0)
train = train.drop(train[train['dropoff_longitude']>180].index, axis = 0)
```

The geographical location may correspond to the real one, but not to New York area, so let's filter the existing data. For this, let's introduce the conditional city limits

In [195]:

```
def select_outside_boundingbox(df, BB):
    filter_df = df.loc[(df['pickup_longitude'] < BB[0]) | (df['pickup_longitude'] > BB[1]) | \
            (df['pickup_latitude'] < BB[2]) | (df['pickup_latitude'] > BB[3]) | \
            (df['dropoff_longitude'] < BB[0]) | (df['dropoff_longitude'] > BB[1]) | \
            (df['dropoff_latitude'] < BB[2]) | (df['dropoff_latitude'] > BB[3])]

    return filter_df

NYC_BB = (-74.5, -72.8, 40.5, 41.8)          #   dropping data which has lon_min (-74.263242) > here are 151 data > lon_max ( -72.986532)
                                              # in simple
                                              #  dropping data are out of range of NYC_BB
```

In [196]:

```
outliers = select_outside_boundingbox(train, NYC_BB)
outliers
```

Out[196]:

	key	fare_amount	pickup_datetime	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passenger_count
11	2012-12-24 11:24:00.00000098	5.5	2012-12-24 11:24:00 UTC	0.0	0.0	0.0	0.0	3
15	2013-11-23 12:57:00.000000190	5.0	2013-11-23 12:57:00 UTC	0.0	0.0	0.0	0.0	1
26	2011-02-07 20:01:00.000000114	6.5	2011-02-07 20:01:00 UTC	0.0	0.0	0.0	0.0	1
124	2013-01-17 17:22:00.00000043	8.0	2013-01-17 17:22:00 UTC	0.0	0.0	0.0	0.0	2
192	2010-09-05 17:08:00.00000092	3.7	2010-09-05 17:08:00 UTC	0.0	0.0	0.0	0.0	5
...	...	...	...	...	...	...	...	...
999713	2013-06-07 20:40:21.0000003	8.0	2013-06-07 20:40:21 UTC	0.0	0.0	0.0	0.0	2
999723	2013-03-03 13:18:00.000000227	3.5	2013-03-03 13:18:00 UTC	0.0	0.0	0.0	0.0	6
999731	2014-05-04 23:27:00.000000103	9.0	2014-05-04 23:27:00 UTC	0.0	0.0	0.0	0.0	6
999888	2010-04-28 21:08:00.00000038	9.3	2010-04-28 21:08:00 UTC	0.0	0.0	0.0	0.0	3
999915	2014-05-12 02:34:05.0000001	8.0	2014-05-12 02:34:05 UTC	0.0	0.0	0.0	0.0	2

20811 rows × 8 columns

In [197]:

```
train = train.drop(outliers.index, axis = 0)    #data are out of range of NYC_BB comes to be 20884  we have to drop it
```

In [198]:

```
print('New size: %d' % len(train))
```

New size: 975498

In [199]:

```
#key column and pickup_datetime column of Test set should also be presented as time data
test['key'] = pd.to_datetime(test['key'])
test['pickup_datetime']  = pd.to_datetime(test['pickup_datetime'])
```

In [200]:

```
test.dtypes
```

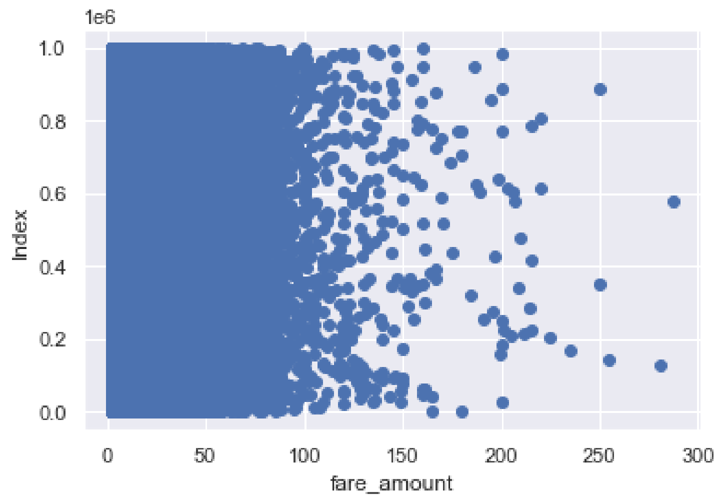
Out[200]:

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

Negative fare Removed

In [201]:

```
plt.scatter(x=train.fare_amount,y=train.index)
plt.ylabel('Index')
plt.xlabel('fare_amount')
plt.show()
```



In [202]:

```
print("Number of Fare_amount <=0 is")
train['fare_amount'][(train.fare_amount<=0)].count()
```

```
Number of Fare_amount <=0 is
```

Out[202]:

```
0
```

In [203]:

```
train.shape
```

Out[203]:

```
(975498, 8)
```

Final checking if still some outliers are left

In [204]:

```
train.drop(train[train.dropoff_longitude.isnull()==True].index,axis=0,inplace=True)
```

In [205]:

```
print('Number of observations out of valid range in coordinate columns:', end="\n")

print('pickup_longitude', end=': ')
print((train.pickup_longitude <-180).sum()+(train.pickup_longitude > 180).sum())

print('pickup_latitude', end=': ')
print((train.pickup_latitude <-90).sum()+(train.pickup_latitude > 90).sum())

print('dropoff_longitude', end=': ')
print((train.dropoff_longitude <-180).sum()+(train.dropoff_longitude > 180).sum())

print('dropoff_latitude', end=': ')
print((train.dropoff_latitude <-90).sum()+(train.dropoff_latitude > 90).sum())

if(((train.pickup_longitude <-180).sum()+(train.pickup_longitude > 180).sum() and (train.pickup_latitude <-90).sum()+(train.pickup_latitude > 90).sum() and (train.dropoff_longitude <-180)
.sum()+(train.dropoff_longitude > 180).sum() and (train.dropoff_latitude <-90).sum()+(train.dropoff_latitude > 90).sum())==0):
    print("No OutLiers Left")
else:
    print("Outliers Still Left")
```

```
Number of observations out of valid range in coordinate columns:
pickup_longitude: 0
pickup_latitude: 0
dropoff_longitude: 0
dropoff_latitude: 0
No OutLiers Left
```

We can understand displacement through start and end points.

We will use the Haversine formula to calculate the distance between two geolocations

In [206]:

```
train["loc1"] = train[["pickup_latitude","pickup_longitude"]].apply(tuple, axis=1)
train["loc2"] = train[["dropoff_latitude","dropoff_longitude"]].apply(tuple, axis=1)
```

Distance

Calculate the distance based on longitude and latitude

Haversine formula:

dlon = lon2 - lon1 dlat = lat2 - lat1 a = (sin(dlat/2))^2 + cos(lat1) *cos(lat2)* (sin(dlon/2))^2 c = 2 *atan2(sqrt(a), sqrt(1-a)) d = R* c (where R is the radius of the Earth)

$a = \sin^2(\Delta\varphi/2) + \cos\varphi_1 \cdot \cos\varphi_2 \cdot \sin^2(\Delta\lambda/2)$

$c = 2 \cdot \text{atan2}(\sqrt{a}, \sqrt{(1-a)})$

$d = R \cdot c$

In [207]:

```
def haversine_distance(lat1, long1, lat2, long2):
    dat = [train, test]
    for i in dat:
        R = 6371  #radius of earth in kilometers
        phi1 = np.radians(i[lat1])
        phi2 = np.radians(i[lat2])

        delta_phi = np.radians(i[lat2]-i[lat1])
        delta_lambda = np.radians(i[long2]-i[long1])

        #a = sin²((φB - φA)/2) + cos φA . cos φB . sin²((λB - λA)/2)
```

```
        a = np.sin(delta_phi / 2.0) ** 2 + np.cos(phi1) * np.cos(phi2) * np.sin(delta_lambda / 2.0) ** 2

        #c = 2 * atan2( √a, √(1−a) )
        c = 2 * np.arctan2(np.sqrt(a), np.sqrt(1-a))

        #d = R*c
        d = (R * c) #in kilometers
        i['H_Distance'] = d
    return d
```

Let's also calculate the distance using the Chebyshev method

The Chebyshev iteration is an iterative method for determining the solutions of a system of linear equations.

Reference https://brilliant.org/wiki/chebyshevs-formula/#:~:text=x%20%3D%20a%20%2B%20b%202%20%2B,%3D1%2C%20t%3D1%2C&text=x%3Db.,-Hence%2C

In [208]:

```
def chebyshev(pickup_long, dropoff_long, pickup_lat, dropoff_lat):
    return np.maximum(np.absolute(pickup_long - dropoff_long), np.absolute(pickup_lat - dropoff_lat))

train['Chebyshev'] = chebyshev(train['pickup_longitude'], train['dropoff_longitude'], train['pickup_latitude'], train['dropoff_latitude'])
```

In [209]:

```
test.dtypes
```

Out[209]:

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

In [210]:

```
haversine_distance('pickup_latitude', 'pickup_longitude', 'dropoff_latitude', 'dropoff_longitude')
```

Out[210]:

```
0        2.323260
1        2.425353
2        0.618628
3        1.961033
4        5.387301
           ...
9909     2.124874
9910     3.270969
9911    19.183941
9912     8.343486
9913     1.180825
Length: 9914, dtype: float64
```

In [211]:

```
dis=train["fare_amount"]/(train["H_Distance"]*train["passenger_count"])
fare_by_distance=train["fare_amount"]/train["H_Distance"]
len(dis)
```

Out[211]:

```
975498
```

In [212]:

```
#drop outliers
train["fare_by_distance"]=fare_by_distance
train['dis']=dis
train=train[train['dis']>=.1]
train=train[train['dis']<=7]
```

In [213]:

```
len(train)
```

Out[213]:

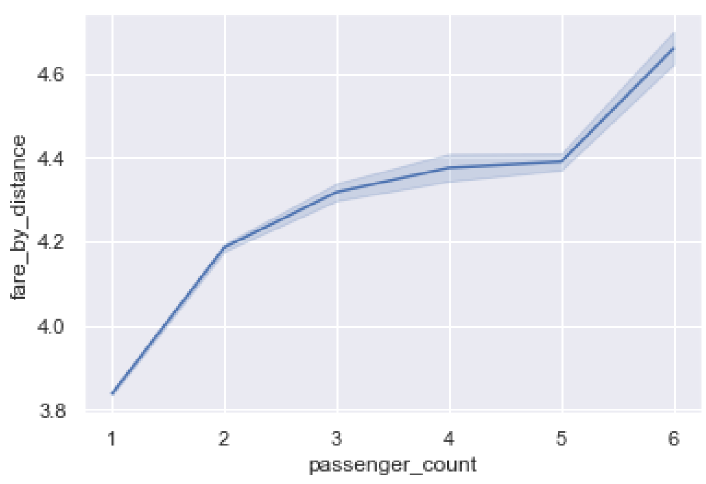
```
900400
```

In [214]:

```
sns.lineplot(x="passenger_count", y="fare_by_distance", data=train)
```

Out[214]:

```
<AxesSubplot:xlabel='passenger_count', ylabel='fare_by_distance'>
```



Type conversion (train formatting) :pickup_datetime

In [215]:

```
train['key'] = pd.to_datetime(train['key'])
train['pickup_datetime']  = pd.to_datetime(train['pickup_datetime'])
```

In [216]:

```
test['key']=pd.to_datetime(test['key'])
test['pickup_datetime']=pd.to_datetime(test['pickup_datetime'])
```

In [217]:

```
train["Hour"] = train['pickup_datetime'].dt.hour
train["day_of_week"] = train['pickup_datetime'].dt.weekday
train["day_of_month"] = train['pickup_datetime'].dt.day
train["week"] = train['pickup_datetime'].dt.week
train["month"] = train['pickup_datetime'].dt.month
train["year"] = train['pickup_datetime'].dt.year - 2000

train['minute'] =train['pickup_datetime'].dt.minute
train['second'] = train['pickup_datetime'].dt.second
train['dayofyear'] = train['pickup_datetime'].dt.dayofyear
```

```
C:\Users\SUDHIR~1\AppData\Local\Temp/ipykernel_6300/2236433926.py:4: FutureWarning: Series.dt.weekofyear and Series.dt.week have been deprecated.  Please use Series.dt.isocalendar().week in
stead.
  train["week"] = train['pickup_datetime'].dt.week
```

In [218]:

```
train.head()
```

Out[218]:

	key	fare_amount	pickup_datetime	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passenger_count	loc1	loc2	...	dis	Hour	day_of_week	day_of_month	week	month	year	minute	second	dayofyear
0	2009-06-15 17:26:21.000000100	4.5	2009-06-15 17:26:21+00:00	-73.844311	40.721319	-73.841610	40.712278	1	(40.721319, -73.844311)	(40.712278, -73.84161)	...	4.365694	17	0	15	25	6	9	26	21	166
1	2010-01-05 16:52:16.000000200	16.9	2010-01-05 16:52:16+00:00	-74.016048	40.711303	-73.979268	40.782004	1	(40.711303, -74.016048)	(40.782004, -73.979268)	...	1.999968	16	1	5	1	1	10	52	16	5
2	2011-08-18 00:35:00.000000490	5.7	2011-08-18 00:35:00+00:00	-73.982738	40.761270	-73.991242	40.750562	2	(40.76127, -73.982738)	(40.750562, -73.991242)	...	2.051060	0	3	18	33	8	11	35	0	230
3	2012-04-21 04:30:42.000000100	7.7	2012-04-21 04:30:42+00:00	-73.987130	40.733143	-73.991567	40.758092	1	(40.733143, -73.98713)	(40.758092, -73.991567)	...	2.750717	4	5	21	16	4	12	30	42	112
4	2010-03-09 07:51:00.000000135	5.3	2010-03-09 07:51:00+00:00	-73.968095	40.768008	-73.956655	40.783762	1	(40.768008, -73.968095)	(40.783762, -73.956655)	...	2.651118	7	1	9	10	3	10	51	0	68

5 rows × 23 columns

Add a variable that determines how much each kilometer of travel costs

In [219]:

```
train["fare_to_dist_ratio"] = train["fare_amount"] / ( train["H_Distance"]+0.0001)
```

Remove those whose start and end points match

In [220]:

```
train = train.drop(train[train['loc1']==train['loc2']].index, axis = 0)
```

Let's repeat the same procedures on the test part

In [221]:

```
test['pickup_datetime']  = pd.to_datetime(test['pickup_datetime'])

test["loc1"] = test[["pickup_latitude","pickup_longitude"]].apply(tuple, axis=1)
test["loc2"] = test[["dropoff_latitude","dropoff_longitude"]].apply(tuple, axis=1)

test['H_Distance'] = test.apply(lambda row: hs.haversine(row.loc1,row.loc2), axis=1)

test['Chebyshev'] = chebyshev(test['pickup_longitude'], test['dropoff_longitude'], test['pickup_latitude'], test['dropoff_latitude'])


test["hour"] = test.pickup_datetime.dt.hour
test["day_of_week"] = test.pickup_datetime.dt.weekday
test["day_of_month"] = test.pickup_datetime.dt.day
test["week"] = test.pickup_datetime.dt.week
test["month"] = test.pickup_datetime.dt.month
test["year"] = test.pickup_datetime.dt.year - 2000

test['minute'] =test['pickup_datetime'].dt.minute
test['second'] = test['pickup_datetime'].dt.second
test['dayofyear'] = test['pickup_datetime'].dt.dayofyear

# test = add_distances_from_airport(test)
```

```
C:\Users\SUDHIR~1\AppData\Local\Temp/ipykernel_6300/4156851343.py:14: FutureWarning: Series.dt.weekofyear and Series.dt.week have been deprecated.  Please use Series.dt.isocalendar().week i
nstead.
  test["week"] = test.pickup_datetime.dt.week
```

In [222]:

```
def downcast(df):

    df_int = df.select_dtypes(include=['int64', 'int32', 'int16', 'int8', 'int'])
    df[df_int.columns] = df_int.apply(pd.to_numeric,downcast='unsigned')

    df_float = df.select_dtypes(include=['float64', 'float32', 'float16', 'float'])
    df[df_float.columns] = df_float.apply(pd.to_numeric,downcast='float')

    return df
downcast(train)
downcast(test)
train.dtypes
```

Out[222]:

```
key                          datetime64[ns]
fare_amount                         float32
pickup_datetime         datetime64[ns, UTC]
pickup_longitude                    float32
pickup_latitude                     float32
dropoff_longitude                   float32
dropoff_latitude                    float32
passenger_count                       uint8
loc1                                 object
loc2                                 object
Chebyshev                           float32
H_Distance                          float32
fare_by_distance                    float32
dis                                 float32
Hour                                  uint8
day_of_week                           uint8
day_of_month                          uint8
week                                  uint8
month                                 uint8
year                                  uint8
minute                                uint8
second                                uint8
dayofyear                            uint16
fare_to_dist_ratio                  float32
dtype: object
```

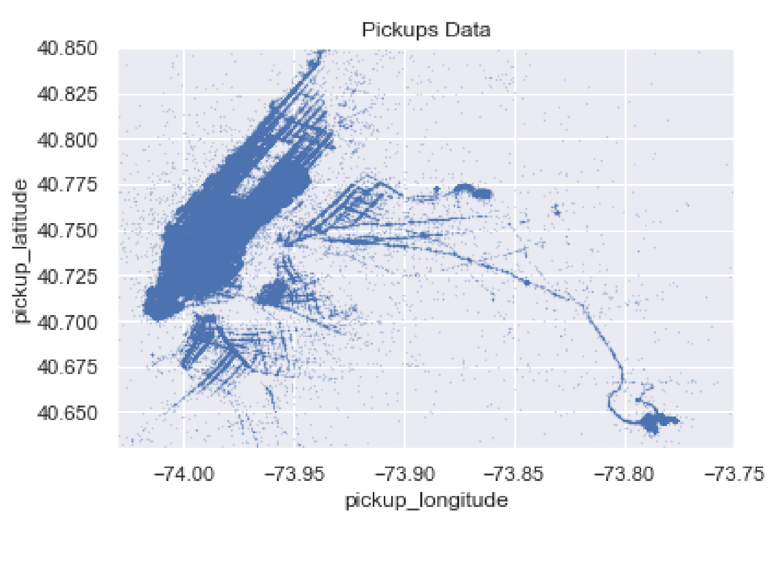
Map visualization

In [223]:

```
train.plot(y='pickup_latitude',x='pickup_longitude',kind="scatter",alpha=0.7,s=0.02)
city_long_border = (-74.03, -73.75)
city_lat_border = (40.63, 40.85)
plt.title("Pickups Data")

plt.ylim(city_lat_border)
plt.xlim(city_long_border)
plt.show()
```

```
*c* argument looks like a single numeric RGB or RGBA sequence, which should be avoided as value-mapping will have precedence in case its length matches with *x* & *y*.  Please use the *colo
r* keyword-argument or provide a 2D array with a single row if you intend to specify the same RGB or RGBA value for all points.
```



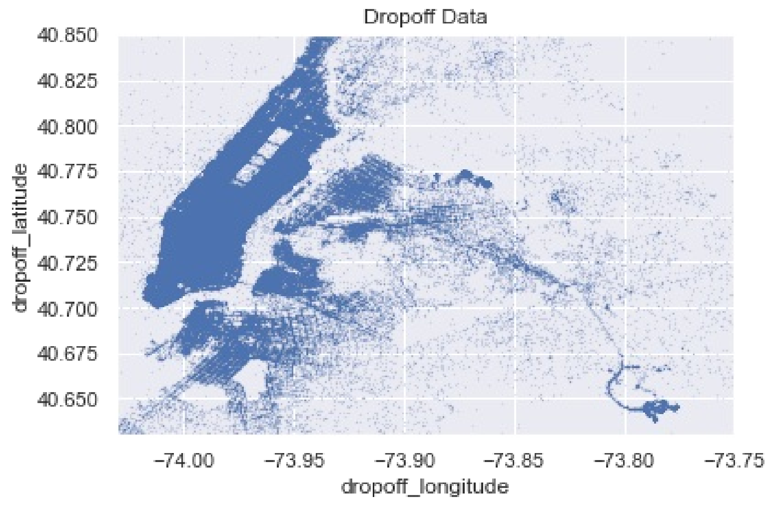
In [224]:

```
train.plot(y='dropoff_latitude',x='dropoff_longitude',kind="scatter",alpha=0.5,s=0.02)
```

```
city_long_border = (-74.03, -73.75)
city_lat_border = (40.63, 40.85)
plt.title("Dropoff Data")

plt.ylim(city_lat_border)
plt.xlim(city_long_border)
plt.show()
```

```
*c* argument looks like a single numeric RGB or RGBA sequence, which should be avoided as value-mapping will have precedence in case its length matches with *x* & *y*.  Please use the *colo
r* keyword-argument or provide a 2D array with a single row if you intend to specify the same RGB or RGBA value for all points.
```



Exploratory Data Analysis

In [225]:

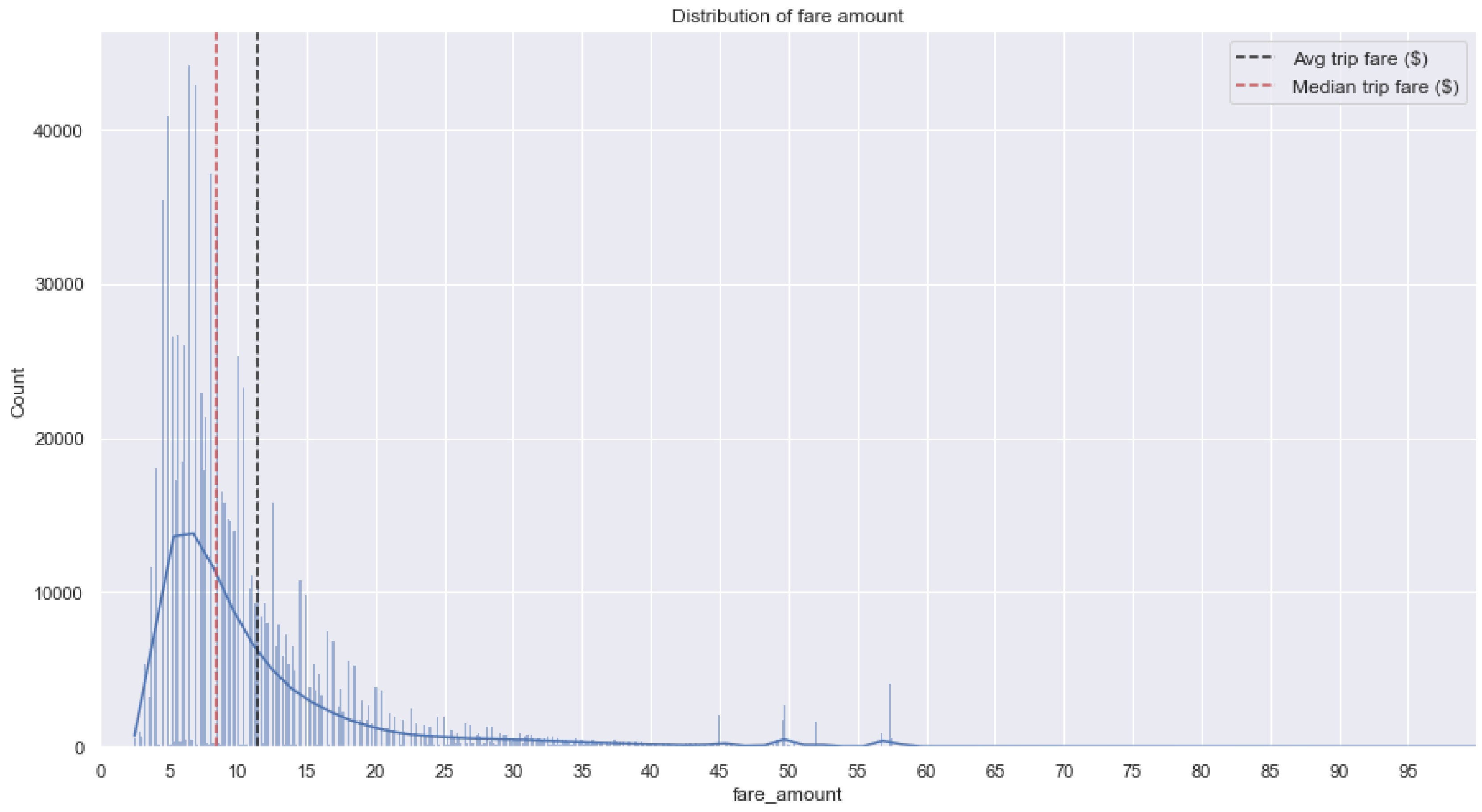
```
sns.histplot(data=train,x="fare_amount",kde=True)

plt.axvline(train["fare_amount"].mean(),color = "k",
            linestyle = "dashed",label = "Avg trip fare ($)")
plt.axvline(train["fare_amount"].median(),color = "r",
            linestyle = "dashed",label = "Median trip fare ($)")

plt.title("Distribution of fare amount")
plt.xticks(np.arange(0, 100, step=5))
plt.legend(loc = "best",prop = {"size" : 12})
plt.gcf().set_size_inches(15,8)
plt.xlim(0,100)
```

Out[225]:

```
(0.0, 100.0)
```



A right-skewed distribution

- **#### Most taxi fares range from 2.5-20$.**

- **#### The average taxi fee varies between 10$-12\$**
- **#### 45$-50\$-57$ peaks are observed, which fixed fee**

In [226]:

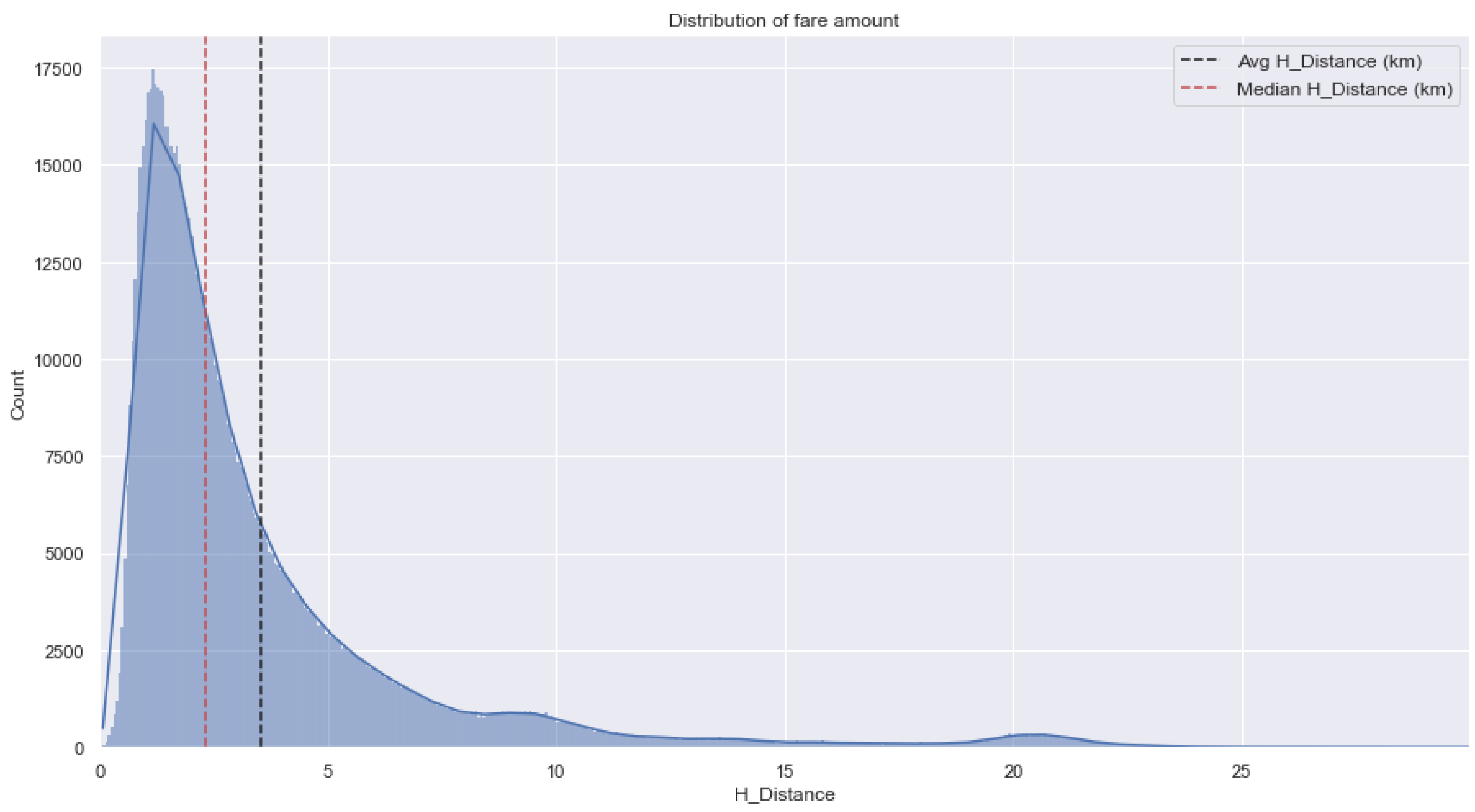
```
sns.histplot(data=train,x="H_Distance",kde=True)

plt.axvline(train["H_Distance"].mean(),color = "k",
            linestyle = "dashed",label = "Avg H_Distance (km)")
plt.axvline(train["H_Distance"].median(),color = "r",
            linestyle = "dashed",label = "Median H_Distance (km)")

plt.title("Distribution of fare amount")
plt.xticks(np.arange(0, 30, step=5))
plt.legend(loc = "best",prop = {"size" : 12})
plt.gcf().set_size_inches(15,8)
plt.xlim(0,30)
```

Out[226]:

```
(0.0, 30.0)
```



- **#### Passengers travel an average of 3-5 km by taxi**

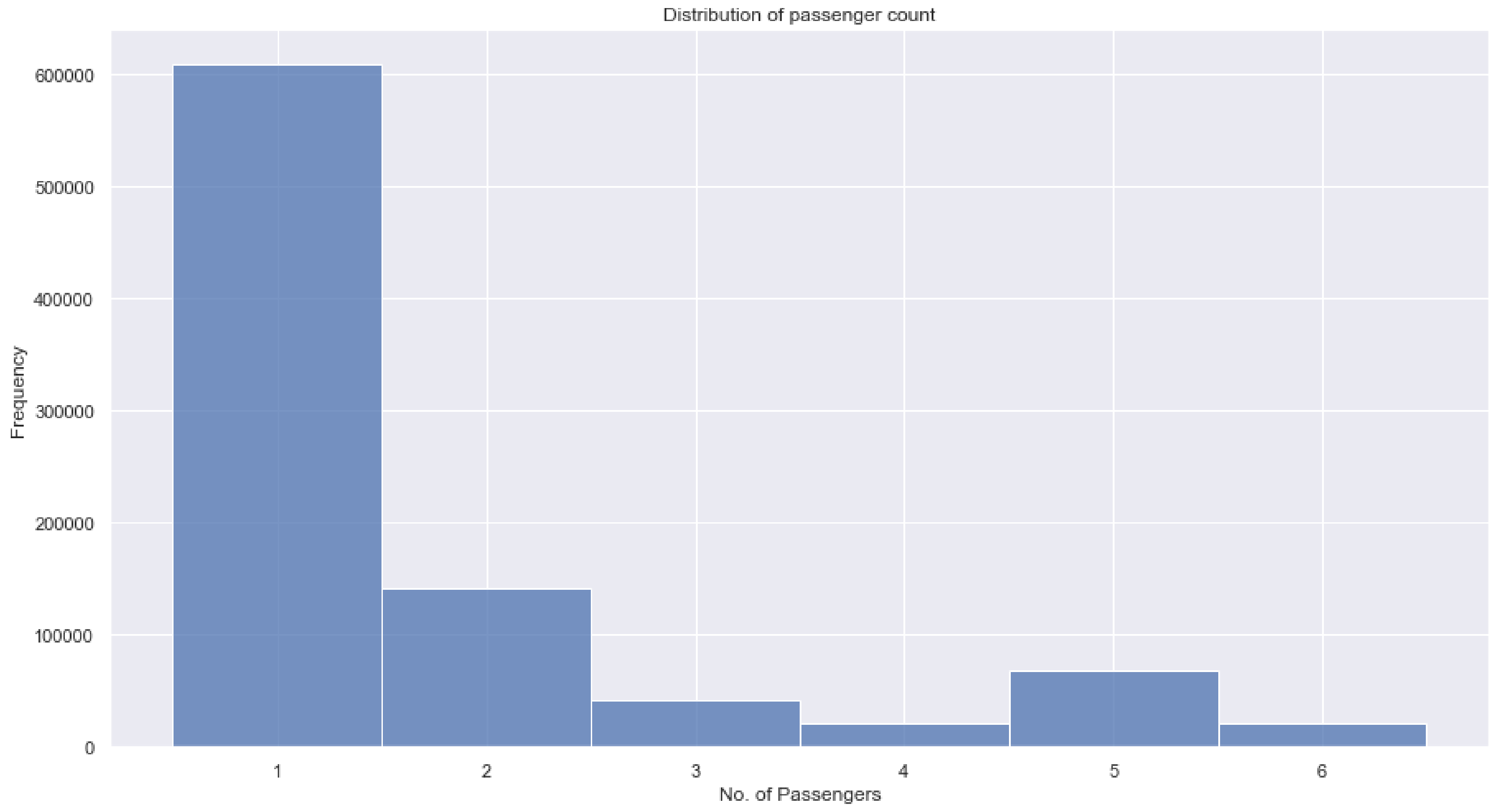
1. Does the number of passengers affect the fare?

In [227]:

```
sns.set(rc = {'figure.figsize':(15,8)})
sns.histplot(data=train, x="passenger_count", stat="count", discrete=True)
plt.title("Distribution of passenger count")
plt.xlabel('No. of Passengers')
plt.ylabel('Frequency')
```

Out[227]:

```
Text(0, 0.5, 'Frequency')
```



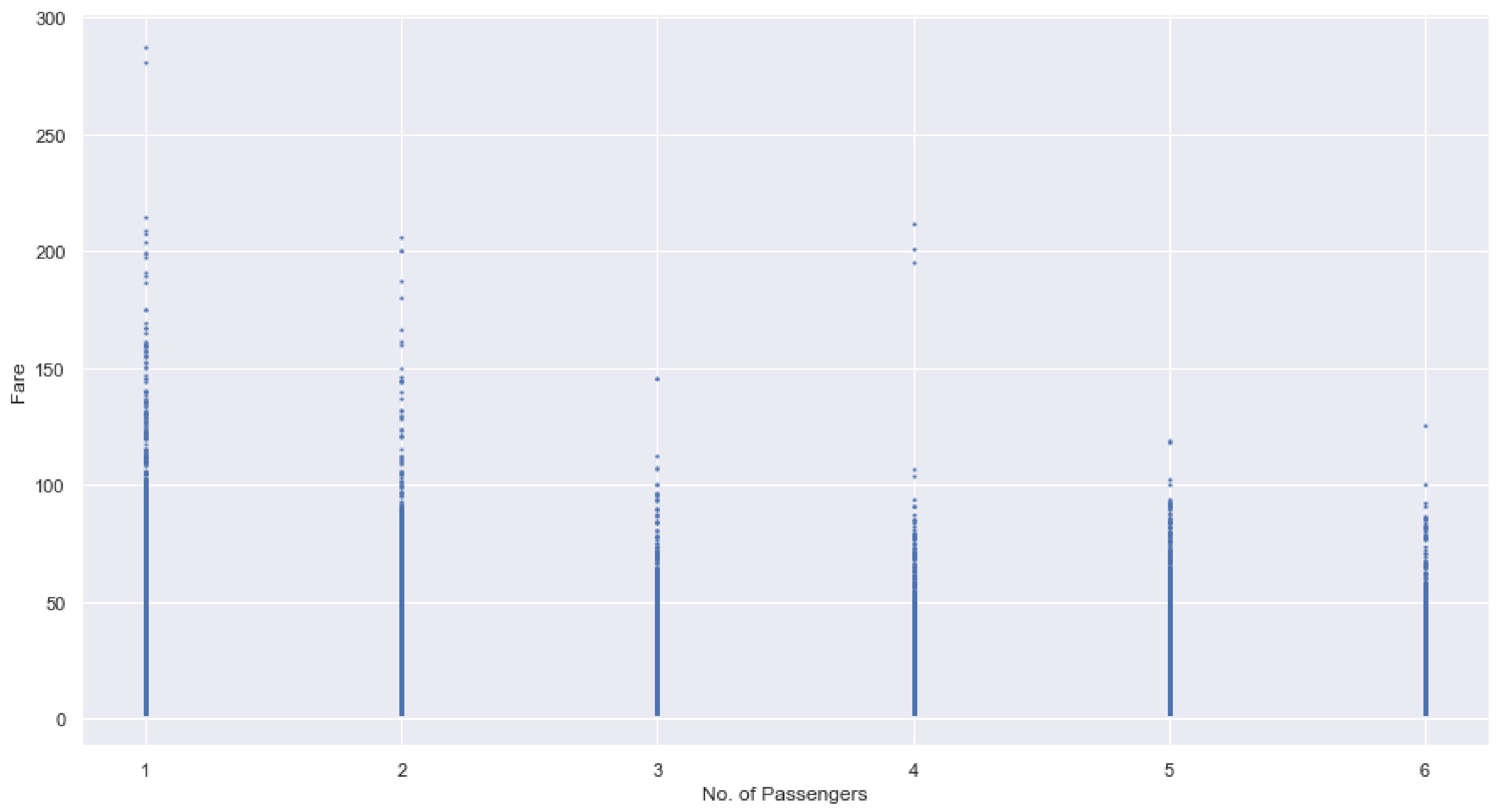
- #### Most of the passengers were traveling alone

In [228]:

```
plt.figure(figsize=(15,8))
plt.scatter(x=train['passenger_count'], y=train['fare_amount'], s=1.5)
plt.xlabel('No. of Passengers')
plt.ylabel('Fare')
```

Out[228]:

```
Text(0, 0.5, 'Fare')
```

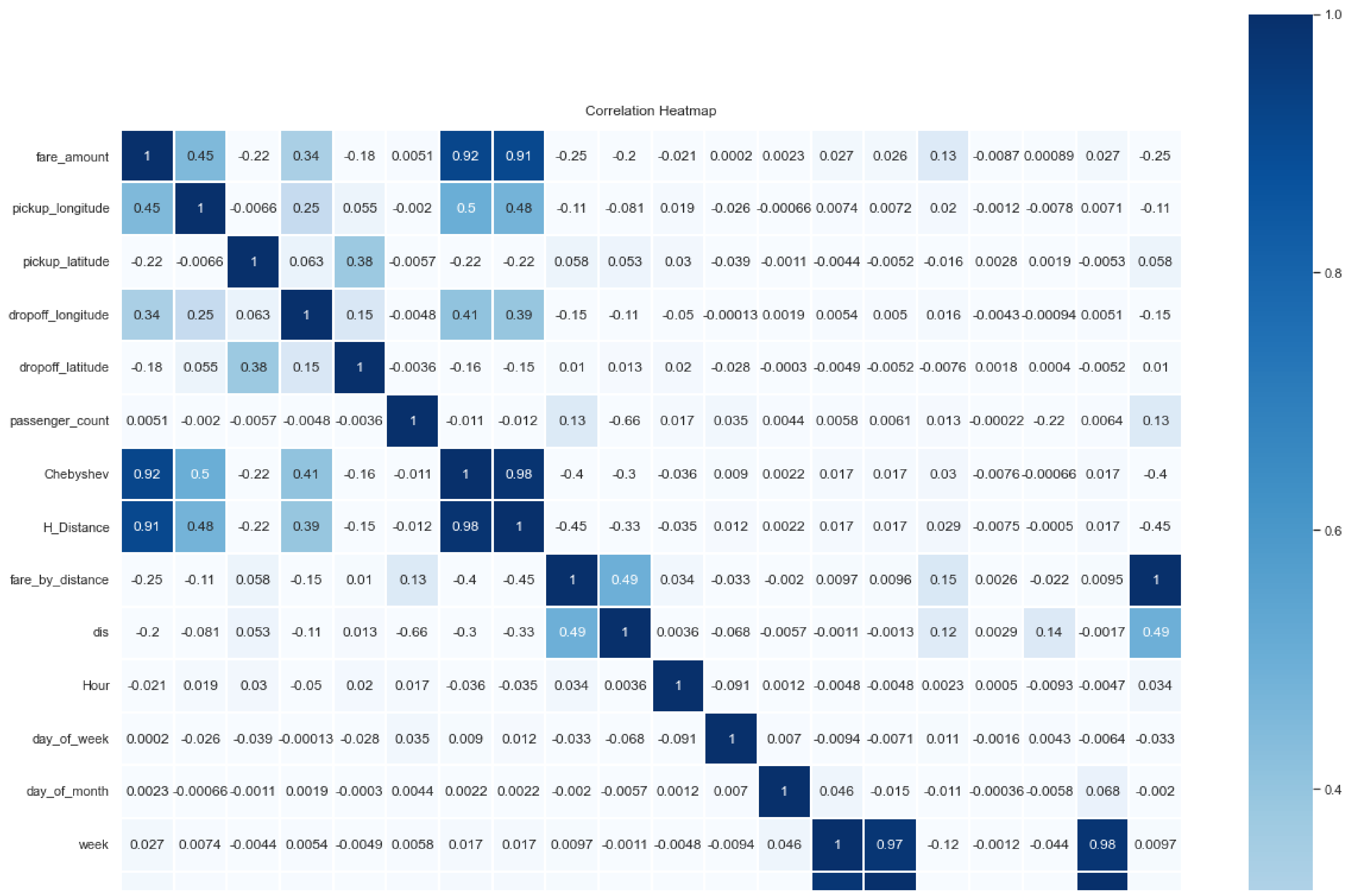


- #### One-passenger taxi has more passengers whose fare is higher

2. Does the date and time of pickup affect the fare?

In [229]:

```
colormap = plt.cm.RdBu
plt.figure(figsize=(20, 20))
heatmap = sns.heatmap(train.corr(),linewidths=0.1,vmax=1.0,vmin=0,
            square=True, cmap="Blues", linecolor='white', annot=True)
heatmap.set_title('Correlation Heatmap', fontdict={'fontsize':12}, pad=12);
```

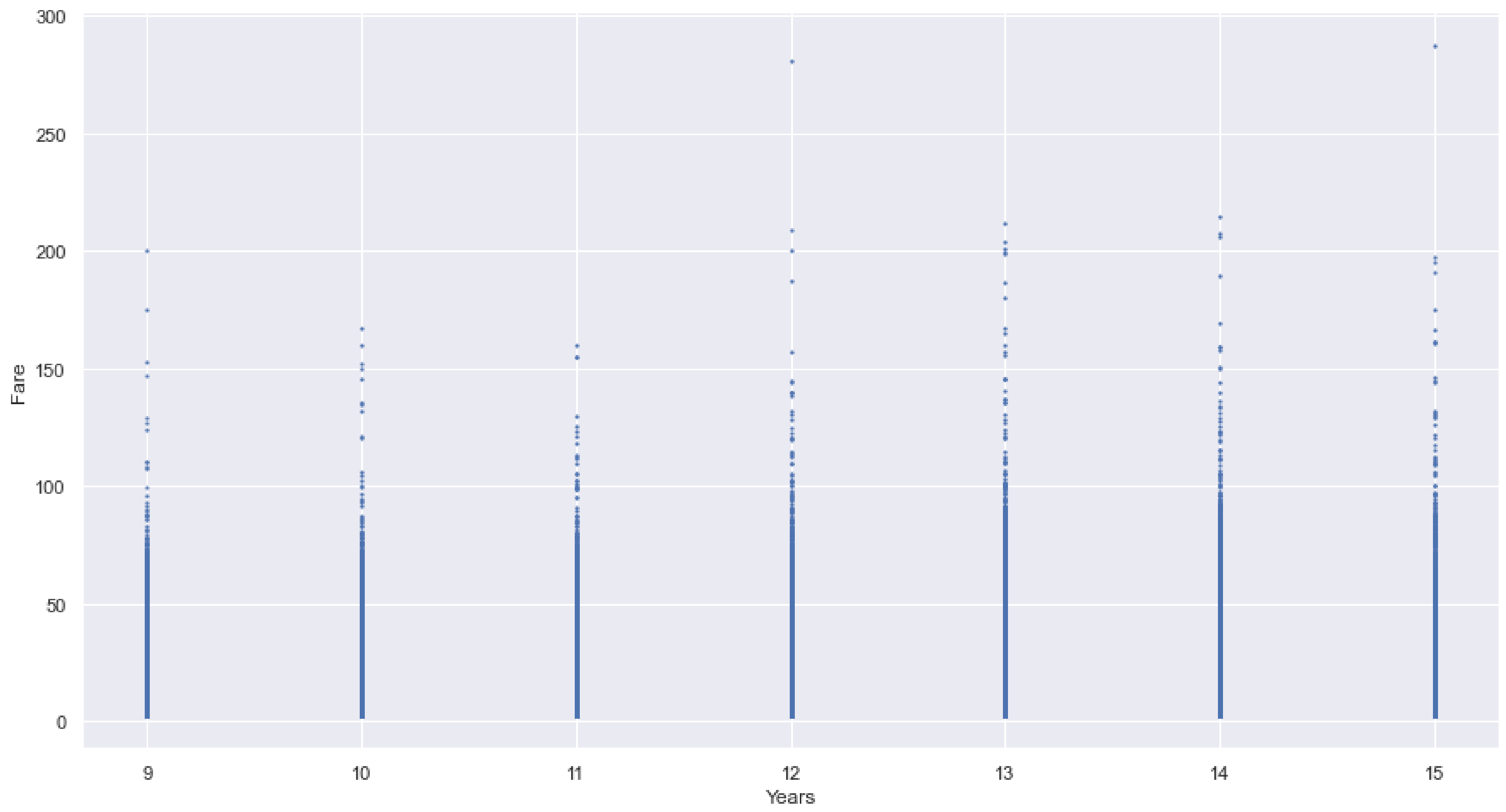


In [230]:

```
plt.figure(figsize=(15,8))
plt.scatter(x=train['year'], y=train['fare_amount'], s=1.5)
plt.xlabel('Years')
plt.ylabel('Fare')
```

Out[230]:

```
Text(0, 0.5, 'Fare')
```



In [231]:

```
train[['fare_amount','year']].corr()
```

Out[231]:

	fare_amount	year
fare_amount	1.000000	0.130865
year	0.130865	1.000000

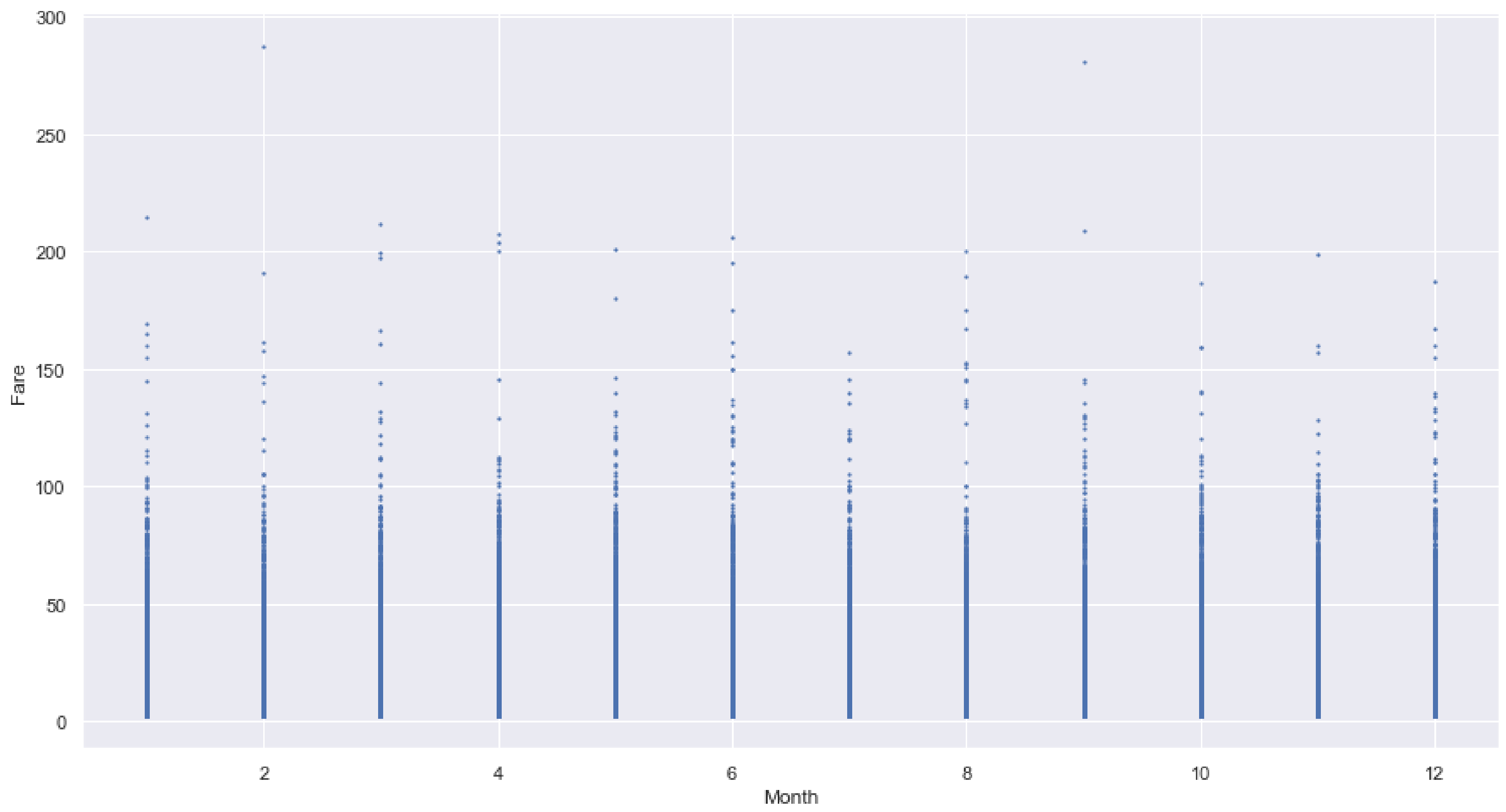
- **#### The rate does not change significantly over the years**

In [232]:

```
plt.figure(figsize=(15,8))
plt.scatter(x=train['month'], y=train['fare_amount'], s=1.5)
plt.xlabel('Month')
plt.ylabel('Fare')
```

Out[232]:

```
Text(0, 0.5, 'Fare')
```



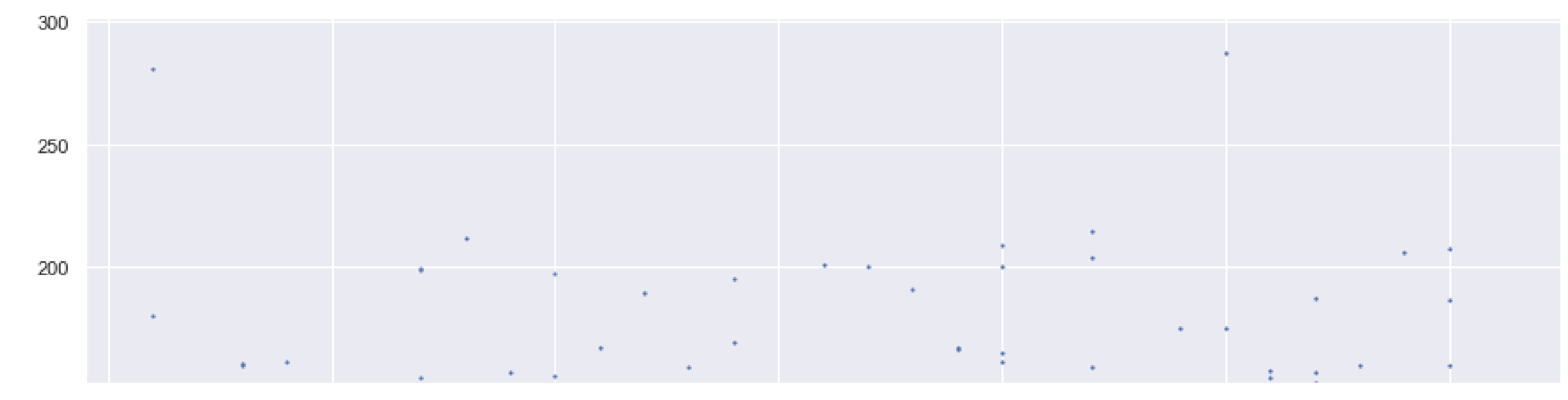
- **#### The rate is uniform throughout the months**

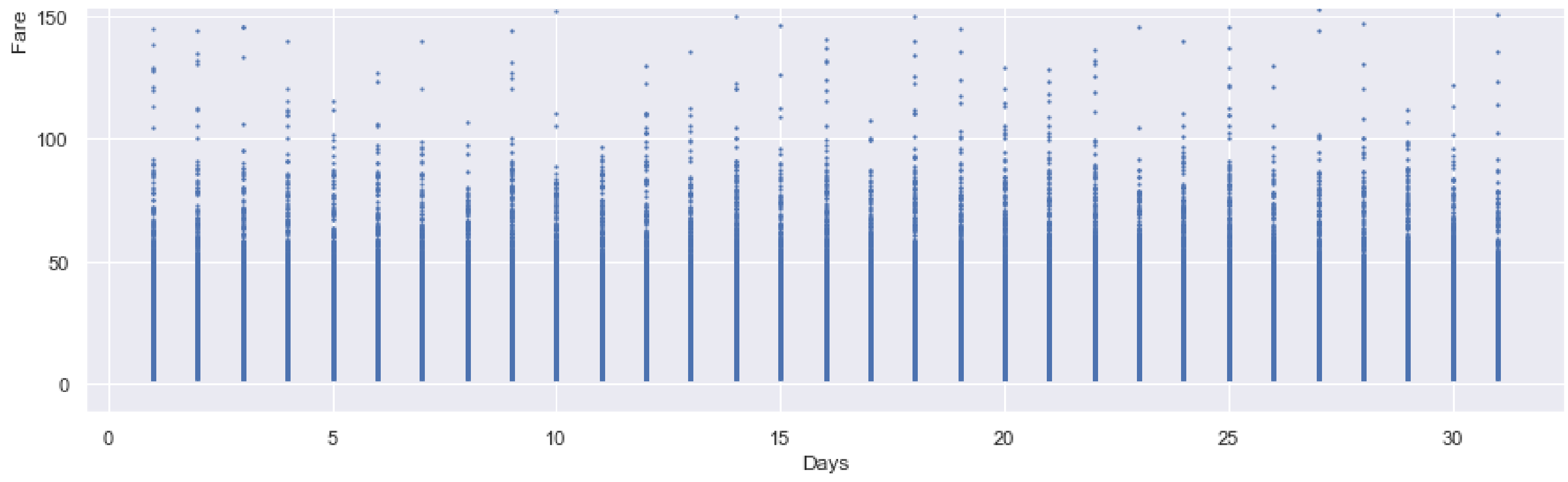
In [233]:

```
plt.figure(figsize=(15,8))
plt.scatter(x=train['day_of_month'], y=train['fare_amount'], s=1.5)
plt.xlabel('Days')
plt.ylabel('Fare')
```

Out[233]:

```
Text(0, 0.5, 'Fare')
```





- #### The fare is uniform throughout the month

In [234]:

```
train.columns
```

Out[234]:

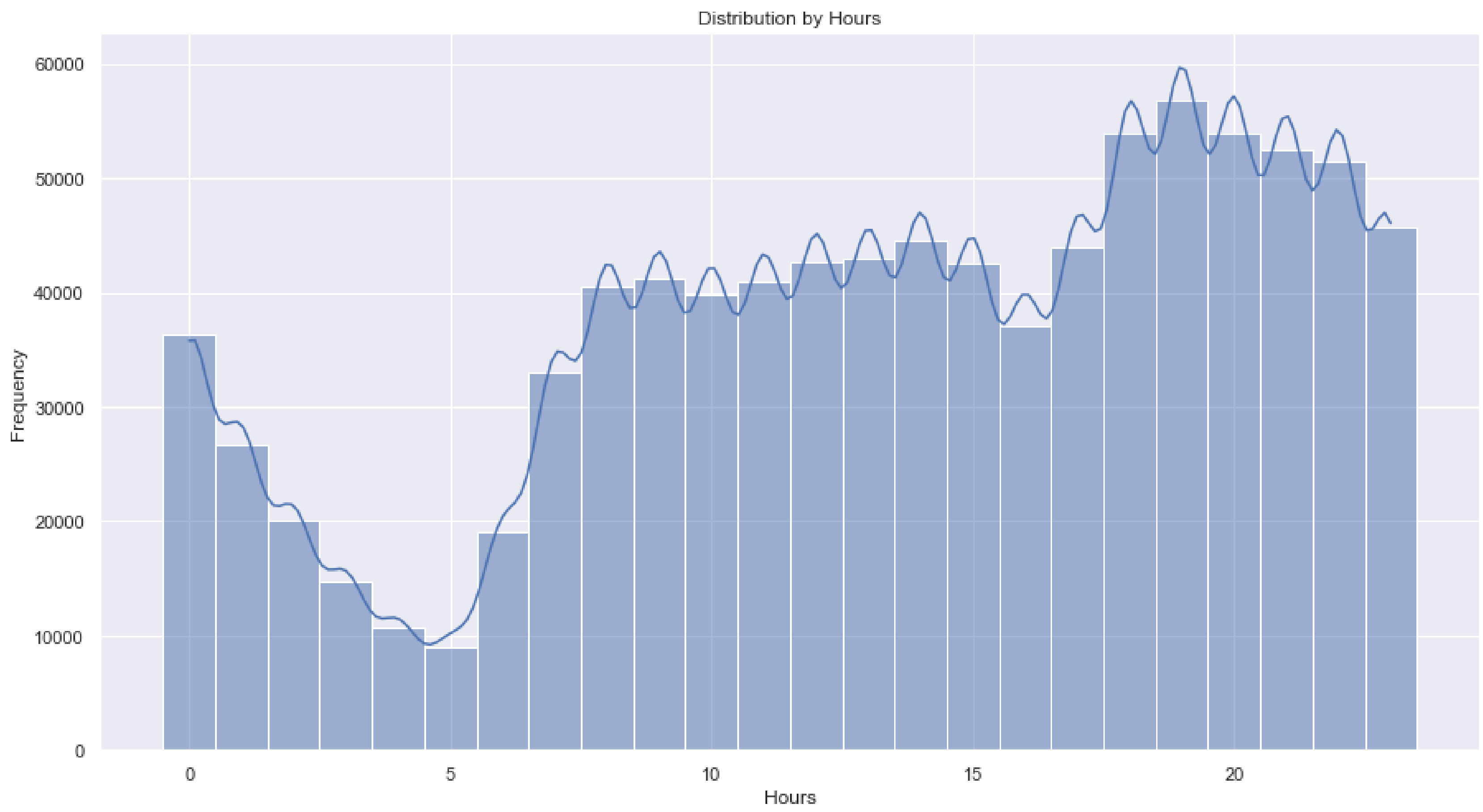
```
Index(['key', 'fare_amount', 'pickup_datetime', 'pickup_longitude',
       'pickup_latitude', 'dropoff_longitude', 'dropoff_latitude',
       'passenger_count', 'loc1', 'loc2', 'Chebyshev', 'H_Distance',
       'fare_by_distance', 'dis', 'Hour', 'day_of_week', 'day_of_month',
       'week', 'month', 'year', 'minute', 'second', 'dayofyear',
       'fare_to_dist_ratio'],
      dtype='object')
```

In [235]:

```
sns.set(rc = {'figure.figsize':(15,8)})
sns.histplot(data=train, x="Hour", stat="count", discrete=True, kde=True)
plt.title("Distribution by Hours")
plt.xlabel('Hours')
plt.ylabel('Frequency')
```

Out[235]:

```
Text(0, 0.5, 'Frequency')
```



- #### Taxi fares are rare at 5am and reaches the maximum at 7pm

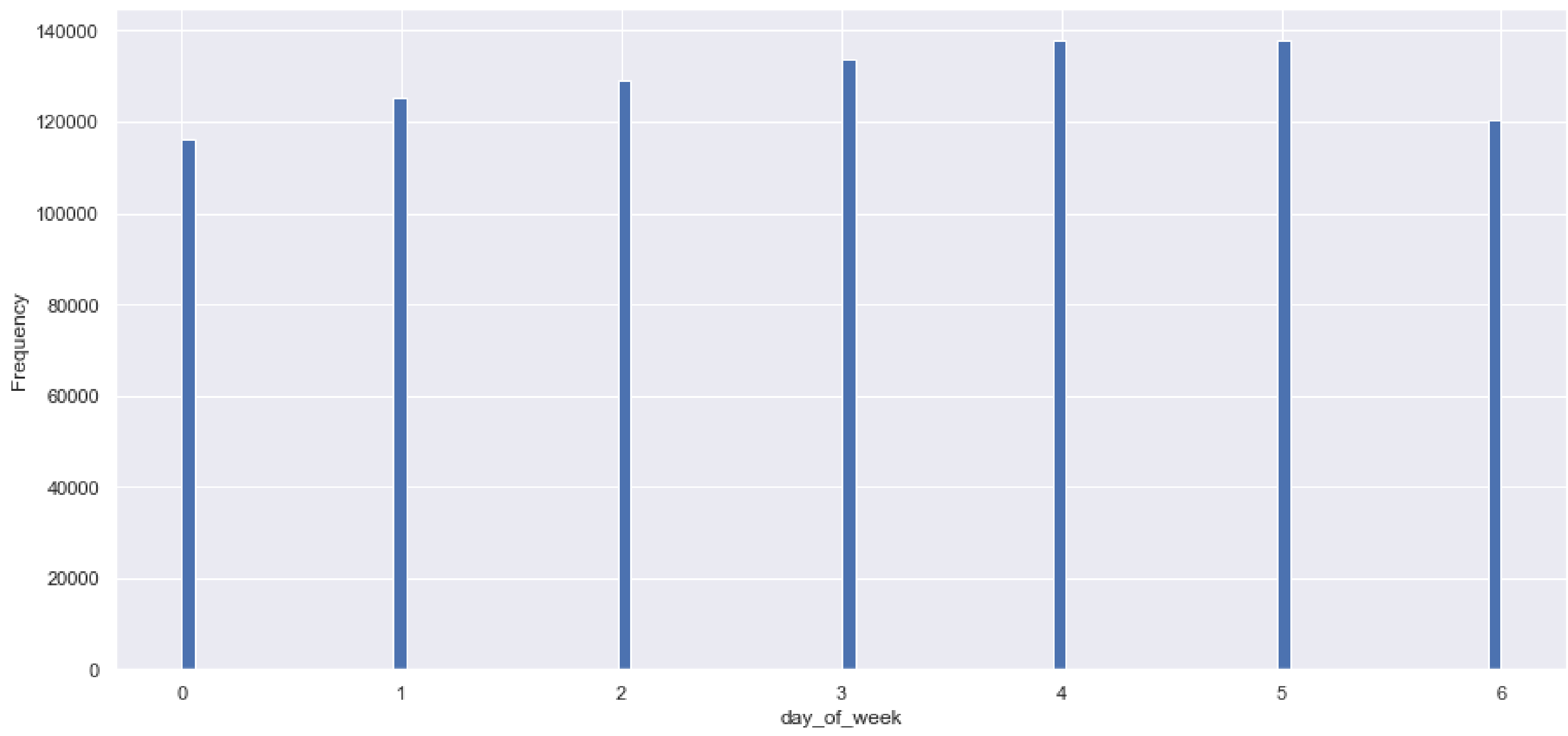
3. Does the day of the week affect the fare?

In [236]:

```
plt.figure(figsize=(15,7))
plt.hist(train['day_of_week'], bins=100)
plt.xlabel('day_of_week')
plt.ylabel('Frequency')
#0 means Saturday
```

Out[236]:

```
Text(0, 0.5, 'Frequency')
```



The fares throught the month mostly seem uniform

In [237]:

```
train[train.passenger_count <7][['fare_amount','passenger_count']].corr()
```

Out[237]:

	fare_amount	passenger_count
fare_amount	1.00000	0.00506
passenger_count	0.00506	1.00000

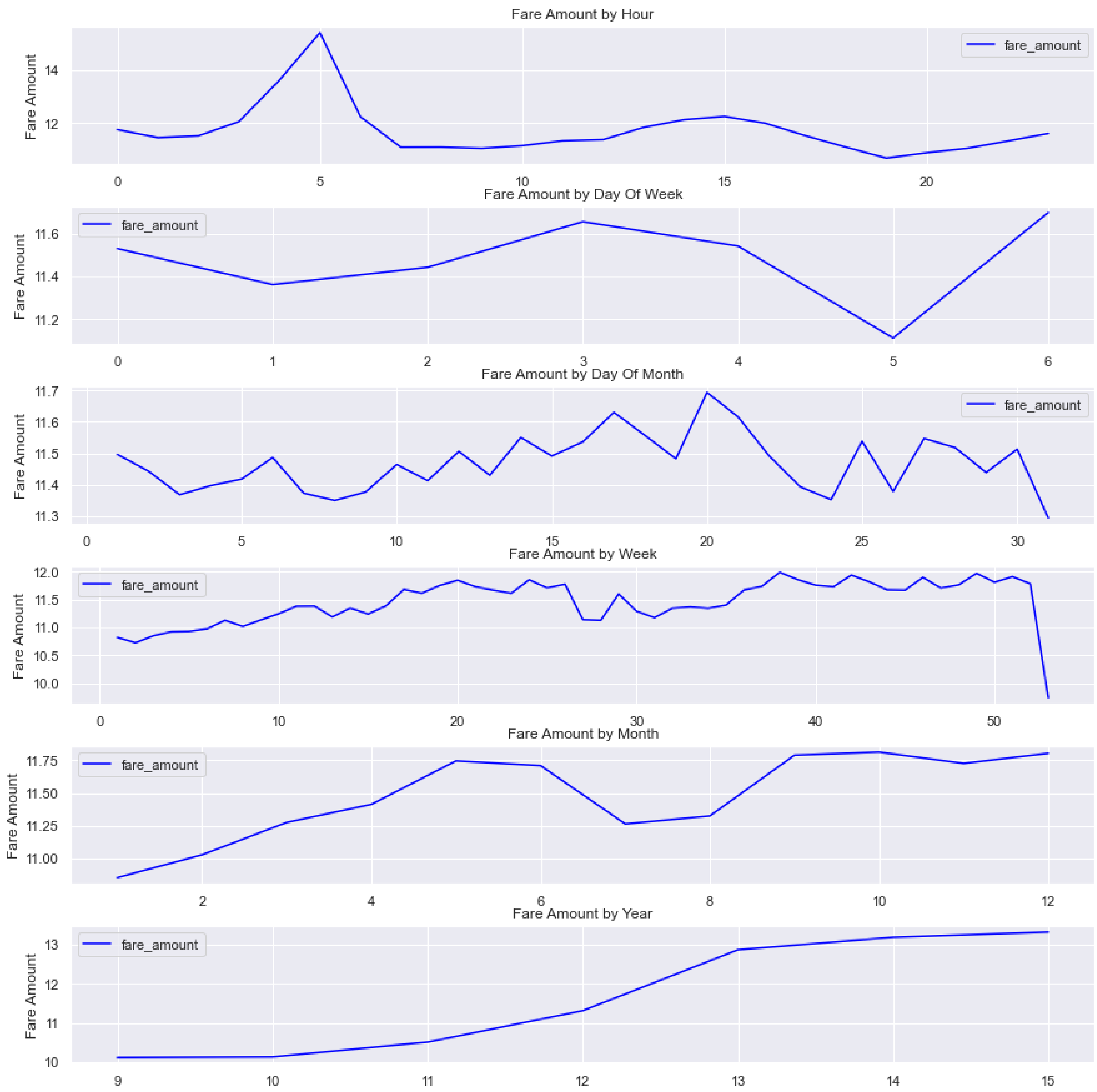
In [238]:

```
#https://www.programcreek.com/python/?CodeExample=time+slice
#**Reference**
def time_slicer(df, timeframes, value, color="purple"):
    """
    Function to count observation occurrence through different lenses of time.
    """
    f, ax = plt.subplots(len(timeframes), figsize = [12,12])
```

```
    for i,x in enumerate(timeframes):
        df.loc[:,[x,value]].groupby([x]).mean().plot(ax=ax[i],color=color)
        ax[i].set_ylabel(value.replace("_", " ").title())
        ax[i].set_title("{} by {}".format(value.replace("_", " ").title(), x.replace("_", " ").title()))
        ax[i].set_xlabel("")
    plt.tight_layout(pad=0)
```

In [239]:

```
time_slicer(df=train, timeframes=['Hour', 'day_of_week','day_of_month', 'week', 'month', 'year',], value = "fare_amount", color="blue")
```



- #### The higher the demand, the lower the fee and vice versa
- #### Average fares peak on Mondays and Thursdays
- #### The average fee has been increasing over the years

In [240]:

```
train[['fare_amount','H_Distance']].corr()
```

Out[240]:

	fare_amount	H_Distance
fare_amount	1.000000	0.906266
H_Distance	0.906266	1.000000

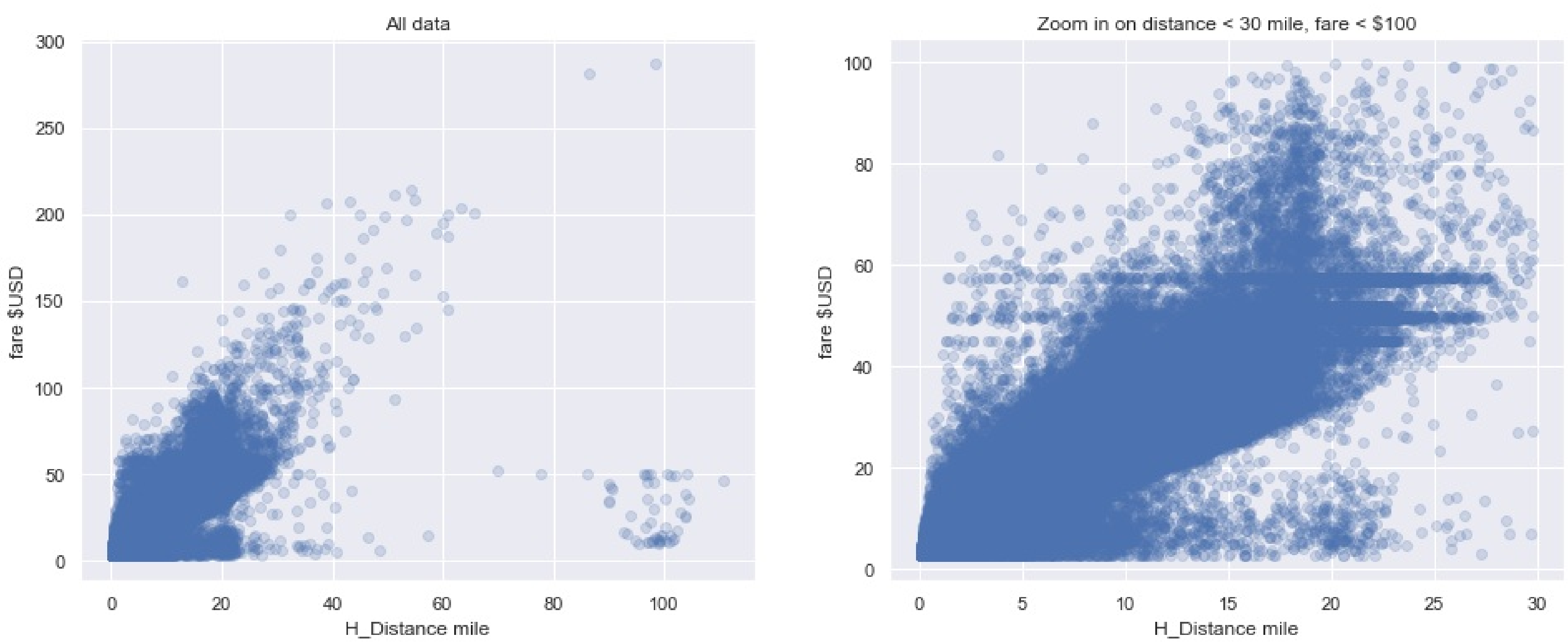
- #### The correlation number between these two values is high, as a result the graphs are very similar to each other
- #### At 5 o'clock in the morning, some people who have a long distance to travel leave home early, but they are not many, so the fare increases.

4. Does the distance affect the fare?

In [241]:

```
# scatter plot distance - fare
fig, axs = plt.subplots(1, 2, figsize=(16,6))
axs[0].scatter(train.H_Distance, train.fare_amount, alpha=0.2)
axs[0].set_xlabel('H_Distance mile')
axs[0].set_ylabel('fare $USD')
axs[0].set_title('All data')

# zoom in on part of data
idx = (train.H_Distance < 30) & (train.fare_amount < 100)
axs[1].scatter(train[idx].H_Distance, train[idx].fare_amount, alpha=0.2)
axs[1].set_xlabel('H_Distance mile')
axs[1].set_ylabel('fare $USD')
axs[1].set_title('Zoom in on distance < 30 mile, fare < $100');
```



In [242]:

```
print("Average $USD/Km : {:0.2f}".format(train.fare_amount.sum()/train.H_Distance.sum()))
```

```
Average $USD/Km : 3.24
```

- #### The horizontal lines on the graph to the right may indicate fixed fares from the airport
- #### Overall, a linear relationship is observed

In [243]:

```
train.reset_index(drop=True, inplace=True)
```

```
train[train["fare_to_dist_ratio"]>500]
```

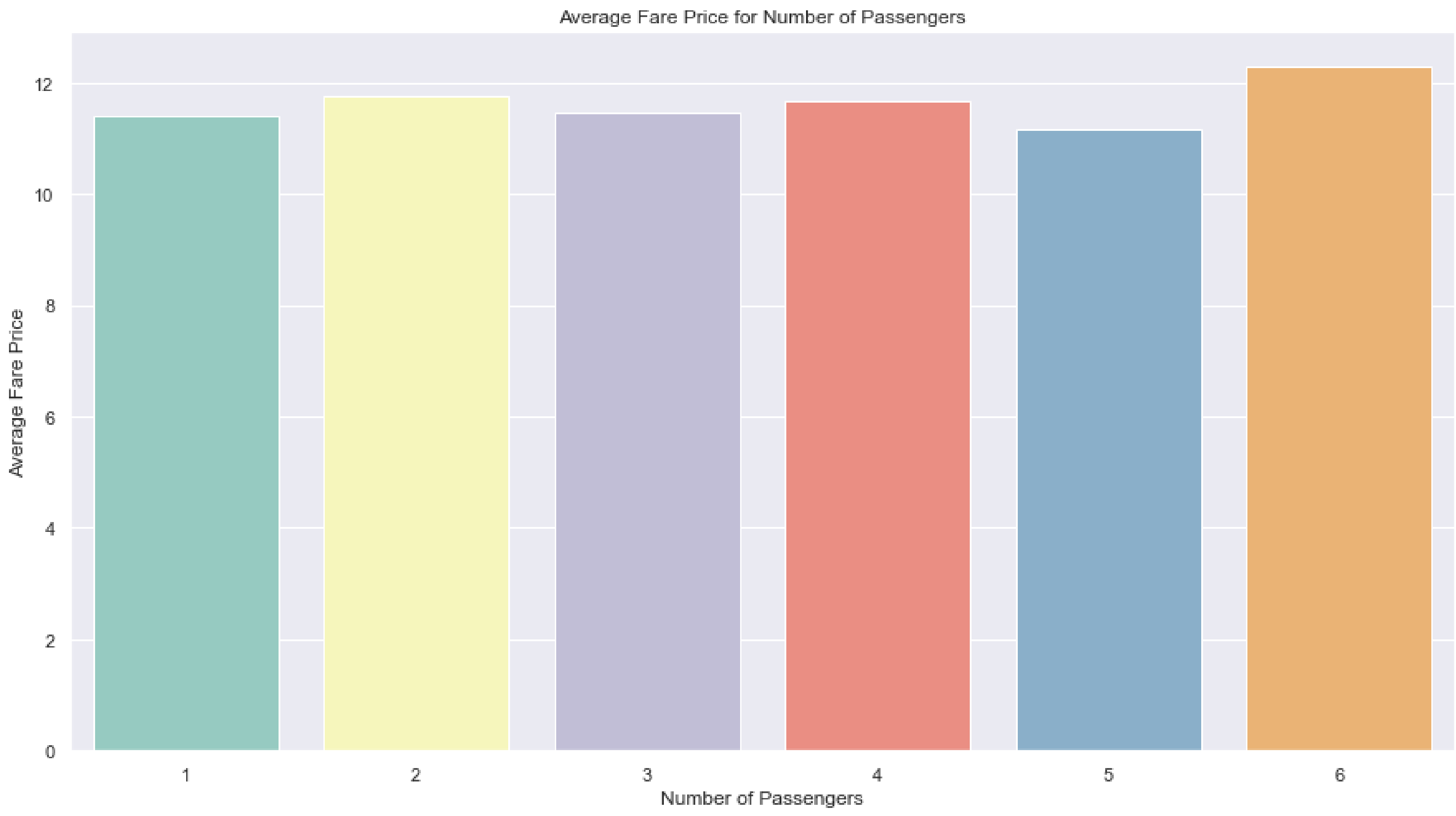
Out[243]:

key	fare_amount	pickup_datetime	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passenger_count	loc1	loc2	...	Hour	day_of_week	day_of_month	week	month	year	minute	second	dayofyear	fare_to_dist_ratio

0 rows × 24 columns

In [244]:

```
passenger_fare = train.groupby(['passenger_count']).mean()
sns.barplot(x=passenger_fare.index, y=passenger_fare['fare_amount'], palette = "Set3")
plt.xlabel('Number of Passengers')
plt.ylabel('Average Fare Price')
plt.title('Average Fare Price for Number of Passengers')
plt.show()
```



B Data Scaling

In [245]:

```
from sklearn.preprocessing import StandardScaler
scalar=StandardScaler()
train2=train
train2["fare_amount"]=scalar.fit_transform(train[["fare_amount"]])
train2["passenger_count"]=scalar.fit_transform(train[["passenger_count"]])
train2["dis"]=scalar.fit_transform(train[["dis"]])
train2["fare_by_distance"]=scalar.fit_transform(train[["fare_by_distance"]])
train2['key']=scalar.fit_transform(train[['key']])
train2["pickup_datetime"]=scalar.fit_transform(train[["pickup_datetime"]])
```

In [246]:

```
train2.head()
```

Out[246]:

	key	fare_amount	pickup_datetime	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passenger_count	loc1	loc2	...	Hour	day_of_week	day_of_month	week	month	year	minute	second	dayofyear	fare_to_dist_ratio
0	-1.482865	-0.738076	-1.482865	-73.844315	40.721317	-73.841614	40.712276	-0.549172	(40.721319, -73.844311)	(40.712278, -73.84161)	...	17	0	15	25	6	9	26	21	166	4.365271
1	-1.181140	0.574565	-1.181140	-74.016045	40.711304	-73.979271	40.782005	-0.549172	(40.711303, -74.016048)	(40.782004, -73.979268)	...	16	1	5	1	1	10	52	16	5	1.999945
2	-0.309410	-0.611046	-0.309410	-73.982735	40.761269	-73.991241	40.750561	0.199800	(40.76127, -73.982738)	(40.750562, -73.991242)	...	0	3	18	33	8	11	35	0	230	4.101825
3	0.056198	-0.399330	0.056198	-73.987129	40.733143	-73.991570	40.758091	-0.549172	(40.733143, -73.98713)	(40.758092, -73.991567)	...	4	5	21	16	4	12	30	42	112	2.750619
4	-1.088506	-0.653389	-1.088506	-73.968094	40.768009	-73.956657	40.783764	-0.549172	(40.768008, -73.968095)	(40.783762, -73.956655)	...	7	1	9	10	3	10	51	0	68	2.650985

5 rows × 24 columns

In [247]:

```
df1 = pd.DataFrame(train2)
corr = df1.corr()
corr.style.background_gradient(cmap ='coolwarm')
```

Out[247]:

	key	fare_amount	pickup_datetime	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passenger_count	Chebyshev	H_Distance	fare_by_distance	dis	Hour	day_of_week	day_of_month	week	month	ye
key	1.000000	0.135806	1.000000	0.021548	-0.016836	0.016751	-0.008441	0.014265	0.032799	0.032185	0.153041	0.122676	0.002004	0.009973	-0.000118	0.028564	0.036667	0.9880
fare_amount	0.135806	1.000000	0.135806	0.449863	-0.221276	0.339737	-0.175460	0.005060	0.917350	0.906266	-0.250758	-0.197675	-0.020644	0.000200	0.002257	0.026661	0.026457	0.1308
pickup_datetime	1.000000	0.135806	1.000000	0.021548	-0.016836	0.016751	-0.008441	0.014265	0.032799	0.032185	0.153041	0.122676	0.002004	0.009973	-0.000118	0.028564	0.036667	0.9880
pickup_longitude	0.021548	0.449863	0.021548	1.000000	-0.006581	0.252102	0.055262	-0.002015	0.501384	0.478949	-0.106370	-0.080715	0.019476	-0.026265	-0.000663	0.007439	0.007163	0.0203
pickup_latitude	-0.016836	-0.221276	-0.016836	-0.006581	1.000000	0.062500	0.379761	-0.005690	-0.218058	-0.218486	0.057547	0.053254	0.029961	-0.038574	-0.001061	-0.004355	-0.005189	0.0159
dropoff_longitude	0.016751	0.339737	0.016751	0.252102	0.062500	1.000000	0.154716	-0.004770	0.408934	0.391575	-0.145164	-0.109297	-0.050103	-0.000127	0.001919	0.005447	0.005002	0.0158
dropoff_latitude	-0.008441	-0.175460	-0.008441	0.055262	0.379761	0.154716	1.000000	-0.003589	-0.159046	-0.149333	0.010274	0.012630	0.019638	-0.028381	-0.000304	-0.004857	-0.005209	0.0075
passenger_count	0.014265	0.005060	0.014265	-0.002015	-0.005690	-0.004770	-0.003589	1.000000	-0.010675	-0.012485	0.133592	-0.664867	0.017438	0.034798	0.004379	0.005788	0.006077	0.0131
Chebyshev	0.032799	0.917350	0.032799	0.501384	-0.218058	0.408934	-0.159046	-0.010675	1.000000	0.981690	-0.403373	-0.295235	-0.035614	0.009012	0.002166	0.017015	0.016624	0.0300
H_Distance	0.032185	0.906266	0.032185	0.478949	-0.218486	0.391575	-0.149333	-0.012485	0.981690	1.000000	-0.445225	-0.325943	-0.034912	0.011951	0.002195	0.016992	0.016722	0.0294
fare_by_distance	0.153041	-0.250758	0.153041	-0.106370	0.057547	-0.145164	0.010274	0.133592	-0.403373	-0.445225	1.000000	0.493122	0.034125	-0.033081	-0.002005	0.009703	0.009646	0.1505
dis	0.122676	-0.197675	0.122676	-0.080715	0.053254	-0.109297	0.012630	-0.664867	-0.295235	-0.325943	0.493122	1.000000	0.003618	-0.068115	-0.005660	-0.001097	-0.001286	0.1221
Hour	0.002004	-0.020644	0.002004	0.019476	0.029961	-0.050103	0.019638	0.017438	-0.035614	-0.034912	0.034125	0.003618	1.000000	-0.090844	0.001184	-0.004764	-0.004811	0.0023
day_of_week	0.009973	0.000200	0.009973	-0.026265	-0.038574	-0.000127	-0.028381	0.034798	0.009012	0.011951	-0.033081	-0.068115	-0.090844	1.000000	0.006965	-0.009416	-0.007070	0.0109
day_of_month	-0.000118	0.002257	-0.000118	-0.000663	-0.001061	0.001919	-0.000304	0.004379	0.002166	0.002195	-0.002005	-0.005660	0.001184	0.006965	1.000000	0.045508	-0.014864	0.0105
week	0.028564	0.026661	0.028564	0.007439	-0.004355	0.005447	-0.004857	0.005788	0.017015	0.016992	0.009703	-0.001097	-0.004764	-0.009416	0.045508	1.000000	0.974972	0.1220
month	0.036667	0.026457	0.036667	0.007163	-0.005189	0.005002	-0.005209	0.006077	0.016624	0.016722	0.009646	-0.001286	-0.004811	-0.007070	-0.014864	0.974972	1.000000	0.1170
year	0.988082	0.130865	0.988082	0.020314	-0.015934	0.015875	-0.007595	0.013175	0.030034	0.029408	0.150582	0.122154	0.002312	0.010934	-0.010582	-0.122049	-0.117063	1.0000

	key	fare_amount	pickup_datetime	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passenger_count	Chebyshev	H_Distance	fare_by_distance	dis	Hour	day_of_week	day_of_month	week	month	ye
minute	-0.000513	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	-0.001205	-0.001408	0.0003
second	0.075145	0.000890	0.075145	-0.007834	0.001886	-0.000936	0.000403	-0.220469	-0.000656	-0.000500	-0.021637	0.137664	-0.009315	0.004300	-0.005778	-0.043569	-0.045671	0.0817
dayofyear	0.036717	0.026523	0.036717	0.007069	-0.005254	0.005125	-0.005203	0.006426	0.016712	0.016812	0.009499	-0.001716	-0.004697	-0.006411	0.067928	0.976628	0.996545	0.1175
fare_to_dist_ratio	0.153073	-0.250737	0.153073	-0.106374	0.057547	-0.145174	0.010268	0.133586	-0.403379	-0.445236	1.000000	0.493152	0.034130	-0.033085	-0.002005	0.009707	0.009650	0.1506

In [248]:

```
X=train[['H_Distance','month','year']].to_numpy()
X
```

Out[248]:

```
array([[ 1.030764  ,  6.        ,  9.        ],
       [ 8.450133  ,  1.        , 10.        ],
       [ 1.3895252 ,  8.        , 11.        ],
       ...,
       [ 1.7617408 ,  4.        , 13.        ],
       [ 1.8426832 ,  7.        , 11.        ],
       [ 0.75805146, 12.        ,  9.        ]], dtype=float32)
```

Split Data

In [249]:

```
X=train[['H_Distance','month','year']]
#X = train.iloc[:,train.columns != "fare_amount"]
y = train["fare_amount"]
X_test = test
X_train, X_valid, y_train, y_valid = train_test_split(X, y, train_size=0.75, test_size=0.15, random_state=3, shuffle=True)


# scaler = MinMaxScaler(feature_range=(0, 1))

# X_train_scaled = scaler.fit_transform(X_train)
# X_train = pd.DataFrame(X_train_scaled)

# X_valid_scaled = scaler.fit_transform(X_valid)
# X_valid = pd.DataFrame(X_valid_scaled)

# X_test_scaled = scaler.fit_transform(X_test)
# X_test = pd.DataFrame(X_test_scaled)
```

In [250]:

```
type(X_valid)
```

Out[250]:

```
pandas.core.frame.DataFrame
```

C Building a Pipeline:

In [251]:

```
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn import linear_model
```

In [252]:

```
class Removing_Outliers:
    def fit(self):pass
    def transform(self, train1):
        train1 = train1[train1['fare_amount']>0]
        trian1 = train1[train1['passenger_count']>0]
        haversine_distance('pickup_latitude', 'pickup_longitude', 'dropoff_latitude', 'dropoff_longitude')
        train1 = train1[train1['H_Distance']>0.5]
        train1['dis']=dis
        train1 = train1[train1['dis']>=.1]
        train1 = train1[train1['dis']<=7]
        return train1



class Features_Selection:
    def fit(self):pass
    def transform(self, train1):
        train1['key'] = pd.to_datetime(train1['key'])
        train1['pickup_datetime']  = pd.to_datetime(train1['pickup_datetime'])
        train1['year'] = train1['pickup_datetime'].dt.year
        train1['Month'] = train1['pickup_datetime'].dt.month
        train1['Date'] = train1['pickup_datetime'].dt.day
        train1['Day of Week'] = train1['pickup_datetime'].dt.dayofweek
        train1['Hour'] = train1['pickup_datetime'].dt.hour
        train1 = train1.reset_index()

        return train1

class Transform:
    def fit(self):pass
    def transform(self, train1):
        a = StandardScaler()
        scaled_train_data = train1
        scaled_train_data['fare_amount'] = a.fit_transform(train1[['fare_amount']])
        scaled_train_data['passenger_count'] = a.fit_transform(train1[['passenger_count']])
        scaled_train_data['dis'] = a.fit_transform(train1[['dis']])
        scaled_train_data['fare_by_distance'] = a.fit_transform(train1[['fare_by_distance']])
        return scaled_train_data


pipe = Pipeline([
    ('anomaly remover', Removing_Outliers()),

    ('features selection', Features_Selection()),
    ('scaler', Transform())
])
```

In [253]:

```
data = train
data = pipe.transform(data)
print(' Resulting dataframe:', data.shape)
data.sample(n=10)
```

```
 Resulting dataframe: (253219, 28)
```

Out[253]:

	index	key	fare_amount	pickup_datetime	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passenger_count	loc1	...	week	month	year	minute	second	dayofyear	fare_to_dist_ratio	Month	Date	Day of Week
83436	297027	1970-01-01 00:00:00.000000001	-0.755720	1970-01-01 00:00:00.000000001	-73.992981	40.742683	-74.009132	40.713699	0.194109	(40.742685, -73.992983)	...	31	8	1970	52	54	214	3.430091	1	1	3
206322	733990	1969-12-31 23:59:59.999999999	2.389765	1969-12-31 23:59:59.999999999	-73.951752	40.782097	-73.789925	40.646908	0.939222	(40.782098, -73.95175)	...	40	10	1969	11	0	274	2.442142	12	31	2
107687	383325	1970-01-01 00:00:00.000000000	0.541991	1970-01-01 00:00:00.000000000	-73.979561	40.677589	-73.950760	40.770756	-0.551004	(40.677588, -73.979564)	...	35	8	1970	32	24	241	2.584511	1	1	3
159419	567925	1969-12-31 23:59:59.999999999	-0.747348	1969-12-31 23:59:59.999999999	-73.973373	40.763866	-73.991150	40.724804	-0.551004	(40.763868, -73.97337)	...	7	2	1969	50	0	43	2.633290	12	31	2
132735	472590	1970-01-01 00:00:00.000000000	-0.588274	1970-01-01 00:00:00.000000000	-73.986702	40.722256	-74.004585	40.740620	-0.551004	(40.722257, -73.986701)	...	37	9	1970	44	46	256	5.516531	1	1	3

	index	key	fare_amount	pickup_datetime	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passenger_count	loc1	...	week	month	year	minute	second	dayofyear	fare_to_dist_ratio	Month	Date	Day of Week
108461	386183	1969-12-31 23:59:59.999999999	-0.111051	1969-12-31 23:59:59.999999999	-73.959785	40.781281	-73.994003	40.722694	0.194109	(40.781282, -73.959787)	...	18	5	1969	16	0	122	2.765337	12	31	2
238738	849178	1969-12-31 23:59:59.999999999	-0.632647	1969-12-31 23:59:59.999999999	-74.016029	40.711281	-74.002739	40.680553	-0.551004	(40.711279, -74.016026)	...	13	3	1969	3	24	90	3.746306	12	31	2
103962	370113	1970-01-01 00:00:00.000000000	0.223843	1970-01-01 00:00:00.000000000	-73.971565	40.756630	-73.864189	40.769924	2.429449	(40.75663, -73.971568)	...	4	1	1970	51	0	24	2.586291	1	1	3
89572	318781	1970-01-01 00:00:00.000000000	-0.178029	1970-01-01 00:00:00.000000000	-73.997421	40.738522	-73.948654	40.782459	-0.551004	(40.73852, -73.997421)	...	12	3	1970	53	38	80	2.961068	1	1	3
93551	333060	1970-01-01 00:00:00.000000000	-0.479433	1970-01-01 00:00:00.000000000	-73.951370	40.785290	-73.987625	40.753551	-0.551004	(40.78529, -73.951373)	...	40	10	1970	51	0	278	3.278852	1	1	3

10 rows × 28 columns

D Use of Validation Set and Cross Validation Approach

Reference

https://neptune.ai/blog/cross-validation-in-machine-learning-how-to-do-it-right

https://machinelearningmastery.com/how-to-configure-k-fold-cross-validation/

In [254]:

```
#The dataset is split into training and test dataset
newdf = df1[["fare_amount","passenger_count","H_Distance","fare_by_distance","dis","year"]].copy()

newdf = newdf.sample(frac = 1)
```

In [255]:

```
for i in range(15):
  k_folding = int(len(df1)/15)    #  900400/15   The training dataset is then split into K-folds.
  validation = newdf[k_folding*i:k_folding*(i+1)][['dis','fare_by_distance']]  # 1 fold is used for validation
  training = newdf[0:k_folding*i][['dis',"fare_by_distance"]]               # Out of the K-folds, (K-1) fold is used for training
  training = training.append(newdf[k_folding*(i+1):len(newdf)][['dis',"fare_by_distance"]], ignore_index=True)
  Y = newdf[0:k_folding*i]['fare_amount']        # The model with specific hyperparameters is trained with training data (K-1 folds) and validation data as 1 fold. The performance of the m
odel is recorded.
  Y = Y.append(newdf[k_folding*(i+1):len(newdf)]['fare_amount'], ignore_index=True)
  expected_Y = newdf[k_folding*i:k_folding*(i+1)]['fare_amount']  #The above steps (step 3, step 4, and step 5) is repeated until each of the k-fold got used for validation purpose. This i
s why it is called k-fold cross-validation.
  # training_mat = training.to_numpy()
  ans = np.dot(np.linalg.inv(np.dot(training.transpose(),training)),training.transpose()),Y)  #Finally, the mean and standard deviation of the model performance is computed by takin
g all of the model scores calculated in step 5 for each of the K models.
  mx=0
  output_Y = []
  sum = 0
  for j in validation.index:
    x = validation['dis'][j]*ans[0]+validation['fare_by_distance'][j]*ans[1]
    output_Y.append(x)
    # print(expected_Y[j],output_Y)
    sum = sum + abs(expected_Y[j]-x)/expected_Y[j]
  mse = mean_squared_error(expected_Y, output_Y)
  print("Mean Squared Error for K_folding=",i, "  " ,mse)
  print("Error for K_folding",i,"  ",sum/len(validation))
```

```
Mean Squared Error for K_folding= 0    0.9287329
Error for K_folding 0    0.2009362177412589
Mean Squared Error for K_folding= 1    0.96248096
Error for K_folding 1    0.1052291077186909
Mean Squared Error for K_folding= 2    0.940493
Error for K_folding 2    0.134126122864156
Mean Squared Error for K_folding= 3    0.93793374
Error for K_folding 3    0.13055165027228924
Mean Squared Error for K_folding= 4    0.93205184
Error for K_folding 4    0.183531445415911
Mean Squared Error for K_folding= 5    0.8949848
Error for K_folding 5    0.13211003071023938
Mean Squared Error for K_folding= 6    0.94008225
Error for K_folding 6    0.20620446982639207
Mean Squared Error for K_folding= 7    0.9121175
Error for K_folding 7    0.14538032268721182
Mean Squared Error for K_folding= 8    0.9189452
Error for K_folding 8    0.20791163244715477
Mean Squared Error for K_folding= 9    0.92644155
Error for K_folding 9    0.15137719080983475
Mean Squared Error for K_folding= 10    0.95583946
Error for K_folding 10    0.1525555421925713
Mean Squared Error for K_folding= 11    0.9314732
Error for K_folding 11    0.14428384552708398
Mean Squared Error for K_folding= 12    0.92546976
Error for K_folding 12    0.08773383608275244
Mean Squared Error for K_folding= 13    0.91933715
Error for K_folding 13    0.19630056794108036
Mean Squared Error for K_folding= 14    0.9220516
Error for K_folding 14    0.14667760710303743
```

E Linear Regression

In [256]:

```
def check_model(X_cols, y_col):
    X = train[X_cols].values
    # y = np.array([[x] for x in train[col].values])
    y = train[y_col].values

    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.33, random_state=1)

    models = [
        {'name_of_mmodel': 'Linear Regression','i': linear_model.LinearRegression()},
        {'name_of_mmodel': 'Ridge Regression','i': linear_model.Ridge(alpha=.1)},
        {'name_of_mmodel': 'Lasso Regularizer( Non-parametric)','i': linear_model.Lasso(alpha=0.1)}
    ]

    for i in models:
        print('Currently training {} '.format(i['name_of_mmodel']))
        i['i'].fit(X_train, y_train)
        print('Result after training on Model:', i['i'].score(X_test, y_test))
        print('Score on test set:', i['i'].coef_)
        print('\n'+'*'*20+'\n')
```

In [257]:

```
check_model(['H_Distance', 'year'], ['fare_amount'])
```

```
Currently training Linear Regression
Result after training on Model: 0.8397013861683362
Score on test set: [[0.2425722  0.05629562]]

********************

Currently training Ridge Regression
Result after training on Model: 0.8397015160639639
Score on test set: [[0.24257429 0.05629703]]

********************

Currently training Lasso Regularizer( Non-parametric)
Result after training on Model: 0.8358861974319874
Score on test set: [0.23577552 0.02790221]

********************
```

K-Neighbors Regression (Non -parametric)

In [258]:

```
rmse_val = []
X = [X_train.to_numpy()]
y = [np.array(y_train.tolist())]
from sklearn.neighbors import KNeighborsRegressor
neigh = KNeighborsRegressor(n_neighbors=5)
neigh.fit(X_train, y_train)
rmse_val=print("Score =",neigh.score(X_valid, y_valid))
```

Stochastic Gradient Descent (SGD) method

In [ ]:

```
from sklearn.linear_model import SGDRegressor
from sklearn.datasets import load_boston
from sklearn.datasets import make_regression
from sklearn.metrics import mean_squared_error
from sklearn.model_selection import train_test_split
from sklearn.model_selection import cross_val_score
from sklearn.preprocessing import scale
import matplotlib.pyplot as plt

x, y = make_regression(n_samples=1000, n_features=30)


sgdr = SGDRegressor()
print(sgdr)

sgdr.fit(X_train, y_train)
rmse_val=print("Score=",sgdr.score(X_valid, y_valid))
```

```
SGDRegressor()
Score= 0.8114598808324572
```

In [ ]: