New York Taxi Prediction

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0.0.1 NYC Taxi Fare Prediction Challenge

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1 Step 1: Reading the dataset

Reading the dataset and understanding what each field represents.

```
In [1]: import pandas as pd
        df = pd.read_csv('/Users/Shared/Work/dsf/hw2/train.csv')

In [2]: df.shape

Out[2]: (55423856, 8)

In [3]: print(df.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 55423856 entries, 0 to 55423855
Data columns (total 8 columns):
key                  object
fare_amount          float64
pickup_datetime      object
pickup_longitude     float64
pickup_latitude      float64
dropoff_longitude    float64
dropoff_latitude     float64
passenger_count      int64
dtypes: float64(5), int64(1), object(2)
memory usage: 3.3+ GB
None
```

```
In [4]: df.describe()

Out[4]:         fare_amount  pickup_longitude  pickup_latitude  dropoff_longitude  \
        count  5.542386e+07      5.542386e+07     5.542386e+07       5.542348e+07
        mean   1.134505e+01     -7.250968e+01     3.991979e+01      -7.251121e+01
```

```
std     2.071083e+01      1.284888e+01     9.642353e+00        1.278220e+01
min    -3.000000e+02     -3.442060e+03    -3.492264e+03       -3.442025e+03
25%     6.000000e+00     -7.399207e+01     4.073493e+01       -7.399140e+01
50%     8.500000e+00     -7.398180e+01     4.075265e+01       -7.398015e+01
75%     1.250000e+01     -7.396708e+01     4.076713e+01       -7.396367e+01
max     9.396336e+04      3.457626e+03     3.408790e+03        3.457622e+03

       dropoff_latitude  passenger_count
count      5.542348e+07     5.542386e+07
mean       3.992068e+01     1.685380e+00
std        9.633346e+00     1.327664e+00
min       -3.547887e+03     0.000000e+00
25%        4.073403e+01     1.000000e+00
50%        4.075316e+01     1.000000e+00
75%        4.076810e+01     2.000000e+00
max        3.537133e+03     2.080000e+02
```

2 Step 2: Cleaning dataset

Conclusion The training data has about 55 million rows.

Most of the columns are float/integer type except the key and pickup datetime.

There are some very obvious extremes in the data when we look at the mean/min/max values of the numerical columns, as follows: * Minimum fare_amount is negative * Maximum fare_amount is absurd - USD 93963 * Latitudes and longitudes have a very long range of values even for a big city like NYC * Minimum passenger_count is 0 * Maximum passenger_count is 208

2.1 Step 2.1: Clean Fare Amount

Let's study the fare amount frequency

In [5]:
```python
import seaborn as sns
sns.distplot(df['fare_amount'])
```

```
/anaconda3/lib/python3.6/site-packages/matplotlib/axes/_axes.py:6462: UserWarning: The 'normed
  warnings.warn("The 'normed' kwarg is deprecated, and has been "
```

Out[5]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x112793748>
```

Conclusion We realize that some fares are absurd, i.e. less than USD 3 (base fare for NYC cabs) and more than USD 500. We'll clean this.

In [6]:
```python
df = df[df.fare_amount>=3.0]
df = df[df.fare_amount<=500]
```

2.2 Step 2.2: Clean Passenger Count

Minimum value of passenger counts as seen above is 0 - this doesn't make sense. Perhaps the taxi was dropping parcels but it's best to not risk data contamination for there are chances that this data was recorded in error. Similarly, the maximum value of a NYC taxi is 6 passengers.

So we'll apply these restrictions and drop rows which have passengers less than 1 or more than 6.

```
In [7]: df.passenger_count.value_counts(dropna=False)
```

```
Out[7]: 1      38056631
        2       8141219
        5       3904012
        3       2423042
        4       1173803
        6       1169847
        0        192396
        208          46
        9            22
        7            14
        8             8
        129           2
        51            1
        34            1
        Name: passenger_count, dtype: int64
```

```
In [8]: df = df[df.passenger_count>0]
        df = df[df.passenger_count<7]
```

2.3 Step 2.3: Clean duplicate data

To avoid any bias, we remove all duplicate data.

```
In [9]: df.drop_duplicates()
        df.describe()
```

```
Out[9]:         fare_amount  pickup_longitude  pickup_latitude  dropoff_longitude  \
        count  5.486855e+07      5.486855e+07     5.486855e+07       5.486855e+07
        mean   1.140599e+01     -7.252981e+01     3.993070e+01      -7.254059e+01
        std    9.791473e+00      1.279479e+01     9.632379e+00       1.270911e+01
        min    3.000000e+00     -3.442060e+03    -3.492264e+03      -3.442025e+03
        25%    6.000000e+00     -7.399208e+01     4.073496e+01      -7.399141e+01
        50%    8.500000e+00     -7.398182e+01     4.075267e+01      -7.398017e+01
        75%    1.250000e+01     -7.396716e+01     4.076714e+01      -7.396376e+01
        max    5.000000e+02      3.457626e+03     3.408790e+03       3.457622e+03

               dropoff_latitude  passenger_count
        count      5.486855e+07     5.486855e+07
        mean       3.993675e+01     1.692090e+00
```

```
std        9.596615e+00     1.307679e+00
min       -3.547887e+03     1.000000e+00
25%        4.073407e+01     1.000000e+00
50%        4.075318e+01     1.000000e+00
75%        4.076811e+01     2.000000e+00
max        3.537133e+03     6.000000e+00
```

2.4 Step 2.4: Clean Null Values

Some rows have null values, these need to be gotten rid of.

```
In [10]: df = df.dropna(how = 'any', axis = 'rows')
         df.describe()
```

```
Out[10]:          fare_amount  pickup_longitude  pickup_latitude  dropoff_longitude  \
         count  5.486855e+07      5.486855e+07     5.486855e+07       5.486855e+07
         mean   1.140599e+01     -7.252981e+01     3.993070e+01      -7.254059e+01
         std    9.791473e+00      1.279479e+01     9.632379e+00       1.270911e+01
         min    3.000000e+00     -3.442060e+03    -3.492264e+03      -3.442025e+03
         25%    6.000000e+00     -7.399208e+01     4.073496e+01      -7.399141e+01
         50%    8.500000e+00     -7.398182e+01     4.075267e+01      -7.398017e+01
         75%    1.250000e+01     -7.396716e+01     4.076714e+01      -7.396376e+01
         max    5.000000e+02      3.457626e+03     3.408790e+03       3.457622e+03

                dropoff_latitude  passenger_count
         count      5.486855e+07     5.486855e+07
         mean       3.993675e+01     1.692090e+00
         std        9.596615e+00     1.307679e+00
         min       -3.547887e+03     1.000000e+00
         25%        4.073407e+01     1.000000e+00
         50%        4.075318e+01     1.000000e+00
         75%        4.076811e+01     2.000000e+00
         max        3.537133e+03     6.000000e+00
```

2.5 Step 2.5: Study Test Data

We can gather a lot of insight from test data to put ranges on the training data.

```
In [11]: import numpy as np
         def distance(lat1, lon1, lat2, lon2):
             p = 0.017453292519943295 # Pi/180
             a = 0.5 - np.cos((lat2 - lat1) * p)/2 + np.cos(lat1 * p) * np.cos(lat2 * p) * (1 
             return 0.6213712 * 12742 * np.arcsin(np.sqrt(a)) # 2*R*asin...

         test_df = pd.read_csv('/Users/Shared/Work/dsf/hw2/test.csv')
         test_df['distance_miles'] = distance(test_df.pickup_latitude, test_df.pickup_longitud
         test_df.describe()
```

```
Out[11]:        pickup_longitude  pickup_latitude  dropoff_longitude  dropoff_latitude  \
         count       9914.000000      9914.000000        9914.000000       9914.000000
         mean         -73.974722        40.751041         -73.973657         40.751743
         std            0.042774         0.033541           0.039072          0.035435
         min          -74.252193        40.573143         -74.263242         40.568973
         25%          -73.992501        40.736125         -73.991247         40.735254
         50%          -73.982326        40.753051         -73.980015         40.754065
         75%          -73.968013        40.767113         -73.964059         40.768757
         max          -72.986532        41.709555         -72.990963         41.696683

                passenger_count  distance_miles
         count      9914.000000     9914.000000
         mean          1.671273        2.134640
         std           1.278747        2.468319
         min           1.000000        0.000000
         25%           1.000000        0.806712
         50%           1.000000        1.377836
         75%           2.000000        2.513634
         max           6.000000       62.134660
```

Conclusions Describing the test data gives us the following insights: 1. Latitute ranges are from 40.573143 to 41.709555 2. Longitude ranges are from -72.986532 to -74.263242
3. If we calculate the euclidean distance between pickup and drop off point, the maximum value is xx miles

2.6 Step 2.6: Clean bad latitudes and longitudes

From the above description of test data, latitudes and longitudes outside of a certain range are never asked for. To improve the model's accuracy, we can get rid of these data points.

Hence, we apply an upper and lower limit on the latitude and longitude values based on our test data above.

```
In [12]: #Longitude
         df = df[df.pickup_longitude>=-74.3]
         df = df[df.dropoff_longitude>=-74.3]
         df = df[df.dropoff_longitude<=-72.8]
         df = df[df.pickup_longitude<=-72.8]

         #Latitude
         df = df[df.pickup_latitude>=40.4]
         df = df[df.dropoff_latitude>=40.4]
         df = df[df.dropoff_latitude<=41.8]
         df = df[df.pickup_latitude<=41.8]

         df.describe()
```

```
Out[12]:         fare_amount  pickup_longitude  pickup_latitude  dropoff_longitude  \
         count  5.372812e+07      5.372812e+07     5.372812e+07       5.372812e+07
```

```
mean    1.137676e+01     -7.397517e+01     4.075110e+01     -7.397431e+01
std     9.646981e+00      3.823226e-02     2.944705e-02      3.738884e-02
min     3.000000e+00     -7.430000e+01     4.040000e+01     -7.430000e+01
25%     6.000000e+00     -7.399228e+01     4.073658e+01     -7.399159e+01
50%     8.500000e+00     -7.398210e+01     4.075338e+01     -7.398061e+01
75%     1.250000e+01     -7.396835e+01     4.076756e+01     -7.396540e+01
max     5.000000e+02     -7.280145e+01     4.178958e+01     -7.280482e+01

       dropoff_latitude  passenger_count
count      5.372812e+07     5.372812e+07
mean       4.075146e+01     1.692215e+00
std        3.273068e-02     1.307575e+00
min        4.040000e+01     1.000000e+00
25%        4.073560e+01     1.000000e+00
50%        4.075387e+01     1.000000e+00
75%        4.076840e+01     2.000000e+00
max        4.179935e+01     6.000000e+00
```

Other idea could be to clean up points which go outside the map of NYC. Open source libraries allow coordinates to be plotted on images on a map.

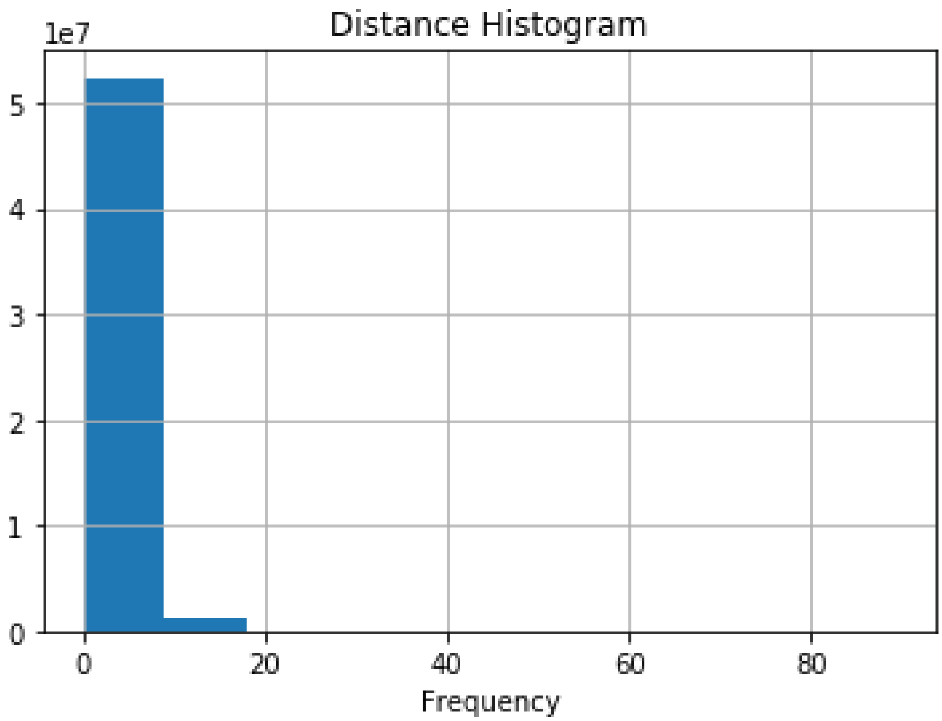
NYC also has water bodies/ large parks. We could further examine and clean out rows which either pickup/drop off from these locations

3 Step 3: Create new features

3.1 Step 3.1.1 : Create Distance column

As one would expect, fare is directly proportional to distance traveled. It makes sense to create this column on our training data.

```
In [14]: import matplotlib.pyplot as plt
         df['distance_miles'] = distance(df.pickup_latitude, df.pickup_longitude, df.dropoff_la
         df.distance_miles.hist()
         plt.xlabel('Frequency')
         plt.title('Distance Histogram')

Out[14]: Text(0.5,1,'Distance Histogram')
```



3.2 Step 3.1.2: Clean bad distance rows

Its safe to say that taxi would travel atleast 0.05 miles and less than 100 miles (exaggerated) within NYC. Data not conforming to this should be removed.

```
In [15]: df = df[df.distance_miles > 0.05]
         df = df[df.distance_miles < 100]
         df.describe()
```

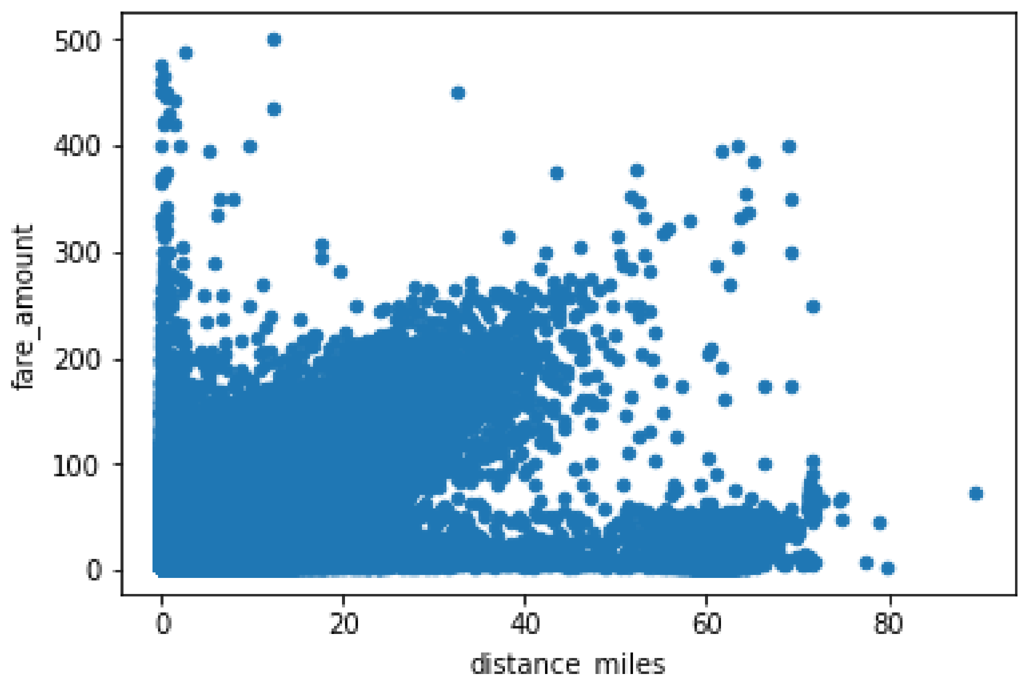
```
Out[15]:        fare_amount  pickup_longitude  pickup_latitude  dropoff_longitude  \
         count  5.302161e+07      5.302161e+07     5.302161e+07       5.302161e+07
         mean   1.132863e+01     -7.397555e+01     4.075100e+01      -7.397468e+01
         std    9.428193e+00      3.539938e-02     2.762060e-02       3.448389e-02
         min    3.000000e+00     -7.430000e+01     4.040000e+01      -7.430000e+01
         25%    6.100000e+00     -7.399229e+01     4.073662e+01      -7.399159e+01
         50%    8.500000e+00     -7.398213e+01     4.075340e+01      -7.398064e+01
         75%    1.250000e+01     -7.396851e+01     4.076755e+01      -7.396560e+01
         max    5.000000e+02     -7.280145e+01     4.178958e+01      -7.280482e+01

                dropoff_latitude  passenger_count  distance_miles
         count      5.302161e+07     5.302161e+07    5.302161e+07
         mean       4.075136e+01     1.692525e+00    2.105537e+00
         std        3.114249e-02     1.307702e+00    2.337850e+00
         min        4.040000e+01     1.000000e+00    5.000107e-02
```

```
25%        4.073564e+01    1.000000e+00    8.055347e-01
50%        4.075390e+01    1.000000e+00    1.363495e+00
75%        4.076840e+01    2.000000e+00    2.463535e+00
max        4.179935e+01    6.000000e+00    8.937474e+01
```

A quick scatter plot will give us more insight

```
In [16]: df.plot.scatter(x='distance_miles',y='fare_amount')
```

```
Out[16]: <matplotlib.axes._subplots.AxesSubplot at 0x1138a4c88>
```



Overall it looks like a linear graph, which makes sense. Let's try to get rid of some extreme anomalies

```
In [17]: df = df[~((df['fare_amount']>=300) & (df['distance_miles']<=20))]
```

```
In [18]: df = df[~((df['fare_amount']<=100) & (df['distance_miles']>=70))]
```

3.3 Step 3.2.1 : Create Day of the Week column

Traffic highly depends on the day of the week. For instance, weekdays tend to have peaker traffic than weekends. It makes sense to create such a column

3.4 Step 3.2.2: Clean bad days of week

Days of the week which are null or other than the 7 days should be deleted!

3.5 Step 3.3.1: Create column for fixed fares

We know that JFK to Manhattan costs $52, a fixed flat rate.

A quick google search gives us the coordinates of JFK and loosening the bounds for accomodating different gates/terminals of the airport, we can classify our rows for fixed distance fares.

```
In [20]: jfk_lat_upper = 40.64
         jfk_lat_lower = 40.65
         jfk_lon_upper = -73.77
         jfk_lon_lower = -73.78

         len(df[(df['pickup_latitude']>=jfk_lat_upper) & (df['pickup_latitude']<=jfk_lat_lower)

Out[20]: 150571
```

It's a significant number of rows, so it definitely calls for a new feature!

```
In [21]: df['airport_fare'] = 0
         df.loc[(df['pickup_latitude']>=jfk_lat_upper) & (df['pickup_latitude']<=jfk_lat_lower)
```

3.6 Step 3.4.1 : Create Hour/Minute columns

Traffic also depends on what hour of the day it is. So its crucial to create this column and study the relationship of time with fare amount.

```
In [22]: df['pickup_hh'] = df.key.str.slice(11,13)
         df['pickup_mm'] = df.key.str.slice(14,16)
         df['pickup_hhmm'] = df["pickup_hh"] + df["pickup_mm"]
         df['pickup_hh'] = df['pickup_hh'].astype(int)
         df['pickup_mm'] = df['pickup_mm'].astype(int)
         df['pickup_hhmm'] = df['pickup_hhmm'].astype(int)
         df.head(10)
         df.describe()
```

Out[22]:

	fare_amount	pickup_longitude	pickup_latitude	dropoff_longitude
count	5.302149e+07	5.302149e+07	5.302149e+07	5.302149e+07
mean	1.132827e+01	-7.397555e+01	4.075100e+01	-7.397468e+01
std	9.422107e+00	3.538606e-02	2.761011e-02	3.448178e-02
min	3.000000e+00	-7.430000e+01	4.040000e+01	-7.430000e+01
25%	6.100000e+00	-7.399229e+01	4.073662e+01	-7.399159e+01
50%	8.500000e+00	-7.398213e+01	4.075340e+01	-7.398064e+01
75%	1.250000e+01	-7.396851e+01	4.076755e+01	-7.396560e+01
max	4.500000e+02	-7.280145e+01	4.178958e+01	-7.280482e+01

	dropoff_latitude	passenger_count	distance_miles	airport_fare
count	5.302149e+07	5.302149e+07	5.302149e+07	5.302149e+07
mean	4.075136e+01	1.692525e+00	2.105434e+00	2.839811e-03
std	3.114109e-02	1.307703e+00	2.336309e+00	5.321416e-02
min	4.040000e+01	1.000000e+00	5.000107e-02	0.000000e+00

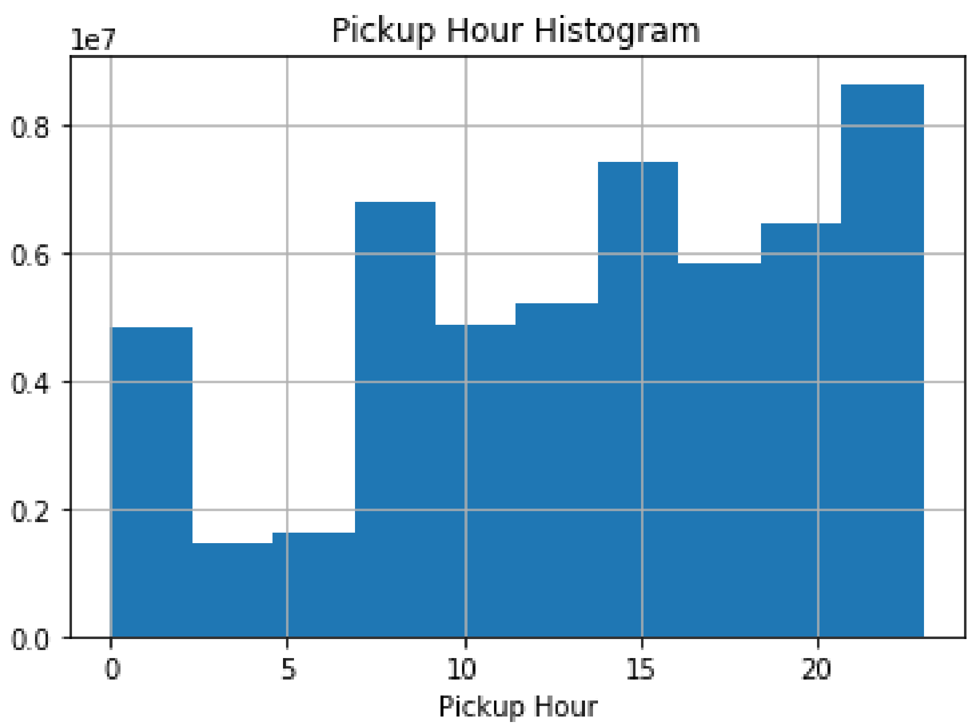
```
25%        4.073564e+01     1.000000e+00     8.055346e-01  0.000000e+00
50%        4.075390e+01     1.000000e+00     1.363493e+00  0.000000e+00
75%        4.076840e+01     2.000000e+00     2.463526e+00  0.000000e+00
max        4.179935e+01     6.000000e+00     7.167200e+01  1.000000e+00

          pickup_hh     pickup_mm    pickup_hhmm
count  5.302149e+07  5.302149e+07  5.302149e+07
mean   1.351816e+01  2.958122e+01  1.381397e+03
std    6.515275e+00  1.732963e+01  6.517775e+02
min    0.000000e+00  0.000000e+00  0.000000e+00
25%    9.000000e+00  1.500000e+01  9.260000e+02
50%    1.400000e+01  3.000000e+01  1.440000e+03
75%    1.900000e+01  4.500000e+01  1.932000e+03
max    2.300000e+01  5.900000e+01  2.359000e+03
```

3.7 Step 3.5.1: Create column to identify peak hours

First lets figure out when is peak hour from simple stats count.

In [23]:
```
df.pickup_hh.hist()
plt.xlabel('Pickup Hour')
plt.title('Pickup Hour Histogram')
```

Out[23]: `Text(0.5,1,'Pickup Hour Histogram')`



In [24]:
```
df.groupby('pickup_hh').pickup_hh.count()
```

Out[24]:
```
pickup_hh
0     2098903
1     1551580
2     1155180
3      844353
4      609771
5      513135
6     1084673
7     1909202
8     2410658
9     2480511
10    2393629
11    2469638
12    2608492
13    2591786
14    2669043
15    2545974
16    2183322
17    2626962
18    3196567
19    3319759
20    3128450
21    3042581
22    2959326
23    2627992
Name: pickup_hh, dtype: int64
```

Let's try to make peak and super peak hours of the day based on this distribution of data: Let peak ~ Greater than 2400000 data rows Let super peak ~ Greater than 3000000 data rows

In [25]:
```
peak_hours = [8,9,10,11,13,15,12,14,17,22,23]
super_peak_hours = [18,19,20,21]
df['peak'] = 1
df.loc[df['pickup_hh'].isin(peak_hours), 'peak'] = 2
df.loc[df['pickup_hh'].isin(super_peak_hours), 'peak'] = 3
df.head(10)
```

Out[25]:
```
                              key  fare_amount          pickup_datetime  \
0    2009-06-15 17:26:21.0000001          4.5  2009-06-15 17:26:21 UTC
1    2010-01-05 16:52:16.0000002         16.9  2010-01-05 16:52:16 UTC
2   2011-08-18 00:35:00.00000049          5.7  2011-08-18 00:35:00 UTC
3    2012-04-21 04:30:42.0000001          7.7  2012-04-21 04:30:42 UTC
4  2010-03-09 07:51:00.000000135          5.3  2010-03-09 07:51:00 UTC
5    2011-01-06 09:50:45.0000002         12.1  2011-01-06 09:50:45 UTC
6    2012-11-20 20:35:00.0000001          7.5  2012-11-20 20:35:00 UTC
7   2012-01-04 17:22:00.00000081         16.5  2012-01-04 17:22:00 UTC
8  2012-12-03 13:10:00.000000125          9.0  2012-12-03 13:10:00 UTC
```

```
9   2009-09-02 01:11:00.00000083          8.9  2009-09-02 01:11:00 UTC

   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
5        -74.000964        40.731630         -73.972892         40.758233
6        -73.980002        40.751662         -73.973802         40.764842
7        -73.951300        40.774138         -73.990095         40.751048
8        -74.006462        40.726713         -73.993078         40.731628
9        -73.980658        40.733873         -73.991540         40.758138

   passenger_count  distance_miles  airport_fare  pickup_hh  pickup_mm  \
0                1        0.640487             0         17         26
1                1        5.250670             0         16         52
2                2        0.863411             0          0         35
3                1        1.739386             0          4         30
4                1        1.242218             0          7         51
5                1        2.353281             0          9         50
6                1        0.966733             0         20         35
7                1        2.582073             0         17         22
8                1        0.778722             0         13         10
9                2        1.770676             0          1         11

   pickup_hhmm  peak
0         1726     2
1         1652     1
2           35     1
3          430     1
4          751     1
5          950     2
6         2035     3
7         1722     2
8         1310     2
9          111     1
```

4 Step 4.1: Finding correlations

Let's try to find pearson correlations between all columns to find our best features for the model.

In [26]:
```
df.corr()
```

Out[26]:
```
                   fare_amount  pickup_longitude  pickup_latitude  \
fare_amount           1.000000          0.428928        -0.212468
pickup_longitude      0.428928          1.000000         0.027260
pickup_latitude      -0.212468          0.027260         1.000000
```

dropoff_longitude	0.324062	0.272095	0.066146
dropoff_latitude	-0.169025	0.059762	0.395898
passenger_count	0.015024	0.001040	-0.008912
distance_miles	0.859417	0.483353	-0.173940
airport_fare	0.181582	0.299545	-0.203861
pickup_hh	-0.017555	0.019702	0.026255
pickup_mm	-0.007717	-0.001698	-0.000098
pickup_hhmm	-0.017754	0.019650	0.026243
peak	-0.037269	0.006057	0.039755

	dropoff_longitude	dropoff_latitude	passenger_count \
fare_amount	0.324062	-0.169025	0.015024
pickup_longitude	0.272095	0.059762	0.001040
pickup_latitude	0.066146	0.395898	-0.008912
dropoff_longitude	1.000000	0.167123	-0.000980
dropoff_latitude	0.167123	1.000000	-0.004826
passenger_count	-0.000980	-0.004826	1.000000
distance_miles	0.384622	-0.128190	0.009396
airport_fare	0.065618	-0.040694	0.002130
pickup_hh	-0.047331	0.018792	0.016664
pickup_mm	-0.003909	0.001796	-0.000863
pickup_hhmm	-0.047417	0.018832	0.016635
peak	-0.064895	0.020958	0.007914

	distance_miles	airport_fare	pickup_hh	pickup_mm \
fare_amount	0.859417	0.181582	-0.017555	-0.007717
pickup_longitude	0.483353	0.299545	0.019702	-0.001698
pickup_latitude	-0.173940	-0.203861	0.026255	-0.000098
dropoff_longitude	0.384622	0.065618	-0.047331	-0.003909
dropoff_latitude	-0.128190	-0.040694	0.018792	0.001796
passenger_count	0.009396	0.002130	0.016664	-0.000863
distance_miles	1.000000	0.200800	-0.029224	-0.006735
airport_fare	0.200800	1.000000	0.000898	-0.000253
pickup_hh	-0.029224	0.000898	1.000000	0.001132
pickup_mm	-0.006735	-0.000253	0.001132	1.000000
pickup_hhmm	-0.029392	0.000891	0.999646	0.027720
peak	-0.056109	-0.004040	0.725921	0.002852

	pickup_hhmm	peak
fare_amount	-0.017754	-0.037269
pickup_longitude	0.019650	0.006057
pickup_latitude	0.026243	0.039755
dropoff_longitude	-0.047417	-0.064895
dropoff_latitude	0.018832	0.020958
passenger_count	0.016635	0.007914
distance_miles	-0.029392	-0.056109
airport_fare	0.000891	-0.004040
pickup_hh	0.999646	0.725921

```
pickup_mm              0.027720  0.002852
pickup_hhmm            1.000000  0.725718
peak                   0.725718  1.000000
```

Conclusion There is a strong notable correlation between the following with respect to fare_amount (in descending order):

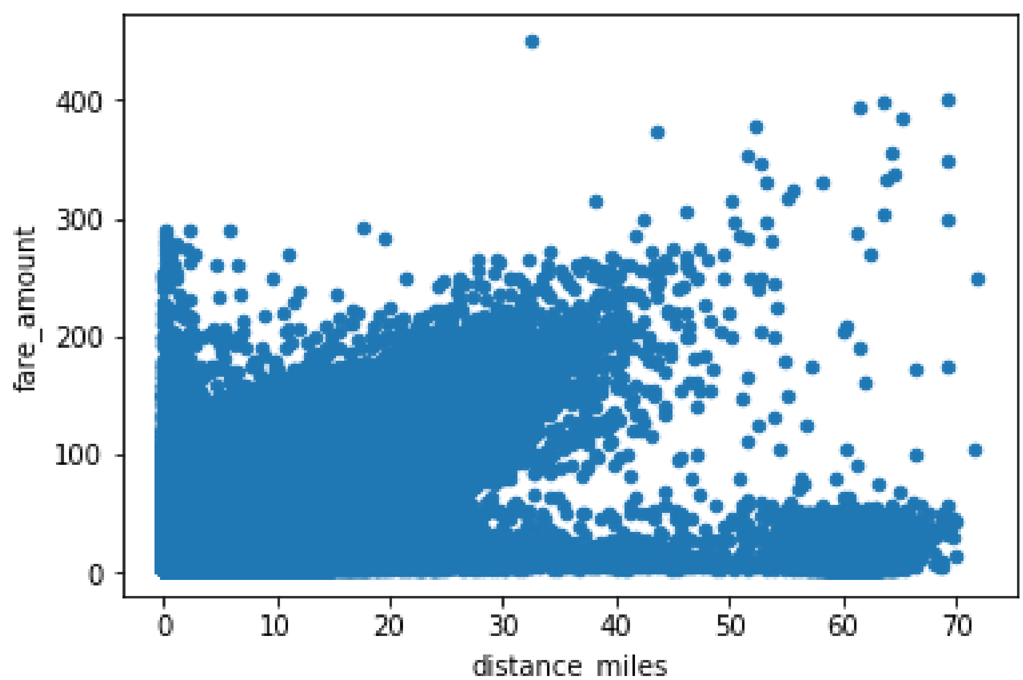
- distance_miles
- pickup_longitude
- dropoff_longitude
- pickup_latitute
- airport_fare
- dropoff_latitude

5 Step 4.2: Plotting correlations

5.1 Step 4.2.1 : Distance vs Fare

```
In [27]: df.plot.scatter(x='distance_miles',y='fare_amount')
```

```
Out[27]: <matplotlib.axes._subplots.AxesSubplot at 0x113840ac8>
```

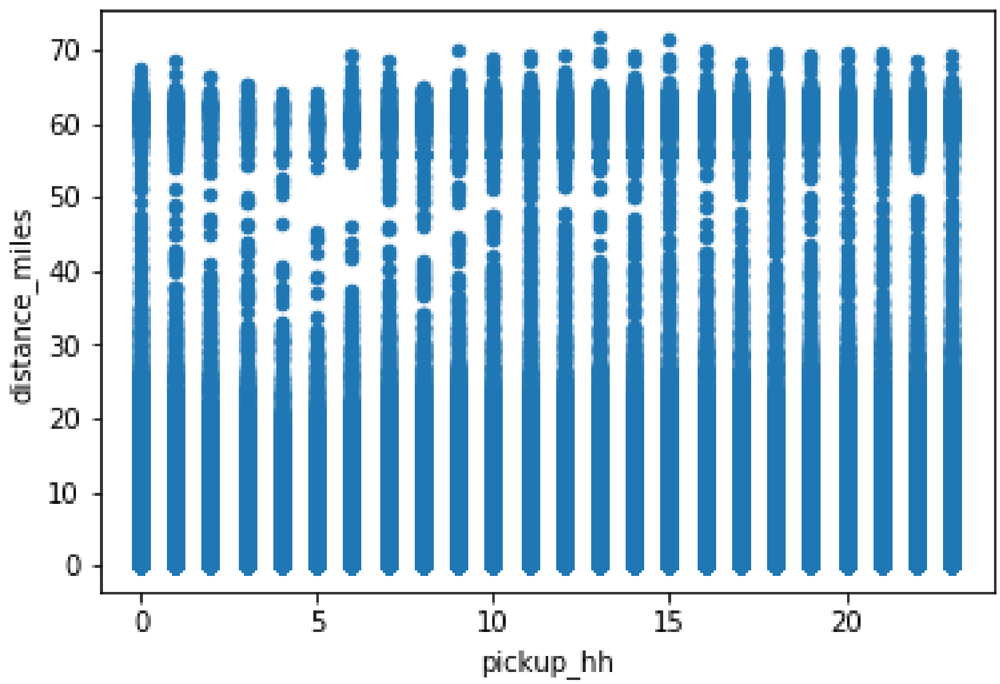


Conclusion We see that as distance increases, fare increases - an expected relationship given the nature of taxi fares. We however see two interesting observations outside the linear fit: 1. For above 35 miles of distance covered, the fare amount is around 50 USD. This perhaps explains the fixed fare from JFK airport to Manhattan. 2. For distances under 10 miles, there are certain plot points above 100 USD which may seem absurd. However given the traffic of the city on a peak hour and a peak day, this might not be far fetched.

5.2 Step 4.2.2 : Pickup Time vs Distance

```
In [28]: df.plot.scatter(x='pickup_hh',y='distance_miles')
```

```
Out[28]: <matplotlib.axes._subplots.AxesSubplot at 0x113e916d8>
```

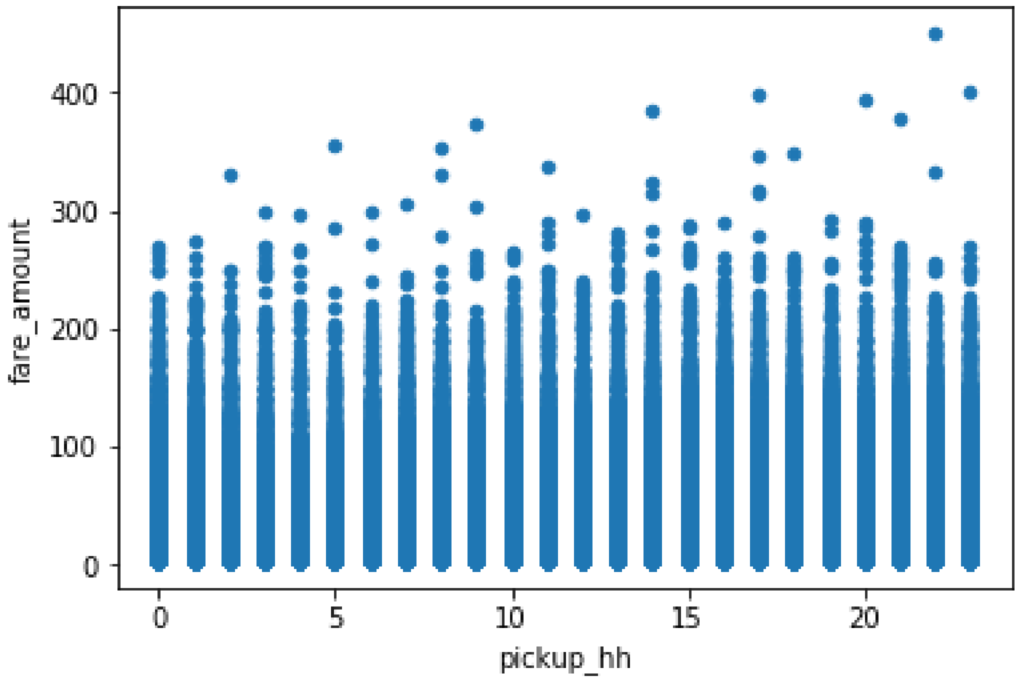


Conclusion The graph doesn't tell us much, since there seems to be a uniform distribution of data for all hours of the day and the miles covered. However, the following comments can be made: 1. Since there's less data for extremely off-peak hours like 5 am, the data points are more isolated. 2. Usually around the off-peak hours, there is less long distance travel. This can be seem with the obvious gaps in the graph at 3-6 am on X axis and 40-50 miles on the Y axis. 3. Being one of the busiest airports in the world, distances of around 35 miles (JFK to Manhattan) seem to be present at all hours.

5.3 Step 4.2.3 : Pickup Time vs Fare

```
In [29]: df.plot.scatter(x='pickup_hh',y='fare_amount')
```

Out[29]: <matplotlib.axes._subplots.AxesSubplot at 0x113ea2da0>



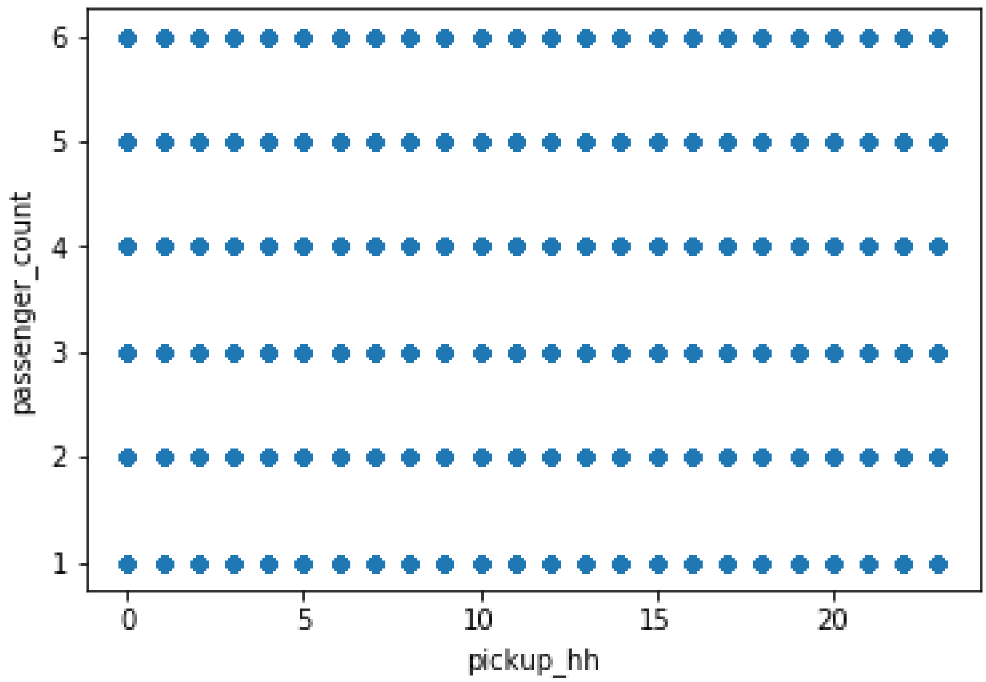
Conclusion

1. The densely populated areas of the graph, almost seem uniform.
2. However around 3-5 AM, there are no/few points for high fare amounts. This can be explained since there should practically be no traffic, thus resulting in lower fares.
3. There are higher frequency of high fare amounts at nights, thus explaining the late night charge phenomenon.

5.4 Step 4.2.3 : Pickup Time vs Number of Passengers

```
In [30]: df.plot.scatter(x='pickup_hh',y='passenger_count')
```

Out[30]: <matplotlib.axes._subplots.AxesSubplot at 0x54764f048>

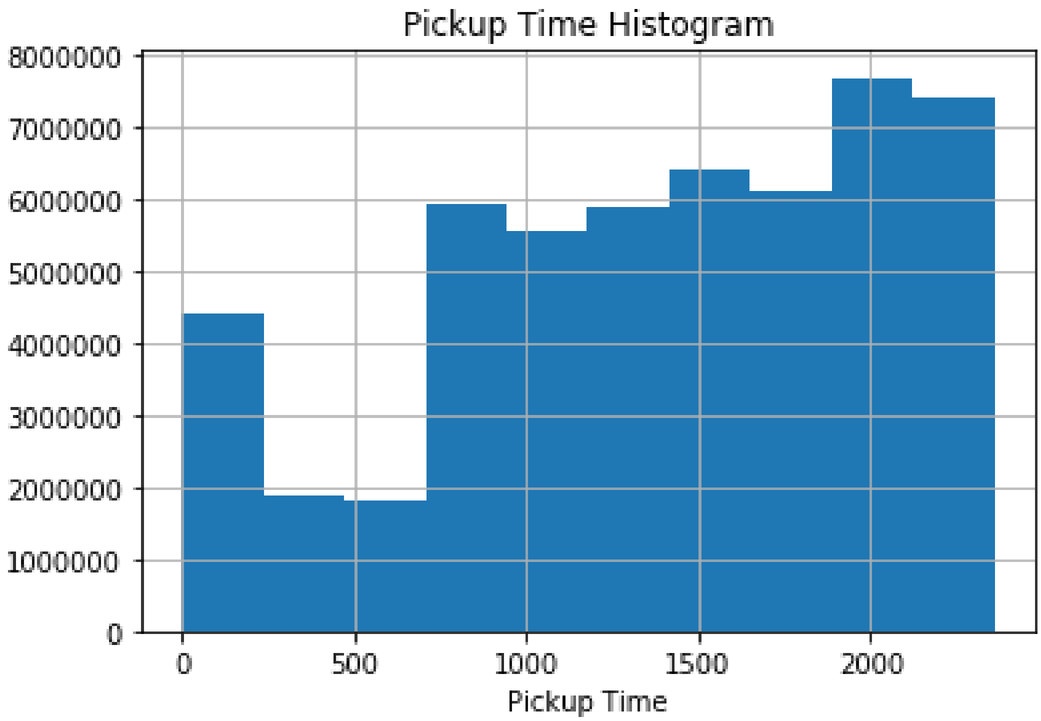


Conclusion This graph tells us that there is enough data in the dataset because there is a dense point for every hour of the day and the number of passengers travelling. This confirms we don't have a biased dataset but rather a well-distributed one.

5.5 Step 4.2.4 : Pickup Time - Histogram

In [32]:
```
df.pickup_hhmm.hist()
plt.xlabel('Pickup Time')
plt.title('Pickup Time Histogram')
```

Out[32]:
```
Text(0.5,1,'Pickup Time Histogram')
```



Conclusion This histogram allows us to predict busier times of the day. We are able to make the following comments: 1. Fewer people take taxis from 2:30 AM to 6 AM 2. A very high number of taxis are used from 7 PM till midnight. This allows us to identify these hours are super peak hours. 3. A considerably large number of taxis are taken from 8 AM to 11 AM and around 2 PM to 4 PM. This allows us to identify our peak hours.

6 Step 5.1 Baseline Prediction Model

6.1 Linear Regression

```
In [33]: from sklearn import linear_model
         X = df[['peak','distance_miles','pickup_longitude','pickup_latitude', 'dropoff_longitu
         Y = df['fare_amount']

         regr = linear_model.LinearRegression()
         regr.fit(X, Y)

         print('Intercept: \n', regr.intercept_)
         print('Coefficients: \n', regr.coef_)

         intercept = regr.intercept_
         coefficients = regr.coef_
```

```
Intercept:
 2172.100117993176
Coefficients:
 [  0.17447503   3.33370428   8.85096023 -18.49860614   2.63679956
 -13.85206052  -1.39137148]
```

6.1.1 Preparing test data for fitting model

```
In [34]: test_df['pickup_hh'] = test_df.key.str.slice(11,13)
         test_df['pickup_hh'] = test_df['pickup_hh'].astype(int)
         test_df['peak'] = 1
         test_df.loc[test_df['pickup_hh'].isin(peak_hours), 'peak'] = 2
         test_df.loc[test_df['pickup_hh'].isin(super_peak_hours), 'peak'] = 3

         #airport_fare column
         test_df['airport_fare'] = 0
         test_df.loc[(test_df['pickup_latitude']>=jfk_lat_upper) & (test_df['pickup_latitude']<
```

```
In [35]: #day_of_week column
         test_df['pickup_datetime'] = pd.to_datetime(test_df['pickup_datetime'])
         test_df['day_of_week'] = test_df['pickup_datetime'].dt.dayofweek
```

```
In [36]: test_df.head()
```

```
Out[36]:                             key     pickup_datetime  pickup_longitude  \
         0  2015-01-27 13:08:24.0000002 2015-01-27 13:08:24        -73.973320
         1  2015-01-27 13:08:24.0000003 2015-01-27 13:08:24        -73.986862
         2  2011-10-08 11:53:44.0000002 2011-10-08 11:53:44        -73.982524
         3  2012-12-01 21:12:12.0000002 2012-12-01 21:12:12        -73.981160
         4  2012-12-01 21:12:12.0000003 2012-12-01 21:12:12        -73.966046

            pickup_latitude  dropoff_longitude  dropoff_latitude  passenger_count  \
         0        40.763805         -73.981430         40.743835                1
         1        40.719383         -73.998886         40.739201                1
         2        40.751260         -73.979654         40.746139                1
         3        40.767807         -73.990448         40.751635                1
         4        40.789775         -73.988565         40.744427                1

            distance_miles  pickup_hh  peak  airport_fare  day_of_week
         0        1.443607         13     2             0            1
         1        1.507044         13     2             0            1
         2        0.384398         11     2             0            5
         3        1.218529         21     3             0            5
         4        3.347514         21     3             0            5
```

6.1.2 Predicting..

```
In [37]: test_df['fare_amount'] = intercept + (coefficients[0]*test_df['peak']) + (coefficients
```

In [38]: test_df.head(10)

Out[38]:
```
                           key      pickup_datetime  pickup_longitude  \
0  2015-01-27 13:08:24.0000002 2015-01-27 13:08:24        -73.973320
1  2015-01-27 13:08:24.0000003 2015-01-27 13:08:24        -73.986862
2  2011-10-08 11:53:44.0000002 2011-10-08 11:53:44        -73.982524
3  2012-12-01 21:12:12.0000002 2012-12-01 21:12:12        -73.981160
4  2012-12-01 21:12:12.0000003 2012-12-01 21:12:12        -73.966046
5  2012-12-01 21:12:12.0000005 2012-12-01 21:12:12        -73.960983
6  2011-10-06 12:10:20.0000001 2011-10-06 12:10:20        -73.949013
7  2011-10-06 12:10:20.0000003 2011-10-06 12:10:20        -73.777282
8  2011-10-06 12:10:20.0000002 2011-10-06 12:10:20        -74.014099
9  2014-02-18 15:22:20.0000002 2014-02-18 15:22:20        -73.969582

   pickup_latitude  dropoff_longitude  dropoff_latitude  passenger_count  \
0        40.763805         -73.981430         40.743835                1
1        40.719383         -73.998886         40.739201                1
2        40.751260         -73.979654         40.746139                1
3        40.767807         -73.990448         40.751635                1
4        40.789775         -73.988565         40.744427                1
5        40.765547         -73.979177         40.740053                1
6        40.773204         -73.959622         40.770893                1
7        40.646636         -73.985083         40.759368                1
8        40.709638         -73.995106         40.741365                1
9        40.765519         -73.980686         40.770725                1

   distance_miles  pickup_hh  peak  airport_fare  day_of_week  fare_amount
0        1.443607         13     2             0            1     8.992855
1        1.507044         13     2             0            1     9.924399
2        0.384398         11     2             0            5     5.585147
3        1.218529         21     3             0            5     8.141754
4        3.347514         21     3             0            5    15.071366
5        2.002399         21     3             0            5    11.165491
6        0.577627         12     2             0            3     5.829916
7       13.384399         12     2             1            3    51.086359
8        2.407168         12     2             0            3    12.844332
9        0.683380         15     2             0            1     6.089357
```

In [39]: submit_df = test_df[['key','fare_amount']]

In [40]: submit_df.to_csv('output_linear.csv', encoding='utf-8', index=False)

7 Step 5.2 Other Models

7.1 Random Forest

In [41]: from sklearn.ensemble import RandomForestRegressor as rf

```
random_forest = rf(n_estimators = 5, random_state = 2, max_depth = 20)
random_forest.fit(df[['peak','distance_miles','pickup_longitude','pickup_latitude', 'c
```

Out[41]:
```
RandomForestRegressor(bootstrap=True, criterion='mse', max_depth=20,
           max_features='auto', 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, n_estimators=5, n_jobs=1,
           oob_score=False, random_state=2, verbose=0, warm_start=False)
```

In [42]:
```
test_df['fare_amount_rf'] = random_forest.predict(test_df[['peak','distance_miles','pi
submit_df_rf = test_df[['key','fare_amount']]
submit_df_rf.to_csv('output_rf.csv', encoding='utf-8', index=False)
```