Assignment2_sub

September 25, 2018

In [1]:
```
import numpy as np
import pandas as pd
import seaborn as sb
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn import preprocessing
from sklearn import metrics
from datetime import datetime
from math import sin, cos, sqrt, atan2, radians
```

In [2]:
```
# First lets read the data into table format so that we can draw some insight
# Next we will clean the data based on some observations.
data = pd.read_csv('train.csv', nrows=10000000)
```

In [3]:
```
# Lets see what kind of data we have
data.describe()
```

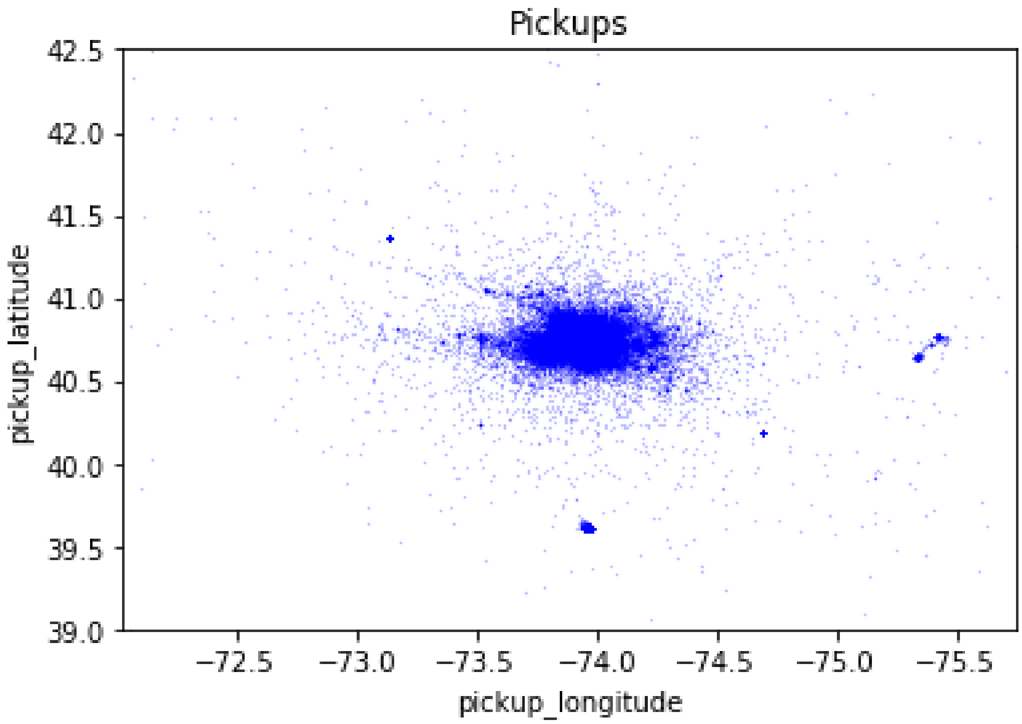
Out[3]:
```
        fare_amount  pickup_longitude  pickup_latitude  dropoff_longitude  \
count  1.000000e+07      1.000000e+07     1.000000e+07       9.999931e+06
mean   1.133854e+01     -7.250775e+01     3.991934e+01      -7.250897e+01
std    9.799930e+00      1.299421e+01     9.322539e+00       1.287532e+01
min   -1.077500e+02     -3.439245e+03    -3.492264e+03      -3.426601e+03
25%    6.000000e+00     -7.399207e+01     4.073491e+01      -7.399139e+01
50%    8.500000e+00     -7.398181e+01     4.075263e+01      -7.398016e+01
75%    1.250000e+01     -7.396710e+01     4.076712e+01      -7.396367e+01
max    1.273310e+03      3.457626e+03     3.344459e+03       3.457622e+03

       dropoff_latitude  passenger_count
count      9.999931e+06     1.000000e+07
mean       3.991913e+01     1.684793e+00
std        9.237280e+00     1.323423e+00
min       -3.488080e+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        3.351403e+03     2.080000e+02
```

In [4]:
```
data[(data['passenger_count'] > 8) | (data['passenger_count'] <= 0)].shape
```

Out[4]: (35347, 8)

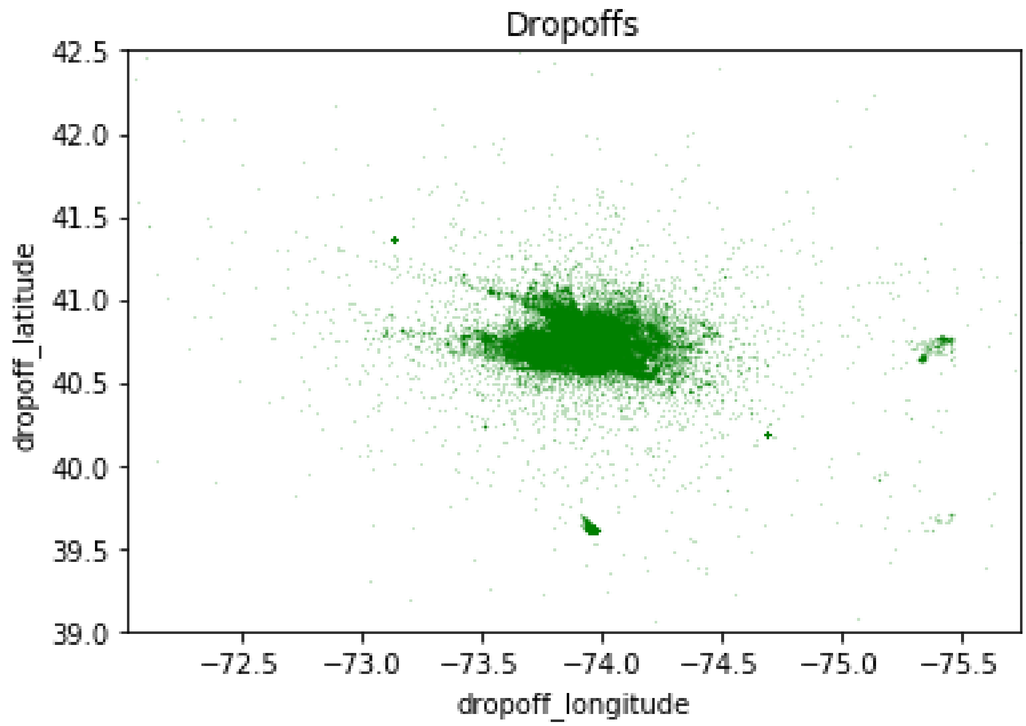
In [5]:
```
# First lets check the variation of latitude and longitude by drawing the scatter plot t
# very relaxed boundary conditions
lat_border = (39, 42.5)
long_border = (-72.03, -75.75)
data.plot(kind='scatter', x='pickup_longitude', y='pickup_latitude',
       color='blue', s=.02, alpha=.6)
plt.title("Pickups")
plt.ylim(lat_border)
plt.xlim(long_border)
```

Out[5]: (-72.03, -75.75)

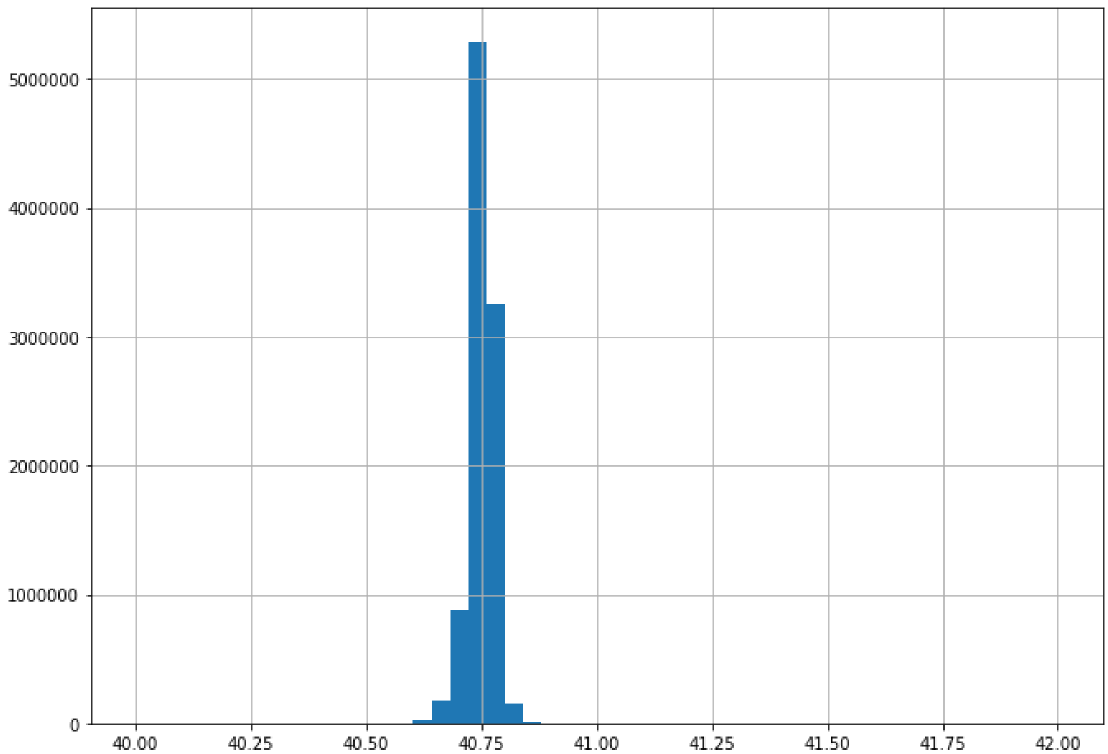


In [6]:
```
lat_border = (39, 42.5)
long_border = (-72.03, -75.75)
data.plot(kind='scatter', x='dropoff_longitude', y='dropoff_latitude',
       color='green', s=.02, alpha=.6)
plt.title("Dropoffs")
plt.ylim(lat_border)
plt.xlim(long_border)
```

Out[6]: (-72.03, -75.75)

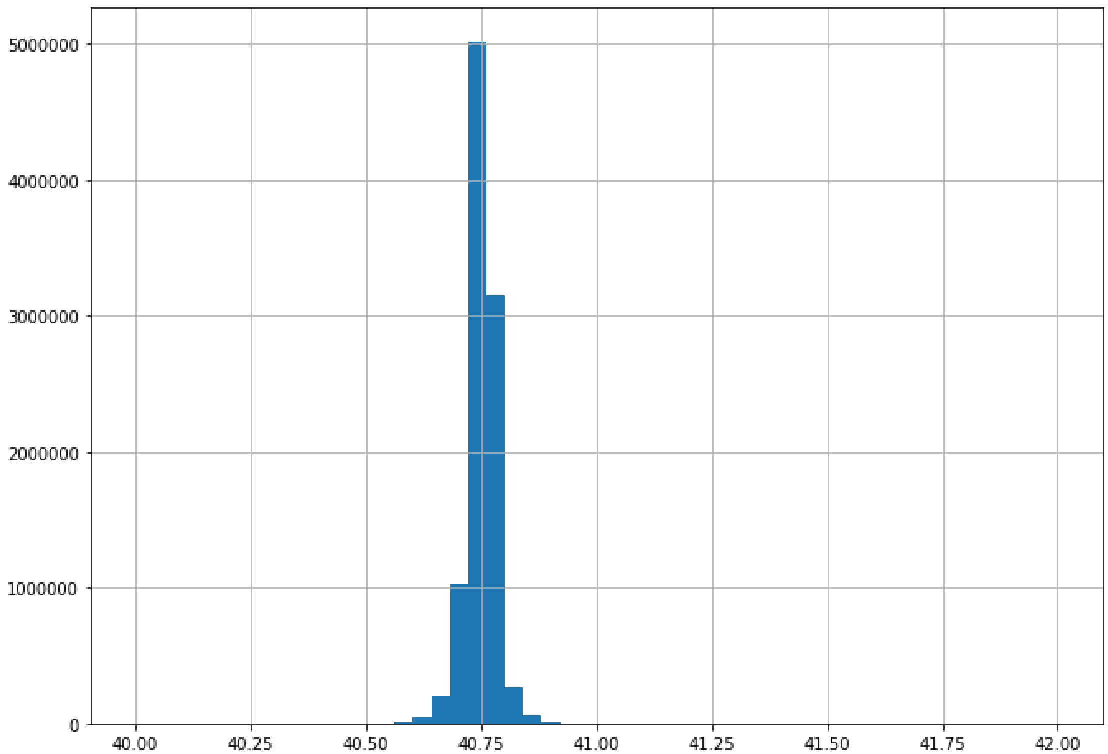



```
In [7]: #Plotting histograms as well to take a more closer look
        data[(data.pickup_latitude > 40) & (data.pickup_latitude < 42)].pickup_latitude.hist(bin

Out[7]: <matplotlib.axes._subplots.AxesSubplot at 0x1a10a306d8>
```



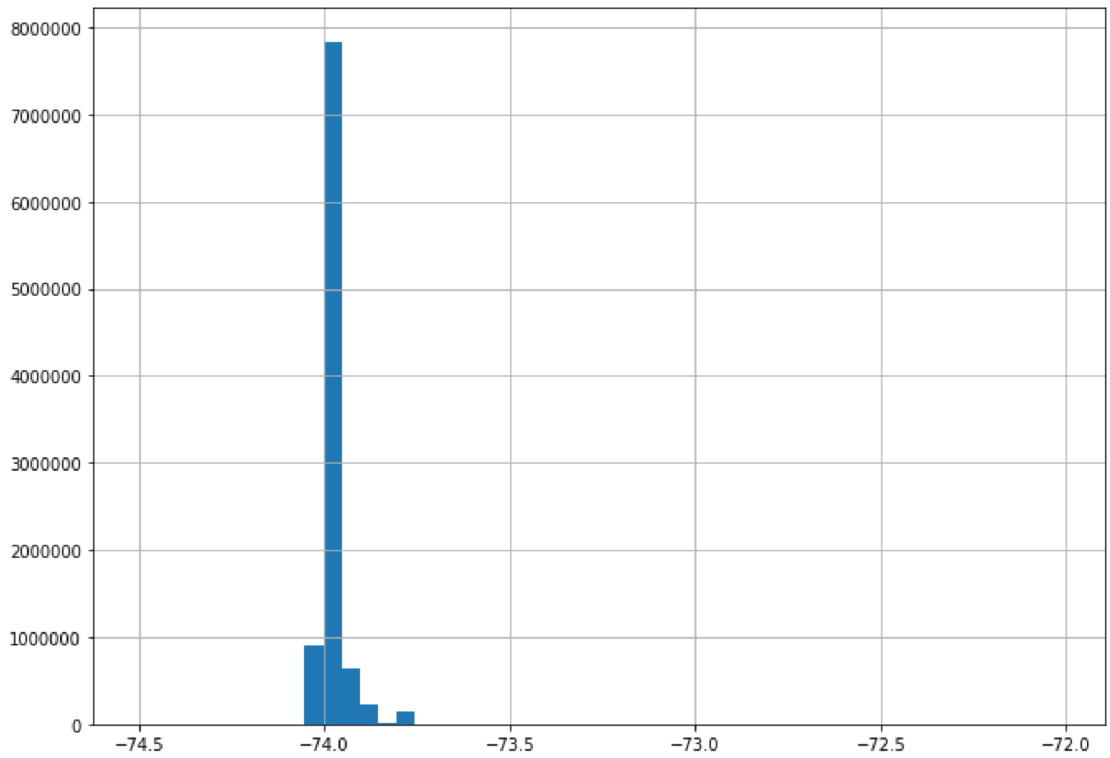

```
In [8]: data[(data.dropoff_latitude > 40) & (data.dropoff_latitude < 42)].dropoff_latitude.hist(
```

```
Out[8]: <matplotlib.axes._subplots.AxesSubplot at 0x1a11401f60>
```



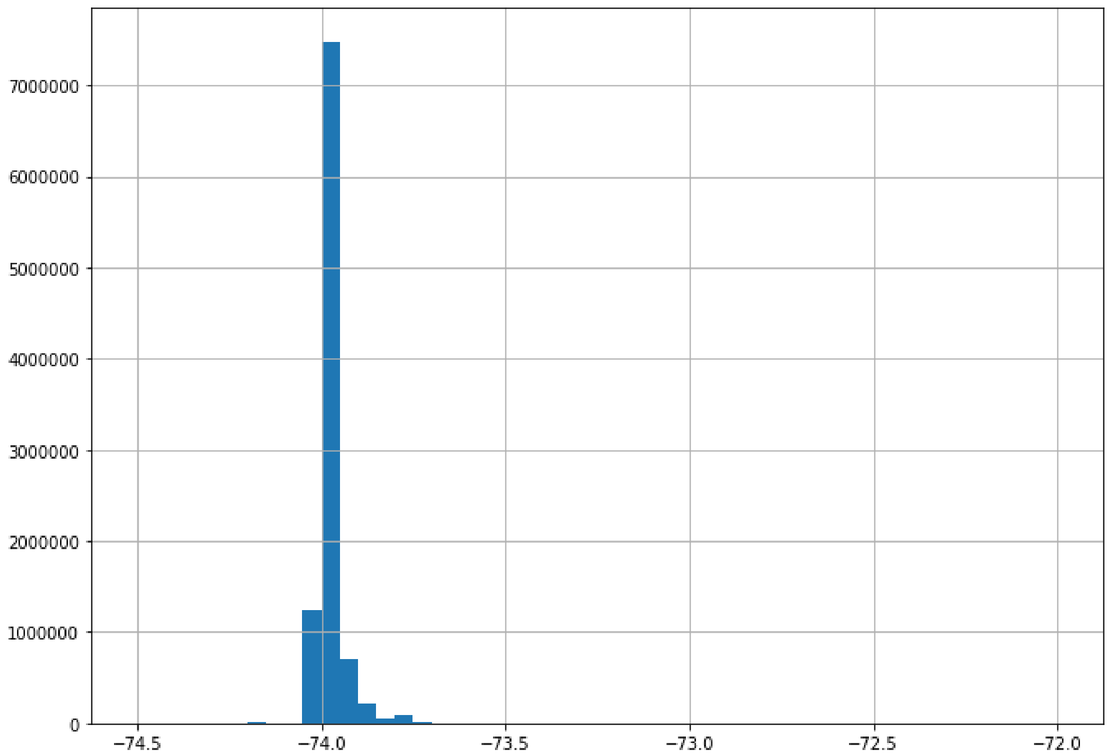

```
In [9]: data[(data.pickup_longitude > -74.5) & (data.pickup_longitude < -72)].pickup_longitude.h
```

```
Out[9]: <matplotlib.axes._subplots.AxesSubplot at 0x1a129c60f0>
```



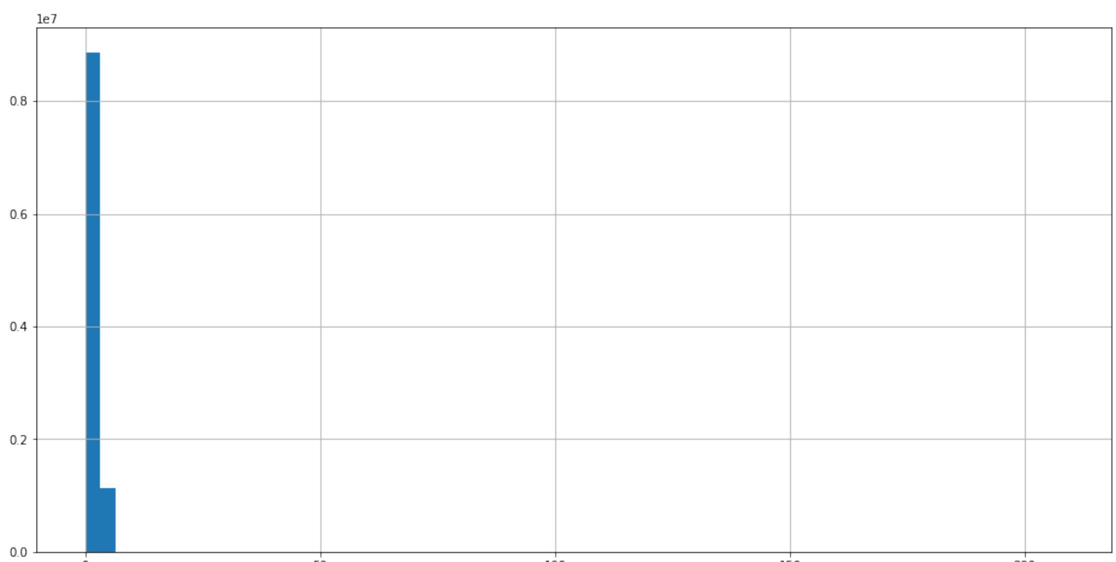

```
In [10]: data[(data.dropoff_longitude > -74.5) & (data.dropoff_longitude < -72)].dropoff_longitu
```

```
Out[10]: <matplotlib.axes._subplots.AxesSubplot at 0x1a12915d30>
```




```
In [11]: data['passenger_count'].hist(bins=64, figsize=(16,8))
```

```
Out[11]: <matplotlib.axes._subplots.AxesSubplot at 0x1a1305db00>
```



In [12]:
```
# This method will be used to do the initial phase opf the data cleaning,
# primarily outlier removals and some approximations.
def clean_data(df):
    # New york city has a central location cordinates of Latitude = 40.7128 and Longitu
    # Therefore we restrict the pickup and dropoff locations to avoid considering rides
    # are lying outside the nyc area.
    nyc_min_latitude = 40.45
    nyc_max_latitude = 40.97
    nyc_min_longitude = -74.28
    nyc_max_longitude = -73.64

    # Removing null entries from the data
    df = df.dropna(how='any', axis = 'rows')

    # Removing entries for which pickup/ dropoff locations do not lie inside the nyc ar
    df = df[(df['pickup_latitude'] >= nyc_min_latitude) & (df['pickup_latitude'] <= nyc
    df = df[(df['pickup_longitude'] >= nyc_min_longitude) & (df['pickup_longitude'] <=
    df = df[(df['dropoff_latitude'] >= nyc_min_latitude) & (df['dropoff_latitude'] <= n
    df = df[(df['dropoff_longitude'] >= nyc_min_longitude) & (df['dropoff_longitude'] <

    # Clean entries which have passenger count greater than 8
    df = df[(df['passenger_count'] > 0) & (df['passenger_count'] <= 8)]
    df = df[(df['fare_amount'] > 0) & (df['fare_amount'] < 100)]
    return df
```

In [13]:
```
# Lets clean the data now to remove outliers and reduce our data to meaningful entries
data = clean_data(data)
```

In [14]:
```
data.shape
```

Out[14]: (9742396, 8)

In [15]:
```
stat = data.describe()
```

In [16]:
```
stat[['pickup_latitude','dropoff_latitude','pickup_longitude','dropoff_longitude']]
```

Out[16]:

	pickup_latitude	dropoff_latitude	pickup_longitude	dropoff_longitude
count	9.742396e+06	9.742396e+06	9.742396e+06	9.742396e+06
mean	4.075084e+01	4.075122e+01	-7.397550e+01	-7.397458e+01
std	2.695317e-02	3.080515e-02	3.453672e-02	3.400300e-02
min	4.045191e+01	4.045191e+01	-7.427998e+01	-7.427996e+01
25%	4.073655e+01	4.073559e+01	-7.399229e+01	-7.399158e+01
50%	4.075334e+01	4.075385e+01	-7.398211e+01	-7.398062e+01
75%	4.076751e+01	4.076838e+01	-7.396836e+01	-7.396540e+01
max	4.096982e+01	4.096999e+01	-7.364037e+01	-7.364002e+01

In [17]:
```
# There has been some reduction in the dataset. (Irrelevant data)
data.shape
```

Out[17]: (9742396, 8)

In [18]:
```
# This code has been took from stack_overflow and gives the
# haversine distance between two points on the earth.

def get_euclidean_dist(loc_data):
    orig_lat , orig_lon, dest_lat, dest_lon = loc_data

    radius = 6371    # This is a constant whose value is equal to Earth's radius

    deltaLat = radians(dest_lat-orig_lat)
    deltaLon = radians(dest_lon-orig_lon)

    a = sin(deltaLat/2)**2 + cos(radians(orig_lat)) * cos(radians(dest_lat)) * sin(delt
    c = 2 * atan2(sqrt(a), sqrt(1-a))
    d = radius * c
    return d
```

In [19]:
```
data.head()
```

Out[19]:
```
                             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

   pickup_longitude  pickup_latitude  dropoff_longitude  dropoff_latitude  \
0        -73.844311        40.721319         -73.841610         40.712278
1        -74.016048        40.711303         -73.979268         40.782004
2        -73.982738        40.761270         -73.991242         40.750562
3        -73.987130        40.733143         -73.991567         40.758092
4        -73.968095        40.768008         -73.956655         40.783762

   passenger_count
0                1
1                1
2                2
3                1
4                1
```

In [20]:
```
# Calculate the distance of each ride and make another entry in the dataset. This is an
# as fare amount is directly related to the distance travelled
columns = ['pickup_latitude','pickup_longitude','dropoff_latitude','dropoff_longitude']
data['distance'] = data[columns].apply(get_euclidean_dist, axis=1)
```

In [21]:
```
data.head(5)
```

Out[21]:
```
                             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

   pickup_longitude  pickup_latitude  dropoff_longitude  dropoff_latitude  \
0        -73.844311        40.721319         -73.841610         40.712278
1        -74.016048        40.711303         -73.979268         40.782004
2        -73.982738        40.761270         -73.991242         40.750562
3        -73.987130        40.733143         -73.991567         40.758092
4        -73.968095        40.768008         -73.956655         40.783762

   passenger_count  distance
0                1  1.030764
1                1  8.450134
2                2  1.389525
3                1  2.799270
4                1  1.999157
```

In [22]:
```
data['pickup_datetime'] = pd.to_datetime(data['pickup_datetime'], format='%Y-%m-%d %H:%
```

In [23]:
```
pdt = data['pickup_datetime']
```

In [24]:
```
dtIdx = pd.DatetimeIndex(data['pickup_datetime'])
```

In [25]:
```
## This function will give us the absolute time of the day in minuites.
## This is done to see if incorporating minutes in the time improves the correlation
def get_time_of_day(dateTime):
    dtIdx = pd.DatetimeIndex(dateTime)
    hours = dtIdx.hour
    minutes = dtIdx.minute
    absTimeofDay = (60*hours) + minutes
    return absTimeofDay
```

In [26]:
```
data['time'] = get_time_of_day(data['pickup_datetime'])
```

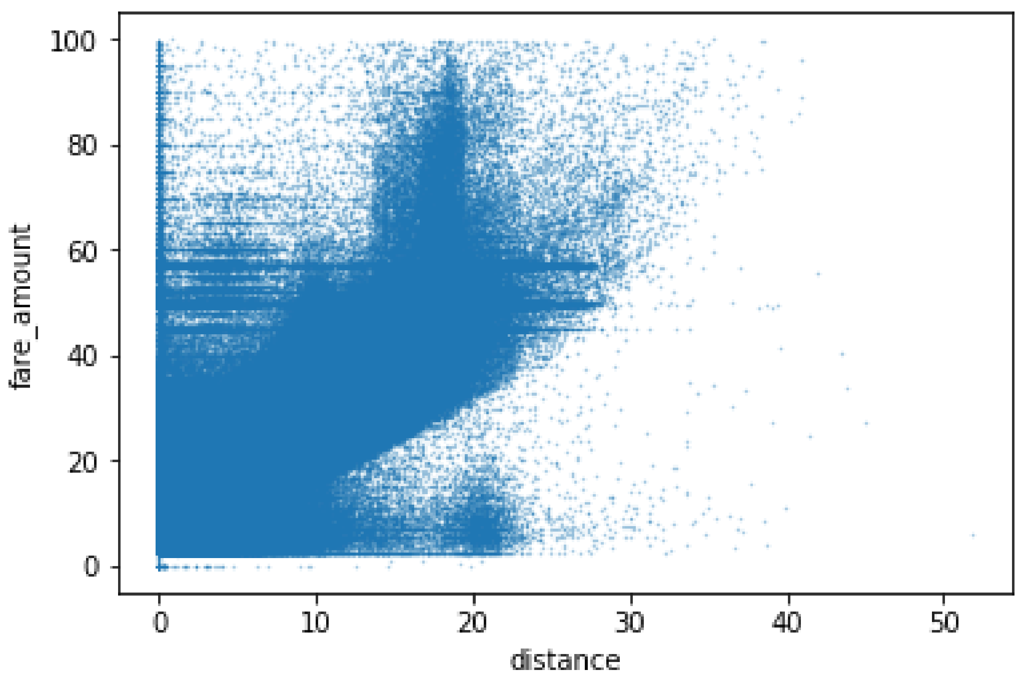
In [27]:
```
data.head()
```

Out[27]:
```
                             key  fare_amount     pickup_datetime  \
0    2009-06-15 17:26:21.0000001          4.5 2009-06-15 17:26:21
1    2010-01-05 16:52:16.0000002         16.9 2010-01-05 16:52:16
2   2011-08-18 00:35:00.00000049          5.7 2011-08-18 00:35:00
3    2012-04-21 04:30:42.0000001          7.7 2012-04-21 04:30:42
4  2010-03-09 07:51:00.000000135          5.3 2010-03-09 07:51:00

   pickup_longitude  pickup_latitude  dropoff_longitude  dropoff_latitude  \
0        -73.844311        40.721319         -73.841610         40.712278
1        -74.016048        40.711303         -73.979268         40.782004
2        -73.982738        40.761270         -73.991242         40.750562
3        -73.987130        40.733143         -73.991567         40.758092
```

```
4        -73.968095        40.768008         -73.956655         40.783762

   passenger_count  distance  time
0                1  1.030764  1046
1                1  8.450134  1012
2                2  1.389525    35
3                1  2.799270   270
4                1  1.999157   471
```

In [28]:
```
## Now we will see the relationship between the distance and the fare amount
## Since it is logical that a shorter ride will cost less than a longer one,
# based on this data we can actually get some insightful information
data.plot(kind='scatter',x='distance',y='fare_amount', s=0.2, alpha=0.4)
```

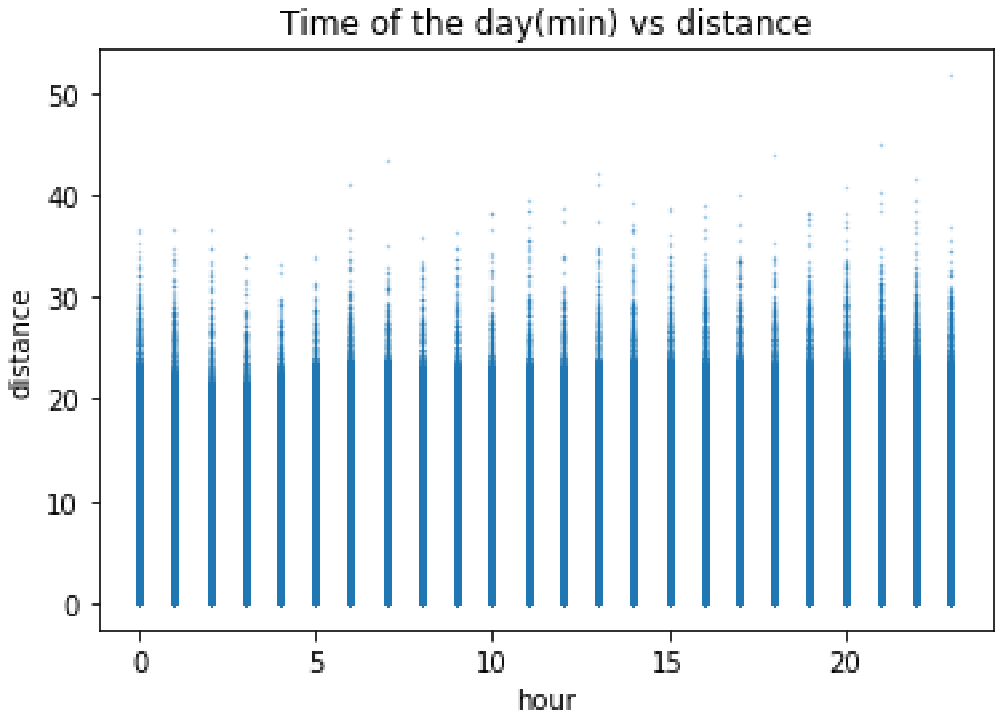
Out[28]: <matplotlib.axes._subplots.AxesSubplot at 0x1a10a1c160>



In [29]:
```
# Preprocessing data to fetch some useful information regarding the time of the ride/ t
data['year'] = pd.to_datetime(data['pickup_datetime']).dt.year
data['month'] = pd.to_datetime(data['pickup_datetime']).dt.month
data['day'] = pd.to_datetime(data['pickup_datetime']).dt.day
data['hour'] = pd.to_datetime(data['pickup_datetime']).dt.hour
```

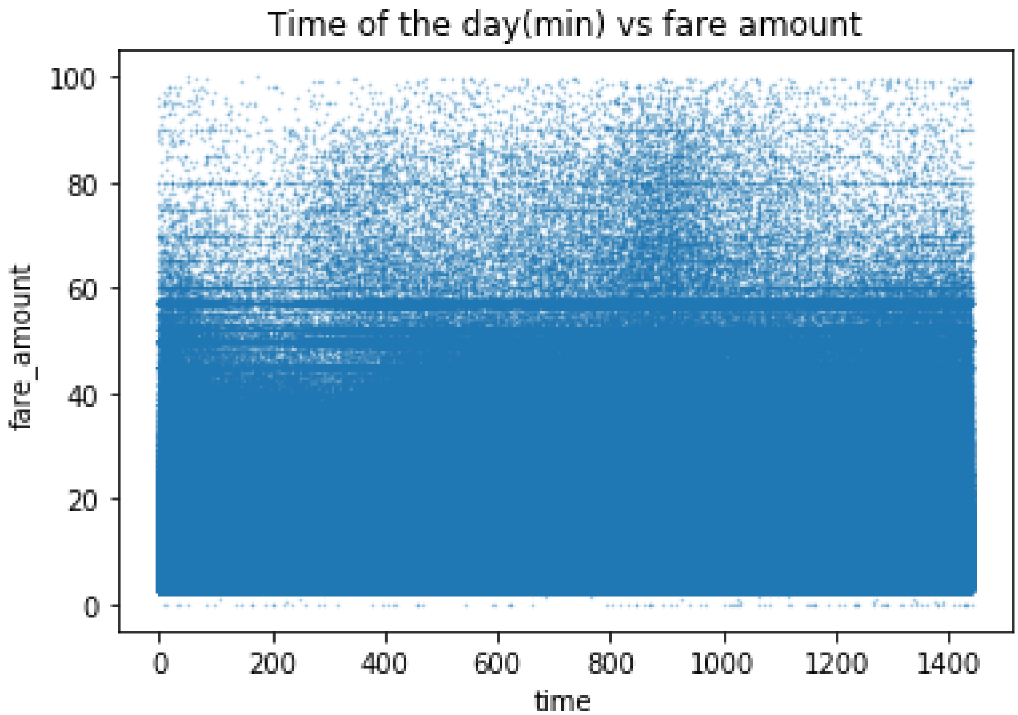
In [30]:
```
#
data.plot(kind='scatter',x='hour',y='distance', s=0.2, alpha=0.4)
plt.title("Time of the day(min) vs distance")
```

Out[30]: Text(0.5,1,'Time of the day(min) vs distance')




```
In [31]: data.plot(kind='scatter',x='hour',y='fare_amount', s=0.2, alpha=0.4)
         plt.title("Time of the day(min) vs fare amount")
```

Out[31]: Text(0.5,1,'Time of the day(min) vs fare amount')



In [32]:
```
data[['fare_amount','distance','time', 'hour']].corr()
```

Out[32]:

	fare_amount	distance	time	hour
fare_amount	1.000000	0.875650	-0.017688	-0.017387
distance	0.875650	1.000000	-0.029439	-0.029175
time	-0.017688	-0.029439	1.000000	0.999019
hour	-0.017387	-0.029175	0.999019	1.000000

In [33]:
```
data['distance'].corr(data['fare_amount'])
```

Out[33]: 0.8756501057696913

In [34]:
```
data.head()
```

Out[34]:

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

	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	\
0	-73.844311	40.721319	-73.841610	40.712278	
1	-74.016048	40.711303	-73.979268	40.782004	

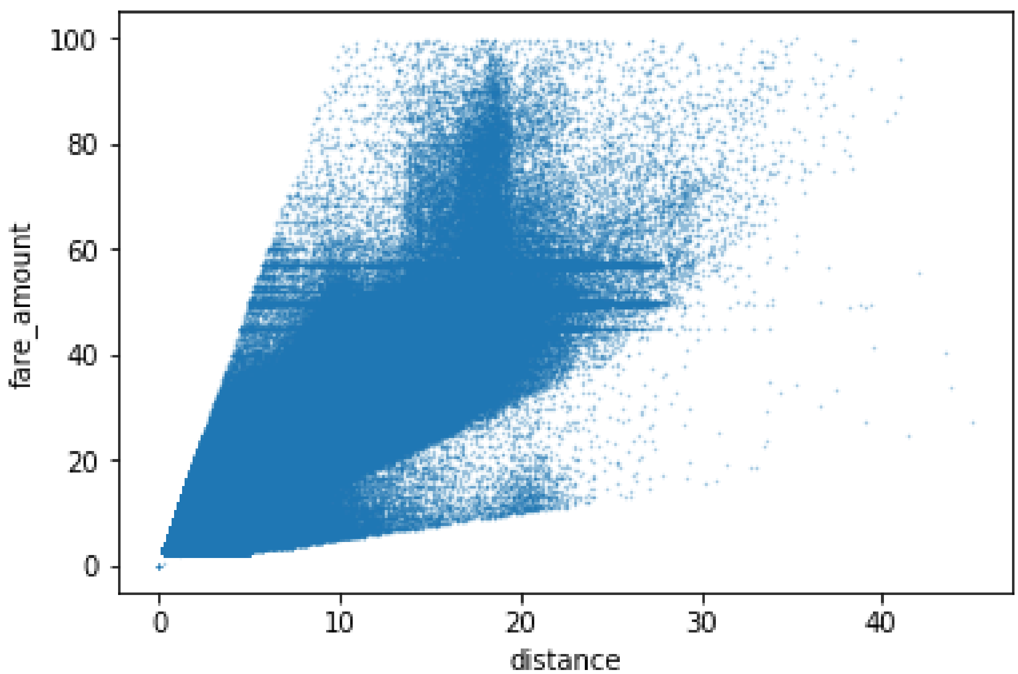
```
2        -73.982738        40.761270        -73.991242         40.750562
3        -73.987130        40.733143        -73.991567         40.758092
4        -73.968095        40.768008        -73.956655         40.783762

   passenger_count  distance  time  year  month  day  hour
0                1  1.030764  1046  2009      6   15    17
1                1  8.450134  1012  2010      1    5    16
2                2  1.389525    35  2011      8   18     0
3                1  2.799270   270  2012      4   21     4
4                1  1.999157   471  2010      3    9     7
```

```
In [35]: data['rate'] = data['fare_amount']/data['distance']
```

```
In [36]: data = data[(data['rate'] > 0.5) & (data['rate'] < 10)]
```

```
In [37]: data.plot(kind='scatter',x='distance',y='fare_amount', s=0.2, alpha=0.4)
```

```
Out[37]: <matplotlib.axes._subplots.AxesSubplot at 0x1a12ab0ba8>
```



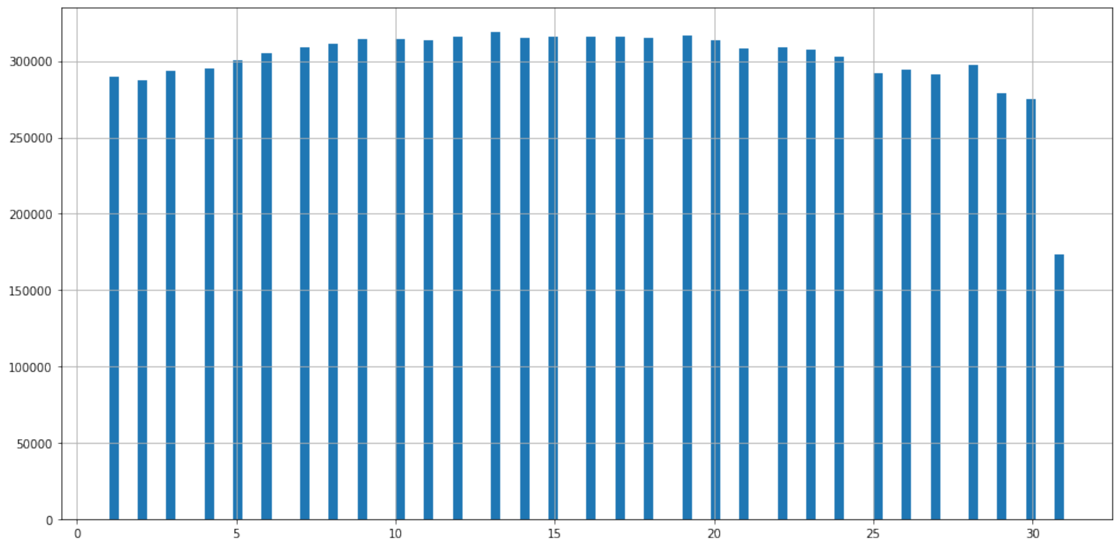

```
In [72]: data[['fare_amount','distance','time', 'hour']].corr()
```

```
Out[72]: 0.9261601234102027
```

```
In [39]: data.shape
```

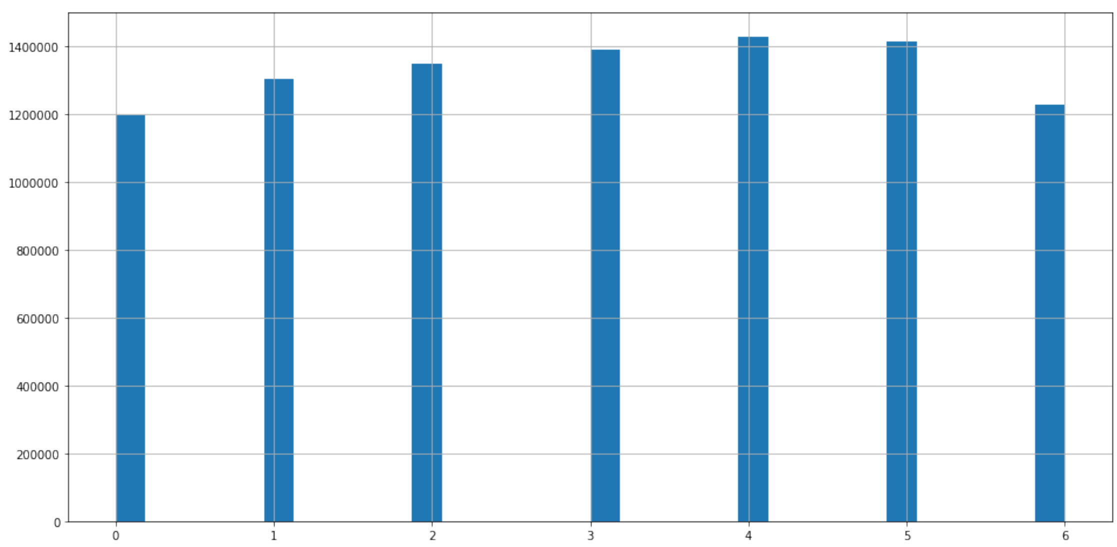
```
Out[39]: (9308183, 15)
```

In [40]:
```
# Lets see if there is some relationship b/w the day of the week and number of rides ta
# Usually more taxi's are booked during weekday.
data['day'].hist(bins=100, figsize=(16,8))
data['weekday'] = pd.to_datetime(data['pickup_datetime']).dt.weekday
```



In [41]:
```
data['weekday'].hist(bins=32, figsize=(16,8))
```

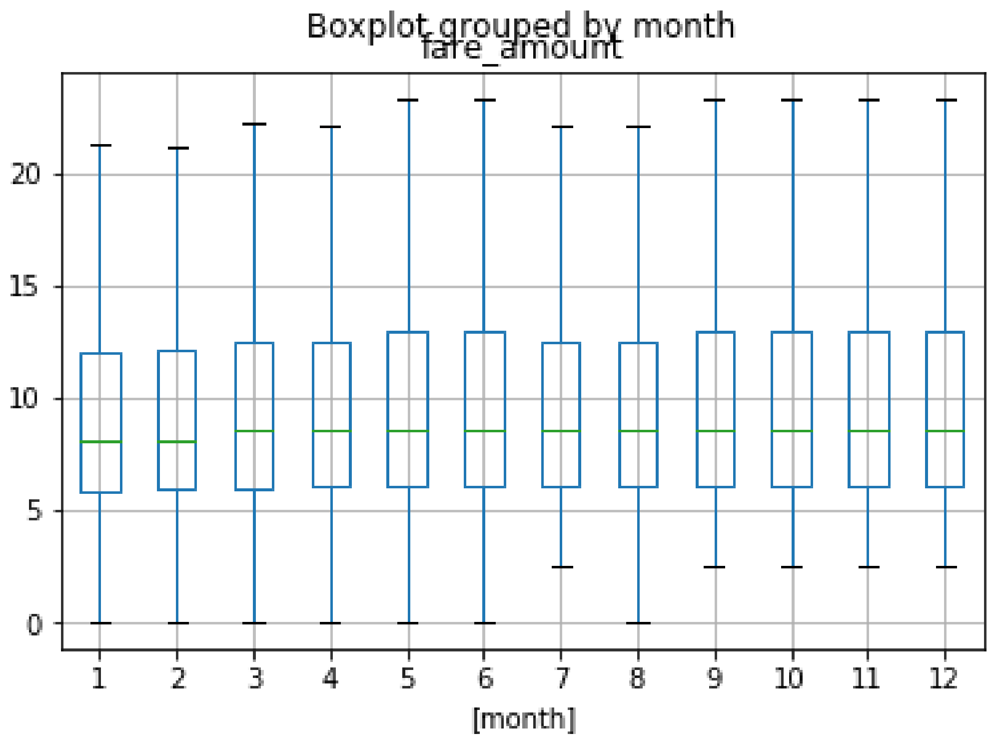
Out[41]: <matplotlib.axes._subplots.AxesSubplot at 0x1a13e43080>

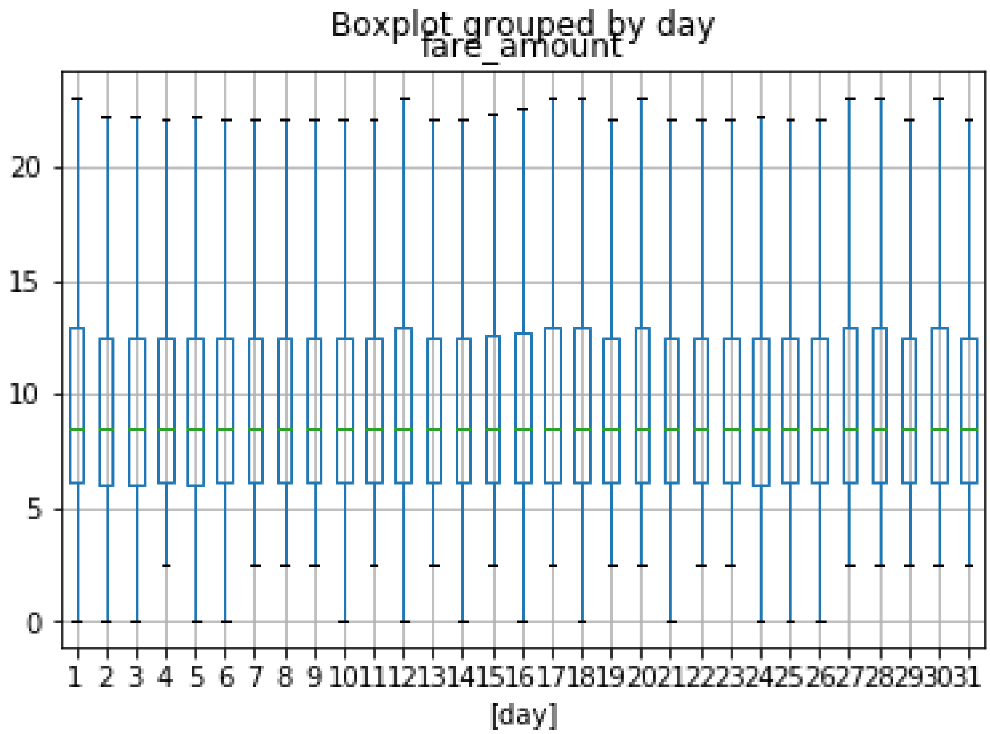


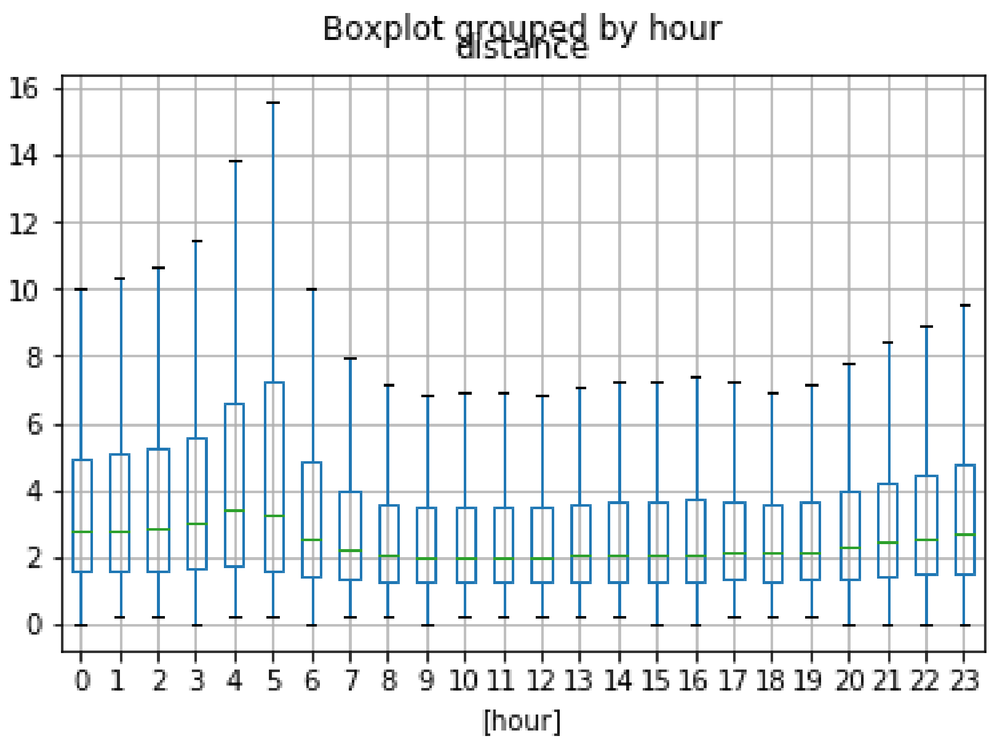
In [42]:
```
# Plotting boxplot to get information regarding the distribution of data . Plotting for
# 1.Finding out if there exist a relation between the hour of taxi pickup and fare amou
```

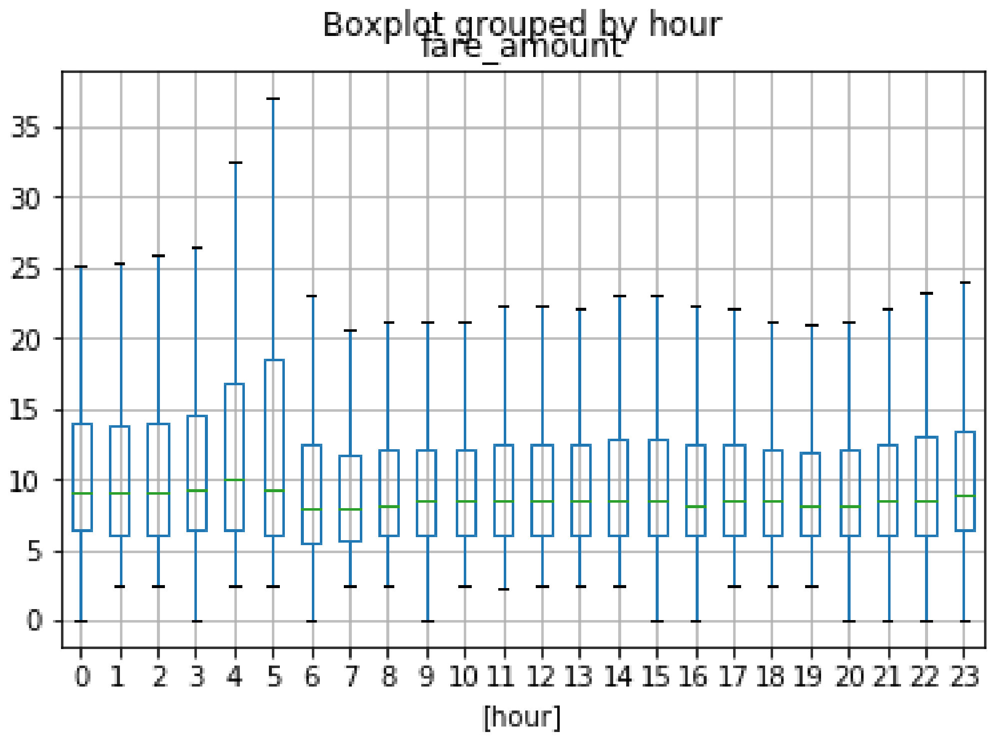
```
# 2.Finding out if there exist a relation between the month of taxi pickup and fare amo
# 3.Finding out if there exist a relation between the year of taxi pickup and fare amou

data[['fare_amount','month']].boxplot(by='month',showfliers=False)
data[['fare_amount','day']].boxplot(by='day',showfliers=False)
data[['distance','hour']].boxplot(by='hour',showfliers=False)
data[['fare_amount','hour']].boxplot(by='hour',showfliers=False)

# From the below plot we can see that the fare is quite high in the morning hours, this
# airport rides as the same relation exist for the hour vs distance plot. Lets try to f
# actually corresponding to airport pickups and drops.
```

Out[42]: <matplotlib.axes._subplots.AxesSubplot at 0x1a16b6b0f0>




Boxplot grouped by day
fare_amount
0
5
10
15
20
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30 31
[day]


Boxplot grouped by hour
distance
0
2
4
6
8
10
12
14
16
0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23
[hour]



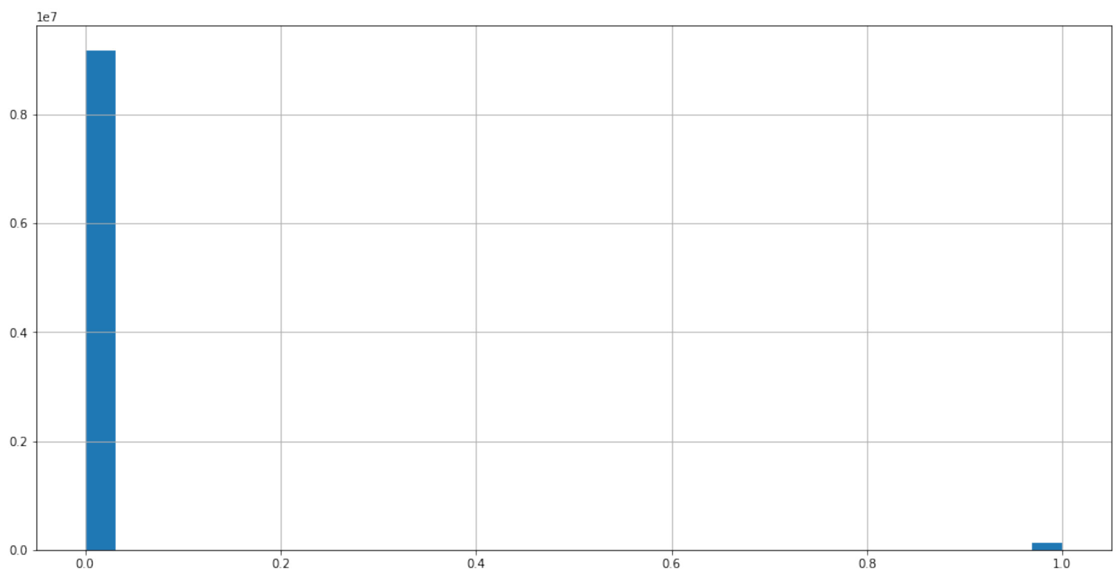
In [43]:
```
# Here we check if the given cordinates of the pickup location or dropoff location is m
# with the airports near the new york city. There are 3 airports near the city:
# 1. JFK
# 2. Laguardia
# 3. Newark
# Getting cordinates of these airports from the web
# JFK ->    Latitude: 40.6413111,   Longitude: -73.7781391
# LaG ->    Latitude: 40.77725,     Longitude: -73.872611
# Newark ->  Latitude: 40.6925,     Longitide: -74.168611


def get_is_airport_ride(column):
    pickup_lat, pickup_lon, dropoff_lat, dropoff_lon = column
    jfk_airport = (40.6413, -73.778)
    lag_airport = (40.777, -73.872)
    newrk_airport = (40.692, -74.168)

    is_drop_at_jkf = (pickup_lat, pickup_lon, jfk_airport[0], jfk_airport[1] )
    is_drop_at_lag = (pickup_lat, pickup_lon, lag_airport[0], lag_airport[1] )
    is_drop_at_newrk = (pickup_lat, pickup_lon, newrk_airport[0], newrk_airport[1] )

    is_pickup_from_jkf = (jfk_airport[0], jfk_airport[1],dropoff_lat, dropoff_lon )
    is_pickup_from_lag = (lag_airport[0], lag_airport[1],dropoff_lat, dropoff_lon )
```

```
        is_pickup_from_newrk = (newrk_airport[0], newrk_airport[1], dropoff_lat, dropoff_lo

        if(get_euclidean_dist(is_pickup_from_jkf) < 1 or get_euclidean_dist(is_pickup_from_
           get_euclidean_dist(is_pickup_from_newrk) < 1 ):
            return 1
        if(get_euclidean_dist(is_drop_at_jkf) < 1 or get_euclidean_dist(is_drop_at_lag) < 1
           get_euclidean_dist(is_drop_at_newrk) < 1 ):
            return 0

        return 0
```

In [44]:
```
# Adding a new feature, which will give us information about airport rides
# Based on this information, I plan to do further analysis on the pattern of long dista
columns = ['pickup_latitude','pickup_longitude','dropoff_latitude','dropoff_longitude']
data['is_airport_ride'] = data[columns].apply(get_is_airport_ride, axis=1)
```

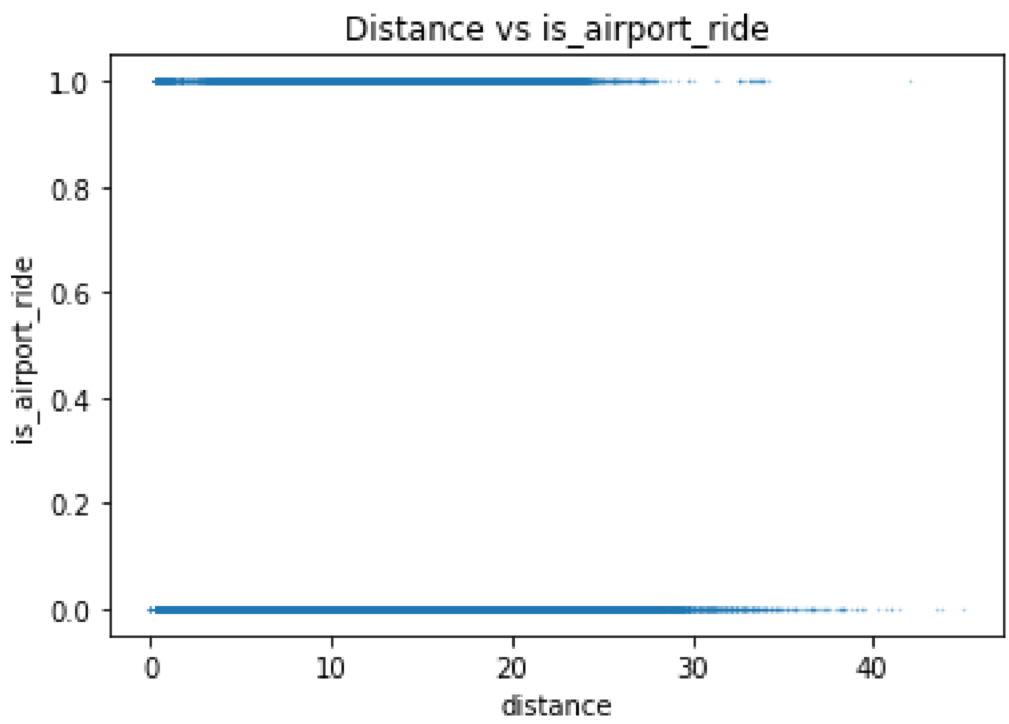
In [45]:
```
data['is_airport_ride'].hist(bins=32, figsize=(16,8))
```

Out[45]: <matplotlib.axes._subplots.AxesSubplot at 0x1a10d06da0>



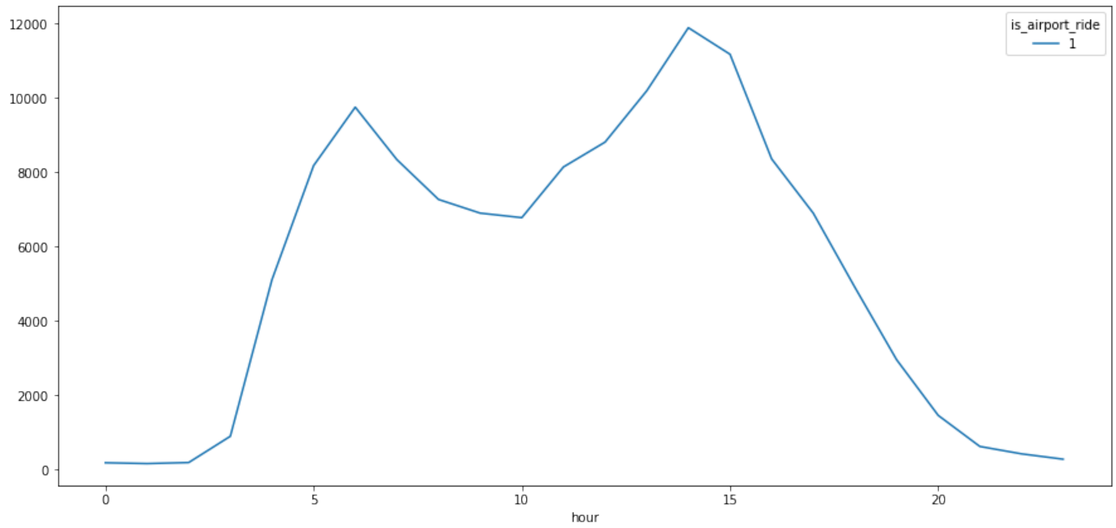
In [46]:
```
data.plot(kind='scatter',x='distance',y='is_airport_ride', s=0.2, alpha=0.4)
plt.title("Distance vs is_airport_ride")
```

Out[46]: Text(0.5,1,'Distance vs is_airport_ride')




```
In [47]: # Lets find out if there is something interesting we can do with the data we collected
         # and the hour of the day. This plot will help us analyze the airport taxi traffic thro
         fig, ax = plt.subplots(figsize=(15,7))
         data_airport = data[data['is_airport_ride'] > 0]
         data_airport.groupby(['hour','is_airport_ride']).count()['key'].unstack().plot(ax=ax)
```

```
Out[47]: <matplotlib.axes._subplots.AxesSubplot at 0x1a16b71b38>
```



```
In [48]: features_to_keep = ['pickup_latitude', 'pickup_longitude', 'dropoff_longitude',
                'dropoff_latitude', 'passenger_count', 'distance', 'hour', 'year','is_airport_ri

In [49]: train_data = data[features_to_keep]

In [50]: train_data.head()

Out[50]:    pickup_latitude  pickup_longitude  dropoff_longitude  dropoff_latitude  \
         0        40.721319        -73.844311         -73.841610         40.712278
         1        40.711303        -74.016048         -73.979268         40.782004
         2        40.761270        -73.982738         -73.991242         40.750562
         3        40.733143        -73.987130         -73.991567         40.758092
         4        40.768008        -73.968095         -73.956655         40.783762

            passenger_count  distance  hour  year  is_airport_ride
         0                1  1.030764    17  2009                0
         1                1  8.450134    16  2010                0
         2                2  1.389525     0  2011                0
         3                1  2.799270     4  2012                0
         4                1  1.999157     7  2010                0

In [51]: output_data = data['fare_amount']

In [52]: from sklearn.linear_model import LinearRegression
         from sklearn.metrics import mean_squared_error
         from sklearn.model_selection import train_test_split

In [53]: X_train, X_test, y_train, y_test = train_test_split(train_data, output_data, test_size

In [54]: linear_reg = LinearRegression()

In [55]: linear_reg.fit(X_train, y_train)

Out[55]: LinearRegression(copy_X=True, fit_intercept=True, n_jobs=1, normalize=False)

In [56]: print(linear_reg.coef_)

[ 6.21710727e+00  1.64002304e+01 -1.49944810e+01 -1.05592095e+01
  3.46015120e-02  2.28005761e+00  1.36026274e-02  5.09205560e-01
  6.70096628e+00]


In [57]: y_pred = linear_reg.predict(X_test)

In [58]: rmse = np.sqrt(mean_squared_error(y_test , y_pred))
         print("root mean Squared error: {}".format(rmse))
```

```
root mean Squared error: 3.202870444918603
```

In [59]:
```python
test_data = pd.read_csv('test.csv')
```

In [60]:
```python
test_data.head()
```

Out[60]:
```
                           key          pickup_datetime  pickup_longitude  \
0  2015-01-27 13:08:24.0000002  2015-01-27 13:08:24 UTC        -73.973320
1  2015-01-27 13:08:24.0000003  2015-01-27 13:08:24 UTC        -73.986862
2  2011-10-08 11:53:44.0000002  2011-10-08 11:53:44 UTC        -73.982524
3  2012-12-01 21:12:12.0000002  2012-12-01 21:12:12 UTC        -73.981160
4  2012-12-01 21:12:12.0000003  2012-12-01 21:12:12 UTC        -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
```

In [61]:
```python
test_data.count()
```

Out[61]:
```
key                  9914
pickup_datetime      9914
pickup_longitude     9914
pickup_latitude      9914
dropoff_longitude    9914
dropoff_latitude     9914
passenger_count      9914
dtype: int64
```

In [62]:
```python
# just like training data , we add the 'distance' field to the test data as part of pre
columns = ['pickup_latitude','pickup_longitude','dropoff_latitude','dropoff_longitude']
test_data['distance'] = test_data[columns].apply(get_euclidean_dist, axis=1)
test_data['is_airport_ride'] = test_data[columns].apply(get_is_airport_ride, axis=1)
```

In [63]:
```python
# Making test data same as training data in terms of representation so that the model
# doesn't complain.
test_data['hour'] = test_data.pickup_datetime.apply(lambda t: pd.to_datetime(t).hour)
test_data['year'] = test_data.pickup_datetime.apply(lambda t: pd.to_datetime(t).year)
# Keeping this as it is requiresd to be output in the submission.csv
test_data_with_key = test_data[['key'] + features_to_keep]
test_data = test_data[features_to_keep]
```

In [64]:
```python
test_data.head()
```

Out[64]:
```
   pickup_latitude  pickup_longitude  dropoff_longitude  dropoff_latitude  \
0        40.763805        -73.973320         -73.981430         40.743835
```

```
1        40.719383       -73.986862        -73.998886        40.739201
2        40.751260       -73.982524        -73.979654        40.746139
3        40.767807       -73.981160        -73.990448        40.751635
4        40.789775       -73.966046        -73.988565        40.744427

   passenger_count  distance  hour  year  is_airport_ride
0                1  2.323260    13  2015                0
1                1  2.425353    13  2015                0
2                1  0.618628    11  2011                0
3                1  1.961033    21  2012                0
4                1  5.387301    21  2012                0
```

In [65]:
```
# Getting the prediction results from the linear regressor model and output it to the s
linear_reg.fit(train_data, output_data)
test_predictions = linear_reg.predict(test_data)
```

In [66]:
```
len(test_predictions)
```

Out[66]:
```
9914
```

In [67]:
```
submission = pd.DataFrame(
    {'key': test_data_with_key.key, 'fare_amount': test_predictions},
    columns = ['key', 'fare_amount'])
```

In [68]:
```
submission.to_csv('submission.csv', index = False)
```

In [69]:
```
# Got a score of 5.35 with k-fold Linear regression
# Now trying random Forest regressor to check if there is any improvement
from sklearn.ensemble import RandomForestRegressor
rfgModel = RandomForestRegressor()
# Trying cross validation first to check if the model is givibng good results. Root mea
# a good approximation of the performance of a prediction model
print("Random Forest Generator Parameters: ")
print(rfgModel.get_params() )
rfgModel.fit(X_train, y_train)
rfgModel_pred = rfgModel.predict(X_test)
rmse = np.sqrt(mean_squared_error(y_test , rfgModel_pred))
print("root mean Squared error: {}".format(rmse))
rfgModel.fit(train_data, output_data)
# Now running the model on actual data test data
rfgModel_pred = rfgModel.predict(test_data)
```

```
Random Forest Generator Parameters:
{'bootstrap': True, 'criterion': 'mse', 'max_depth': None, 'max_features': 'auto', 'max_leaf_nod
root mean Squared error: 2.4442165252751806
```

In [70]:
```
submission = pd.DataFrame(
    {'key': test_data_with_key.key, 'fare_amount': rfgModel_pred},
    columns = ['key', 'fare_amount'])
```

In [71]:
```
submission.to_csv('submission.csv', index = False)
```