Untitled7

September 25, 2018

In [1]:
```
# used in Data processing
import pandas as pd
import numpy as np
import datetime as dt

# Visualization libraries
import seaborn as sns
import matplotlib.pyplot as plt
from math import sin, cos, sqrt, atan2, radians
%matplotlib inline
```

In [2]:
```
 # Machine Learning
from sklearn.model_selection import train_test_split

from pandas.tseries.holiday import USFederalHolidayCalendar

# loads data frame
df = pd.read_csv("train.csv",nrows = 50_00_000)
```

In [3]:
```
# check statistics of the given parameters
df.describe()
```

Out[3]:

	fare_amount	pickup_longitude	pickup_latitude	dropoff_longitude	\
count	5.000000e+06	5.000000e+06	5.000000e+06	4.999964e+06	
mean	1.134080e+01	-7.250678e+01	3.991974e+01	-7.250652e+01	
std	9.820175e+00	1.280970e+01	8.963509e+00	1.284777e+01	
min	-1.000000e+02	-3.426609e+03	-3.488080e+03	-3.412653e+03	
25%	6.000000e+00	-7.399206e+01	4.073491e+01	-7.399139e+01	
50%	8.500000e+00	-7.398181e+01	4.075263e+01	-7.398016e+01	
75%	1.250000e+01	-7.396711e+01	4.076712e+01	-7.396367e+01	
max	1.273310e+03	3.439426e+03	3.310364e+03	3.457622e+03	

	dropoff_latitude	passenger_count
count	4.999964e+06	5.000000e+06
mean	3.991725e+01	1.684695e+00
std	9.486767e+00	1.331854e+00
min	-3.488080e+03	0.000000e+00
25%	4.073404e+01	1.000000e+00

```
50%         4.075315e+01      1.000000e+00
75%         4.076811e+01      2.000000e+00
max         3.345917e+03      2.080000e+02
```

In [4]:
```
df.shape
```

Out[4]:
```
(5000000, 8)
```

In [5]:
```
# Let's see the first 5 rows of our training data
df.head(5)
```

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

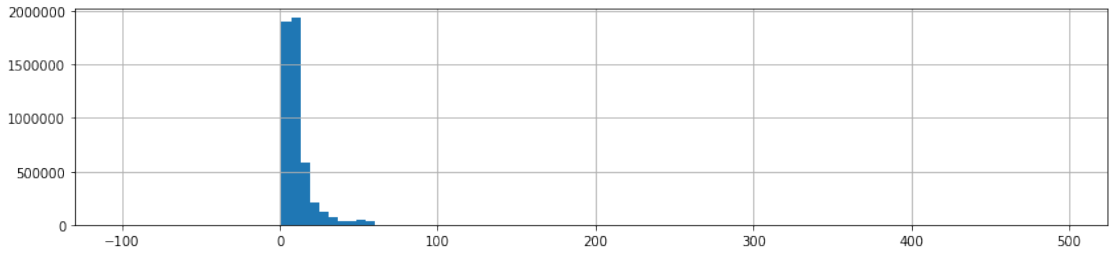
In [6]:
```
# checking how many rows contain atleast a blank entry in it.
df.isna().sum()
```

Out[6]:
```
key                  0
fare_amount          0
pickup_datetime      0
pickup_longitude     0
pickup_latitude      0
dropoff_longitude    36
dropoff_latitude     36
passenger_count      0
dtype: int64
```

In [7]:
```
# data set contains some null entries. Removing them from the dataset
df = df.dropna()
```

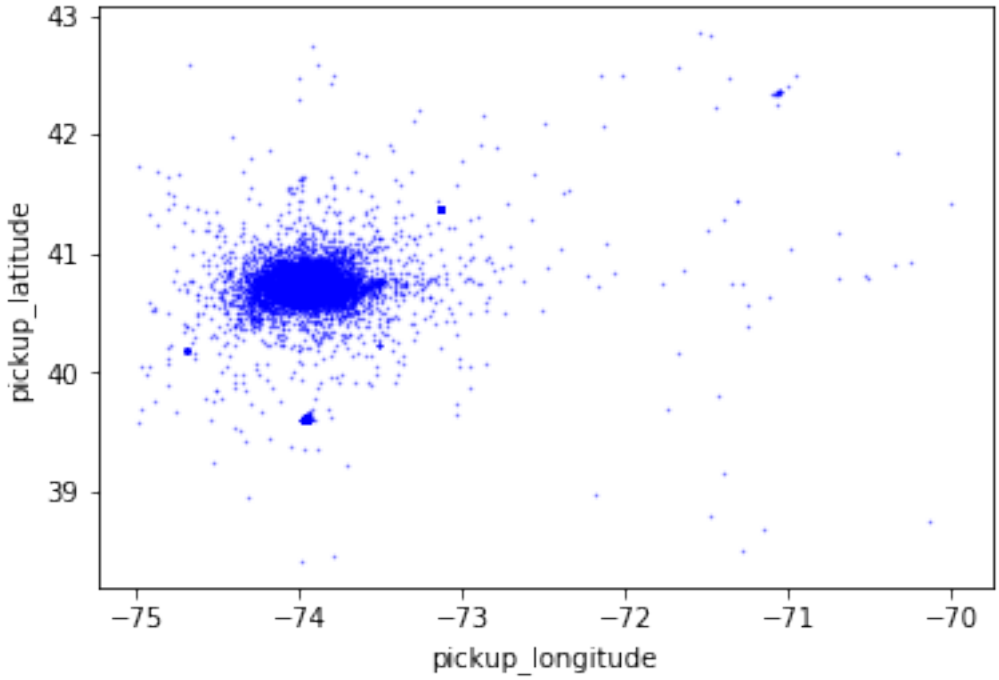
In [8]:
```
#df.shape
```

```
In [9]: # Now remove some of the outliers
        # Plot the histogram of passenger_count
        #plt.hist(df['passenger_count'], bins=np.arange(0, 10))

In [10]: #Passengers count should range from 1 to 7, rest all are outliers let's remove them
         df = df[(df.passenger_count > 0) & (df.passenger_count < 8)]

In [11]: df.shape

Out[11]: (4982350, 8)

In [12]: # Lets consider the histogram of fare_amount
         df[df.fare_amount<500].fare_amount.hist(bins=100, figsize=(14,3))

Out[12]: <matplotlib.axes._subplots.AxesSubplot at 0x1a141b46a0>
```




```
In [13]: df.shape

Out[13]: (4982350, 8)

In [14]: # As we can see we have outliers for fare_amount > 60. Remove them from data set
         df = df[(df.fare_amount > 0) & (df.fare_amount <= 60)]

In [15]: df.shape

Out[15]: (4968604, 8)

In [16]: # Now we now that new york city had latitude around 40.71 and longitude around -74.00
         # So taking a rough estimate remove outliers out of range
         df = df[(df.pickup_longitude > -75) & (df.pickup_longitude < -70)]
         df = df[(df.dropoff_longitude > -75) & (df.dropoff_longitude < -70)]
         df = df[(df.pickup_latitude > 38) & (df.pickup_latitude < 43)]
         df = df[(df.dropoff_latitude > 38) & (df.dropoff_latitude < 43)]

In [17]: df.shape

Out[17]: (4865432, 8)

In [18]: #Plotting scatter plot of longitude and latitude
         df.plot(kind='scatter',x='pickup_longitude',y='pickup_latitude',c='blue',s=0.2,alpha=
```

Out[18]: <matplotlib.axes._subplots.AxesSubplot at 0x1a16127e48>



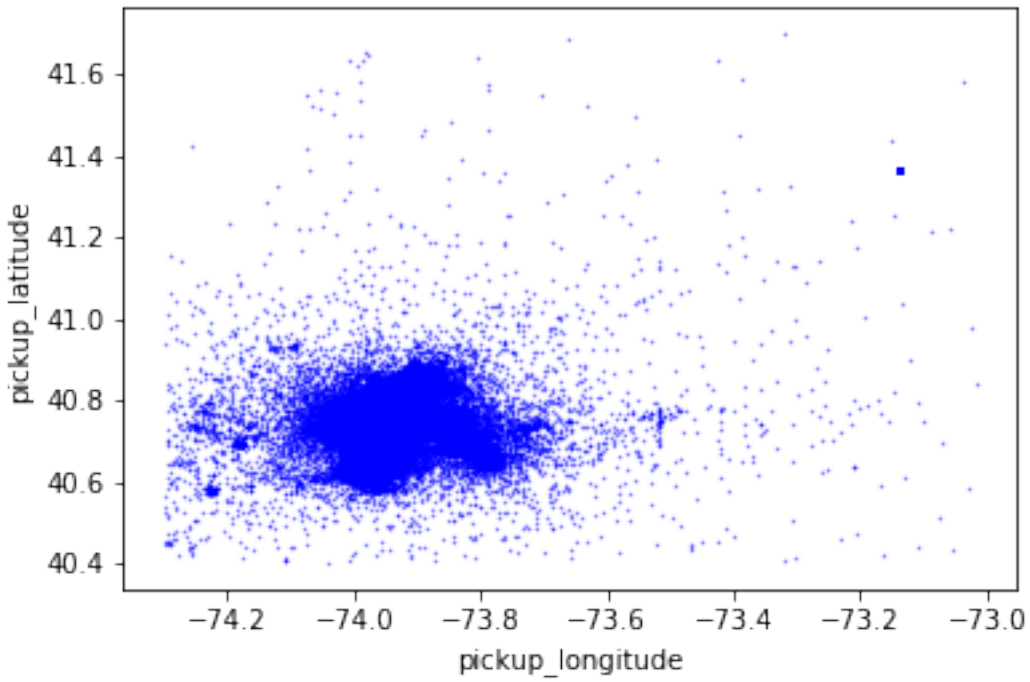
In [19]:
```
# Remove more outliers of latitude and longitude
df = df[(df.pickup_longitude > -74.30) & (df.pickup_longitude < -73.00)]
df = df[(df.dropoff_longitude > -74.30) & (df.dropoff_longitude < -73.00)]
df = df[(df.pickup_latitude > 40.40) & (df.pickup_latitude < 41.71)]
df = df[(df.dropoff_latitude > 40.40) & (df.dropoff_latitude < 41.71)]
```

In [20]:
```
df.shape
```

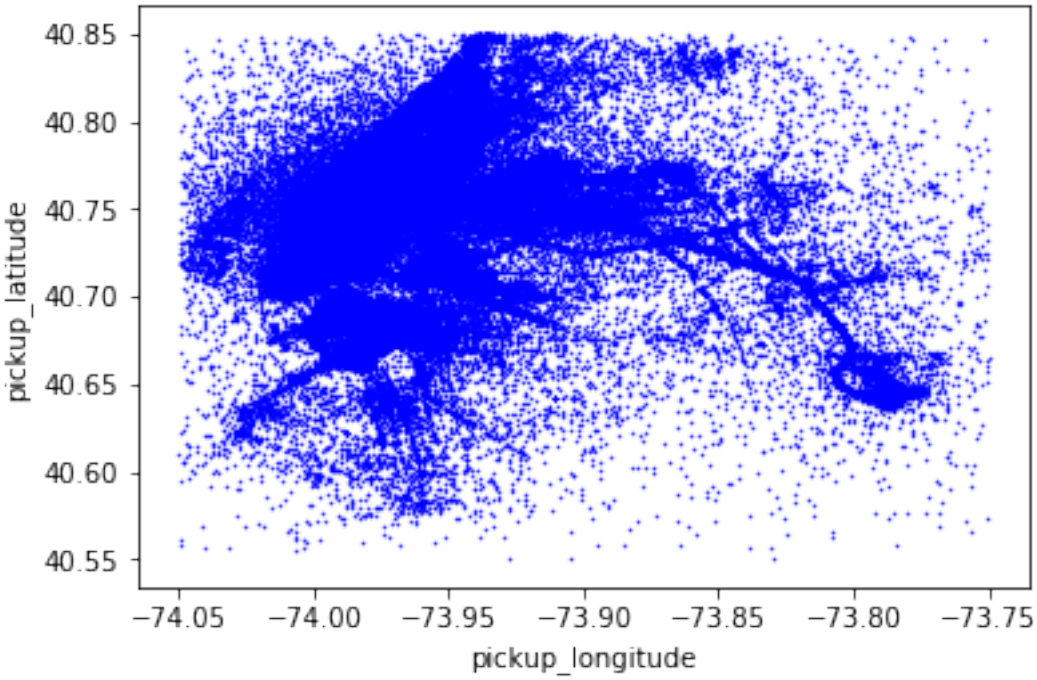
Out[20]: (4863823, 8)

In [21]:
```
df.plot(kind='scatter',x='pickup_longitude',y='pickup_latitude',c='blue',s=0.2,alpha=
```

Out[21]: <matplotlib.axes._subplots.AxesSubplot at 0x1a14da6cc0>




```
In [22]: # Remove more outliers of latitude and longitude
         df = df[(df.pickup_longitude > -74.05) & (df.pickup_longitude < -73.75)]
         df = df[(df.dropoff_longitude > -74.05) & (df.dropoff_longitude < -73.75)]
         df = df[(df.pickup_latitude > 40.55) & (df.pickup_latitude < 40.85)]
         df = df[(df.dropoff_latitude > 40.55) & (df.dropoff_latitude < 40.85)]

In [23]: df.plot(kind='scatter',x='pickup_longitude',y='pickup_latitude',c='blue',s=0.2,alpha=

Out[23]: <matplotlib.axes._subplots.AxesSubplot at 0x112b78e10>
```



In [24]:
```
#Lets calculate distance travelled in each trip using HaverSine distance
#Reference : https://community.esri.com/groups/coordinate-reference-systems/blog/2017
def cal_haversinedistance(pickup_lat : float, pickup_long : float, dropoff_lat : float
    R = 6373.0
    long_diff = dropoff_long - pickup_long
    lat_diff = dropoff_lat - pickup_lat

    a = sin(lat_diff / 2)**2 + cos(pickup_lat) * cos(dropoff_lat) * sin(long_diff / 2
    c = 2 * atan2(sqrt(a), sqrt(1 - a))

    distance = R * c
    return distance
```

In [25]:
```
def dist_calc(df):
    R = 6373.0

    for i,row in df.iterrows():

        pickup_lat = radians(row['pickup_latitude'])
        pickup_long = radians(row['pickup_longitude'])
        dropoff_lat = radians(row['dropoff_latitude'])
        dropoff_long = radians(row['dropoff_longitude'])

        distance = cal_haversinedistance(pickup_lat, pickup_long, dropoff_lat, dropof
        df.at[i,'distance'] = distance
```

```
In [26]: dist_calc(df)

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

Out[27]:

	key	fare_amount	pickup_datetime	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passenger_count	distance
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	1.031088
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	8.452786
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	1.389961
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	2.800149
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	1.999784

```
In [28]: df.describe()
```

Out[28]:

	fare_amount	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passenger_count	distance
count	4.827651e+06	4.827651e+06	4.827651e+06	4.827651e+06	4.827651e+06	4.827651e+06	4.827651e+06
mean	1.103789e+01	-7.397566e+01	4.075081e+01	-7.397473e+01	4.075081e+01	1.690423e+00	3.225354e+00
std	8.755385e+00	3.367307e-02	2.649189e-02	3.176368e-02	2.934162e-02	1.306251e+00	3.399770e+00
min	1.000000e-02	-7.404989e+01	4.055018e+01	-7.404997e+01	4.055046e+01	1.000000e+00	0.000000e+00
25%	6.000000e+00	-7.399228e+01	4.073657e+01	-7.399157e+01	4.073567e+01	1.000000e+00	1.250420e+00
50%	8.500000e+00	-7.398212e+01	4.075330e+01	-7.398069e+01	4.075375e+01	1.000000e+00	2.138349e+00
75%	1.250000e+01	-7.396847e+01	4.076741e+01	-7.396584e+01	4.076819e+01	2.000000e+00	3.847439e+00
max	6.000000e+01	-7.375001e+01	4.084999e+01	-7.375001e+01	4.085000e+01	7.000000e+00	2.878735e+01

```
In [29]: df = df[~((df.fare_amount > 40) & (df.distance < 5))]
```

In [30]:
```
# Feature Engineering
df['pickup_datetime'] = pd.to_datetime(df['pickup_datetime'])
df['hour'] = df['pickup_datetime'].dt.hour
df['day'] = df['pickup_datetime'].dt.day
df['week'] = df['pickup_datetime'].dt.week
df['month'] = df['pickup_datetime'].dt.month
df['day_of_year'] = df['pickup_datetime'].dt.dayofyear
df['week_of_year'] = df['pickup_datetime'].dt.weekofyear
df['year'] = df['pickup_datetime'].dt.year
```

In [31]:
```
# There is no outlier in hour, day, week, month, day_of_year, week_of_year as evident
df.describe()
```

In [32]:
```
# Let's compute correlation coefficient
df.corr()
```

Out[32]:

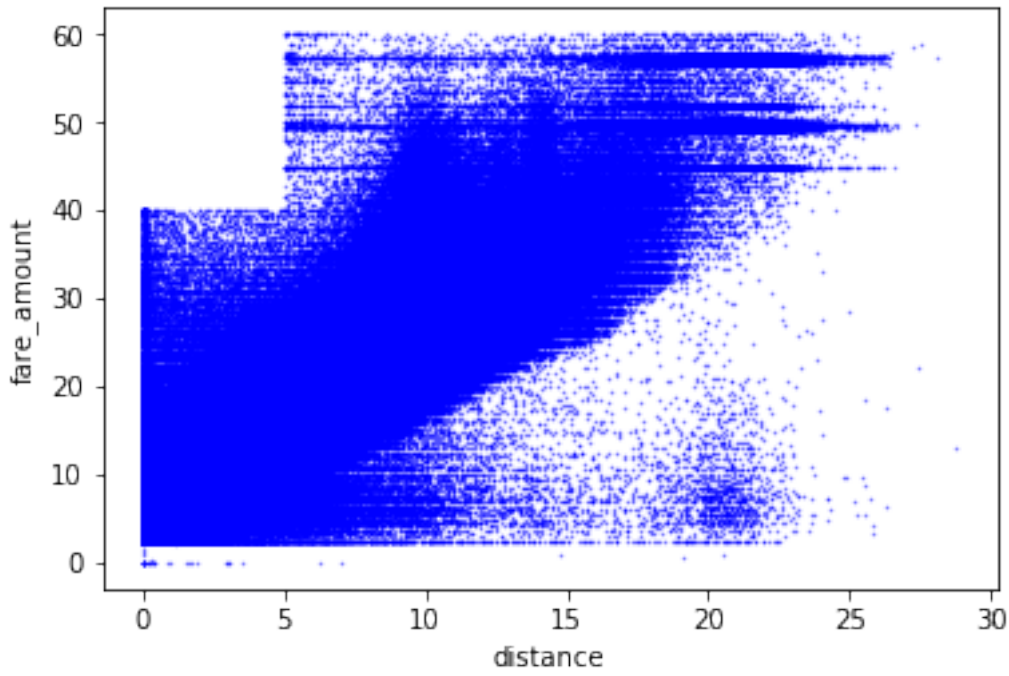
	fare_amount	pickup_longitude	pickup_latitude	\
fare_amount	1.000000	0.458470	-0.227462	
pickup_longitude	0.458470	1.000000	-0.023924	
pickup_latitude	-0.227462	-0.023924	1.000000	
dropoff_longitude	0.393536	0.272631	0.073017	
dropoff_latitude	-0.215770	0.053097	0.425640	
passenger_count	0.017260	0.002084	-0.008415	
distance	0.914287	0.456312	-0.254068	
hour	-0.013955	0.019801	0.028354	
day	0.001369	-0.000415	-0.002663	
week	0.026391	0.007803	-0.004228	
month	0.026601	0.007588	-0.004898	
day_of_year	0.026589	0.007511	-0.005081	
week_of_year	0.026391	0.007803	-0.004228	
year	0.126142	0.011172	-0.011886	

	dropoff_longitude	dropoff_latitude	passenger_count	\
fare_amount	0.393536	-0.215770	0.017260	
pickup_longitude	0.272631	0.053097	0.002084	
pickup_latitude	0.073017	0.425640	-0.008415	
dropoff_longitude	1.000000	0.110417	-0.000045	
dropoff_latitude	0.110417	1.000000	-0.005172	
passenger_count	-0.000045	-0.005172	1.000000	
distance	0.409930	-0.211630	0.011905	
hour	-0.051818	0.022135	0.016268	
day	-0.000299	-0.002865	0.004122	
week	0.006234	-0.004345	0.004404	
month	0.005917	-0.004856	0.004594	
day_of_year	0.005854	-0.005063	0.004938	
week_of_year	0.006234	-0.004345	0.004404	
year	0.008012	-0.007002	0.004889	

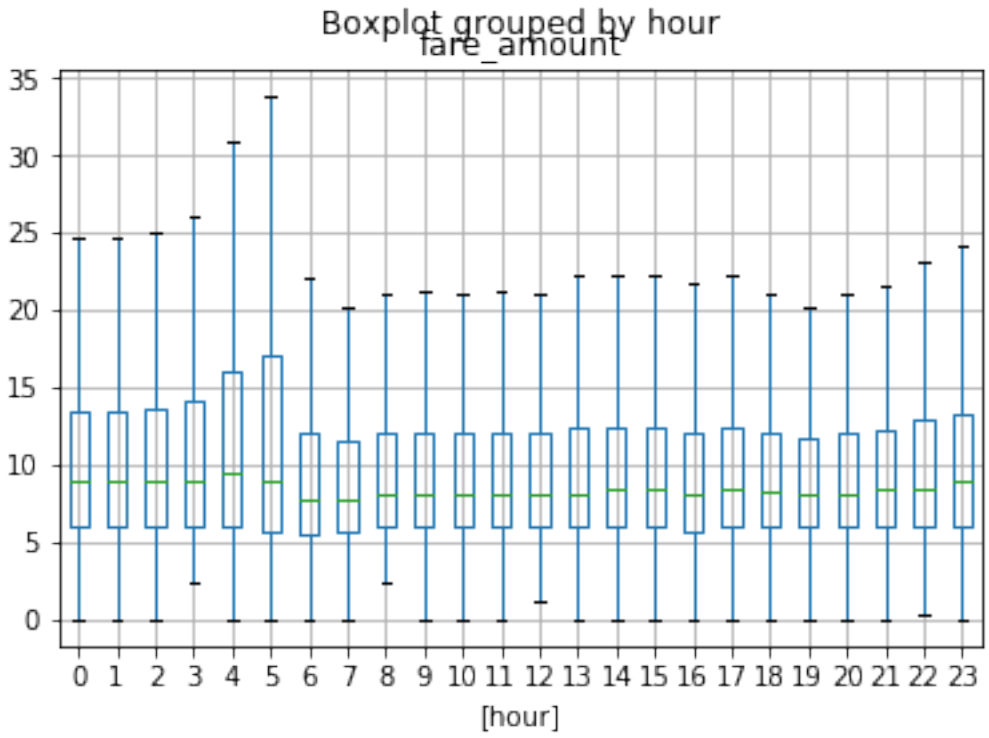
```
                    distance      hour       day      week     month  \
fare_amount         0.914287 -0.013955  0.001369  0.026391  0.026601
pickup_longitude    0.456312  0.019801 -0.000415  0.007803  0.007588
pickup_latitude    -0.254068  0.028354 -0.002663 -0.004228 -0.004898
dropoff_longitude   0.409930 -0.051818 -0.000299  0.006234  0.005917
dropoff_latitude   -0.211630  0.022135 -0.002865 -0.004345 -0.004856
passenger_count     0.011905  0.016268  0.004122  0.004404  0.004594
distance            1.000000 -0.027091  0.001373  0.013376  0.013419
hour               -0.027091  1.000000  0.001254 -0.004915 -0.004733
day                 0.001373  0.001254  1.000000  0.044756 -0.015682
week                0.013376 -0.004915  0.044756  1.000000  0.975111
month               0.013419 -0.004733 -0.015682  0.975111  1.000000
day_of_year         0.013441 -0.004608  0.067058  0.976771  0.996549
week_of_year        0.013376 -0.004915  0.044756  1.000000  0.975111
year                0.022895 -0.000008 -0.009569 -0.123089 -0.118439

                    day_of_year  week_of_year      year
fare_amount            0.026589      0.026391  0.126142
pickup_longitude       0.007511      0.007803  0.011172
pickup_latitude       -0.005081     -0.004228 -0.011886
dropoff_longitude      0.005854      0.006234  0.008012
dropoff_latitude      -0.005063     -0.004345 -0.007002
passenger_count        0.004938      0.004404  0.004889
distance               0.013441      0.013376  0.022895
hour                  -0.004608     -0.004915 -0.000008
day                    0.067058      0.044756 -0.009569
week                   0.976771      1.000000 -0.123089
month                  0.996549      0.975111 -0.118439
day_of_year            1.000000      0.976771 -0.118851
week_of_year           0.976771      1.000000 -0.123089
year                  -0.118851     -0.123089  1.000000
```

In [33]:
```
# Let's check some relationships:
# (1) fare_amount and distance
df.plot(kind='scatter',x='distance',y='fare_amount',c='blue',s=0.2,alpha=.6)
```

Out[33]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1a161a37b8>
```




```
In [34]: df['fare_amount'].corr(df['distance'])
         # Linear Plot and correlation factor of 0.88 signifies linear relationship between fa

Out[34]: 0.9142873503796988

In [35]: # (2) fare_amount and day of time
         df[['fare_amount', 'hour']].boxplot(by = 'hour', showfliers = False)

Out[35]: <matplotlib.axes._subplots.AxesSubplot at 0x1b12e8e400>
```

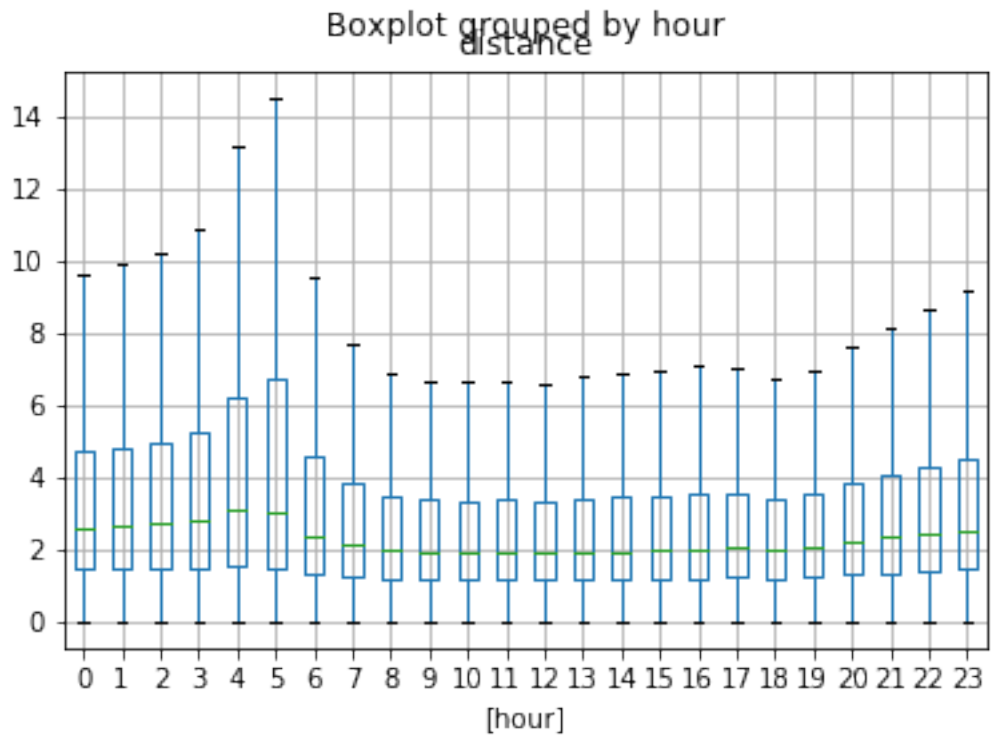



```
In [36]: df['fare_amount'].corr(df['hour'])
         # Findings : 1) Correlation factor = -0.01607561723255814 which does not implies any
         # max fare_amount is in the morning at 5 am which keeps on decreasing till 7 am and i
         #may be due to the fact of people going to/from airport.
```

```
Out[36]: -0.013955057562161444
```

```
In [37]: # (3) distance and day of time
         df[['distance', 'hour']].boxplot(by = 'hour', showfliers = False)
```

```
Out[37]: <matplotlib.axes._subplots.AxesSubplot at 0x1a14724278>
```

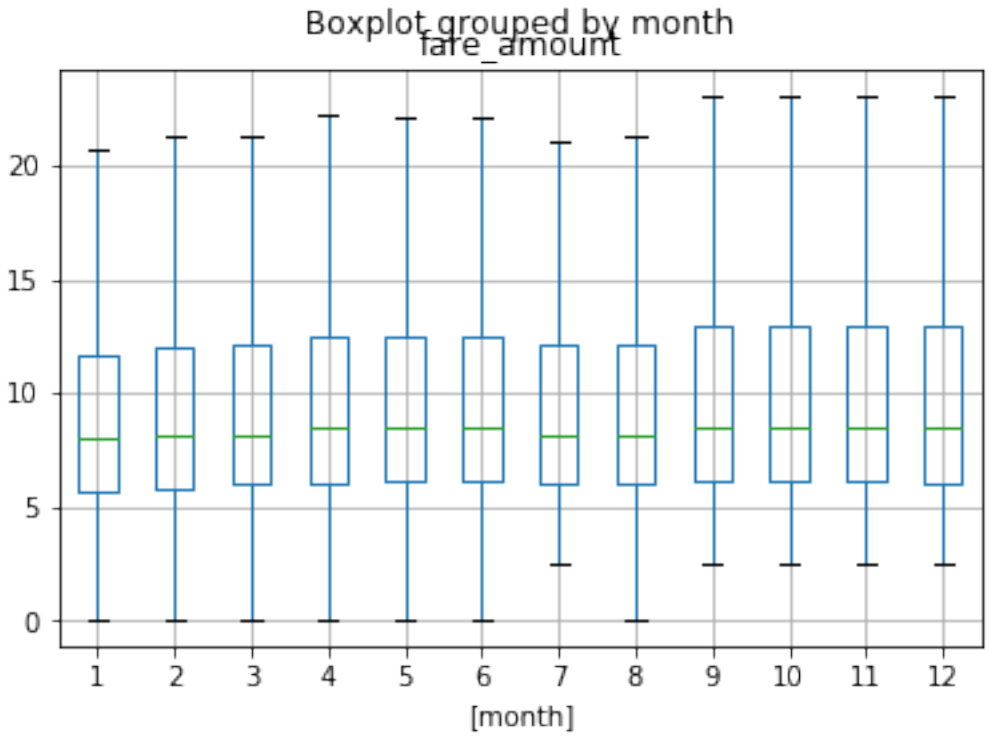


In [38]:
```
df['distance'].corr(df['hour'])
# Findings : 1) Correlation factor = -0.029914726054103426 which does not implies any
# max_distance travelled is in the morning at 5 am may be due to the same fact of tax
```

Out[38]:
```
-0.027091010165026273
```

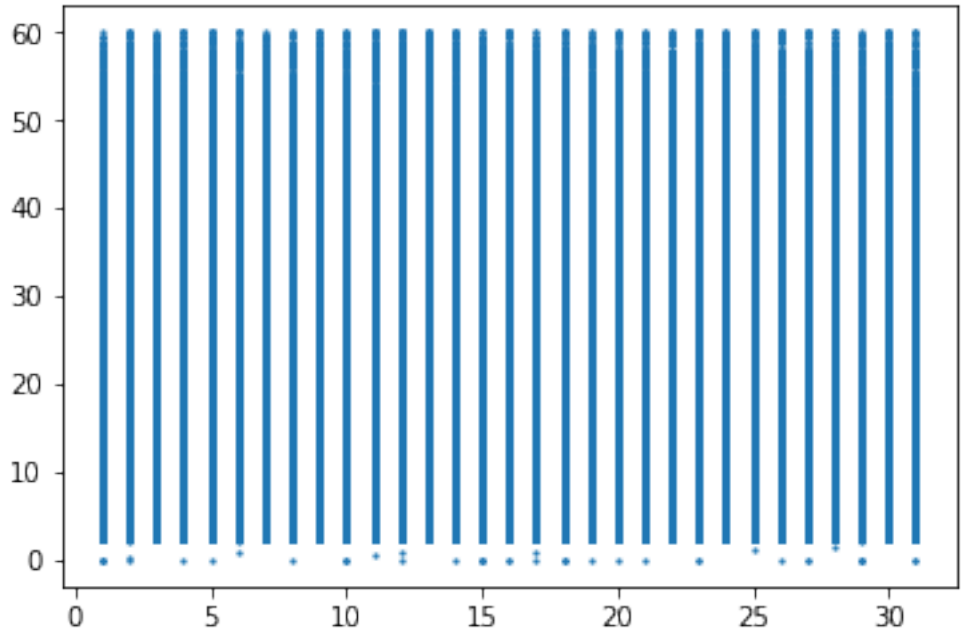
In [39]:
```
df[['fare_amount', 'month']].boxplot(by = 'month', showfliers = False)
#It shows the maximum fare received in the months of may and June due to summer vacat
#to december may be to the new year.
```

Out[39]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1a19163b38>
```




```
In [40]: plt.scatter(x=df['day'], y=df['fare_amount'], s=1.5)
         #No correlation between date and fare_amount
```

```
Out[40]: <matplotlib.collections.PathCollection at 0x1a148d70b8>
```

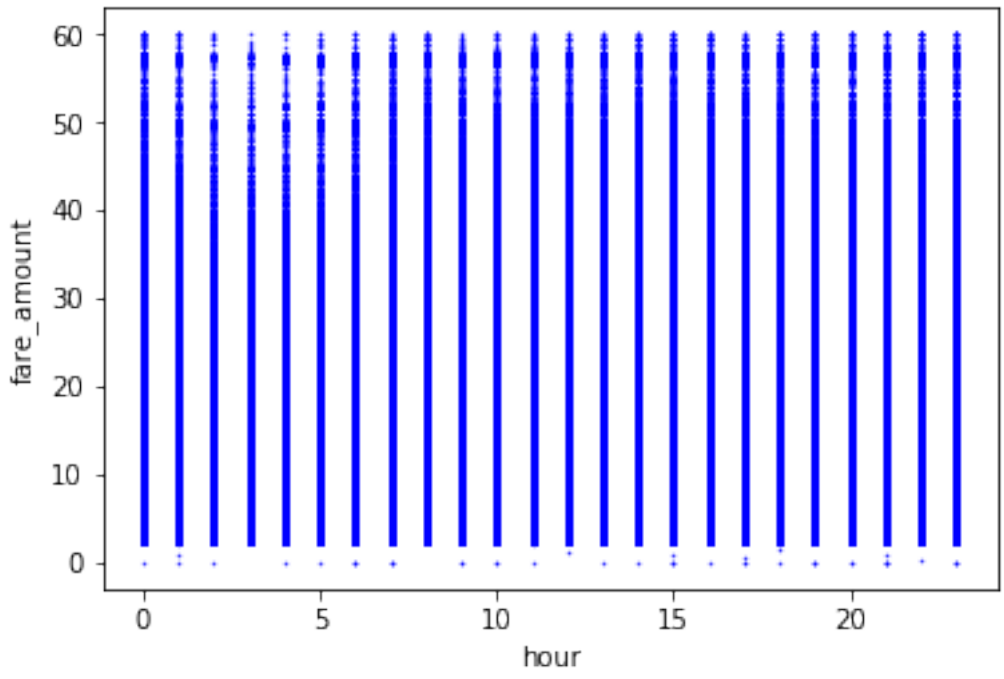


```
In [41]:     def populateAirportDataSet(data):
                 jfk_coord = (40.639722, -73.778889)
                 ewr_coord = (40.6925, -74.168611)
                 lga_coord = (40.77725, -73.872611)
                 mylist = []
                 for i,row in data.iterrows():
                     pickup_lat = radians(row['pickup_latitude'])
                     dropoff_lat = radians(row['dropoff_latitude'])
                     pickup_lon = radians(row['pickup_longitude'])
                     dropoff_lon = radians(row['dropoff_longitude'])
                     #print('vivek')
                     pickup_jfk = cal_haversinedistance(pickup_lat, pickup_lon, jfk_coord[0], j
                     dropoff_jfk = cal_haversinedistance(jfk_coord[0], jfk_coord[1], dropoff_la
                     pickup_ewr = cal_haversinedistance(pickup_lat, pickup_lon, ewr_coord[0], e
                     dropoff_ewr = cal_haversinedistance(ewr_coord[0], ewr_coord[1], dropoff_la
                     pickup_lga = cal_haversinedistance(pickup_lat, pickup_lon, lga_coord[0], l
                     dropoff_lga = cal_haversinedistance(lga_coord[0], lga_coord[1], dropoff_la
                     if(pickup_jfk < 2 or dropoff_jfk < 2 or pickup_ewr < 2 or dropoff_ewr < 2
                         mylist.append(1)
                     else:
                         mylist.append(0)
                 return mylist

In [42]: df['isAirportRide'] = populateAirportDataSet(df)

In [43]: df.describe()

Out[43]:         fare_amount  pickup_longitude  pickup_latitude  dropoff_longitude  \
         count  4.816588e+06      4.816588e+06     4.816588e+06       4.816588e+06
         mean   1.094843e+01     -7.397574e+01     4.075086e+01      -7.397480e+01
         std    8.560810e+00      3.343625e-02     2.640386e-02       3.150210e-02
         min    1.000000e-02     -7.404989e+01     4.055018e+01      -7.404996e+01
         25%    6.000000e+00     -7.399228e+01     4.073660e+01      -7.399156e+01
         50%    8.500000e+00     -7.398213e+01     4.075332e+01      -7.398070e+01
         75%    1.250000e+01     -7.396850e+01     4.076743e+01      -7.396586e+01
         max    6.000000e+01     -7.375001e+01     4.084999e+01      -7.375001e+01

                dropoff_latitude  passenger_count      distance          hour  \
         count      4.816588e+06     4.816588e+06  4.816588e+06  4.816588e+06
         mean       4.075085e+01     1.690647e+00  3.230506e+00  1.351978e+01
         std        2.926771e-02     1.306435e+00  3.401233e+00  6.504249e+00
         min        4.055046e+01     1.000000e+00  0.000000e+00  0.000000e+00
         25%        4.073572e+01     1.000000e+00  1.253646e+00  9.000000e+00
         50%        4.075377e+01     1.000000e+00  2.141089e+00  1.400000e+01
         75%        4.076821e+01     2.000000e+00  3.851992e+00  1.900000e+01
         max        4.085000e+01     7.000000e+00  2.878735e+01  2.300000e+01
```

```
                day          week         month   day_of_year  week_of_year  \
count  4.816588e+06  4.816588e+06  4.816588e+06  4.816588e+06  4.816588e+06
mean   1.571701e+01  2.546496e+01  6.269116e+00  1.753048e+02  2.546496e+01
std    8.684374e+00  1.494863e+01  3.436639e+00  1.048094e+02  1.494863e+01
min    1.000000e+00  1.000000e+00  1.000000e+00  1.000000e+00  1.000000e+00
25%    8.000000e+00  1.300000e+01  3.000000e+00  8.500000e+01  1.300000e+01
50%    1.600000e+01  2.400000e+01  6.000000e+00  1.670000e+02  2.400000e+01
75%    2.300000e+01  3.900000e+01  9.000000e+00  2.670000e+02  3.900000e+01
max    3.100000e+01  5.300000e+01  1.200000e+01  3.660000e+02  5.300000e+01

               year  isAirportRide
count  4.816588e+06      4816588.0
mean   2.011739e+03            0.0
std    1.865292e+00            0.0
min    2.009000e+03            0.0
25%    2.010000e+03            0.0
50%    2.012000e+03            0.0
75%    2.013000e+03            0.0
max    2.015000e+03            0.0
```

In [44]:
```
df.plot(kind='scatter',x='hour',y='fare_amount',c='blue',s=0.2,alpha=.99)
```

Out[44]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1b1efc5128>
```



```
In [45]: test = pd.read_csv('test.csv')

In [46]: USFederal_Holidays = USFederalHolidayCalendar().holidays(start='2005-01-01', end='201

         USFederal_Holidays = USFederal_Holidays.tolist()

         def IsUSFederalHoliday(data):
             date = data['pickup_datetime']
             if date in USFederal_Holidays:
                 return 1
             else:

                 return 0

In [47]: df['is_holiday'] = df.apply(IsUSFederalHoliday,axis = 1)

In [48]: # Modelling of data

In [49]: feature_names = ['pickup_longitude', 'pickup_latitude', 'dropoff_longitude', 'dropoff_
         label_name = 'fare_amount'
         x_train = df[feature_names]
         y_train = df[label_name]
         test = pd.read_csv('test.csv')
         dist_calc(test)
         test['hour'] = pd.to_datetime(test['pickup_datetime']).dt.hour
         test['year'] = pd.to_datetime(test['pickup_datetime']).dt.year
         test['isAirportRide'] = populateAirportDataSet(test)
         test['is_holiday'] = test.apply(IsUSFederalHoliday,axis = 1)

In [50]: from sklearn.ensemble import RandomForestRegressor
         from sklearn.model_selection import train_test_split
         from sklearn.metrics import mean_squared_error, make_scorer
         from sklearn.model_selection import GridSearchCV
         from sklearn.linear_model import LinearRegression

In [51]: #Random Forest Model
         x_train1, x_test1, y_train1, y_test1 = train_test_split(x_train,y_train, test_size=0.2

         rfr = RandomForestRegressor()
         rfr.fit(x_train1, y_train1)
         rfr_prediction = rfr.predict(x_test1)

         #rfr_submission = pd.DataFrame({"key": test['key'],"fare_amount": rfr_prediction},col
         rmse = np.sqrt(mean_squared_error(rfr_prediction,y_test1))
         print ("root mean Squared Error : {}".format(rmse))

root mean Squared Error : 2.740465470517641
```

```
In [52]: xtest = test[feature_names]
         rfr.fit(x_train, y_train)
         rfr_prediction = rfr.predict(xtest)

In [53]: submission = pd.read_csv('sample_submission.csv')
         submission['fare_amount'] = rfr_prediction
         submission.to_csv('vivek_submission.csv', index=False)

In [54]: # Linear Regression
         x_train1, x_test1, y_train1, y_test1 = train_test_split(x_train,y_train, test_size=0.
         linear_reg = LinearRegression()
         linear_reg.fit(x_train1, y_train1)

Out[54]: LinearRegression(copy_X=True, fit_intercept=True, n_jobs=1, normalize=False)

In [55]: print(linear_reg.coef_)

[ 1.42244609e+01  3.94576281e+00  6.75630186e+00 -1.22194397e+01
  3.94864599e-02  2.19223575e+00  1.35045531e-02  4.83529209e-01
  0.00000000e+00 -6.60865977e-01]


In [56]: y_pred = linear_reg.predict(x_test1)

In [57]: rmse = np.sqrt(mean_squared_error(y_pred, y_test1))
         print ("root mean Squared Error : {}".format(rmse))

root mean Squared Error : 3.3033718199477162
```