Homework 2: Modeling

Task 1 - Data Cleaning

In [1]:
```
# import necessary library
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import sklearn
import matplotlib.lines as mlines
import matplotlib.transforms as mtransforms
%matplotlib inline
```

In [2]:
```
#read data
fare = pd.read_csv("taxi_fare.csv")
# from google.colab import drive
# drive.mount('/content/drive')
```

In [3]:
```
#explore our data
fare.head()
# passenger is 0, location is 0
```

Out[3]:

	key	fare_amount	pickup_datetime	pickup_longitude	pickup_latitude	dropoff_lo
0	2009-06-15 17:26:21.0000001	4.5	2009-06-15 17:26:21 UTC	-73.844311	40.721319	-73
1	2010-01-05 16:52:16.0000002	16.9	2010-01-05 16:52:16 UTC	-74.016048	40.711303	-73
2	2011-08-18 00:35:00.00000049	5.7	2011-08-18 00:35:00 UTC	-73.982738	40.761270	-73
3	2012-04-21 04:30:42.0000001	7.7	2012-04-21 04:30:42 UTC	-73.987130	40.733143	-73
4	2010-03-09 07:51:00.000000135	5.3	2010-03-09 07:51:00 UTC	-73.968095	40.768008	-73

In [4]:
```
fare.head(6)
```

Out[4]:

	key	fare_amount	pickup_datetime	pickup_longitude	pickup_latitude	dropoff_lo
0	2009-06-15 17:26:21.0000001	4.5	2009-06-15 17:26:21 UTC	-73.844311	40.721319	-73
1	2010-01-05 16:52:16.0000002	16.9	2010-01-05 16:52:16 UTC	-74.016048	40.711303	-73
2	2011-08-18 00:35:00.00000049	5.7	2011-08-18 00:35:00 UTC	-73.982738	40.761270	-73
3	2012-04-21 04:30:42.0000001	7.7	2012-04-21 04:30:42 UTC	-73.987130	40.733143	-73
4	2010-03-09 07:51:00.000000135	5.3	2010-03-09 07:51:00 UTC	-73.968095	40.768008	-73
5	2011-01-06 09:50:45.0000002	12.1	2011-01-06 09:50:45 UTC	-74.000964	40.731630	-73

In [5]:
```
fare.describe()
```

Out[5]:

	fare_amount	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passer
count	2.000000e+06	2.000000e+06	2.000000e+06	1.999986e+06	1.999986e+06	2.0
mean	1.134779e+01	-7.252321e+01	3.992963e+01	-7.252395e+01	3.992808e+01	1.6
std	9.852883e+00	1.286804e+01	7.983352e+00	1.277497e+01	1.032382e+01	1.3
min	-6.200000e+01	-3.377681e+03	-3.458665e+03	-3.383297e+03	-3.461541e+03	0.0
25%	6.000000e+00	-7.399208e+01	4.073491e+01	-7.399141e+01	4.073400e+01	1.0
50%	8.500000e+00	-7.398181e+01	4.075263e+01	-7.398016e+01	4.075312e+01	1.0
75%	1.250000e+01	-7.396713e+01	4.076710e+01	-7.396369e+01	4.076809e+01	2.0
max	1.273310e+03	2.856442e+03	2.621628e+03	3.414307e+03	3.345917e+03	2.0

Delete missing values

In [6]:
```
fare.isna().sum()
# Now, we have no missing values
```

Out[6]:
```
key                   0
fare_amount           0
pickup_datetime       0
pickup_longitude      0
pickup_latitude       0
dropoff_longitude    14
dropoff_latitude     14
passenger_count       0
dtype: int64
```

In [7]:
```
fare[fare.dropoff_longitude.isna()]
```

Out[7]:

	key	fare_amount	pickup_datetime	pickup_longitude	pickup_latitude	drop
120227	2012-12-11 12:57:00.00000013	12.50	2012-12-11 12:57:00 UTC	-73.992760	40.743098	
245696	2013-03-21 18:07:07.0000001	86.50	2013-03-21 18:07:07 UTC	-73.991572	40.740591	
340533	2012-12-11 12:50:52.00000010	27.50	2012-12-11 12:50:52 UTC	-73.979639	40.784742	
428108	2011-09-08 09:12:52.0000001	11.80	2011-09-08 09:12:52 UTC	-73.987041	40.751542	
471472	2012-12-11 12:34:20.0000006	7.80	2012-12-11 12:34:20 UTC	0.000000	0.000000	
524834	2011-09-25 23:01:12.0000005	14.76	2011-09-25 23:01:12 UTC	-73.985374	40.768518	
574023	2013-11-04 20:59:15.0000001	10.20	2013-11-04 20:59:15 UTC	-73.998460	40.745406	
580338	2012-12-11 12:00:53.0000002	21.00	2012-12-11 12:00:53 UTC	-73.974743	40.752057	
794694	2013-11-04 20:07:59.0000006	7.20	2013-11-04 20:07:59 UTC	-73.977048	40.787565	
895400	2011-06-20 11:34:44.0000001	40.00	2011-06-20 11:34:44 UTC	-73.862900	40.768900	
1220978	2012-12-11 12:12:15.0000002	29.35	2012-12-11 12:12:15 UTC	-74.015247	40.714325	
1476796	2013-09-05 00:02:14.0000003	80.00	2013-09-05 00:02:14 UTC	-73.990479	40.755656	
1521628	2012-12-11 13:32:14.0000002	28.00	2012-12-11 13:32:14 UTC	-73.952428	40.792340	
1882440	2012-12-11 11:54:17.0000003	8.40	2012-12-11 11:54:17 UTC	-73.982518	40.742460	

In [8]:
```
fare[fare.dropoff_latitude.isna()]
# We can see that 14 records are missing both dropoff_latitude and dropo
ff_longtitude
```

Out[8]:

	key	fare_amount	pickup_datetime	pickup_longitude	pickup_latitude	drop
120227	2012-12-11 12:57:00.00000013	12.50	2012-12-11 12:57:00 UTC	-73.992760	40.743098	
245696	2013-03-21 18:07:07.0000001	86.50	2013-03-21 18:07:07 UTC	-73.991572	40.740591	
340533	2012-12-11 12:50:52.00000010	27.50	2012-12-11 12:50:52 UTC	-73.979639	40.784742	
428108	2011-09-08 09:12:52.0000001	11.80	2011-09-08 09:12:52 UTC	-73.987041	40.751542	
471472	2012-12-11 12:34:20.0000006	7.80	2012-12-11 12:34:20 UTC	0.000000	0.000000	
524834	2011-09-25 23:01:12.0000005	14.76	2011-09-25 23:01:12 UTC	-73.985374	40.768518	
574023	2013-11-04 20:59:15.0000001	10.20	2013-11-04 20:59:15 UTC	-73.998460	40.745406	
580338	2012-12-11 12:00:53.0000002	21.00	2012-12-11 12:00:53 UTC	-73.974743	40.752057	
794694	2013-11-04 20:07:59.0000006	7.20	2013-11-04 20:07:59 UTC	-73.977048	40.787565	
895400	2011-06-20 11:34:44.0000001	40.00	2011-06-20 11:34:44 UTC	-73.862900	40.768900	
1220978	2012-12-11 12:12:15.0000002	29.35	2012-12-11 12:12:15 UTC	-74.015247	40.714325	
1476796	2013-09-05 00:02:14.0000003	80.00	2013-09-05 00:02:14 UTC	-73.990479	40.755656	
1521628	2012-12-11 13:32:14.0000002	28.00	2012-12-11 13:32:14 UTC	-73.952428	40.792340	
1882440	2012-12-11 11:54:17.0000003	8.40	2012-12-11 11:54:17 UTC	-73.982518	40.742460	

In [9]:
```
# Since we are predicting the fare of a taxi ride using pickup and drop
 off location information.
# Missing values will not contribute to our prediction, so we will delet
e it.
fare = fare.dropna(subset=['dropoff_longitude','dropoff_latitude'], how
= 'any')
```

In [10]:
```
fare.isna().sum()
# Now we have get a dataframe with no missing values
```

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

In [11]:
```
fare.shape
# We dropped 14 rows
```

Out[11]:
```
(1999986, 8)
```

Now we consider some values that are abnormal

In [12]:
```
((fare['passenger_count'] == 0) | (fare['passenger_count']> 6) ).sum()
```

Out[12]:
```
7111
```

In [13]:
```
# Drop records that have 0 passenger_count or more than 6 passengers
fare = fare[(fare['passenger_count'] != 0) & (fare['passenger_count'] <=
6)]
((fare['passenger_count'] == 0) | (fare['passenger_count'] >6 ) ).sum()
```

Out[13]:
```
0
```

In [14]:
```
fare[(fare['pickup_longitude'] == fare['dropoff_longitude']) & (fare['pi
ckup_latitude'] == fare['dropoff_latitude'])].shape
```

Out[14]:
```
(56703, 8)
```

Examine longtitude and latitude

In [15]:
```
# Drop records that have distance equal to 0. Since this only happens un
der a special and reare situation.
fare = fare[(fare['pickup_longitude'] != fare['dropoff_longitude']) | (f
are['pickup_latitude'] != fare['dropoff_latitude'])]
```

In [16]:
```
fare[(fare['pickup_longitude'] == fare['dropoff_longitude']) & (fare['pi
ckup_latitude'] == fare['dropoff_latitude'])].shape
```

Out[16]:
```
(0, 8)
```

In [17]:
```
# # See how pickup and dropoff locations are distributed
# fig,axs = plt.subplots(1, 2, figsize=(20,8))
# axs[0].scatter(fare['pickup_longitude'], fare['pickup_latitude'], c
='r',s = 1)
# axs[0].set_title('Pickup locations')
# axs[1].scatter(fare['dropoff_longitude'], fare['dropoff_latitude'], c
='b', s = 1)
# axs[1].set_title('Dropoff locations')
```

There are many outliers. Use Interquantile Range Method to deal with these outliers

In [18]:
```
# I used some outlier detection method instead of deleting points that a
re outside NYC, which may happens when someone take a ride from city to
 some other place outside NYC
```

In [19]:
```
# pickup_longitude
temp = fare['pickup_longitude']
sorted(temp)
quantile1, quantile3= np.percentile( fare['pickup_longitude'],[25,75])
print(quantile1,quantile3)
iqr=quantile3-quantile1
# Find the IQR
print(iqr)
## Find the lower bound value and the higher bound value
lower_bound_val = quantile1 -(3 * iqr)
upper_bound_val = quantile3 +(3 * iqr)
print(lower_bound_val,upper_bound_val)
fare = fare[(fare['pickup_longitude']<=upper_bound_val) & (fare['pickup_
longitude']>=lower_bound_val)]
```

```
-73.992287 -73.96838000000002
0.023906999999979917
-74.06400799999994 -73.89665900000008
```

In [20]:
```
# pickup_lagitude
temp = fare['pickup_latitude']
sorted(temp)
quantile1, quantile3= np.percentile( fare['pickup_latitude'],[25,75])
print(quantile1,quantile3)
iqr=quantile3-quantile1
# Find the IQR
print(iqr)
## Find the lower bound value and the higher bound value
lower_bound_val = quantile1 -(3 * iqr)
upper_bound_val = quantile3 +(3 * iqr)
print(lower_bound_val,upper_bound_val)
fare = fare[(fare['pickup_latitude']<=upper_bound_val) & (fare['pickup_l
atitude']>=lower_bound_val)]
```

```
40.737203 40.766578674316406
0.029375674316405031
40.649075977050785 40.85470569726562
```

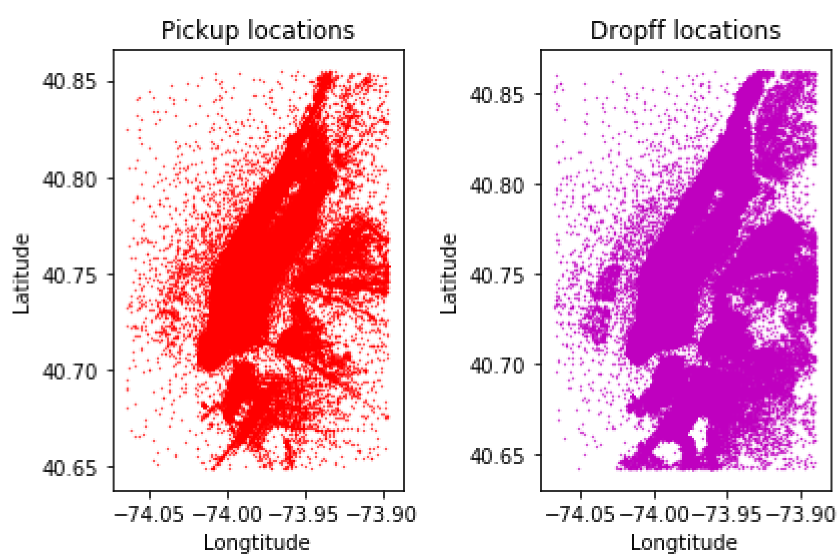
In [21]:
```
# dropoff_longitude
temp = fare['dropoff_longitude']
sorted(temp)
quantile1, quantile3= np.percentile( fare['dropoff_longitude'],[25,75])
print(quantile1,quantile3)
iqr=quantile3-quantile1
# Find the IQR
print(iqr)
## Find the lower bound value and the higher bound value
lower_bound_val = quantile1 -(3 * iqr)
upper_bound_val = quantile3 +(3 * iqr)
print(lower_bound_val,upper_bound_val)
fare = fare[(fare['dropoff_longitude']<=upper_bound_val) & (fare['dropof
f_longitude']>=lower_bound_val)]
```

```
-73.991743 -73.966233
0.025509999999997035
-74.06827299999999 -73.88970300000001
```

In [22]:
```
# dropoff_latitude
temp = fare['dropoff_latitude']
sorted(temp)
quantile1, quantile3= np.percentile( fare['dropoff_latitude'],[25,75])
print(quantile1,quantile3)
iqr=quantile3-quantile1
# Find the IQR
print(iqr)
## Find the lower bound value and the higher bound value
lower_bound_val = quantile1 -(3 * iqr)
upper_bound_val = quantile3 +(3 * iqr)
print(lower_bound_val,upper_bound_val)
fare = fare[(fare['dropoff_latitude']<=upper_bound_val) & (fare['dropoff
_latitude']>=lower_bound_val)]
```

```
40.73661 40.768131
0.031520999999999791
40.642047000000005 40.86269399999999
```

In [23]:
```
# Plot my pickup and dropff locations in 2 plots
# Red points are pickup locations and purple points are dropoff location
s
fig, ax = plt.subplots(1,2)
ax[0].scatter(fare['pickup_longitude'], fare['pickup_latitude'], c='r',s
= 0.1)
ax[1].scatter(fare['dropoff_longitude'], fare['dropoff_latitude'], c='m'
, s = 0.1)
ax[0].set_title('Pickup locations')
ax[0].set_xlabel("Longtitude")
ax[0].set_ylabel("Latitude")
ax[1].set_title('Dropff locations')
ax[1].set_xlabel("Longtitude")
ax[1].set_ylabel("Latitude")
plt.tight_layout()
```



In [24]:
```
# check out the type,columns,entries of data
fare.info()
# Here the datatype of pickup_datetime is wrong
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1790706 entries, 1 to 1999999
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: 123.0+ MB
```

Convert the pickup_datetime datatype to timestamp

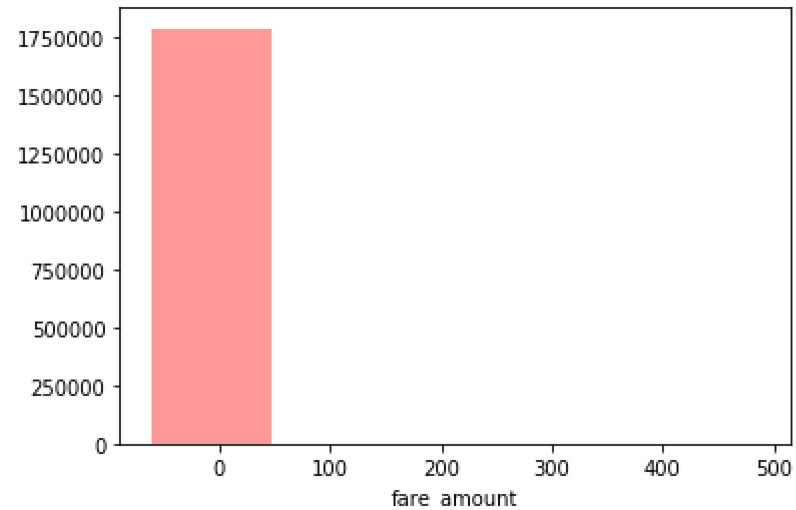
In [25]:
```
fare['pickup_datetime'] = pd.to_datetime(fare['pickup_datetime'],
                                       format='%Y-%m-%d %H:%M:%S %Z',
                                     errors='raise')
fare.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1790706 entries, 1 to 1999999
Data columns (total 8 columns):
key                  object
fare_amount          float64
pickup_datetime      datetime64[ns, UTC]
pickup_longitude     float64
pickup_latitude      float64
dropoff_longitude    float64
dropoff_latitude     float64
passenger_count      int64
dtypes: datetime64[ns, UTC](1), float64(5), int64(1), object(1)
memory usage: 123.0+ MB
```

Examine fare_amount

In [26]:
```
sns.distplot(fare['fare_amount'],bins=5
             ,kde=False,color='red')
# We can see that most of the fares are from 0 to 100, the data is right
-skewed
```

Out[26]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1a220c5710>
```



In [27]:
```
# Clear negative fare amount
fare = fare[fare['fare_amount'] > 0 ]
fare[fare['fare_amount'] <= 0 ]
```

Out[27]:

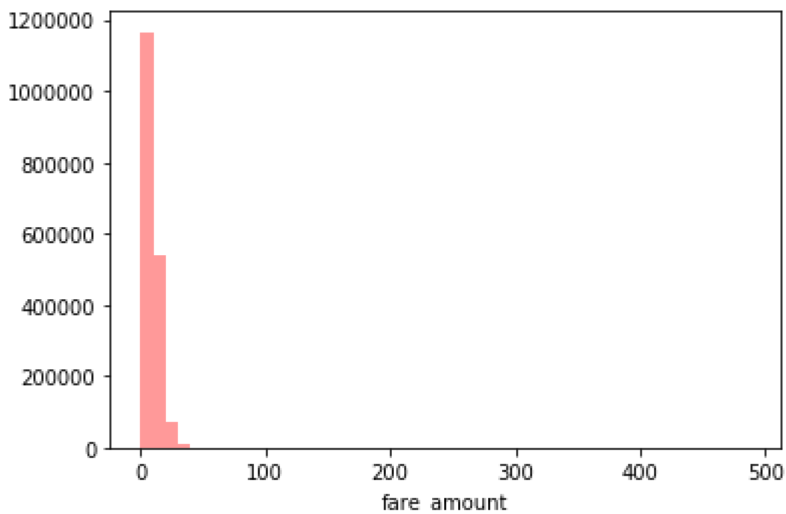
key	fare_amount	pickup_datetime	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff

In [28]:
```
fare['fare_amount']
```

Out[28]:
```
1          16.9
2           5.7
3           7.7
4           5.3
5          12.1
           ...
1999995     4.0
1999996     7.0
1999997    10.5
1999998    10.9
1999999    12.9
Name: fare_amount, Length: 1790624, dtype: float64
```

In [29]:
```
sns.distplot(fare['fare_amount'],bins=50,kde=False,color='red')
```

Out[29]: <matplotlib.axes._subplots.AxesSubplot at 0x1a23c85550>



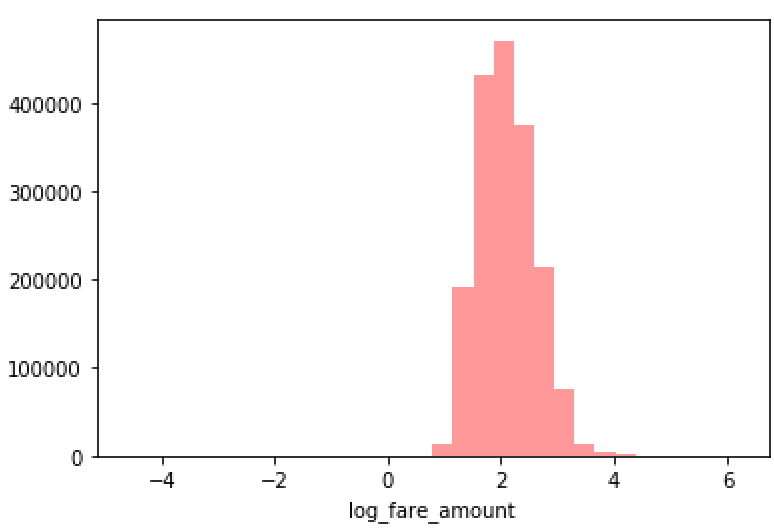
Deal with out right-skewed fare amount

It can be seen that there are too much skewness in the data, our analysis may not work well if we do not handle it. I will the log of fare_amount so that the distribution looks more normal and more easy to deal with outliers. Normality assumption of our response variable is an important part of the linear regression.

In [30]:
```
# Apply log transformation to the right-skewed data will normalize the d
ata
fare['log_fare_amount'] = [np.log(x) for x in fare['fare_amount']]
```

In [31]:
```
sns.distplot(fare['log_fare_amount'],bins=30,kde=False,color='red')
```

Out[31]: <matplotlib.axes._subplots.AxesSubplot at 0x1a216d6790>



In [32]:
```
fare['log_fare_amount']
```

Out[32]:
```
1          2.827314
2          1.740466
3          2.041220
4          1.667707
5          2.493205
             ...
1999995    1.386294
1999996    1.945910
1999997    2.351375
1999998    2.388763
1999999    2.557227
Name: log_fare_amount, Length: 1790624, dtype: float64
```

In [33]:
```
fare.describe()
```

Out[33]:

	fare_amount	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passen
count	1.790624e+06	1.790624e+06	1.790624e+06	1.790624e+06	1.790624e+06	1.7(
mean	9.465687e+00	-7.398136e+01	4.075218e+01	-7.397928e+01	4.075241e+01	1.6ℓ
std	5.488743e+00	1.710798e-02	2.298978e-02	1.932822e-02	2.662725e-02	1.3(
min	1.000000e-02	-7.406394e+01	4.064915e+01	-7.406807e+01	4.064205e+01	1.0(
25%	6.000000e+00	-7.399283e+01	4.073719e+01	-7.399197e+01	4.073678e+01	1.0(
50%	8.100000e+00	-7.398273e+01	4.075315e+01	-7.398144e+01	4.075393e+01	1.0(
75%	1.150000e+01	-7.397092e+01	4.076667e+01	-7.396823e+01	4.076807e+01	2.0(
max	4.880000e+02	-7.389666e+01	4.085470e+01	-7.388971e+01	4.086269e+01	6.0(

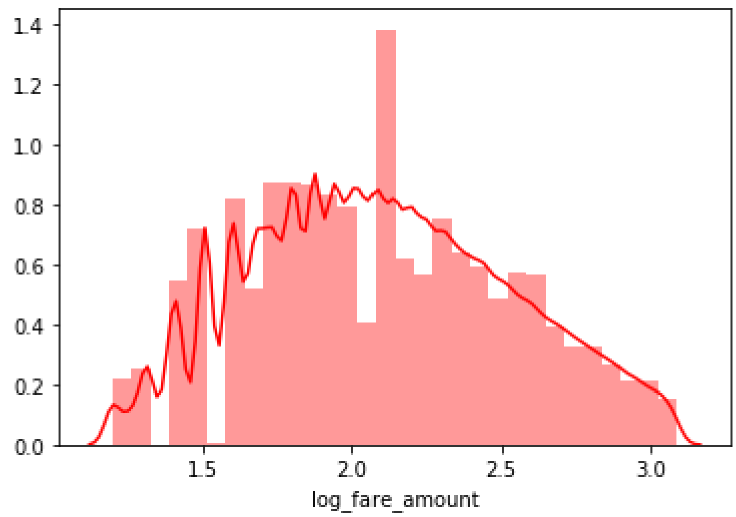
Now we also want to deal with the outliers in log_fare_amount

In [34]:
```
# Detecting outliers using Z score
outliers=[]
def outlier(data,column):
    sd=2
    mean = np.mean(data[column])
    std =np.std(data[column])
    for i in data.index:
        zscore= (data.loc[i,column] - mean)/std
        if np.abs(zscore) > sd:
            outliers.append(i)
    return outliers
```

In [35]:
```
# Removing outliers
indexes = outlier(fare,'log_fare_amount')
# Drop all outliers of fare_amount
fare = fare[~fare.index.isin(indexes)]
```

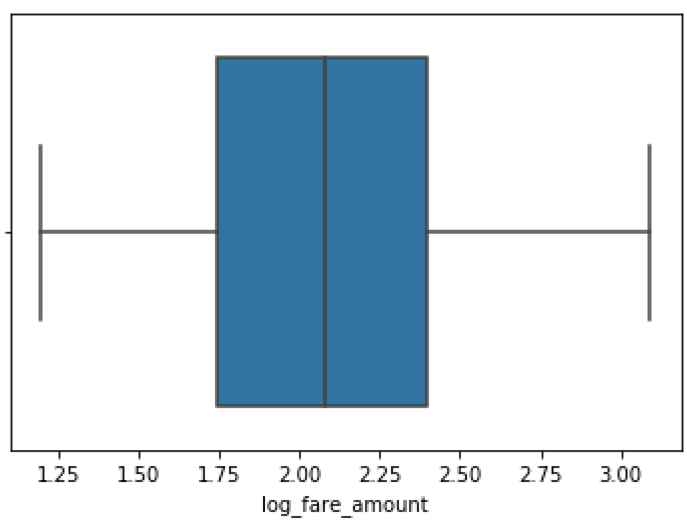
In [36]:
```
sns.distplot(fare['log_fare_amount'],bins=30,kde=True,color='red')
# We can see that our fare amount follows a right skewed distribution.
# In such a situation, it is not suitable to apply statistical measures
# We still need to apply data transformation comes to our aid in such si
tuations.
```

Out[36]: <matplotlib.axes._subplots.AxesSubplot at 0x1a1ddcfe90>



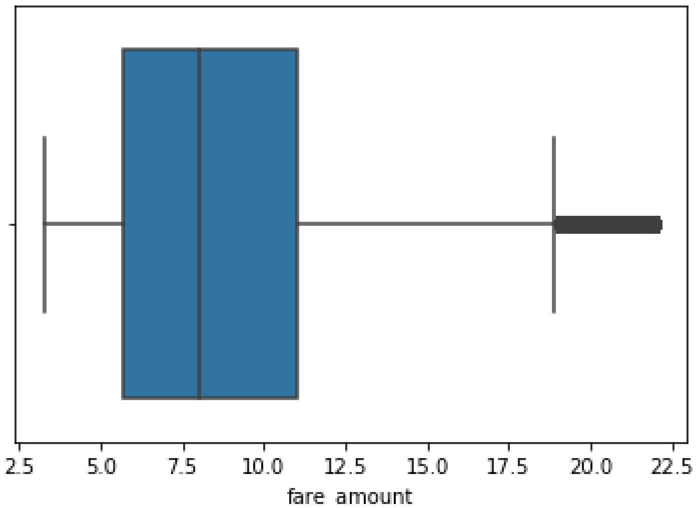
In [37]:
```
sns.boxplot(fare['log_fare_amount'])
# We can see that there are still many extreme values and are right-skew
ed
```

Out[37]: <matplotlib.axes._subplots.AxesSubplot at 0x1a24ad8750>



In [38]:
```
sns.boxplot(fare['fare_amount'])
```

Out[38]: <matplotlib.axes._subplots.AxesSubplot at 0x1a279b3090>



ANS:

To clean the data, I did the following things:

1. I dropped the missing values in the data
2. I dropped the records that have 0 passenger_count or more than 6 passengers
3. I dropped the records that have the same pickup and dropoff locations as well as extreme locations
4. I converted the datatype of pickup_datetime from string to timestamp
5. I dropped the records that have fare_amount <= 0
6. I transformed the fare_amount data to log form
7. I detected the outliers in fare_amount using Z scores method and dropped it

Task 2 - Train Test Split

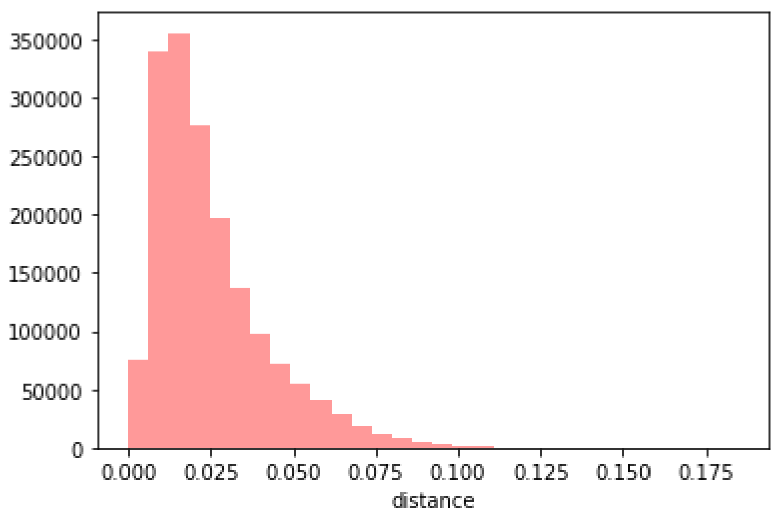
In [39]:
```
#Before spill it into train and test set, I first add attribute 'distanc
e' to our dataframe
```

In [40]:
```
# calculate the distance in each travel
x =  fare['pickup_longitude'] - fare['dropoff_longitude']
xsq = x**2
y = fare['pickup_latitude'] - fare['dropoff_latitude']
ysq = y**2
distance = np.sqrt(xsq+ysq)
fare['distance'] = distance
fare['distance']
```

Out[40]:
```
1          0.079696
2          0.013674
3          0.025340
4          0.019470
5          0.038675
             ...
1999995    0.003716
1999996    0.010427
1999997    0.034417
1999998    0.046952
1999999    0.057692
Name: distance, Length: 1726236, dtype: float64
```

In [41]:
```
sns.distplot(fare['distance'],bins=30,kde=False,color='red')
```

Out[41]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1a23c99a10>
```



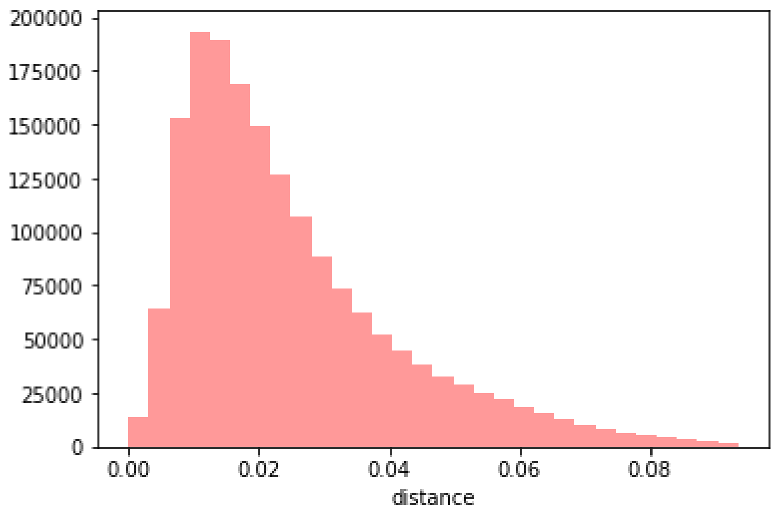
In [42]:

```
#InterQuantile Range
temp = fare['distance']
sorted(temp)
quantile1, quantile3= np.percentile(temp,[25,75])
print(quantile1,quantile3)
## Find the IQR

iqr=quantile3-quantile1
print(iqr)
## Find the lower bound value and the higher bound value

lower_bound_val = quantile1 -(3 * iqr)
upper_bound_val = quantile3 +(3 * iqr)
print(lower_bound_val,upper_bound_val)
fare = fare[(fare['distance']<=upper_bound_val) & (fare['distance']>=low
er_bound_val)]

# Detecting outliers using Z score
# outliers=[]
# def outlier(data,column):
#     sd=2
#     mean = np.mean(data[column])
#     std =np.std(data[column])
#     for i in data.index:
#         zscore= (data.loc[i,column] - mean)/std
#         if np.abs(zscore) > sd:
#             outliers.append(i)
#     return outliers
# # Removing outliers
# indexes = outlier(fare,'distance')
# # Drop all outliers of fare_amount
# fare = fare[~fare.index.isin(indexes)]
```

```
0.012569127823755483 0.03278928751133555
0.020220159687580067
-0.048091351238984725 0.09344976657407575
```

In [43]:
```
sns.distplot(fare['distance'],bins=30,kde=False,color='red')
# We can see that our distance also follows a right skewed distribution.
```

Out[43]: <matplotlib.axes._subplots.AxesSubplot at 0x1a246f9150>



In [44]:
```
# Extrat the hour of day
hour = fare['pickup_datetime'].dt.hour
fare['hour'] = hour
```

In [45]:
```
# TODO: code to split the data into training set and test set
from sklearn.model_selection import train_test_split
train,test = train_test_split(fare,train_size = 0.75,random_state = 101)
```

In [46]:
```
# See how many rows we have in train data
train.shape
```

Out[46]: (1291443, 11)

In [47]:
```
# Save train data to csv file
train.to_csv('taxi_fare_train.csv')
```

In [48]:
```
# See how many rows we have in test data
test.shape
```

Out[48]: (430481, 11)

ANS

I split my cleaned dataset into 2 parts: train and test. Train contains 75% of the original data and test contains 25% of the original dataset

Task 3 - Pearson Correlation

Distance and hour of a day is calculated at the beginning of task2 . The dataframe now contains distance as one feature.

In [49]:
```
train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1291443 entries, 1997692 to 1423644
Data columns (total 11 columns):
key                  1291443 non-null object
fare_amount          1291443 non-null float64
pickup_datetime      1291443 non-null datetime64[ns, UTC]
pickup_longitude     1291443 non-null float64
pickup_latitude      1291443 non-null float64
dropoff_longitude    1291443 non-null float64
dropoff_latitude     1291443 non-null float64
passenger_count      1291443 non-null int64
log_fare_amount      1291443 non-null float64
distance             1291443 non-null float64
hour                 1291443 non-null int64
dtypes: datetime64[ns, UTC](1), float64(7), int64(2), object(1)
memory usage: 118.2+ MB
```

In [50]:
```
from scipy.stats import pearsonr
corr1,pvalue1= pearsonr(train['distance'] , train['fare_amount'])
print(corr1)
```

```
0.825837047635312
```

In [51]:
```
corr2,pvalue2= pearsonr(train['hour'], train['distance'])
print(corr2)
```

```
-0.03815685838404937
```

In [52]:
```
corr3,pvalue3= pearsonr(train['hour'], train['fare_amount'])
print(corr3)
```

```
-0.009064474967195113
```

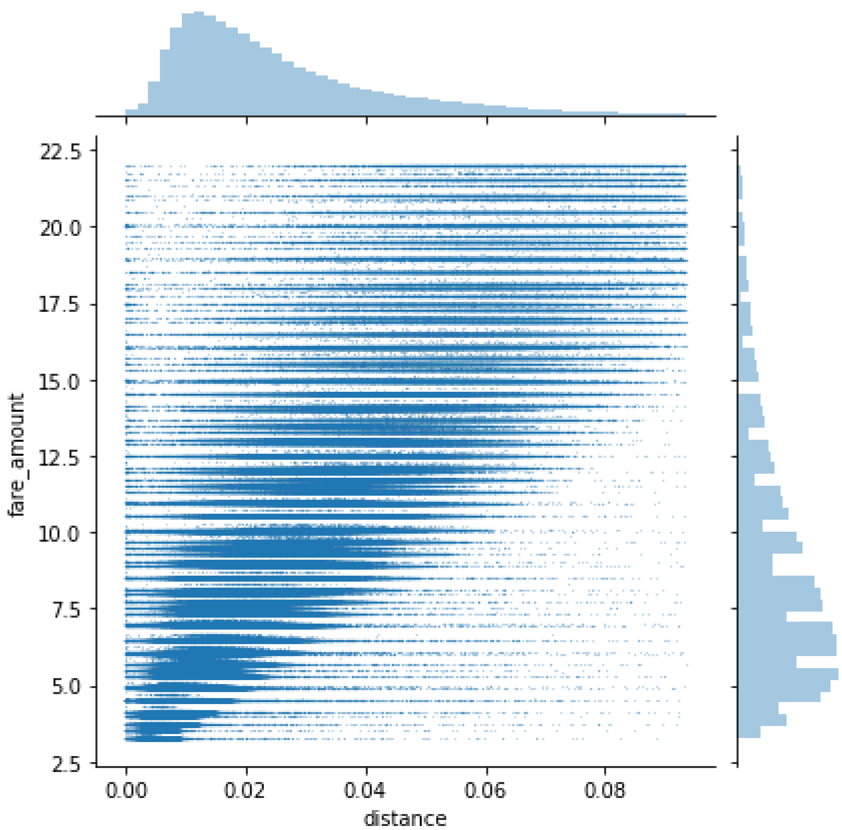
ANS

The highest correlation was between the distance and the taxi fare. Hence, we will use distance as predictors to predict taxi fare in a simple linenar model

Task 4 - Visualization

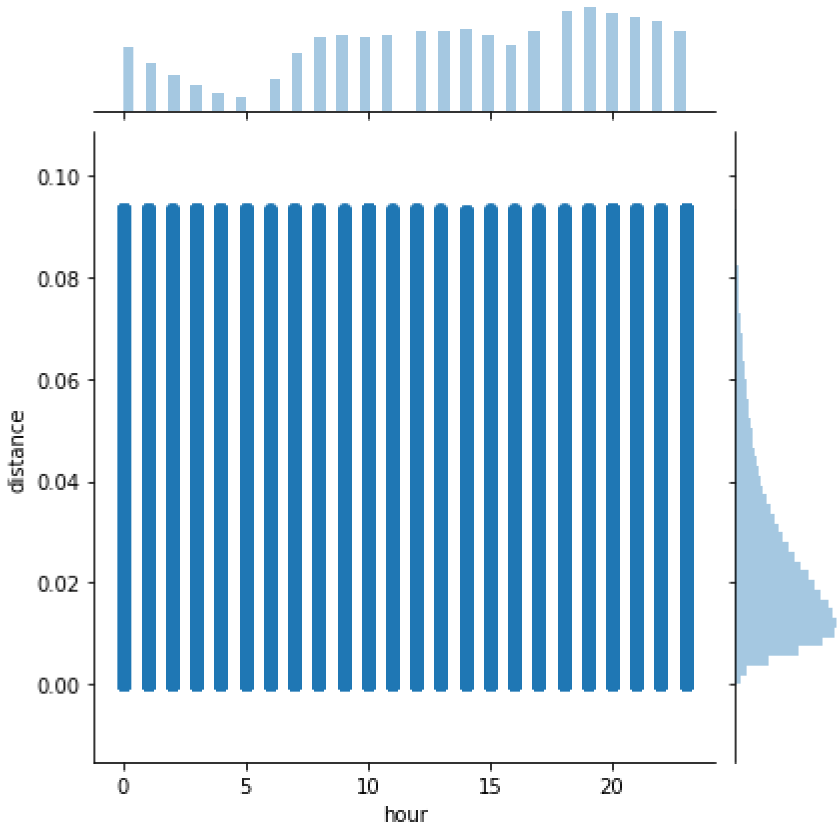
In [53]:
```
# TODO: code to visualize Task 3
sns.jointplot(x=train['distance'],y=train['fare_amount'],data = train,s=0.01)
# g = sns.pairplot(fare_cld, vars = ['hour','fare_amount','distance'])
# Create plots to see the relationship between variables of the 'x' and 'y' axis
```

Out[53]: <seaborn.axisgrid.JointGrid at 0x1a1c3f4a90>



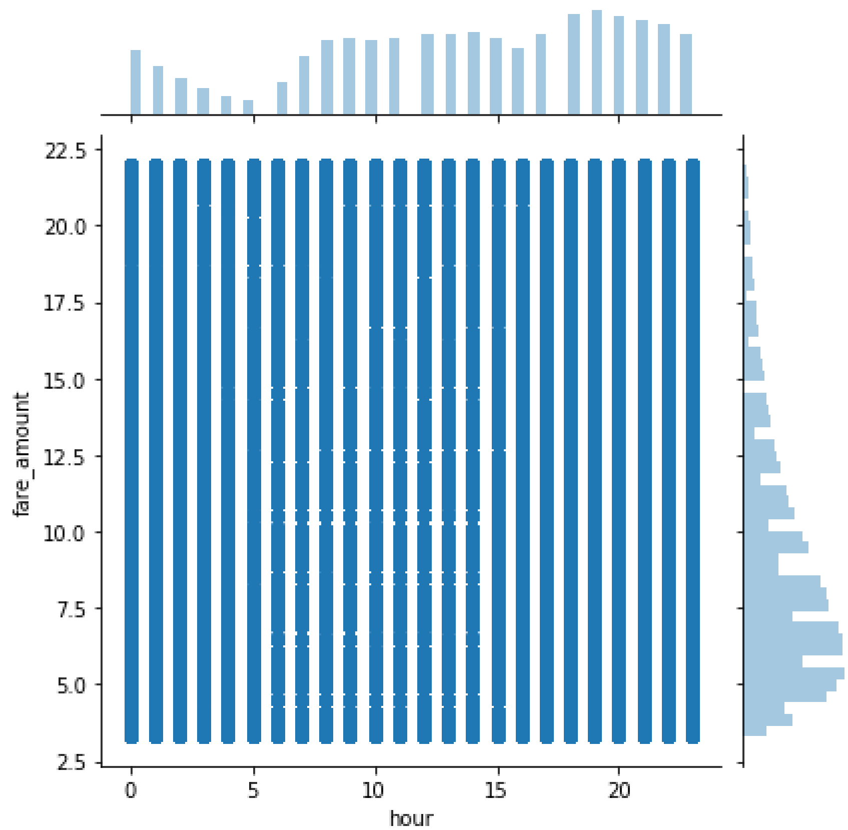
In [54]:
```
sns.jointplot(data= train,x='hour',y='distance')
# No linear relationship
```

Out[54]: <seaborn.axisgrid.JointGrid at 0x1a275b0fd0>



In [55]:
```
sns.jointplot(data= train,x='hour',y='fare_amount')
# No linear relationship
```

Out[55]: <seaborn.axisgrid.JointGrid at 0x1a1ec34910>



distance v.s fare_amount: We can see that there is strong linear relationship between these variables. Namely, the further the distance, the higher the fare_amount would be.

distance v.s hour: We can see there is no linear relationship bwtween these two variables Most of distance was below 1000.

hour v.s fare_amount: We can see that there is no linear relationship between hour and distance.

Part 5 - Linear Regression

In [56]:
```
train.columns
```

Out[56]:
```
Index(['key', 'fare_amount', 'pickup_datetime', 'pickup_longitude',
       'pickup_latitude', 'dropoff_longitude', 'dropoff_latitude',
       'passenger_count', 'log_fare_amount', 'distance', 'hour'],
      dtype='object')
```

Model specification

In task3, we observe that only the distance is strongly correlated with fare_amount. So I choose to use distance as my predictor variable

For outcome variable, I will use fare_amount;

In [57]:
```
X_train = train['distance']
y_train = train['fare_amount']
X_train
```

Out[57]:
```
1997692    0.054614
1355136    0.038861
1114747    0.026026
1522907    0.027807
539078     0.010094
             ...
767922     0.006564
237726     0.018481
1771372    0.010981
1467300    0.023060
1423644    0.035474
Name: distance, Length: 1291443, dtype: float64
```

In [58]:
```
# # log_fare_amount & distance
# from sklearn.linear_model import LinearRegression
# lm = LinearRegression()
# lm.fit(X_train.values.reshape(-1,1),y_train.values.reshape(-1,1))
# intercept, coefficients = lm.intercept_, lm.coef_
# print("intercept",intercept)
# print("coefficients",coefficients)
```

In [59]:
```
# fare_amount & distance
from sklearn.linear_model import LinearRegression
lm = LinearRegression()
lm.fit(X_train.values.reshape(-1,1),train['fare_amount'].values.reshape(
-1,1))
```

Out[59]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normaliz
e=False)
```

The coefficients

The distance feature seems pretty important has a coefficient of nearly 199.76844064.

In [60]:
```
intercept, coefficients = lm.intercept_, lm.coef_
print("intercept",intercept)
print("coefficients",coefficients)
```

```
intercept [3.94995852]
coefficients [[199.76844064]]
```

Now predict taxi fares in test dataset

In [61]:
```
X_test = test['distance']
y_test =  test['fare_amount']
max(X_test)
```

Out[61]:
```
0.09342412755814092
```

In [62]:
```
predictions = lm.predict(X_test.values.reshape(-1,1))
```

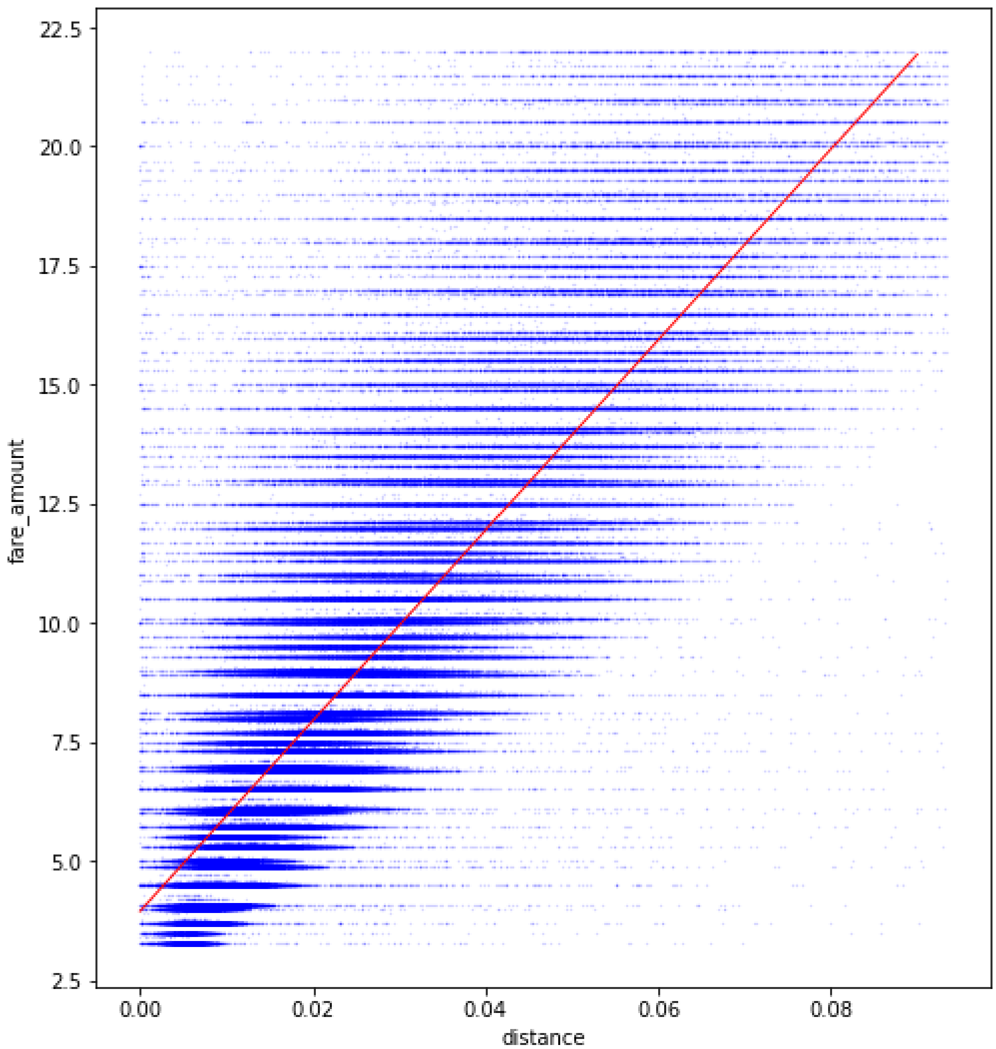
In [63]:
```
predictions
p = predictions.ravel()
```

In [64]:
```
from sklearn import metrics
print('MAE:', metrics.mean_absolute_error(y_test, predictions))
print('MSE:', metrics.mean_squared_error(y_test, predictions))
print('RMSE:', np.sqrt(metrics.mean_squared_error(y_true = y_test, y_pre
d = predictions)))
```

```
MAE: 1.63049863546229
MSE: 5.106544092840312
RMSE: 2.259766380146477
```

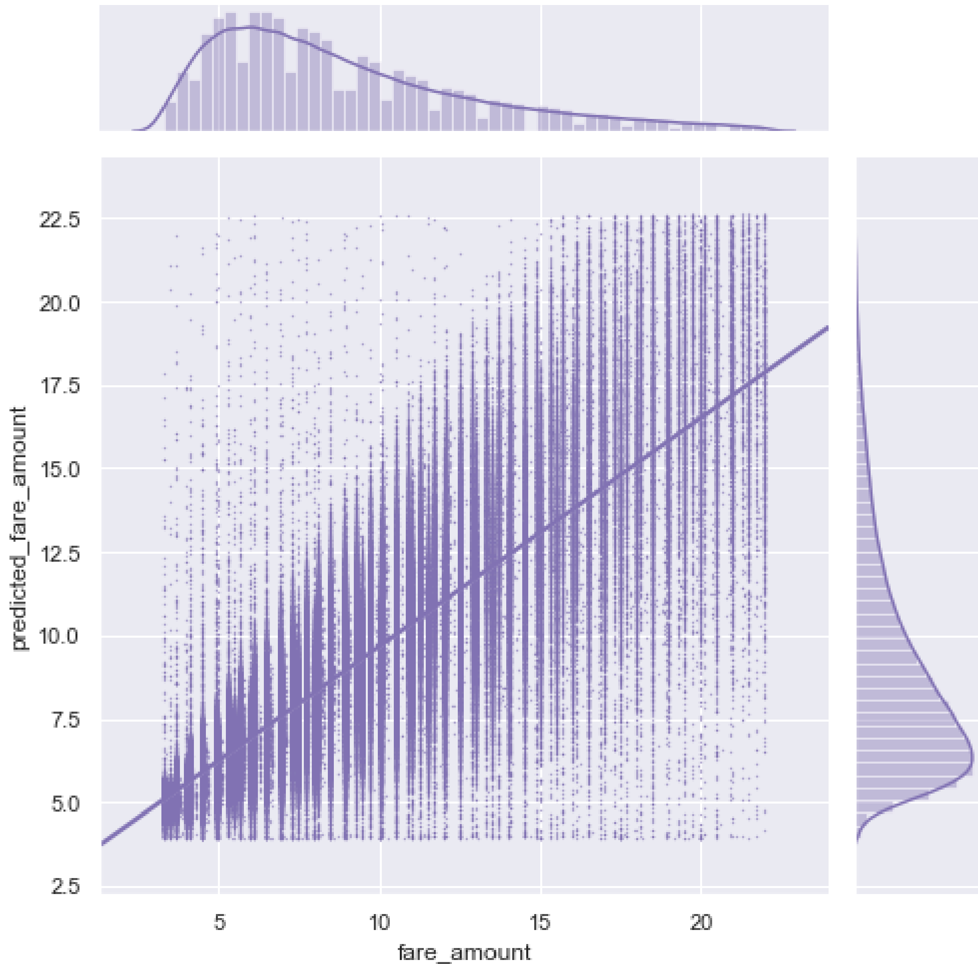
In [65]:
```
# Now I plots our distance against fare_amount and also adds out a red p
redicting line in the plot
# This plot might take some time to run
plt.figure(figsize= (8,9))
plt
plt.scatter(X_test,y_test, alpha=0.2, s=0.1, c = 'b')
x = np.linspace(0, 0.09, 100)
g = plt.plot(x, lm.intercept_ + x * lm.coef_[0], '-', c='r', lw=1)
plt.xlabel('distance')
plt.ylabel('fare_amount')
# Our predicted line predicts most of the points successfully
```

Out[65]: Text(0, 0.5, 'fare_amount')



In [66]:
```
# Create a dataframe df.
# Use this dataframe later to examine how well our data predict
p = predictions.flatten()
a = pd. DataFrame(y_test,columns= ['fare_amount'])
b = pd. DataFrame(p,columns = ['predicted_fare_amount'])
a.reset_index(drop=True, inplace=True)
b.reset_index(drop=True, inplace=True)
df = pd.concat([a,b],axis =1)
```

In [67]:
```
sns.set(style="darkgrid")
g = sns.jointplot("fare_amount", "predicted_fare_amount", data=df,
                  kind="reg", truncate=False, color="m", height=7, scatt
er_kws={'s':0.1})
# The regression line in the plot indicates that the log_fare_amount
# and predicted_log_fare_amount are quite close to each other (The point
s fall approximately on a 45 degree straight line)
```



Evaluating the predictions results and our model

Our simple linear regression model on the train set is : fare_amount = 3.94995852 + 199.76844064*distance The model works pretty well although there are still some errors probably because of the outliers.

We can see most of our data points fall in a line with predicted values and true values This is a good indication

Part 6 - Another Prediction Model

In [68]:
```
from sklearn.neighbors import KNeighborsRegressor
train.columns
# I will still use the train and test dataset from simple linear regress
ion as a comparison
```

Out[68]:
```
Index(['key', 'fare_amount', 'pickup_datetime', 'pickup_longitude',
       'pickup_latitude', 'dropoff_longitude', 'dropoff_latitude',
       'passenger_count', 'log_fare_amount', 'distance', 'hour'],
      dtype='object')
```

In [69]:
```
# When using K nearest neighbourhood, the scale of variables will affect
a lot in the prediction
# we will have to standardize every variable
df = pd.DataFrame(train,columns=['fare_amount','distance','hour'])
```

In [70]:
```
# Scale variable in the dataset
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
scaler.fit(df)
scaler.fit(df.drop('fare_amount',axis=1))
scaled_features = scaler.transform(df.drop('fare_amount',axis=1))

# Convert the scaled features to a dataframe and check the head of this
 dataframe to make sure the scaling worked.
# df_feat = pd.DataFrame(scaled_features,columns=fare.columns[:-2])
# df_feat.head()
```

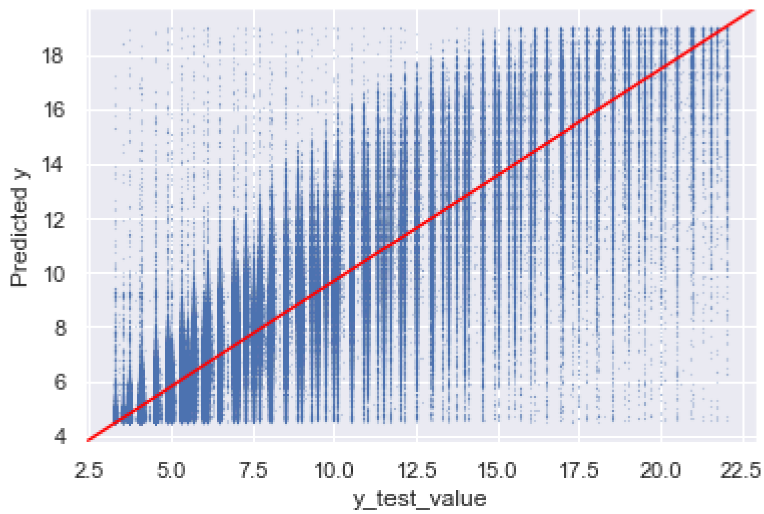
In [71]:
```
X_train2 = train['distance']
y_train2 = train['fare_amount']
```

In [72]:
```
len(X_train2)
# The n_neighbors parameter is usually the square root of number of obse
rvations
# Here we will use 1000 in our number of neighbors to consider
```

Out[72]:
```
1291443
```

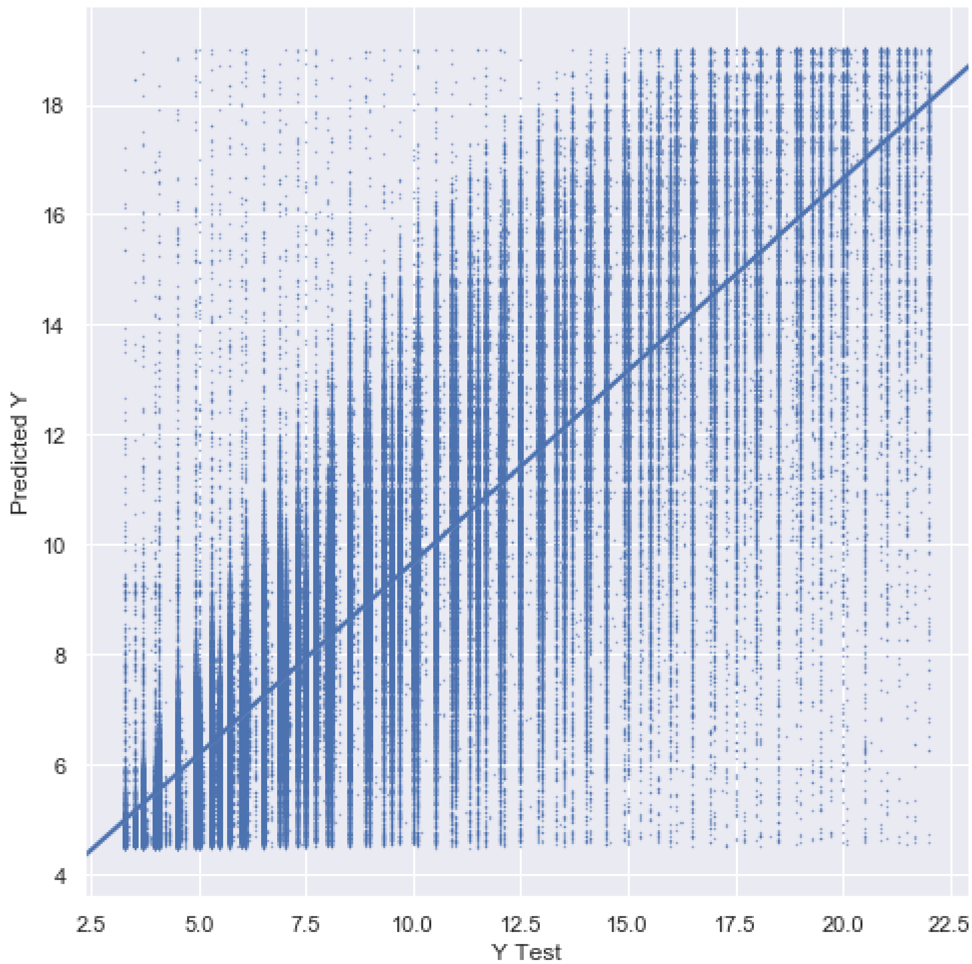
In [73]:
```
# instantiate the model
# This takes time
reg = KNeighborsRegressor(n_neighbors= 1000)
# fit the model using the training data
reg.fit(X_train2.values.reshape(-1,1), y_train2.values.reshape(-1,1))
y_pred2 = reg.predict(X_test.values.reshape(-1,1))
```

In [74]:
```
# Plot predicted values against test values
# Add a 45 degree red line
fig, ax = plt.subplots()
plt.scatter(y_test, y_pred2.flatten(),s=0.01)
plt.xlabel('y_test_value')
plt.ylabel('Predicted y')
# Adding a red line which indicates: y_test_value = predicted_y
line = mlines.Line2D([0, 1], [0, 1], color='red')
transform = ax.transAxes
line.set_transform(transform)
ax.add_line(line)
plt.show()
```



In [75]:
```
# Plot predicted values against test values
# uss sns's lmplot to estimate a regression line
a2 = pd. DataFrame(y_test,columns= ['fare_amount'])
b2 = pd. DataFrame(y_pred2,columns = ['predicted_value'])
a2.reset_index(drop=True, inplace=True)
b2.reset_index(drop=True, inplace=True)
df2 = pd.concat([a2,b2],axis =1)
sns.lmplot(data = df2,x = 'fare_amount', y = 'predicted_value',height=7,
scatter_kws={'s':0.1} )
plt.xlabel('Y Test')
plt.ylabel('Predicted Y')
```

Out[75]:
```
Text(12.085, 0.5, 'Predicted Y')
```



In [75]:
```
print('MAE:', metrics.mean_absolute_error(y_true = y_test, y_pred = y_pred2))
print('MSE:', metrics.mean_squared_error(y_true = y_test, y_pred = y_pred2))
print('RMSE:', np.sqrt(metrics.mean_squared_error(y_true = y_test, y_pred = y_pred2)))
#COMPARE TO FIRST MODEL:
# MAE: 1.63049863546229
# MSE: 5.106544092840312
# RMSE: 2.259766380146477
#Second:
# MAE: 1.5955803388535148
# MSE: 4.893758840353611
# RMSE: 2.212184178669039
```

```
MAE: 1.5955803388535148
MSE: 4.893758840353611
RMSE: 2.212184178669039
```

Analysis of improvement

1. Our second model has a better straight line in the plot of pred_value : test_value.
2. Mean_absolute_error,mean_squared_error,mean_squared_error all decreased compared to the simple model
3. This approach approximates it better. The reason is that the algorithm of k-nearest neighbour is more robust to outliers

In [ ]:
```
```