Data exploration

September 20, 2020

0.1 Data Exploration

My task during this test is to analyse data of yellow cab trips in NYC, and build a model that is able to suggest a passenger the amount of tip after their ride.

The data contains taxi rides from the months of March, June and November of 2017. Each month's data is stored in a CSV file. An accompanying pdf file explains the meaning of the columns.

First let's take a quick look at the data

[1]:
```
#Importing necessary modules
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
import gc
import warnings
warnings.filterwarnings('ignore')
import geopandas
import os
```

[2]:
```
#Download the data
os.chdir('./data')
!wget 'https://s3.amazonaws.com/nyc-tlc/trip+data/yellow_tripdata_2017-03.csv'
!wget 'https://s3.amazonaws.com/nyc-tlc/trip+data/yellow_tripdata_2017-06.csv'
!wget 'https://s3.amazonaws.com/nyc-tlc/trip+data/yellow_tripdata_2017-11.csv'
os.chdir('..')
```

[3]:
```
#Loading the data
march = pd.read_csv('./data/yellow_tripdata_2017-03.csv')
june = pd.read_csv('./data/yellow_tripdata_2017-06.csv')
nov = pd.read_csv('./data/yellow_tripdata_2017-11.csv')
df = pd.concat([march, june, nov], ignore_index=True)
del march, june, nov
gc.collect()
```

[3]:
```
10
```

[4]:
```
#General information about the DataFrame
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 29236424 entries, 0 to 29236423
Data columns (total 17 columns):
 #   Column                 Dtype
---  ------                 -----
 0   VendorID               int64
 1   tpep_pickup_datetime   object
 2   tpep_dropoff_datetime  object
 3   passenger_count        int64
 4   trip_distance          float64
 5   RatecodeID             int64
 6   store_and_fwd_flag     object
 7   PULocationID           int64
 8   DOLocationID           int64
 9   payment_type           int64
 10  fare_amount            float64
 11  extra                  float64
 12  mta_tax                float64
 13  tip_amount             float64
 14  tolls_amount           float64
 15  improvement_surcharge  float64
 16  total_amount           float64
dtypes: float64(8), int64(6), object(3)
memory usage: 3.7+ GB
```

[5]:
```
df.head(10)
```

[5]:

	VendorID	tpep_pickup_datetime	tpep_dropoff_datetime	passenger_count	trip_distance	RatecodeID	store_and_fwd_flag	PULocationID	DOLocationID
0	2	2017-03-09 21:30:11	2017-03-09 21:44:20	1	4.06	1	N	148	48
1	2	2017-03-09 21:47:00	2017-03-09 21:58:01	1	2.73	1	N	48	107
2	2	2017-03-09 22:01:08	2017-03-09 22:11:16	1	2.27	1	N	79	162
3	2	2017-03-09 22:16:05	2017-03-10 06:26:11	1	3.86	1	N	237	41
4	2	2017-03-31 06:31:53	2017-03-31 06:41:48	1					
5	1	2017-03-01 00:00:00	2017-03-01 00:14:22	1					
6	1	2017-03-01 00:00:00	2017-03-01 00:19:30	1					
7	1	2017-03-01 00:00:00	2017-03-01 00:34:27	1					
8	1	2017-03-01 00:00:00	2017-03-01 00:21:31	1					
9	2	2017-03-15 00:07:59	2017-03-15 00:38:08	1					

```
4           3.45           1                  N           41           162
5           2.80           1                  N          261            79
6           6.00           1                  N           87           142
7           8.70           1                  N          142           181
8           3.70           1                  N           68           141
9           4.21           1                  N          261           163

   payment_type  fare_amount  extra  mta_tax  tip_amount  tolls_amount  \
0             1         14.0    0.5      0.5        3.06           0.0
1             2         11.5    0.5      0.5        0.00           0.0
2             1         10.0    0.5      0.5        2.82           0.0
3             1         12.0    0.5      0.5        3.99           0.0
4             2         12.0    0.5      0.5        0.00           0.0
5             1         12.5    0.5      0.5        1.00           0.0
6             1         19.5    0.5      0.5        3.50           0.0
7             1         30.0    0.5      0.5        7.80           0.0
8             1         16.5    0.5      0.5        1.50           0.0
9             1         20.5    0.0      0.5        4.26           0.0

   improvement_surcharge  total_amount
0                    0.3         18.36
1                    0.3         12.80
2                    0.3         14.12
3                    0.3         17.29
4                    0.3         13.30
5                    0.3         14.80
6                    0.3         24.30
7                    0.3         39.10
8                    0.3         19.30
9                    0.3         25.56
```

[6]:
```
#Number of unique values in each column
df.nunique()
```

[6]:
```
VendorID                    2
tpep_pickup_datetime     7021748
tpep_dropoff_datetime    7032908
passenger_count             11
trip_distance             5485
RatecodeID                   7
store_and_fwd_flag           2
PULocationID               262
DOLocationID               263
payment_type                 5
fare_amount               3442
extra                       76
mta_tax                     46
```

```
tip_amount                 4742
tolls_amount               1918
improvement_surcharge         7
total_amount              16789
dtype: int64
```

[7]:
```
#Number of missing values in each column
df.isna().sum()
```

[7]:
```
VendorID                 0
tpep_pickup_datetime     0
tpep_dropoff_datetime    0
passenger_count          0
trip_distance            0
RatecodeID               0
store_and_fwd_flag       0
PULocationID             0
DOLocationID             0
payment_type             0
fare_amount              0
extra                    0
mta_tax                  0
tip_amount               0
tolls_amount             0
improvement_surcharge    0
total_amount             0
dtype: int64
```

[8]:
```
#List unique values of some of the columns
for col in ['VendorID', 'passenger_count', 'RatecodeID', 'store_and_fwd_flag',␣
 ↪'payment_type']:
    print(f'{col}: {df[col].unique()}')
```

```
VendorID: [2 1]
passenger_count: [  1   2   5   3   4   6   0   9   8   7 192]
RatecodeID: [ 1  5  2  3  4 99  6]
store_and_fwd_flag: ['N' 'Y']
payment_type: [1 2 3 4 5]
```

[9]:
```
#There's a strange value in the passenger count column
df[df['passenger_count']==192]
```

[9]:
```
          VendorID tpep_pickup_datetime tpep_dropoff_datetime  \
28795318         2  2017-11-29 18:49:11   2017-11-29 18:55:47

          passenger_count  trip_distance  RatecodeID store_and_fwd_flag  \
28795318              192           1.07           1                  N
```

```
          PULocationID  DOLocationID  payment_type  fare_amount  extra  \
28795318           158            68             1          6.5    1.0

          mta_tax  tip_amount  tolls_amount  improvement_surcharge  \
28795318      0.5        1.24           0.0                    0.3

          total_amount
28795318          9.54
```

[10]:
```
#Take a look at the numerical columns
#df[['trip_distance', 'PULocationID', 'DOLocationID', 'fare_amount', 'extra',␣
 ↪'mta_tax', 'tip_amount', 'improvement_surcharge', 'total_amount']].describe()
df.describe()
```

[10]:
```
            VendorID  passenger_count  trip_distance    RatecodeID  \
count  2.923642e+07     2.923642e+07   2.923642e+07  2.923642e+07
mean   1.545904e+00     1.617798e+00   2.919386e+00  1.043350e+00
std    4.978884e-01     1.260992e+00   4.476535e+00  5.095108e-01
min    1.000000e+00     0.000000e+00   0.000000e+00  1.000000e+00
25%    1.000000e+00     1.000000e+00   9.700000e-01  1.000000e+00
50%    2.000000e+00     1.000000e+00   1.600000e+00  1.000000e+00
75%    2.000000e+00     2.000000e+00   3.010000e+00  1.000000e+00
max    2.000000e+00     1.920000e+02   9.496980e+03  9.900000e+01

       PULocationID  DOLocationID  payment_type   fare_amount         extra  \
count  2.923642e+07  2.923642e+07  2.923642e+07  2.923642e+07  2.923642e+07
mean   1.632024e+02  1.611910e+02  1.329500e+00  1.310930e+01  3.339407e-01
std    6.661417e+01  7.047819e+01  4.903471e-01  1.472817e+02  4.615744e-01
min    1.000000e+00  1.000000e+00  1.000000e+00 -5.500000e+02 -5.371000e+01
25%    1.140000e+02  1.070000e+02  1.000000e+00  6.500000e+00  0.000000e+00
50%    1.620000e+02  1.620000e+02  1.000000e+00  9.500000e+00  0.000000e+00
75%    2.330000e+02  2.330000e+02  2.000000e+00  1.450000e+01  5.000000e-01
max    2.650000e+02  2.650000e+02  5.000000e+00  6.304618e+05  6.980000e+01

            mta_tax    tip_amount  tolls_amount  improvement_surcharge  \
count  2.923642e+07  2.923642e+07  2.923642e+07           2.923642e+07
mean   4.973104e-01  1.874055e+00  3.290113e-01           2.996283e-01
std    7.081708e-02  2.645570e+00  1.968881e+00           1.408904e-02
min   -5.000000e-01 -1.120000e+02 -1.750000e+01          -3.000000e-01
25%    5.000000e-01  0.000000e+00  0.000000e+00           3.000000e-01
50%    5.000000e-01  1.360000e+00  0.000000e+00           3.000000e-01
75%    5.000000e-01  2.460000e+00  0.000000e+00           3.000000e-01
max    1.400000e+02  4.500000e+02  1.018950e+03           1.000000e+00

       total_amount
count  2.923642e+07
```

```
mean    1.644710e+01
std     1.475248e+02
min    -5.503000e+02
25%     8.750000e+00
50%     1.180000e+01
75%     1.780000e+01
max     6.304631e+05
```

[11]:
```
#There are some strangely hight total_amount values
df[df['total_amount']>1000].head(10)
```

[11]:

	VendorID	tpep_pickup_datetime	tpep_dropoff_datetime	passenger_count	trip_distance	RatecodeID	store_and_fwd_flag	PULocationID	DOLocationID	payment_type	fare_amount	extra	mta_tax	tip_amount
592656	1	2017-03-01 16:58:17	2017-03-01 18:14:19	1	18.6	3	N	161	1	3	82.00	0.00	0.00	0.0
971076	1	2017-03-02 17:57:18	2017-03-02 18:20:10	1	4.1	1	N	264	264	3	8015.00	-13.68	14.48	0.0
1926622	1	2017-03-04 21:27:09	2017-03-04 21:43:13	2	3.5	1	N	264	264	3	3012.00	-53.71	54.51	0.0
1960809	1	2017-03-04 22:38:45	2017-03-04 22:44:54	1	1.7	1	N	264	264	3	8006.50	-45.72	46.52	0.0
2310518	1	2017-03-05 21:21:56	2017-03-05 21:31:20	2	2.4	1	N	264	264	3	3008.00	0.00	0.50	0.0
3955474	1	2017-03-10 13:12:57	2017-03-10 13:56:48	5	25.9	3	N	158	1	3	86.50	0.00	0.00	0.0
4146145	1	2017-03-11 23:07:12	2017-03-11 23:21:00	1	3.2	1	N	264	264	2	3011.00	-17.73	18.53	0.0
4835686	1	2017-03-13 23:36:19	2017-03-13 23:40:36	1	1.6	1	N	264	264	2	8005.50	-52.73	53.53	0.0
6617066	1	2017-03-25 14:40:26	2017-03-25 14:40:58	1	0.0	4	N	144	144	3	2759.07	0.00	0.00	0.0
6618420	1	2017-03-25 14:45:26	2017-03-25 14:45:29	1	0.0	4	N	148	148	3	2759.07	0.00	0.00	0.0

	tolls_amount	improvement_surcharge	total_amount
592656	923.5	0.3	1005.80
971076	0.0	0.0	8015.80
1926622	0.0	0.0	3012.80
1960809	0.0	0.0	8007.30
2310518	0.0	0.3	3008.80
3955474	919.5	0.3	1006.30
4146145	0.0	0.0	3011.80
4835686	0.0	0.0	8006.30
6617066	0.0	0.3	2759.37
6618420	0.0	0.3	2759.37

Summary The entire dataset contains almost 30 million entries. There are no obvious missing values in the data. There are two columns with datetime objects, several categorical columns encoded as integers, and some columns with floats. At the first look, there are some strange entries, such as an entry with a passenger count of 192, or several really short, but very expensive trips.

Let's take a bit deeper look at the columns.

0.1.1 fare_amount, extra, mta_tax, tip_amount, tolls_amount, improvement_surcharge, total_amount

First let's take a look at the different columns that add up the cost of the trips.

[12]:
```
df[['fare_amount', 'extra', 'mta_tax', 'tip_amount', 'tolls_amount',␣
↪'improvement_surcharge', 'total_amount']].describe()
```

[12]:

	fare_amount	extra	mta_tax	tip_amount	tolls_amount	\
count	2.923642e+07	2.923642e+07	2.923642e+07	2.923642e+07	2.923642e+07	
mean	1.310930e+01	3.339407e-01	4.973104e-01	1.874055e+00	3.290113e-01	
std	1.472817e+02	4.615744e-01	7.081708e-02	2.645570e+00	1.968881e+00	
min	-5.500000e+02	-5.371000e+01	-5.000000e-01	-1.120000e+02	-1.750000e+01	
25%	6.500000e+00	0.000000e+00	5.000000e-01	0.000000e+00	0.000000e+00	
50%	9.500000e+00	0.000000e+00	5.000000e-01	1.360000e+00	0.000000e+00	
75%	1.450000e+01	5.000000e-01	5.000000e-01	2.460000e+00	0.000000e+00	
max	6.304618e+05	6.980000e+01	1.400000e+02	4.500000e+02	1.018950e+03	

	improvement_surcharge	total_amount
count	2.923642e+07	2.923642e+07
mean	2.996283e-01	1.644710e+01
std	1.408904e-02	1.475248e+02
min	-3.000000e-01	-5.503000e+02
25%	3.000000e-01	8.750000e+00
50%	3.000000e-01	1.180000e+01
75%	3.000000e-01	1.780000e+01

```
max              1.000000e+00  6.304631e+05
```

There are cases where the total_amount paid is a negative value. Let's check if any of them include a positive amount of tip.

[13]:
```
#Find entries where the total_amount is negative but the tip_amount is positive.
df[(df['total_amount']<0) & (df['tip_amount']>0)]
```

[13]:
```
Empty DataFrame
Columns: [VendorID, tpep_pickup_datetime, tpep_dropoff_datetime,
passenger_count, trip_distance, RatecodeID, store_and_fwd_flag, PULocationID,
DOLocationID, payment_type, fare_amount, extra, mta_tax, tip_amount,
tolls_amount, improvement_surcharge, total_amount]
Index: []
```

The total amount is supposed to be the total of the different costs. Let's double check if this is true.

[14]:
```
#find columns where the sum of the different costs is different from the␣
↪total_amount
df[df[['fare_amount', 'extra', 'mta_tax', 'tip_amount', 'tolls_amount',␣
↪'improvement_surcharge']].sum(axis=1) -␣
↪df['total_amount']>1e3][['fare_amount', 'extra', 'mta_tax', 'tip_amount',␣
↪'tolls_amount', 'improvement_surcharge', 'total_amount']].head()
```

[14]:
```
Empty DataFrame
Columns: [fare_amount, extra, mta_tax, tip_amount, tolls_amount,
improvement_surcharge, total_amount]
Index: []
```

In the pdf explaining the contents of the columns it is noted that the column 'total_amount' includes the tips when the passenger paid by credit card. Let's check if there's any tip included with other payment types.

[15]:
```
#Number of entries with payment_type other than credit card
df[df['payment_type']!=1]['payment_type'].count()
```

[15]:
```
9391893
```

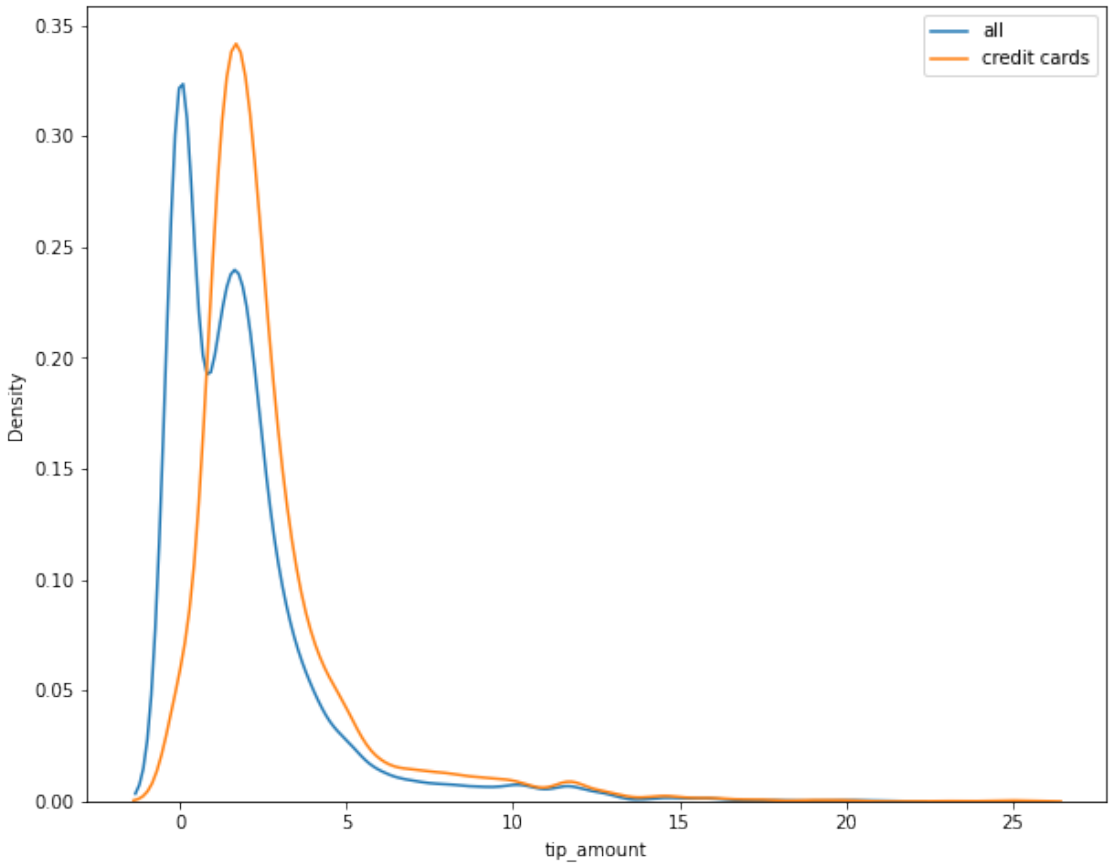
[16]:
```
#Number of entries where the payment_type is not credit card and the tip_amount␣
↪is not zero
df[(df['payment_type']!=1) & (df['tip_amount']!=0)]['payment_type'].count()
```

[16]:
```
475
```

Out of the almost 10 million transactions made by other than credit card only 475 includes a tip. Below is the distribution of all of the tips (left) and the tips of the credit card payments (right).

[17]:
```
fig, ax = plt.subplots(figsize=(10,8))
sns.distplot(df['tip_amount'].sample(5000), ax=ax, hist=False, label='all')
sns.distplot(df[df['payment_type']==1]['tip_amount'].sample(5000), ax=ax,␣
↪hist=False, label='credit cards')
ax.legend()
```

[17]:
```
<matplotlib.legend.Legend at 0x7ff95c7b6cf8>
```



Since the goal of this project is to predict tips, any entry without tips is useless. Therefore from now on I will only focus on the credit card payments.

[18]:
```
#Keep only credit card paid entries
df = df[df['payment_type']==1]
df.drop(['payment_type'],axis=1, inplace=True)
df.shape
```

[18]:
```
(19844531, 16)
```

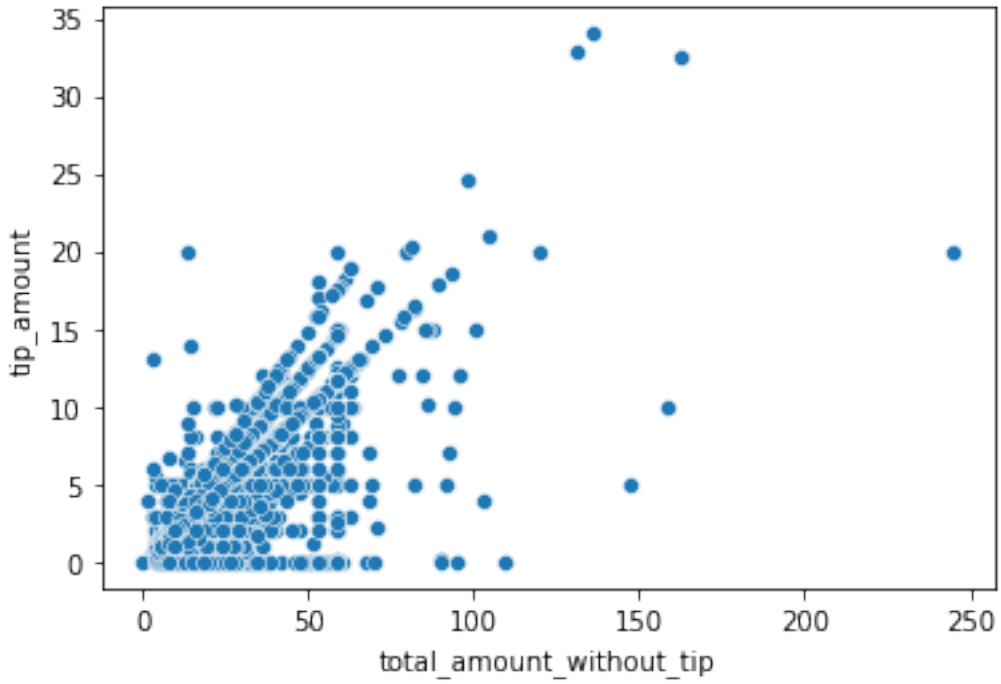
The total_amount column includes the tip, so let's create a column of the total amount without the tip.

[19]:
```
#Add up the costs without the tip included
df['total_amount_without_tip'] = df[['fare_amount', 'extra', 'mta_tax',␣
↪'tolls_amount', 'improvement_surcharge']].sum(axis=1).round(2)
gc.collect()
```

[19]:
```
0
```

[20]:
```
sns.scatterplot(data=df.sample(10000), x='total_amount_without_tip',␣
↪y='tip_amount')
```

[20]:
```
<AxesSubplot:xlabel='total_amount_without_tip', ylabel='tip_amount'>
```



There are entries where the amount of the tip is unusually high:

[21]:
```
df[df['tip_amount']>df['total_amount_without_tip']].head(10)
```

[21]:

	VendorID	tpep_pickup_datetime	tpep_dropoff_datetime	passenger_count	\
2681	1	2017-03-10 14:18:00	2017-03-10 14:37:14	1	
3743	1	2017-03-10 14:21:39	2017-03-10 14:21:41	1	
4491	1	2017-03-10 14:24:12	2017-03-10 14:24:14	1	
4915	1	2017-03-10 14:25:42	2017-03-10 14:27:09	1	
7073	2	2017-03-10 14:33:02	2017-03-10 14:33:06	1	
7478	1	2017-03-10 14:34:27	2017-03-10 14:34:36	1	
7551	2	2017-03-10 14:34:45	2017-03-10 14:34:58	1	
8236	1	2017-03-10 14:37:05	2017-03-10 14:37:08	1	

```
12537         1  2017-03-10 14:50:29   2017-03-10 14:52:45                1
12665         1  2017-03-10 14:50:54   2017-03-10 14:53:31                1

       trip_distance  RatecodeID store_and_fwd_flag  PULocationID  \
2681             6.5           1                  N           244
3743             4.6           1                  N           237
4491             0.0           1                  N           211
4915             0.8           1                  N           236
7073             0.0           1                  N           236
7478             0.0           1                  N           138
7551             0.0           1                  N           230
8236             1.8           1                  N           162
12537            0.3           1                  N           107
12665            0.1           1                  N           144

       DOLocationID  fare_amount  extra  mta_tax  tip_amount  tolls_amount  \
2681            265         21.0    0.0      0.5        68.0          10.5
3743            237          2.5    0.0      0.5        15.0           0.0
4491            211          2.5    0.0      0.5         5.0           0.0
4915            236          3.0    0.0      0.5        50.0           0.0
7073            236          2.5    0.0      0.5         5.0           0.0
7478            138          2.5    0.0      0.5        10.0           0.0
7551            230          2.5    0.0      0.5        10.0           0.0
8236            162          2.5    0.0      0.5        11.0           0.0
12537           107          3.5    0.0      0.5         5.0           0.0
12665           144          3.5    0.0      0.5         5.0           0.0

       improvement_surcharge  total_amount  total_amount_without_tip
2681                     0.3         100.3                      32.3
3743                     0.3          18.3                       3.3
4491                     0.3           8.3                       3.3
4915                     0.3          53.8                       3.8
7073                     0.3           8.3                       3.3
7478                     0.3          13.3                       3.3
7551                     0.3          13.3                       3.3
8236                     0.3          14.3                       3.3
12537                    0.3           9.3                       4.3
12665                    0.3           9.3                       4.3
```

[22]:
```
df[df['tip_amount']>df['total_amount_without_tip']]['tip_amount'].count()
```

[22]:
```
18671
```

0.1.2 VendorID

There are 2 kinds of vendors.

[23]:
```
df['VendorID'].value_counts()
```

[23]:
```
2    10880495
1     8964036
Name: VendorID, dtype: int64
```

Both provider is represented almost equally.

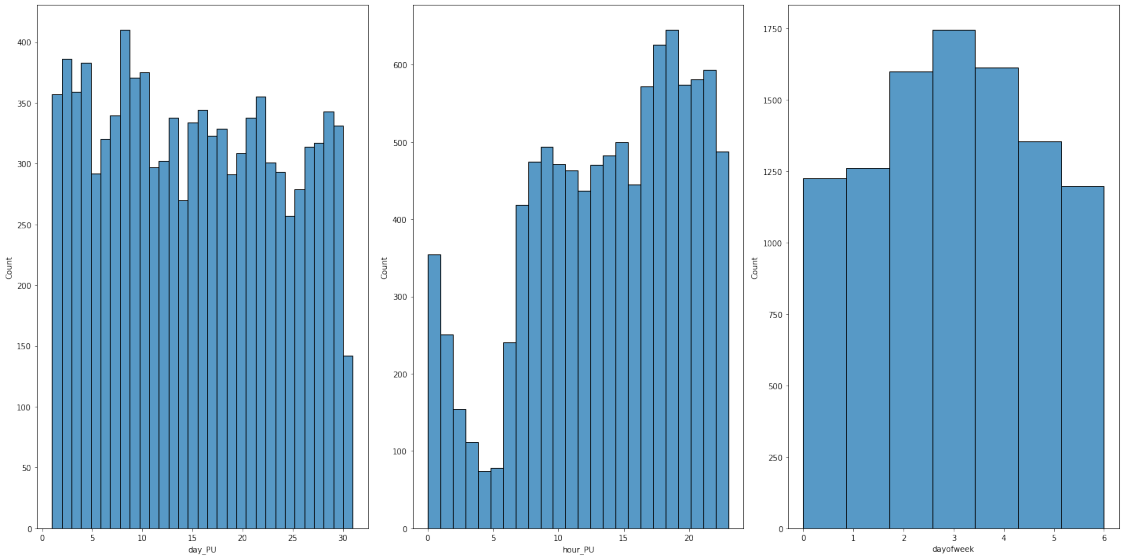
0.1.3 tpep_pickup_datetime and tpep_dropoff_datetime

These ones are the pickup and dropoff times, they are probably more useful converted into datetime formats.

[24]:
```
df['tpep_dropoff_datetime'] = pd.to_datetime(df['tpep_dropoff_datetime'])
df['tpep_pickup_datetime'] = pd.to_datetime(df['tpep_pickup_datetime'])
```

[25]:
```
#Creating features based on the pickup and dropoff times
df['month'] = df['tpep_pickup_datetime'].dt.month
df['day_PU'] = df['tpep_pickup_datetime'].dt.day
df['day_DO'] = df['tpep_dropoff_datetime'].dt.day
df['dayofweek'] = df['tpep_pickup_datetime'].dt.dayofweek
df['hour_PU'] = df['tpep_pickup_datetime'].dt.hour
df['hour_DO'] = df['tpep_dropoff_datetime'].dt.hour
```

[26]:
```
#Some quick plots, sampling the data
fig, ax = plt.subplots(1, 3, figsize=(20,10), )
#fig.suptitle('Mean tip amount per taxi zones', fontsize=20)
sns.histplot(df['day_PU'].sample(10000),bins=31,  ax=ax[0])
#ax[0].set_title('Pickup', fontsize=16)

sns.histplot(df['hour_PU'].sample(10000), bins=24, ax=ax[1])
#ax[1].set_title('Dropoff', fontsize=16)

sns.histplot(df['dayofweek'].sample(10000), bins=7, ax=ax[2])
#ax[1].set_title('Dropoff', fontsize=16)
fig.tight_layout()
```



0.1.4 trip_distance

[27]:
```
#The majority of the trips are short.
df['trip_distance'].describe()
```

[27]:
```
count    1.984453e+07
mean     3.067932e+00
std      3.817437e+00
min      0.000000e+00
25%      1.000000e+00
50%      1.700000e+00
75%      3.200000e+00
max      7.025000e+02
Name: trip_distance, dtype: float64
```

[28]:
```
#Cost per mile
(df[df['trip_distance']>0]['total_amount_without_tip']/
 ↪df[df['trip_distance']>0]['trip_distance']).describe()
```

[28]:
```
count    1.976972e+07
mean     7.560795e+00
std      5.663953e+01
min     -1.650000e+02
25%      4.708333e+00
50%      6.181818e+00
75%      8.076923e+00
max      3.208000e+04
```

```
dtype: float64
```

There are some strangely hight cost per mile values

[29]:
```
(df[df['trip_distance']>0]['total_amount_without_tip']/
 ↪df[df['trip_distance']>0]['trip_distance']).sort_values(ascending=False).
 ↪head(10)
```

[29]:
```
19892667    32080.0
6333969     30080.0
7256023     30030.0
6879091     30030.0
18302488    27356.0
19541238    25080.0
8462202     21680.0
2769076     20100.0
27103774    18080.0
6975295     18030.0
dtype: float64
```

[30]:
```
#Number of trips with highter than 30 dollars per mile fare.
df2 = df[df['trip_distance']>0]['total_amount_without_tip']/
 ↪df[df['trip_distance']>0]['trip_distance']
df2[df2>30].count()
```

[30]:
```
46265
```

0.1.5 passenger_count

[31]:
```
df['passenger_count'].value_counts()
```

[31]:
```
1      14372788
2       2792865
5        947421
3        781269
6        577417
4        337850
0         34725
8            72
7            72
9            51
192           1
Name: passenger_count, dtype: int64
```

[32]:
```
#There's a lot of trips with 0 passengers
df[df['passenger_count']==0].head(10)
```

[32]:

	VendorID	tpep_pickup_datetime	tpep_dropoff_datetime	passenger_count	\
4900	1	2017-03-10 14:25:40	2017-03-10 14:25:40	0	
11857	1	2017-03-10 14:48:25	2017-03-10 14:48:25	0	
197676	2	2017-03-10 22:50:47	2017-03-10 22:50:50	0	
210864	2	2017-03-10 23:24:59	2017-03-10 23:25:06	0	
270075	2	2017-03-11 02:10:22	2017-03-11 02:10:37	0	
277251	2	2017-03-11 02:45:12	2017-03-11 02:45:19	0	
282743	2	2017-03-11 03:16:05	2017-03-11 03:16:08	0	
506566	2	2017-03-01 12:19:34	2017-03-01 12:19:39	0	
517145	2	2017-03-01 13:00:50	2017-03-01 13:01:10	0	
526821	1	2017-03-01 13:39:00	2017-03-01 13:39:00	0	

	trip_distance	RatecodeID	store_and_fwd_flag	PULocationID	\
4900	0.0	99	N	264	
11857	0.0	99	N	264	
197676	0.0	5	N	236	
210864	0.0	5	N	265	
270075	0.0	5	N	37	
277251	0.0	5	N	41	
282743	0.0	5	N	137	
506566	0.0	5	N	170	
517145	0.0	5	N	236	
526821	0.0	99	Y	163	

	DOLocationID	fare_amount	…	tolls_amount	improvement_surcharge	\
4900	264	117.00	…	0.0	0.0	
11857	264	7.55	…	0.0	0.0	
197676	236	14.50	…	0.0	0.3	
210864	265	87.00	…	0.0	0.3	
270075	37	27.00	…	0.0	0.3	
277251	41	18.50	…	0.0	0.3	
282743	137	12.00	…	0.0	0.3	
506566	170	30.50	…	0.0	0.3	
517145	236	4.00	…	0.0	0.3	
526821	264	12.70	…	0.0	0.0	

	total_amount	total_amount_without_tip	month	day_PU	day_DO	\
4900	117.00	117.00	3	10	10	
11857	7.55	7.55	3	10	10	
197676	19.12	15.30	3	10	10	
210864	105.36	87.80	3	10	10	
270075	34.75	27.80	3	11	11	
277251	23.16	19.30	3	11	11	
282743	13.88	12.80	3	11	11	
506566	37.56	31.30	3	1	1	
517145	5.76	4.80	3	1	1	
526821	12.70	12.70	3	1	1	

```
        dayofweek  hour_PU  hour_DO
4900            4       14       14
11857           4       14       14
197676          4       22       22
210864          4       23       23
270075          5        2        2
277251          5        2        2
282743          5        3        3
506566          2       12       12
517145          2       13       13
526821          2       13       13

[10 rows x 23 columns]
```

[33]:
```
df[(df['passenger_count']==0) & (df['trip_distance']>0)].head(10)
```

[33]:
```
         VendorID tpep_pickup_datetime tpep_dropoff_datetime  passenger_count  \
717129          2  2017-03-01 23:10:12   2017-03-01 23:10:21                0
763058          2  2017-03-02 07:00:11   2017-03-02 07:00:22                0
1384534         1  2017-03-03 17:50:45   2017-03-03 17:50:47                0
1433410         2  2017-03-03 19:24:24   2017-03-03 19:24:27                0
1824731         2  2017-03-11 15:33:40   2017-03-11 16:35:40                0
1890837         2  2017-03-04 20:07:25   2017-03-04 20:07:28                0
1987253         2  2017-03-04 23:46:55   2017-03-04 23:56:01                0
2100555         2  2017-03-05 09:58:07   2017-03-05 10:27:22                0
2464814         2  2017-03-06 12:04:40   2017-03-06 13:10:22                0
2468870         2  2017-03-06 12:20:22   2017-03-06 12:20:47                0

         trip_distance  RatecodeID store_and_fwd_flag  PULocationID  \
717129            0.01           5                  N           265
763058            0.04           5                  N           143
1384534           1.40           5                  N             1
1433410           0.01           5                  N           114
1824731          24.77           5                  N           138
1890837           0.04           5                  N           262
1987253           3.42           5                  N           249
2100555           8.95           5                  N            14
2464814          30.04           5                  N           223
2468870           0.49           5                  N           107

         DOLocationID  fare_amount  …  tolls_amount  improvement_surcharge  \
717129            265         60.0  …          0.00                    0.3
763058            143          8.0  …          0.00                    0.3
1384534             1         85.5  …          0.00                    0.3
1433410           114         23.0  …          0.00                    0.3
1824731           265        105.0  …         18.04                    0.3
```

```
1890837           262         13.5  …          0.00                    0.3
1987253           265         50.0  …          0.00                    0.3
2100555            13         49.5  …          0.00                    0.3
2464814           265        125.0  …         16.04                    0.3
2468870           234         20.0  …          0.00                    0.3

         total_amount  total_amount_without_tip  month  day_PU  day_DO  \
717129          65.85                     60.30      3       1       1
763058          10.56                      8.80      3       2       2
1384534        100.80                     85.80      3       3       3
1433410         28.56                     23.80      3       3       3
1824731        138.84                    123.84      3      11      11
1890837         17.16                     14.30      3       4       4
1987253         50.80                     50.80      3       4       4
2100555         65.39                     50.30      3       5       5
2464814        170.21                    141.84      3       6       6
2468870         21.30                     20.80      3       6       6

         dayofweek  hour_PU  hour_DO
717129           2       23       23
763058           3        7        7
1384534          4       17       17
1433410          4       19       19
1824731          5       15       16
1890837          5       20       20
1987253          5       23       23
2100555          6        9       10
2464814          0       12       13
2468870          0       12       12

[10 rows x 23 columns]
```

There are several trips with 0 passengers and 1 with 192. Since they are rare, I will not remove them from the data. Usually a small number of errors don't interfere with the model, instead they help to represent real world situationxs.

0.1.6 RateCodeID

[34]:
```
df['RatecodeID'].value_counts()
```

[34]:
```
1     19246763
2       466272
5        75380
3        45850
4         9842
99         406
```

```
6           18
Name: RatecodeID, dtype: int64
```

[35]:
```
# The value 99 has no explanation in the documentation.
df[df['RatecodeID']==99].head()
```

[35]:

	VendorID	tpep_pickup_datetime	tpep_dropoff_datetime	passenger_count	trip_distance	RatecodeID	store_and_fwd_flag	PULocationID	DOLocationID	fare_amount	…	tolls_amount	improvement_surcharge	total_amount	total_amount_without_tip	month	day_PU	day_DO	dayofweek	hour_PU	hour_DO
4900	1	2017-03-10 14:25:40	2017-03-10 14:25:40	0	0.0	99	N	264	264	117.00	…	0.0	0.0	117.00	117.00	3	10	10	4	14	14
11857	1	2017-03-10 14:48:25	2017-03-10 14:48:25	0	0.0	99	N	264	264	7.55	…	0.0	0.0	7.55	7.55	3	10	10	4	14	14
526821	1	2017-03-01 13:39:00	2017-03-01 13:39:00	0	0.0	99	Y	163	264	12.70	…	0.0	0.0	12.70	12.70	3	1	1	2	13	13
561863	1	2017-03-01 15:07:51	2017-03-01 15:07:51	0	0.0	99	N	264	264	118.04	…	0.0	0.3	138.84	118.84	3	1	1	2	15	15
781108	1	2017-03-02 08:01:04	2017-03-02 08:01:04	0	0.0	99	N	264	264	16.00	…	0.0	0.0	16.00	16.00	3	2	2	3	8	8

[5 rows x 23 columns]

[36]:
```
df[(df['RatecodeID']==99) & (df['trip_distance']!=0)].head()
```

[36]:

	VendorID	tpep_pickup_datetime	tpep_dropoff_datetime
6694366	1	2017-03-25 18:29:15	2017-03-25 18:35:35

```
10942680         1  2017-06-11 01:36:50   2017-06-11 01:59:29
13559971         1  2017-06-13 19:38:29   2017-06-13 19:47:24
14450234         1  2017-06-16 08:54:45   2017-06-16 09:16:41
17747664         1  2017-06-25 18:04:40   2017-06-25 18:13:21

          passenger_count  trip_distance  RatecodeID store_and_fwd_flag  \
6694366                 2            1.6          99                  N
10942680                1           10.6          99                  N
13559971                1            2.2          99                  N
14450234                1            2.5          99                  N
17747664                1            1.6          99                  N

          PULocationID  DOLocationID  fare_amount  …  tolls_amount  \
6694366            145           112          7.5  …           0.0
10942680           231           223         31.5  …           0.0
13559971           100           237          9.0  …           0.0
14450234           161            79         14.5  …           0.0
17747664           162           141          8.0  …           0.0

          improvement_surcharge  total_amount  total_amount_without_tip  \
6694366                     0.3          9.30                       8.3
10942680                    0.3         39.35                      32.8
13559971                    0.3         12.95                      10.8
14450234                    0.3         18.35                      15.3
17747664                    0.3         10.55                       8.8

          month  day_PU  day_DO  dayofweek  hour_PU  hour_DO
6694366       3      25      25          5       18       18
10942680      6      11      11          6        1        1
13559971      6      13      13          1       19       19
14450234      6      16      16          4        8        9
17747664      6      25      25          6       18       18

[5 rows x 23 columns]
```

0.1.7 PULocationID and DOLocationID

These two columns contain the ID of the pickup and dropoff zones.

The webpage of the data contains the lookup file for these zones:

[37]:
```
taxi_zones = pd.read_csv('./data/taxi+_zone_lookup.csv')
```

[38]:
```
taxi_zones.head()
```

[38]:
	LocationID	Borough	Zone	service_zone
0	1	EWR	Newark Airport	EWR
1	2	Queens	Jamaica Bay	Boro Zone
2	3	Bronx	Allerton/Pelham Gardens	Boro Zone
3	4	Manhattan	Alphabet City	Yellow Zone
4	5	Staten Island	Arden Heights	Boro Zone

[39]:
```
taxi_zones.tail()
```

[39]:
	LocationID	Borough	Zone	service_zone
260	261	Manhattan	World Trade Center	Yellow Zone
261	262	Manhattan	Yorkville East	Yellow Zone
262	263	Manhattan	Yorkville West	Yellow Zone
263	264	Unknown	NV	NaN
264	265	Unknown	NaN	NaN

[40]:
```
taxi_zones.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 265 entries, 0 to 264
Data columns (total 4 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   LocationID    265 non-null    int64
 1   Borough       265 non-null    object
 2   Zone          264 non-null    object
 3   service_zone  263 non-null    object
dtypes: int64(1), object(3)
memory usage: 8.4+ KB
```

[41]:
```
print(taxi_zones['Borough'].nunique(), taxi_zones['Zone'].nunique(),␣
↪taxi_zones['service_zone'].nunique())
```

```
7 261 4
```

[42]:
```
print(taxi_zones['Borough'].unique(), taxi_zones['service_zone'].unique())
```

```
['EWR' 'Queens' 'Bronx' 'Manhattan' 'Staten Island' 'Brooklyn' 'Unknown'] ['EWR'
'Boro Zone' 'Yellow Zone' 'Airports' nan]
```

[43]:
```
for col in taxi_zones['service_zone'].unique():
    print(col, taxi_zones[taxi_zones['service_zone']==col]['Borough'].unique(),␣
↪'\n')
```

```
EWR ['EWR']

Boro Zone ['Queens' 'Bronx' 'Staten Island' 'Brooklyn' 'Manhattan']
```

```
Yellow Zone ['Manhattan']

Airports ['Queens']

nan []
```

There are 265 zones, each belongs to one of the 6 boroughs and one of the 4 service zones. There are a few NaN and Unknown values. Let's merge these data with the taxi trips.

[44]:
```
df = df.merge(taxi_zones, how='left', left_on='PULocationID',␣
↪right_on='LocationID')
```

[45]:
```
df = df.merge(taxi_zones, how='left', left_on='DOLocationID',␣
↪right_on='LocationID', suffixes=(None, '_DO'))
```

[46]:
```
df = df.rename(columns={'Borough': 'Borough_PU', 'service_zone':␣
↪'service_zone_PU', 'Zone': 'Zone_PU'})
df.drop(['LocationID', 'LocationID_DO'], axis=1, inplace=True)
gc.collect()
```

[46]:
```
85
```

[47]:
```
df.head()
```

[47]:

	VendorID	tpep_pickup_datetime	tpep_dropoff_datetime	passenger_count	\
0	2	2017-03-09 21:30:11	2017-03-09 21:44:20	1	
1	2	2017-03-09 22:01:08	2017-03-09 22:11:16	1	
2	2	2017-03-09 22:16:05	2017-03-10 06:26:11	1	
3	1	2017-03-01 00:00:00	2017-03-01 00:14:22	1	
4	1	2017-03-01 00:00:00	2017-03-01 00:19:30	1	

	trip_distance	RatecodeID	store_and_fwd_flag	PULocationID	DOLocationID	\
0	4.06	1	N	148	48	
1	2.27	1	N	79	162	
2	3.86	1	N	237	41	
3	2.80	1	N	261	79	
4	6.00	1	N	87	142	

	fare_amount	…	day_DO	dayofweek	hour_PU	hour_DO	Borough_PU	\
0	14.0	…	9	3	21	21	Manhattan	
1	10.0	…	9	3	22	22	Manhattan	
2	12.0	…	10	3	22	6	Manhattan	
3	12.5	…	1	2	0	0	Manhattan	
4	19.5	…	1	2	0	0	Manhattan	

	Zone_PU	service_zone_PU	Borough_DO	Zone_DO	\
0	Lower East Side	Yellow Zone	Manhattan	Clinton East	

```
1              East Village      Yellow Zone   Manhattan         Midtown East
2     Upper East Side South      Yellow Zone   Manhattan       Central Harlem
3        World Trade Center      Yellow Zone   Manhattan         East Village
4  Financial District North      Yellow Zone   Manhattan  Lincoln Square East

   service_zone_DO
0      Yellow Zone
1      Yellow Zone
2        Boro Zone
3      Yellow Zone
4      Yellow Zone

[5 rows x 29 columns]
```

The website of the data also includes the shapefiles of the taxi zones. Let's try to visualize our data.

[48]:
```
#Load shapefile
shape = './data/taxi_zones/taxi_zones.shp'
zone_shapes = geopandas.read_file(shape)
```

[49]:
```
zone_shapes.head()
```

[49]:
```
   OBJECTID  Shape_Leng  Shape_Area                     zone  LocationID  \
0         1    0.116357    0.000782           Newark Airport           1
1         2    0.433470    0.004866              Jamaica Bay           2
2         3    0.084341    0.000314  Allerton/Pelham Gardens           3
3         4    0.043567    0.000112            Alphabet City           4
4         5    0.092146    0.000498            Arden Heights           5

         borough                                           geometry
0            EWR  POLYGON ((933100.918 192536.086, 933091.011 19…
1         Queens  MULTIPOLYGON (((1033269.244 172126.008, 103343…
2          Bronx  POLYGON ((1026308.770 256767.698, 1026495.593 …
3      Manhattan  POLYGON ((992073.467 203714.076, 992068.667 20…
4  Staten Island  POLYGON ((935843.310 144283.336, 936046.565 14…
```

[50]:
```
zone_shapes.info()
```

```
<class 'geopandas.geodataframe.GeoDataFrame'>
RangeIndex: 263 entries, 0 to 262
Data columns (total 7 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   OBJECTID    263 non-null    int64
 1   Shape_Leng  263 non-null    float64
 2   Shape_Area  263 non-null    float64
 3   zone        263 non-null    object
```

```
 4   LocationID  263 non-null    int64
 5   borough     263 non-null    object
 6   geometry    263 non-null    geometry
dtypes: float64(2), geometry(1), int64(2), object(2)
memory usage: 14.5+ KB
```

[51]:
```
#I will visualize the average tip amount, and the number of trips per zone for both pickup and dropoff.
df_PU=df.groupby('PULocationID')['tip_amount'].agg(['mean', 'count']).reset_index()
df_DO=df.groupby('DOLocationID')['tip_amount'].agg(['mean', 'count']).reset_index()
df_PU.head()
```

[51]:

	PULocationID	mean	count
0	1	13.376485	1636
1	2	7.061579	19
2	3	2.839111	45
3	4	2.351583	48583
4	5	5.000000	2

[52]:
```
zone_shapes = zone_shapes.merge(df_PU, left_on='LocationID', right_on='PULocationID').merge(df_DO, left_on='LocationID', right_on='DOLocationID', suffixes=('_PU','_DO'))
```

[53]:
```
zone_shapes.head()
```

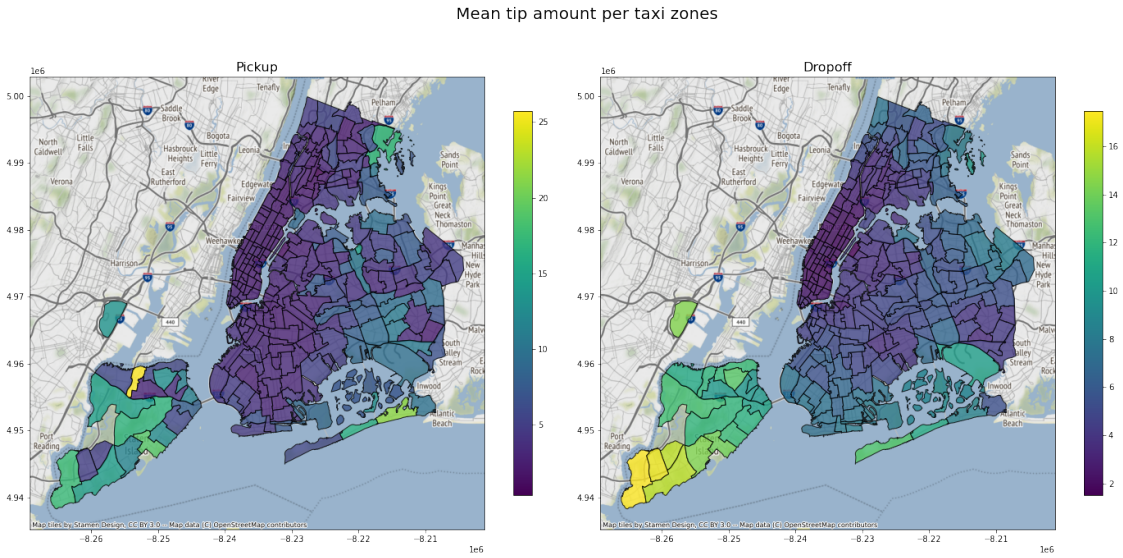
[53]:

	OBJECTID	Shape_Leng	Shape_Area	zone	LocationID	borough	geometry
0	1	0.116357	0.000782	Newark Airport	1	EWR	POLYGON ((933100.918 192536.086, 933091.011 19…
1	2	0.433470	0.004866	Jamaica Bay	2	Queens	MULTIPOLYGON (((1033269.244 172126.008, 103343…
2	3	0.084341	0.000314	Allerton/Pelham Gardens	3	Bronx	POLYGON ((1026308.770 256767.698, 1026495.593 …
3	4	0.043567	0.000112	Alphabet City	4	Manhattan	POLYGON ((992073.467 203714.076, 992068.667 20…
4	5	0.092146	0.000498	Arden Heights	5	Staten Island	POLYGON ((935843.310 144283.336, 936046.565 14…

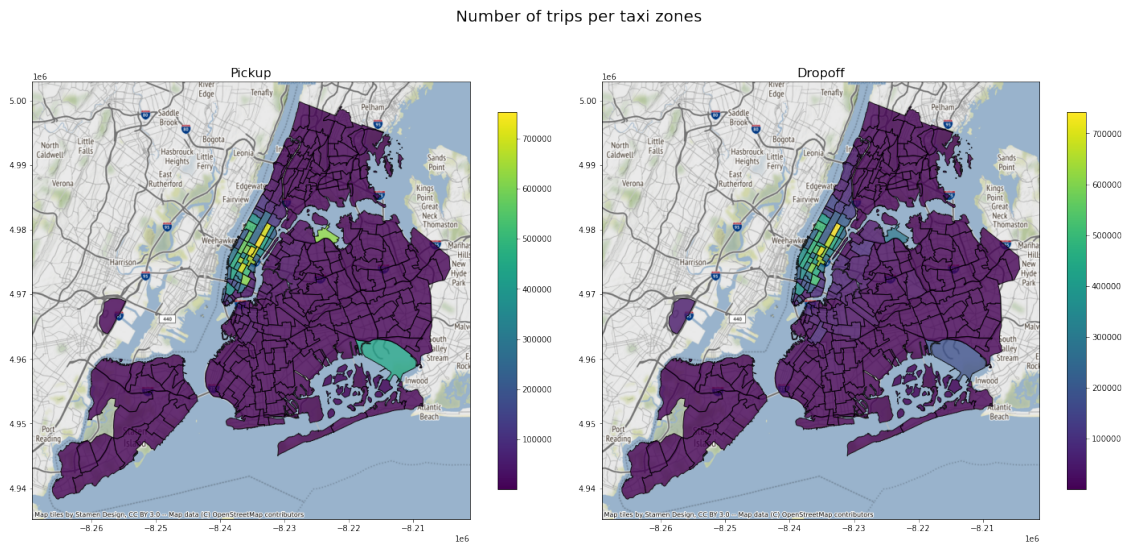
	PULocationID	mean_PU	count_PU	DOLocationID	mean_DO	count_DO
0	1	13.376485	1636	1	14.470256	46454
1	2	7.061579	19	2	8.731429	7
2	3	2.839111	45	3	6.359371	811
3	4	2.351583	48583	4	2.271078	95470
4	5	5.000000	2	5	15.880198	101

[54]:
```
import contextily as ctx
zone_shapes = zone_shapes.to_crs(epsg=3857)
```

[55]:
```
fig, ax = plt.subplots(1, 2, figsize=(20,10))
fig.suptitle('Mean tip amount per taxi zones', fontsize=20)
zone_shapes.plot(column='mean_PU', ax=ax[0], alpha=0.8, edgecolor='k',␣
 ↪legend=True, legend_kwds={'shrink': 0.7})
ctx.add_basemap(ax[0])
ax[0].set_title('Pickup', fontsize=16)
zone_shapes.plot(column='mean_DO', ax=ax[1], alpha=0.8, edgecolor='k',␣
 ↪legend=True, legend_kwds={'shrink': 0.7})
ctx.add_basemap(ax[1])
ax[1].set_title('Dropoff', fontsize=16)
fig.tight_layout()
```



[56]:
```
fig, ax = plt.subplots(1, 2, figsize=(20,10))
fig.suptitle('Number of trips per taxi zones', fontsize=20)
zone_shapes.plot(column='count_PU', ax=ax[0], alpha=0.8, edgecolor='k',␣
 ↪legend=True, legend_kwds={'shrink': 0.7})
ctx.add_basemap(ax[0])
ax[0].set_title('Pickup', fontsize=16)
zone_shapes.plot(column='count_DO', ax=ax[1], alpha=0.8, edgecolor='k',␣
 ↪legend=True, legend_kwds={'shrink': 0.7})
ctx.add_basemap(ax[1])
ax[1].set_title('Dropoff', fontsize=16)
fig.tight_layout()
```



[57]:
```
zone_shapes.sort_values(by='count_PU', ascending=True).head(10)
```

[57]:

	OBJECTID	Shape_Leng	Shape_Area	zone	LocationID	borough	geometry	PULocationID
4	5	0.092146	0.000498	Arden Heights	5	Staten Island	POLYGON ((-8257036.109 4948033.095, -8256954.5…	5
26	27	0.202509	0.001341	Breezy Point/Fort Tilden/Riis Beach	27	Queens	POLYGON ((-8222639.296 4949189.354, -8222563.1…	27
239	245	0.095983	0.000466	West Brighton	245	Staten Island		
58	59	0.037795	0.000063	Crotona Park	59	Bronx		
43	44	0.235689	0.001945	Charleston/Tottenville	44	Staten Island		
181	187	0.126868	0.000421	Port Richmond	187	Staten Island		
170	176	0.151995	0.000658	Oakwood	176	Staten Island		
83	84	0.233624	0.002074	Eltingville/Annadale/Prince's Bay	84	Staten Island		
45	46	0.134475	0.000926	City Island	46	Bronx		
29	30	0.094510	0.000146	Broad Channel	30	Queens		

```
239  POLYGON ((-8248538.236 4959438.413, -8248515.2…          245
58   POLYGON ((-8225332.303 4988685.328, -8225251.3…           59
43   POLYGON ((-8261264.353 4947135.681, -8261409.2…           44
181  MULTIPOLYGON (((-8252598.392 4959662.686, -825…          187
170  POLYGON ((-8251209.046 4949870.698, -8251209.0…          176
83   POLYGON ((-8255459.819 4942915.636, -8255440.3…           84
45   MULTIPOLYGON (((-8213655.676 4991783.793, -821…           46
29   POLYGON ((-8217689.294 4955753.159, -8217347.2…           30

       mean_PU  count_PU  DOLocationID    mean_DO  count_DO
4     5.000000         2             5  15.880198       101
26    5.920000         3            27  12.818254       126
239  12.775000         4           245  13.289063       192
58    0.375000         4            59   3.420600        50
43   17.484000         5            44  17.481774        62
181  25.736000         5           187  11.926400        75
170  18.932000         5           176  14.009927       137
83   14.276000         5            84  15.815455       110
45    6.918333         6            46   9.789046       283
29   12.810000         6            30   9.113810        42
```

[58]:
```
zone_shapes.sort_values(by='count_PU', ascending=True).tail(10)
```

[58]:
```
     OBJECTID  Shape_Leng  Shape_Area                          zone  \
224       230    0.031028    0.000056     Times Sq/Theatre District
78         79    0.042625    0.000108                East Village
132       138    0.107467    0.000537             LaGuardia Airport
180       186    0.024696    0.000037  Penn Station/Madison Sq West
164       170    0.045769    0.000074                   Murray Hill
228       234    0.036072    0.000073                      Union Sq
156       162    0.035270    0.000048                 Midtown East
230       236    0.044252    0.000103         Upper East Side North
155       161    0.035804    0.000072                Midtown Center
231       237    0.042213    0.000096         Upper East Side South

     LocationID    borough                                       geometry  \
224         230  Manhattan  POLYGON ((-8235819.388 4976346.988, -8235874.2…
78           79  Manhattan  POLYGON ((-8235836.707 4971354.640, -8235841.6…
132         138     Queens  MULTIPOLYGON (((-8223309.774 4980833.380, -822…
180         186  Manhattan  POLYGON ((-8236636.918 4974863.512, -8236687.0…
164         170  Manhattan  POLYGON ((-8234529.081 4974919.946, -8234539.7…
228         234  Manhattan  POLYGON ((-8236525.713 4973318.432, -8236518.3…
156         162  Manhattan  POLYGON ((-8234438.215 4976299.518, -8234489.4…
230         236  Manhattan  POLYGON ((-8232943.947 4979004.836, -8232995.3…
155         161  Manhattan  POLYGON ((-8234897.601 4976315.150, -8234949.2…
231         237  Manhattan  POLYGON ((-8233871.646 4977326.198, -8233922.3…
```

	PULocationID	mean_PU	count_PU	DOLocationID	mean_DO	count_DO
224	230	2.918897	603668	230	2.932685	526035
78	79	2.324913	614826	79	2.224761	515422
132	138	7.421858	618972	138	7.535576	285925
180	186	2.575260	650796	186	2.391845	487178
164	170	2.440758	666492	170	2.296030	657471
228	234	2.321541	700878	234	2.118000	597761
156	162	2.599566	702964	162	2.559604	605215
230	236	2.130528	710803	236	2.058093	742637
155	161	2.615711	737028	161	2.485044	715049
231	237	2.060550	754351	237	2.055474	664459

[59]:
```
zone_shapes.sort_values(by='mean_PU', ascending=True).head(10)
```

[59]:

	OBJECTID	Shape_Leng	Shape_Area	zone	LocationID	\
58	59	0.037795	0.000063	Crotona Park	59	
187	193	0.065530	0.000146	Queensbridge/Ravenswood	193	
161	167	0.090816	0.000168	Morrisania/Melrose	167	
46	47	0.089828	0.000163	Claremont/Bathgate	47	
141	147	0.058765	0.000106	Longwood	147	
41	42	0.092709	0.000264	Central Harlem North	42	
147	153	0.024737	0.000032	Marble Hill	153	
231	237	0.042213	0.000096	Upper East Side South	237	
40	41	0.052793	0.000143	Central Harlem	41	
135	141	0.041514	0.000077	Lenox Hill West	141	

	borough	geometry	\
58	Bronx	POLYGON ((-8225332.303 4988685.328, -8225251.3…	
187	Queens	POLYGON ((-8230431.841 4978405.968, -8230492.4…	
161	Bronx	POLYGON ((-8226165.299 4987450.974, -8226195.5…	
46	Bronx	POLYGON ((-8225497.589 4990847.692, -8225638.3…	
141	Bronx	POLYGON ((-8225970.779 4986980.331, -8225935.4…	
41	Manhattan	POLYGON ((-8230335.443 4988211.231, -8230345.5…	
147	Manhattan	POLYGON ((-8227252.349 4994026.992, -8227281.2…	
231	Manhattan	POLYGON ((-8233871.646 4977326.198, -8233922.3…	
40	Manhattan	POLYGON ((-8231824.746 4984298.100, -8231526.5…	
135	Manhattan	POLYGON ((-8233387.319 4976988.232, -8233408.3…	

	PULocationID	mean_PU	count_PU	DOLocationID	mean_DO	count_DO
58	59	0.375000	4	59	3.420600	50
187	193	1.344525	6617	193	1.524264	9470
161	167	1.652574	202	167	3.097548	1725
46	47	1.815361	97	47	2.918116	934
141	147	1.895679	81	147	3.546314	1134
41	42	1.947090	22866	42	3.101484	74766
147	153	1.999478	115	153	5.240678	723
231	237	2.060550	754351	237	2.055474	664459

```
40            41  2.084120     59696            41  2.748839    114644
135          141  2.084321    448357           141  2.147619    467307
```

[60]:
```
zone_shapes.sort_values(by='mean_PU', ascending=True).tail(10)
```

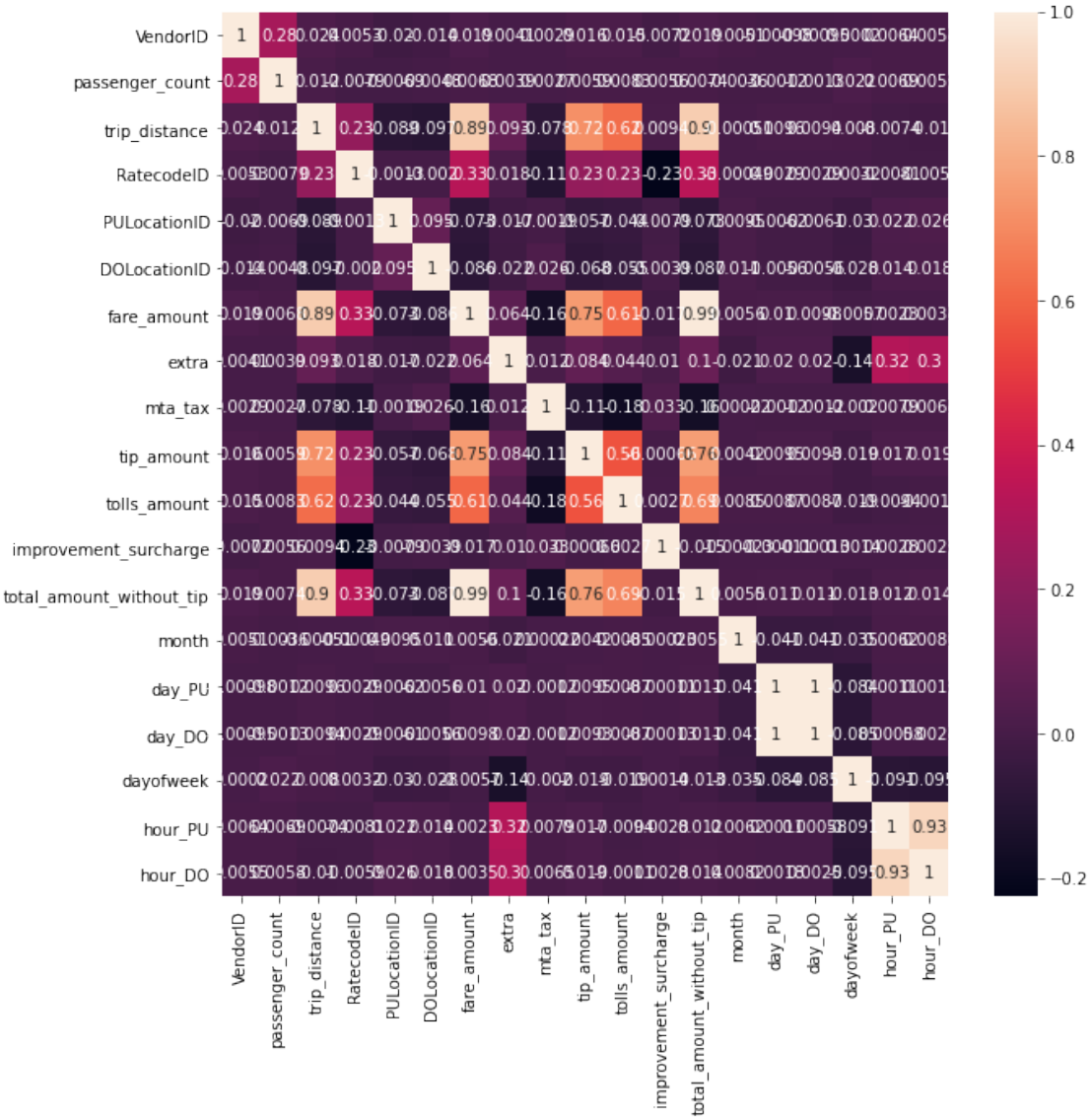
[60]:
```
     OBJECTID  Shape_Leng  Shape_Area                              zone  \
83         84    0.233624    0.002074  Eltingville/Annadale/Prince's Bay
247       253    0.036051    0.000078                      Willets Point
22         23    0.290556    0.002196           Bloomfield/Emerson Hill
195       201    0.130404    0.000619                      Rockaway Park
112       118    0.243966    0.001827       Heartland Village/Todt Hill
178       184    0.260816    0.001989                   Pelham Bay Park
43         44    0.235689    0.001945            Charleston/Tottenville
170       176    0.151995    0.000658                          Oakwood
111       117    0.169886    0.000904                 Hammels/Arverne
181       187    0.126868    0.000421                   Port Richmond

     LocationID        borough  \
83           84  Staten Island
247         253         Queens
22           23  Staten Island
195         201         Queens
112         118  Staten Island
178         184          Bronx
43           44  Staten Island
170         176  Staten Island
111         117         Queens
181         187  Staten Island

                                              geometry  PULocationID  \
83   POLYGON ((-8255459.819 4942915.636, -8255440.3…            84
247  POLYGON ((-8219729.181 4977778.527, -8219597.9…           253
22   POLYGON ((-8259425.995 4958654.880, -8259413.8…            23
195  POLYGON ((-8217437.722 4951666.911, -8217415.1…           201
112  POLYGON ((-8249703.138 4955020.258, -8249641.0…           118
178  MULTIPOLYGON (((-8216189.547 4995531.164, -821…           184
43   POLYGON ((-8261264.353 4947135.681, -8261409.2…            44
170  POLYGON ((-8251209.046 4949870.698, -8251209.0…           176
111  POLYGON ((-8212746.654 4954935.366, -8212736.2…           117
181  MULTIPOLYGON (((-8252598.392 4959662.686, -825…           187

       mean_PU  count_PU  DOLocationID    mean_DO  count_DO
83   14.276000         5            84  15.815455       110
247  14.479545        22           253   5.387826        46
22   14.576667        27            23  12.617873       409
195  15.940000        16           201  11.046267       651
112  16.754000        10           118  11.990128       312
```

178	16.789091	11	184	7.735345	116
43	17.484000	5	44	17.481774	62
170	18.932000	5	176	14.009927	137
111	21.370000	36	117	8.426045	574
181	25.736000	5	187	11.926400	75

There is a great variation in the mean amount of tips among the different zones, for example both pickup and dropoff on Staten Island comes with good tip. However, the number of such trips seem to be quite low. In fact, the majority of the trips seem to be taken place in Manhattan (plus the LaGuardia Airport in Queens).

0.1.8 Correlation among the columns

[61]:
```
#Let's plot the correlation matrix of the columns
df.drop(['total_amount'],axis=1, inplace=True)
fig, ax = plt.subplots(1, 1, figsize=(10,10))
sns.heatmap(df.corr(), annot=True)
plt.show()
```



Above is the correlation matrix of the data. There are several features that are highly correlated with each other, for example the day of the pickup and dropoff, since the majority of the trips are short.

The tip_amount is correlated with the trip_distance, the fare_amount, and the total_amount_without_tip, which makes sense, since most people calculates the tip from the amount they need to pay. None of the features correlate with the location of the pickup or dropoff.

0.1.9 Summary

In this notebook I took a quick look at the NYC yellow taxi data. From the document describing the data, and the data ifself, it is clear that only the trips paid by credit card are important for

our problem.

Within the data there are few missing or strange entries. There are entries where the amount of tip is higher than the total fare, there are extremely high cost per mile trips, etc. Fortunately, these strange entries are very rare. Usually such a low percentage do not need to be fixed to achieve a good model, on the contrary, sometimes they can be useful to simulate real world cases.

From the analysis it is clear that the amount of tip given is most correlated with the total fare of the taxi ride, the rest of the features are only weakly correlated.

The next step in the next notebook is to create a model that is able to predict the amount of the tip.