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  \
0         2  2017-03-09 21:30:11   2017-03-09 21:44:20                1
1         2  2017-03-09 21:47:00   2017-03-09 21:58:01                1
2         2  2017-03-09 22:01:08   2017-03-09 22:11:16                1
3         2  2017-03-09 22:16:05   2017-03-10 06:26:11                1
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

   trip_distance  RatecodeID store_and_fwd_flag  PULocationID  DOLocationID  \
0           4.06           1                  N           148            48
1           2.73           1                  N            48           107
2           2.27           1                  N            79           162
3           3.86           1                  N           237            41
```

```
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]:

```python
#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]:
```python
#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]:
```python
#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  \
592656          1  2017-03-01 16:58:17   2017-03-01 18:14:19                1
971076          1  2017-03-02 17:57:18   2017-03-02 18:20:10                1
1926622         1  2017-03-04 21:27:09   2017-03-04 21:43:13                2
1960809         1  2017-03-04 22:38:45   2017-03-04 22:44:54                1
2310518         1  2017-03-05 21:21:56   2017-03-05 21:31:20                2
3955474         1  2017-03-10 13:12:57   2017-03-10 13:56:48                5
4146145         1  2017-03-11 23:07:12   2017-03-11 23:21:00                1
4835686         1  2017-03-13 23:36:19   2017-03-13 23:40:36                1
6617066         1  2017-03-25 14:40:26   2017-03-25 14:40:58                1
6618420         1  2017-03-25 14:45:26   2017-03-25 14:45:29                1

         trip_distance  RatecodeID store_and_fwd_flag  PULocationID  \
592656            18.6           3                  N           161
971076             4.1           1                  N           264
1926622            3.5           1                  N           264
1960809            1.7           1                  N           264
2310518            2.4           1                  N           264
3955474           25.9           3                  N           158
4146145            3.2           1                  N           264
4835686            1.6           1                  N           264
6617066            0.0           4                  N           144
6618420            0.0           4                  N           148

         DOLocationID  payment_type  fare_amount  extra  mta_tax  tip_amount  \
592656              1             3        82.00   0.00     0.00         0.0
971076            264             3      8015.00 -13.68    14.48         0.0
1926622           264             3      3012.00 -53.71    54.51         0.0
1960809           264             3      8006.50 -45.72    46.52         0.0
2310518           264             3      3008.00   0.00     0.50         0.0
3955474             1             3        86.50   0.00     0.00         0.0
4146145           264             2      3011.00 -17.73    18.53         0.0
4835686           264             2      8005.50 -52.73    53.53         0.0
6617066           144             3      2759.07   0.00     0.00         0.0
6618420           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
```

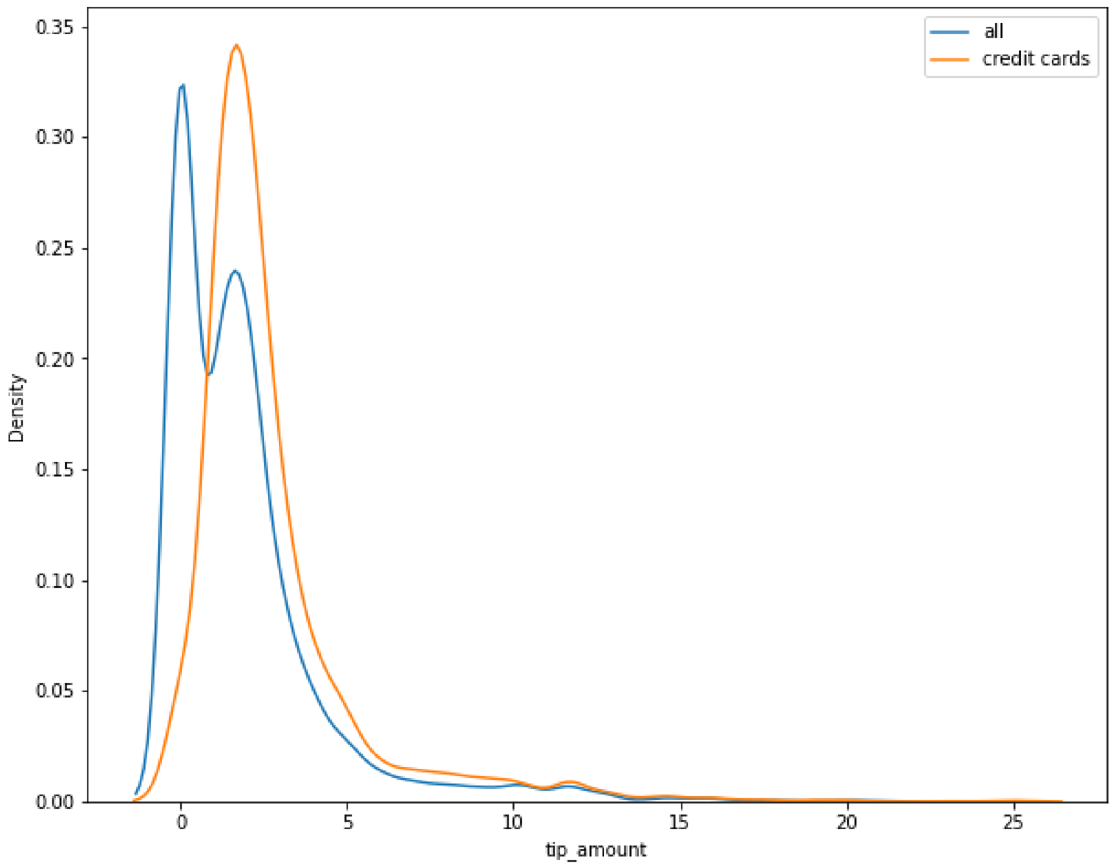
[16]:
```
#Number of entries where the payment_type is not credit card and the tip_amount␣
↪is not zero
df[(df['payment_type']!=1) & (df['tip_amount']!=0)]['payment_type'].count()
```

[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)
```

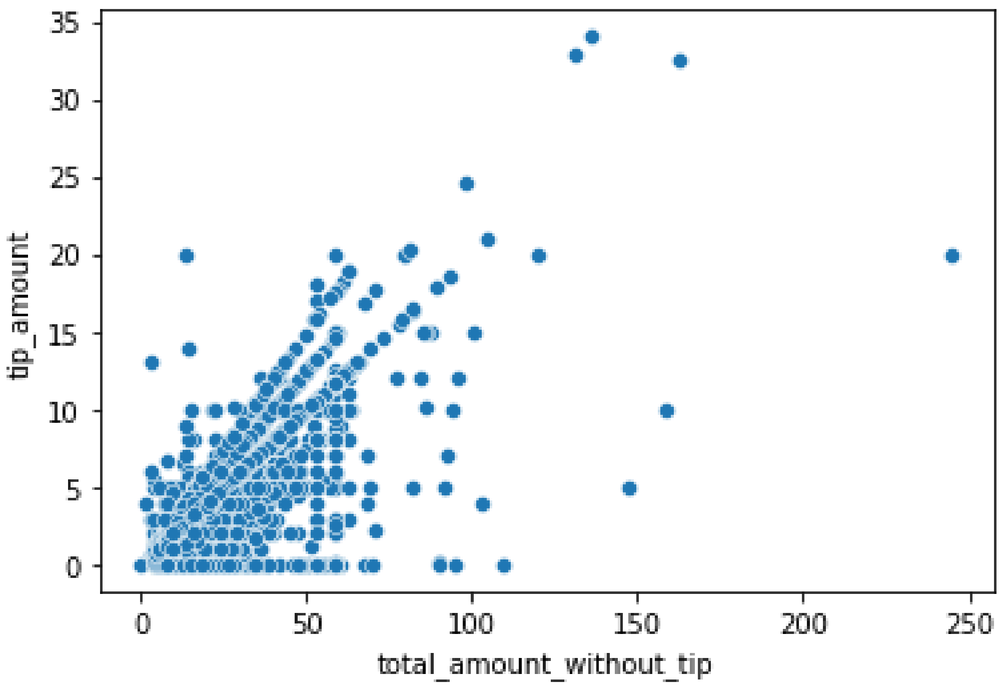
The total_amount column includes the tip, so let's create a column of the total amount without the tip.

[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.

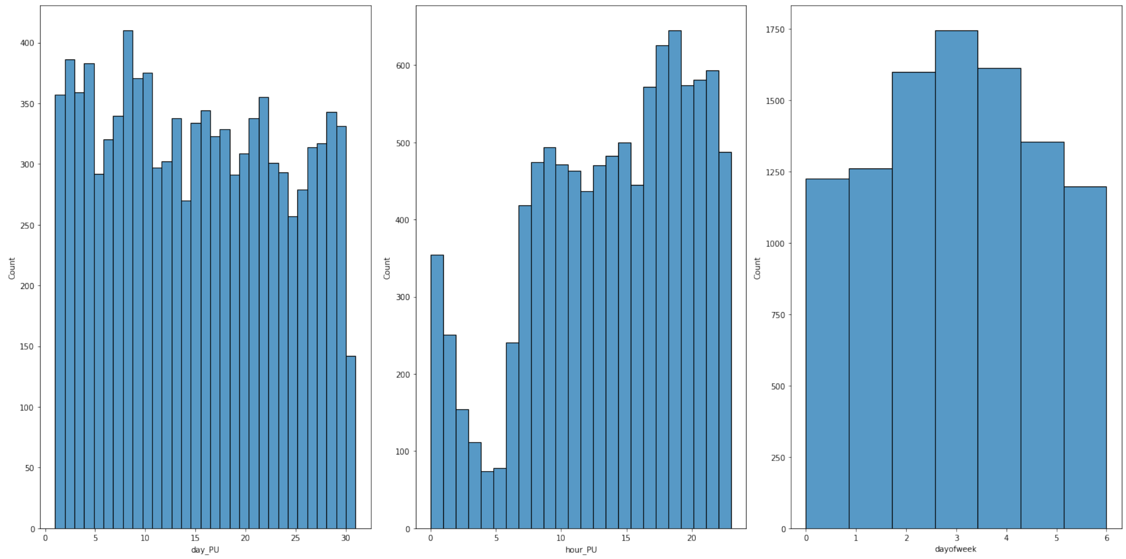
0.1.3 tpep_pickup_datetime and tpep_dropoff_datetime

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]:
```python
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  \
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
526821         1  2017-03-01 13:39:00   2017-03-01 13:39:00                0
561863         1  2017-03-01 15:07:51   2017-03-01 15:07:51                0
781108         1  2017-03-02 08:01:04   2017-03-02 08:01:04                0

        trip_distance  RatecodeID store_and_fwd_flag  PULocationID  \
4900              0.0          99                  N           264
11857             0.0          99                  N           264
526821            0.0          99                  Y           163
561863            0.0          99                  N           264
781108            0.0          99                  N           264

        DOLocationID  fare_amount  …  tolls_amount  improvement_surcharge  \
4900             264       117.00  …           0.0                    0.0
11857            264         7.55  …           0.0                    0.0
526821           264        12.70  …           0.0                    0.0
561863           264       118.04  …           0.0                    0.3
781108           264        16.00  …           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
526821         12.70                     12.70      3       1       1
561863        138.84                    118.84      3       1       1
781108         16.00                     16.00      3       2       2

        dayofweek  hour_PU  hour_DO
4900            4       14       14
11857           4       14       14
526821          2       13       13
561863          2       15       15
781108          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]:
```python
taxi_zones = pd.read_csv('./data/taxi+_zone_lookup.csv')
```

[38]:
```python
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]:
```python
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]:
```python
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]:
```python
print(taxi_zones['Borough'].nunique(), taxi_zones['Zone'].nunique(),␣
↪taxi_zones['service_zone'].nunique())
```

```
7 261 4
```

[42]:
```python
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]:
```python
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]:
```python
df = df.merge(taxi_zones, how='left', left_on='PULocationID',␣
↪right_on='LocationID')
```

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

[46]:
```python
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]:
```python
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
```

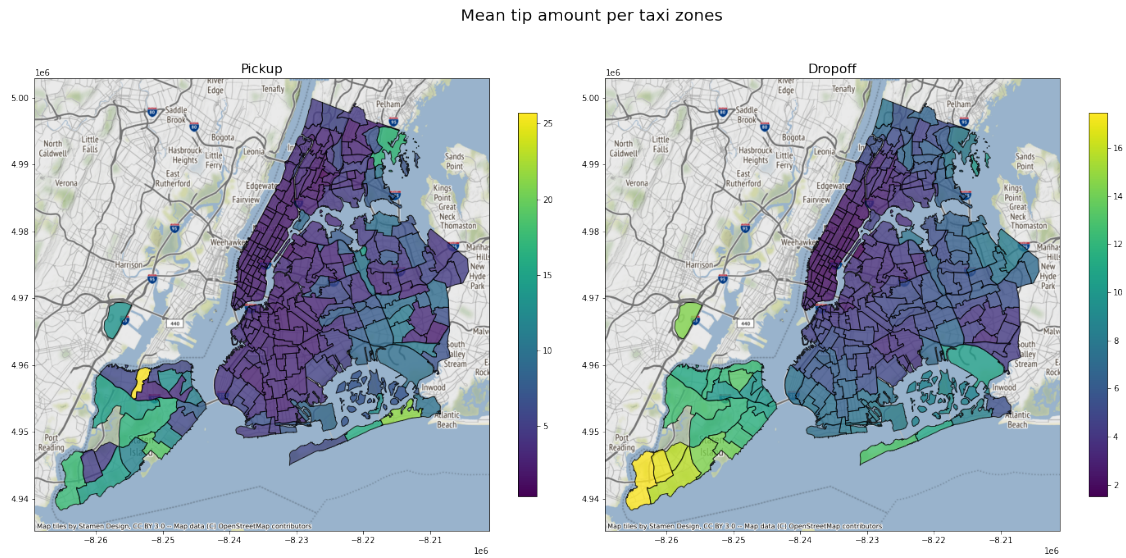
[52]:
```
zone_shapes = zone_shapes.merge(df_PU, left_on='LocationID',␣
↪right_on='PULocationID').merge(df_DO, left_on='LocationID',␣
↪right_on='DOLocationID', suffixes=('_PU','_DO'))
```

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

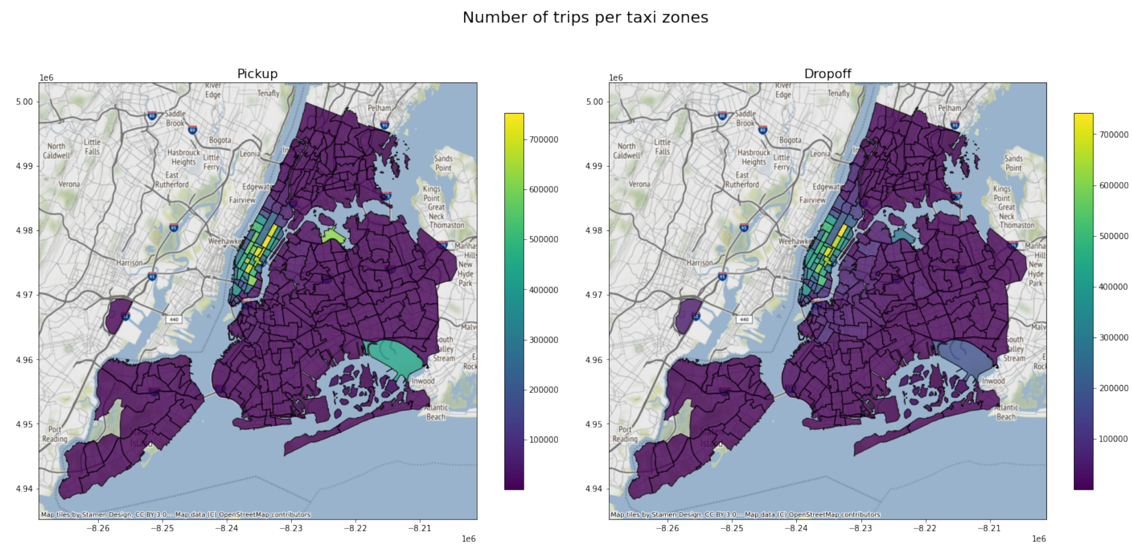
[53]:
```
   OBJECTID  Shape_Leng  Shape_Area                     zone  LocationID  \
0         1    0.116357    0.000782           Newark Airport           1
1         2    0.433470    0.004866              Jamaica Bay           2
2         3    0.084341    0.000314  Allerton/Pelham Gardens           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…

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

[57]:
```
     OBJECTID  Shape_Leng  Shape_Area                                 zone  \
4           5    0.092146    0.000498                       Arden Heights
26         27    0.202509    0.001341  Breezy Point/Fort Tilden/Riis Beach
239       245    0.095983    0.000466                       West Brighton
58         59    0.037795    0.000063                        Crotona Park
43         44    0.235689    0.001945           Charleston/Tottenville
181       187    0.126868    0.000421                       Port Richmond
170       176    0.151995    0.000658                             Oakwood
83         84    0.233624    0.002074    Eltingville/Annadale/Prince's Bay
45         46    0.134475    0.000926                         City Island
29         30    0.094510    0.000146                       Broad Channel

     LocationID        borough  \
4             5  Staten Island
26           27         Queens
239         245  Staten Island
58           59          Bronx
43           44  Staten Island
181         187  Staten Island
170         176  Staten Island
83           84  Staten Island
45           46          Bronx
29           30         Queens

                                              geometry  PULocationID  \
4    POLYGON ((-8257036.109 4948033.095, -8256954.5…             5
26   POLYGON ((-8222639.296 4949189.354, -8222563.1…            27
```

```
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]:
```python
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]:

```python
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)
```

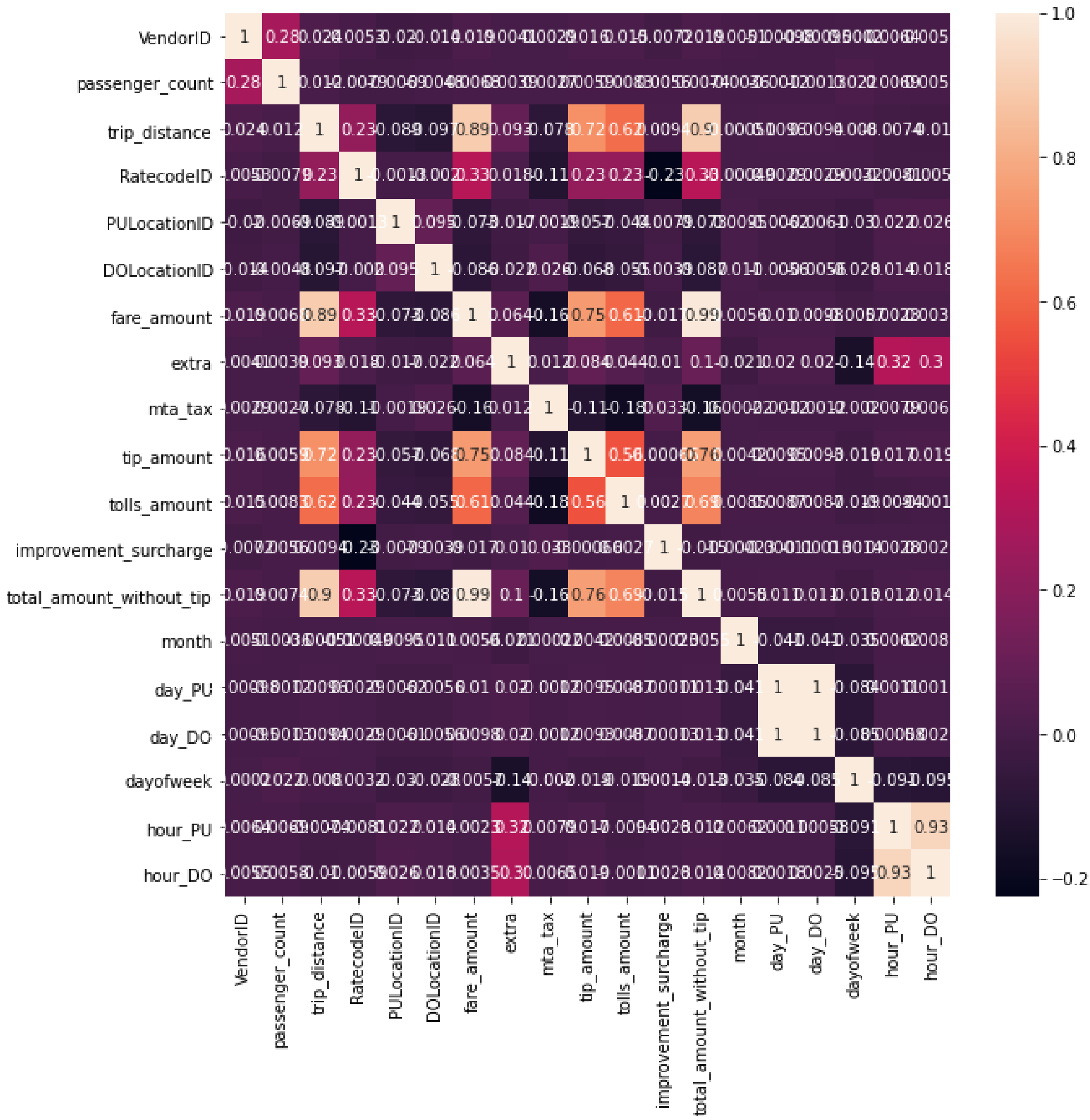
[60]:
```
     OBJECTID  Shape_Leng  Shape_Area                               zone  \
83         84    0.233624    0.002074  Eltingville/Annadale/Prince's Bay
247       253    0.036051    0.000078                     Willets Point
22         23    0.290556    0.002196           Bloomfield/Emerson Hill
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.