Exploring the Factors Affecting Taxi Fares in New York City Using Data Science Techniques.

The dataset used in this project is related to taxi trips in New York City. The data was obtained from the New York City Taxi and Limousine Commission (TLC) and includes information on taxi trips taken during 2013. The dataset is composed of approximately 12 million records, each representing a taxi trip and includes features such as pickup and dropoff location, pickup and dropoff time, trip distance, fare amount, payment type, and several other variables. The dataset provides a rich source of information on taxi trips in New York City and can be used for a variety of applications such as predicting taxi fares, understanding travel patterns, and optimizing transportation services.

Importing Library's

In [1]:

```
import  numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
import warnings
warnings.filterwarnings('ignore')
```

Importing Dataset

In [2]:

```
taxi = pd.read_csv('taxi.csv')
```

In [3]:

```
taxi
```

Out[3]:

	trip_distance	rate_code	store_and_fwd_flag	payment_type	fare_amount	extra	mta_tax	tip_amoun
0	9.01	1	N	1	26.0	0.0	0.5	8.1
1	0.20	1	N	1	3.0	0.0	0.5	0.7
2	9.65	1	N	1	41.5	0.0	0.5	9.6
3	9.50	1	N	1	30.0	0.5	0.5	9.2
4	5.80	1	N	1	21.5	0.5	0.5	4.5
...	...	...	...	...	...	...	...	.
34995	22.43	1	N	1	59.5	0.5	0.5	10.0
34996	9.16	1	N	1	30.0	0.0	0.5	6.5
34997	6.78	1	N	1	23.0	0.0	0.5	5.9
34998	0.26	1	N	2	3.0	0.0	0.5	0.0

In [4]:

```
taxi.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 35000 entries, 0 to 34999
Data columns (total 20 columns):
 #   Column                  Non-Null Count  Dtype  
---  ------                  --------------  -----  
 0   trip_distance           35000 non-null  float64
 1   rate_code               35000 non-null  int64  
 2   store_and_fwd_flag      35000 non-null  object 
 3   payment_type            35000 non-null  int64  
 4   fare_amount             35000 non-null  float64
 5   extra                   35000 non-null  float64
 6   mta_tax                 35000 non-null  float64
 7   tip_amount              35000 non-null  float64
 8   tolls_amount            35000 non-null  float64
 9   imp_surcharge           35000 non-null  float64
 10  total_amount            35000 non-null  float64
 11  pickup_location_id      35000 non-null  int64  
 12  dropoff_location_id     35000 non-null  int64  
 13  year                    35000 non-null  int64  
 14  month                   35000 non-null  int64  
 15  day                     35000 non-null  int64  
 16  day_of_week             35000 non-null  int64  
 17  hour_of_day             35000 non-null  int64  
 18  trip_duration           35000 non-null  float64
 19  calculated_total_amount  35000 non-null  float64
dtypes: float64(10), int64(9), object(1)
memory usage: 5.3+ MB
```

In [5]:

```
taxi.duplicated().sum()  # checking duplicates
```

Out[5]:

```
0
```

In [6]:

```
taxi.isnull().sum() # checking null values from each column
```

Out[6]:

```
trip_distance              0
rate_code                  0
store_and_fwd_flag         0
payment_type               0
fare_amount                0
extra                      0
mta_tax                    0
tip_amount                 0
tolls_amount               0
imp_surcharge              0
total_amount               0
pickup_location_id         0
dropoff_location_id        0
year                       0
month                      0
day                        0
day_of_week                0
hour_of_day                0
trip_duration              0
calculated_total_amount    0
dtype: int64
```

In [7]:

```
taxi.describe() # dataset describe in statistics method
```

Out[7]:

	trip_distance	rate_code	payment_type	fare_amount	extra	mta_tax
count	35000.000000	35000.000000	35000.000000	35000.000000	35000.000000	35000.000000
mean	9.088815	1.110086	1.123400	31.920911	0.320337	0.486929
std	4.496854	0.581456	0.350842	14.689516	0.402590	0.079781
min	0.010000	1.000000	1.000000	0.010000	0.000000	0.000000
25%	6.470000	1.000000	1.000000	24.000000	0.000000	0.500000
50%	8.700000	1.000000	1.000000	29.000000	0.000000	0.500000
75%	10.990000	1.000000	1.000000	36.000000	0.500000	0.500000
max	79.010000	5.000000	4.000000	400.000000	18.500000	0.500000

In [ ]:

```
```

In [8]:

```
taxi.nunique() # checking the continuous and category columns
```

Out[8]:

```
trip_distance              2317
rate_code                     5
store_and_fwd_flag            2
payment_type                  4
fare_amount                 360
extra                         7
mta_tax                       2
tip_amount                 1406
tolls_amount                177
imp_surcharge                 2
total_amount               2692
pickup_location_id          216
dropoff_location_id         253
year                          1
month                        12
day                          31
day_of_week                   7
hour_of_day                  24
trip_duration              3913
calculated_total_amount    2678
dtype: int64
```

EDA

In [9]:

```
taxi.drop(['pickup_location_id','dropoff_location_id','year'],axis=1,inplace=True) #remov
```

In [10]:

```
taxi['store_and_fwd_flag']=taxi['store_and_fwd_flag'].astype('category').cat.codes #value
taxi['trip_distance']=taxi['trip_distance']*1.6093
taxi['trip_duration']=taxi['trip_duration']/60    # distance (miles) into kilometer and d
taxi=taxi.rename(columns={'trip_distance':'trip_distance(km)','trip_duration':'trip_durat
```

Type *Markdown* and LaTeX: α^2

In [ ]:

```
```

In [11]:

```
percentages = [0, 0.25, 0.5, 0.75,0.76,0.8, 0.9,0.95,0.98,0.99,1]
taxi.describe(percentiles=percentages) # cheacking values at particular percentage
```

Out[11]:

	trip_distance(km)	rate_code	store_and_fwd_flag	payment_type	fare_amount	
count	35000.000000	35000.000000	35000.000000	35000.000000	35000.000000	350(
mean	14.626629	1.110086	0.005057	1.123400	31.920911	
std	7.236787	0.581456	0.070935	0.350842	14.689516	
min	0.016093	1.000000	0.000000	1.000000	0.010000	
0%	0.016093	1.000000	0.000000	1.000000	0.010000	
25%	10.412171	1.000000	0.000000	1.000000	24.000000	
50%	14.000910	1.000000	0.000000	1.000000	29.000000	
75%	17.686207	1.000000	0.000000	1.000000	36.000000	
76%	17.863230	1.000000	0.000000	1.000000	36.500000	
80%	18.667880	1.000000	0.000000	1.000000	38.000000	
90%	22.835967	1.000000	0.000000	2.000000	45.000000	
95%	27.036240	1.000000	0.000000	2.000000	55.000000	
98%	32.540690	3.000000	0.000000	2.000000	70.000000	
99%	37.899176	5.000000	0.000000	2.000000	80.000000	
100%	127.150793	5.000000	1.000000	4.000000	400.000000	
max	127.150793	5.000000	1.000000	4.000000	400.000000	

In [12]:

```
taxi['fare_amount'].nlargest(5) #highest paid amounts
```

Out[12]:

```
7012     400.0
26895    350.5
15154    350.0
19542    300.0
21959    270.0
Name: fare_amount, dtype: float64
```

In [13]:

```
taxi
```

Out[13]:

	trip_distance(km)	rate_code	store_and_fwd_flag	payment_type	fare_amount	extra	n
0	14.499793	1	0	1	26.0	0.0	
1	0.321860	1	0	1	3.0	0.0	
2	15.529745	1	0	1	41.5	0.0	
3	15.288350	1	0	1	30.0	0.5	
4	9.333940	1	0	1	21.5	0.5	
...	...	...	...	...	...	...	
34995	36.096599	1	0	1	59.5	0.5	
34996	14.741188	1	0	1	30.0	0.0	
34997	10.911054	1	0	1	23.0	0.0	
34998	0.418418	1	0	2	3.0	0.0	
34999	29.611120	1	0	1	53.0	1.0	

35000 rows × 17 columns

In [14]:

```
quantile_vals = taxi.quantile(0.95)
mask = taxi[taxi > quantile_vals]
result = taxi.loc[mask.all(axis=1)] #finding outlier
```

In [15]:

```
mask
```

Out[15]:

	trip_distance(km)	rate_code	store_and_fwd_flag	payment_type	fare_amount	extra	m
0	NaN	NaN	NaN	NaN	NaN	NaN	
1	NaN	NaN	NaN	NaN	NaN	NaN	
2	NaN	NaN	NaN	NaN	NaN	NaN	
3	NaN	NaN	NaN	NaN	NaN	NaN	
4	NaN	NaN	NaN	NaN	NaN	NaN	
...	...	...	...	...	...	...	
34995	36.096599	NaN	NaN	NaN	59.5	NaN	
34996	NaN	NaN	NaN	NaN	NaN	NaN	
34997	NaN	NaN	NaN	NaN	NaN	NaN	
34998	NaN	NaN	NaN	NaN	NaN	NaN	
34999	29.611120	NaN	NaN	NaN	NaN	NaN	

35000 rows × 17 columns

In [16]:

```
result
```

Out[16]:

	trip_distance(km)	rate_code	store_and_fwd_flag	payment_type	fare_amount	extra	m
0	14.499793	1	0	1	26.0	0.0	
1	0.321860	1	0	1	3.0	0.0	
2	15.529745	1	0	1	41.5	0.0	
3	15.288350	1	0	1	30.0	0.5	
4	9.333940	1	0	1	21.5	0.5	
...	...	...	...	...	...	...	
34995	36.096599	1	0	1	59.5	0.5	
34996	14.741188	1	0	1	30.0	0.0	
34997	10.911054	1	0	1	23.0	0.0	
34998	0.418418	1	0	2	3.0	0.0	
34999	29.611120	1	0	1	53.0	1.0	

35000 rows × 17 columns

In [17]:

```
threshold = 0.75
filtered_mask = mask[mask > mask.max() * threshold].dropna(how='all')
```

In [18]:

```
filtered_mask
```

Out[18]:

	trip_distance(km)	rate_code	store_and_fwd_flag	payment_type	fare_amount	extra	m
22	NaN	NaN	NaN	NaN	NaN	NaN	
34	NaN	NaN	NaN	NaN	NaN	NaN	
40	NaN	NaN	NaN	NaN	NaN	NaN	
51	NaN	NaN	NaN	NaN	NaN	NaN	
52	NaN	NaN	NaN	NaN	NaN	NaN	
...	...	...	...	...	...	...	
34970	NaN	5.0	NaN	NaN	NaN	NaN	
34971	NaN	NaN	NaN	NaN	NaN	NaN	
34976	NaN	NaN	NaN	NaN	NaN	NaN	
34987	NaN	NaN	NaN	NaN	NaN	NaN	
34991	NaN	NaN	1.0	NaN	NaN	NaN	

3556 rows × 17 columns

In [19]:

```
filtered_mask.describe()
```

Out[19]:

	trip_distance(km)	rate_code	store_and_fwd_flag	payment_type	fare_amount	ex
count	7.000000	683.000000	177.0	43.0	3.000000	3.000(
mean	117.361651	4.733529	1.0	4.0	366.833333	17.8333
std	8.564978	0.442438	0.0	0.0	28.724264	0.5773
min	104.765430	4.000000	1.0	4.0	350.000000	17.500(
25%	112.168210	4.000000	1.0	4.0	350.250000	17.500(
50%	118.251364	5.000000	1.0	4.0	350.500000	17.500(
75%	123.513775	5.000000	1.0	4.0	375.250000	18.000(
max	127.150793	5.000000	1.0	4.0	400.000000	18.500(

In [20]:

```
taxi.drop(filtered_mask.index,inplace=True) #removing outliers from dataset
```

In [21]:

```
taxi.shape
```

Out[21]:

```
(31444, 17)
```

In [22]:

```
taxi.describe()
```

Out[22]:

	trip_distance(km)	rate_code	store_and_fwd_flag	payment_type	fare_amount	
count	31444.000000	31444.000000	31444.0	31444.000000	31444.000000	3144
mean	14.474895	1.038418	0.0	1.107270	31.065147	
std	6.527335	0.274405	0.0	0.319673	11.409093	
min	0.016093	1.000000	0.0	1.000000	2.500000	
25%	10.460450	1.000000	0.0	1.000000	24.000000	
50%	14.017003	1.000000	0.0	1.000000	29.000000	
75%	17.541370	1.000000	0.0	1.000000	35.500000	
max	63.245490	3.000000	0.0	3.000000	116.500000	

In [23]:

```
print(taxi.columns)
```

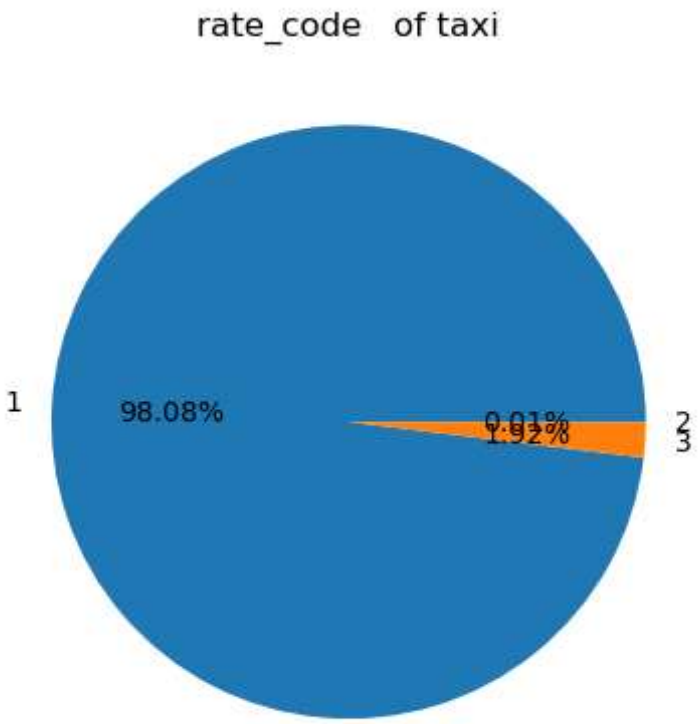
```
Index(['trip_distance(km)', 'rate_code', 'store_and_fwd_flag', 'payment_ty
pe',
       'fare_amount', 'extra', 'mta_tax', 'tip_amount', 'tolls_amount',
       'imp_surcharge', 'total_amount', 'month', 'day', 'day_of_week',
       'hour_of_day', 'trip_duration(minutes)', 'calculated_total_amoun
t'],
      dtype='object')
```

In [24]:

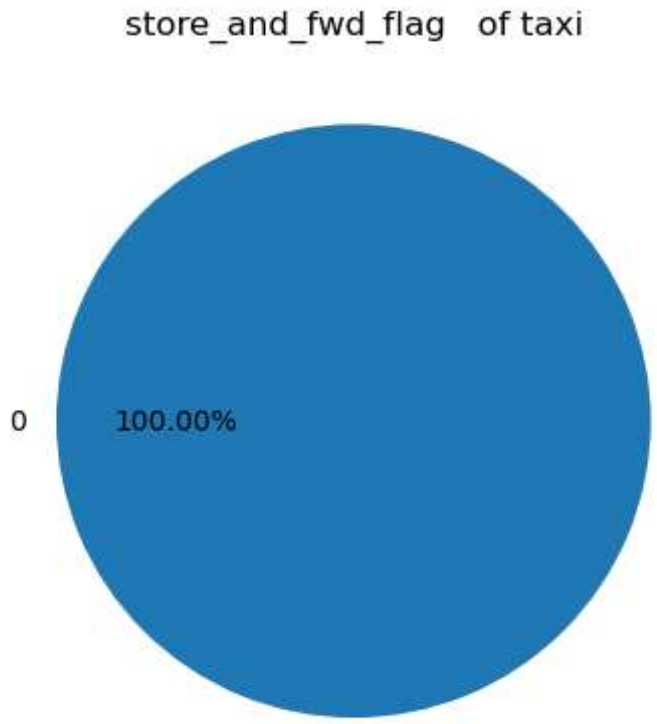
```
taxicolumns=taxi[['rate_code','store_and_fwd_flag','payment_type','extra','mta_tax','imp_
```

In [25]:

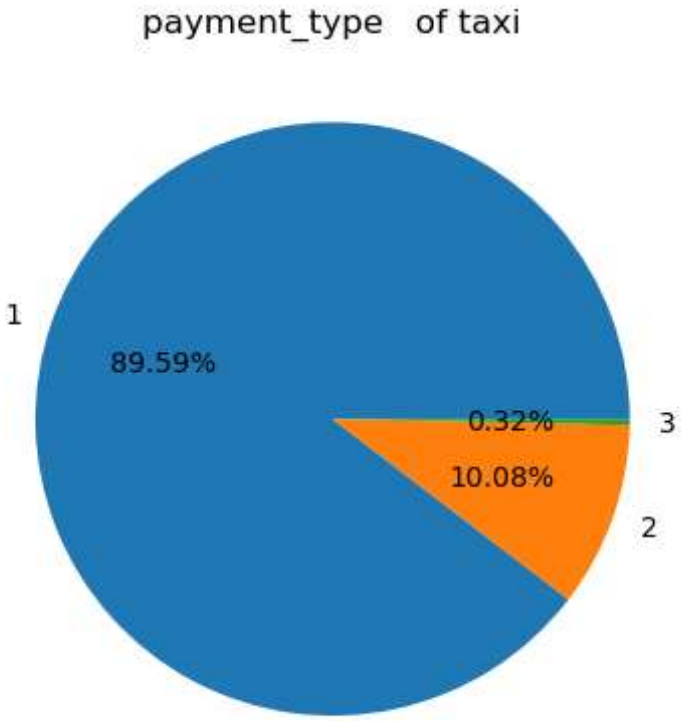
```
for col in taxicolumns:
    plot=plt.pie(taxi[col].value_counts(),autopct='%0.2f%%',labels=taxi[col].unique())
    plt.title(f'{col}   of taxi')
    plt.show()
    print(f'inferences of {col} -\ncount  of {col} highest values are-\n     {pd.DataFram

#By using for loops  plotting pie plots of unique values counts from categorical colum
```



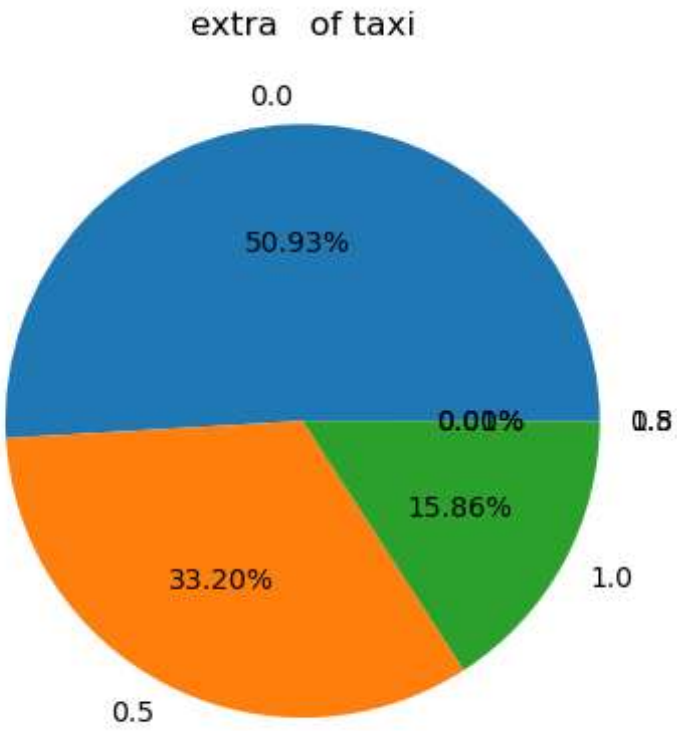

```
inferences of rate_code -
count  of rate_code highest values are-
        rate_code
1       30839
count of rate_code lowest values are-
     rate_code
2            2
```



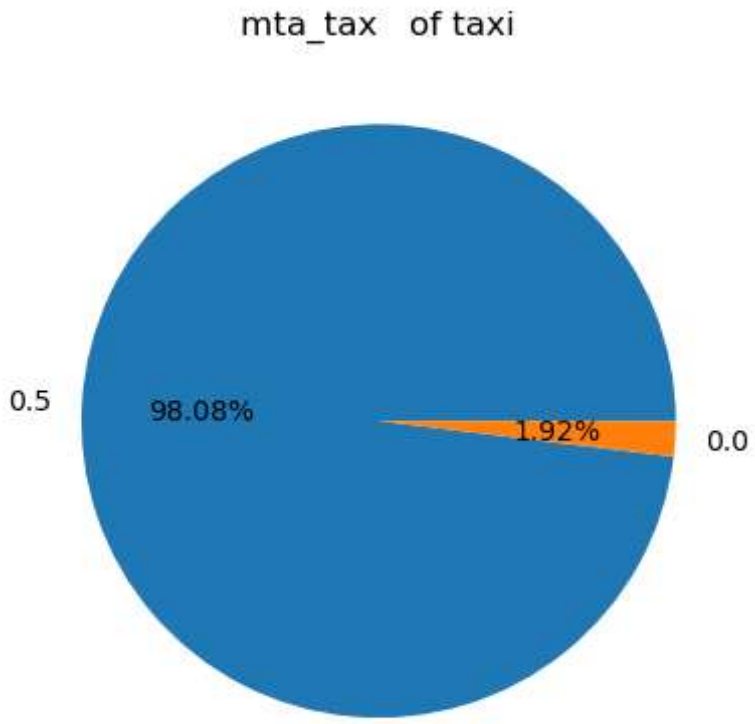

```
inferences of store_and_fwd_flag -
count  of store_and_fwd_flag highest values are-
        store_and_fwd_flag
0                31444
count of store_and_fwd_flag lowest values are-
     store_and_fwd_flag
0                31444
```



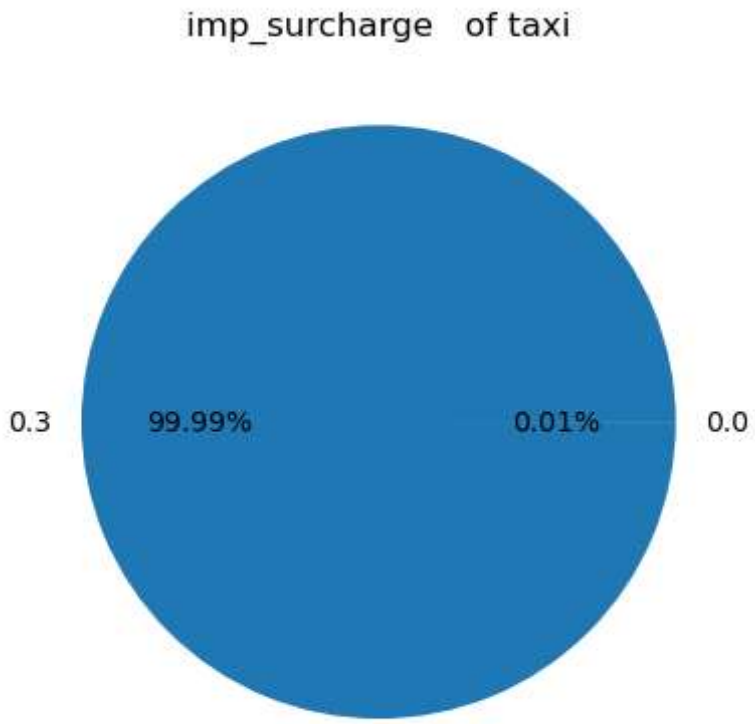
```
inferences of payment_type -
count  of payment_type highest values are-
        payment_type
1          28172
count of payment_type lowest values are-
     payment_type
3            101
```



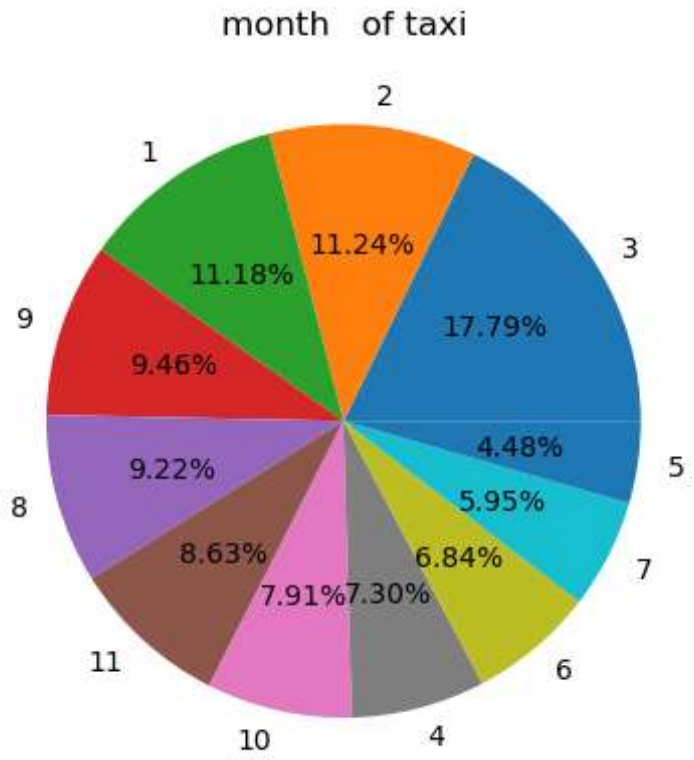

```
inferences of extra -
count  of extra highest values are-
          extra
0.0  16014
count of extra lowest values are-
       extra
0.8      1
```



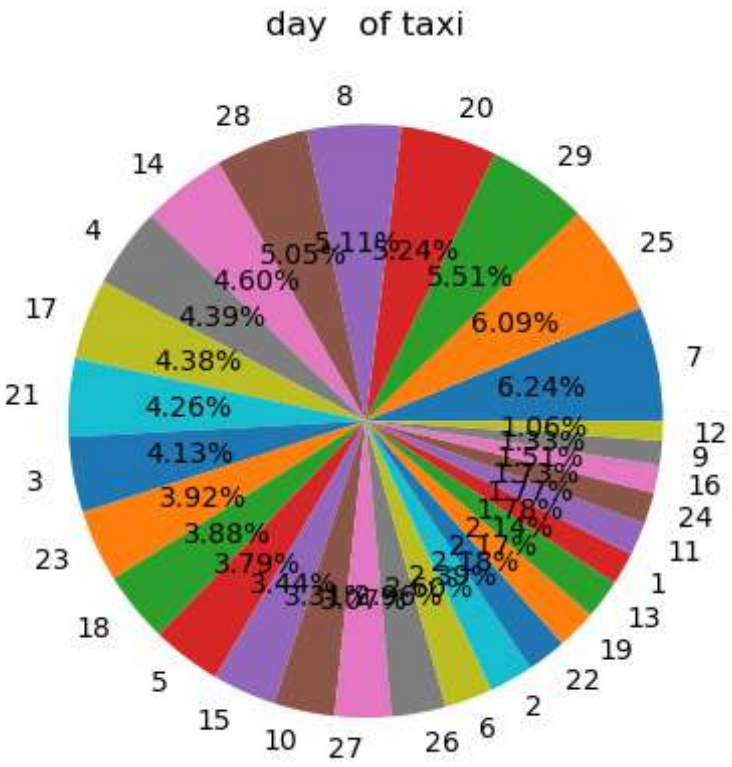

```
inferences of mta_tax -
count  of mta_tax highest values are-
         mta_tax
0.5    30839
count of mta_tax lowest values are-
       mta_tax
0.0      605
```



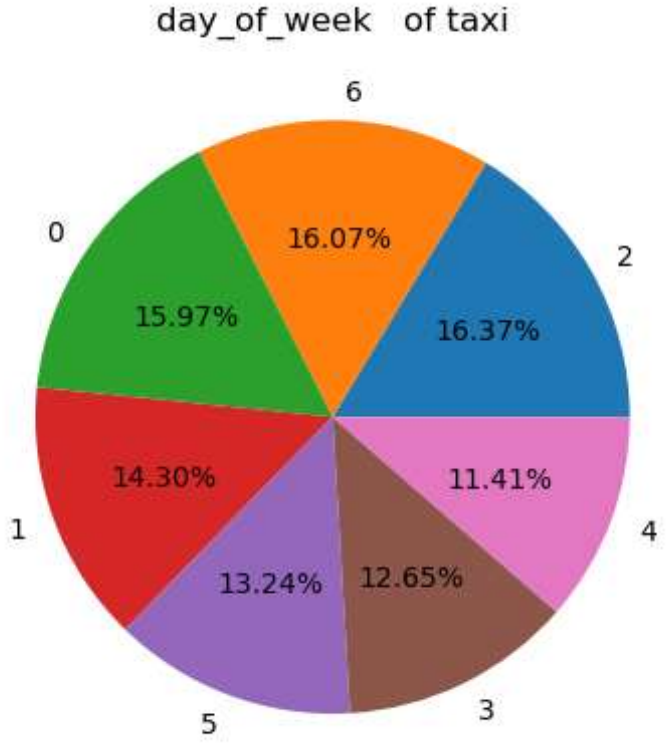
```
inferences of imp_surcharge -
count  of imp_surcharge highest values are-
          imp_surcharge
0.3           31441
count of imp_surcharge lowest values are-
       imp_surcharge
0.0                3
```



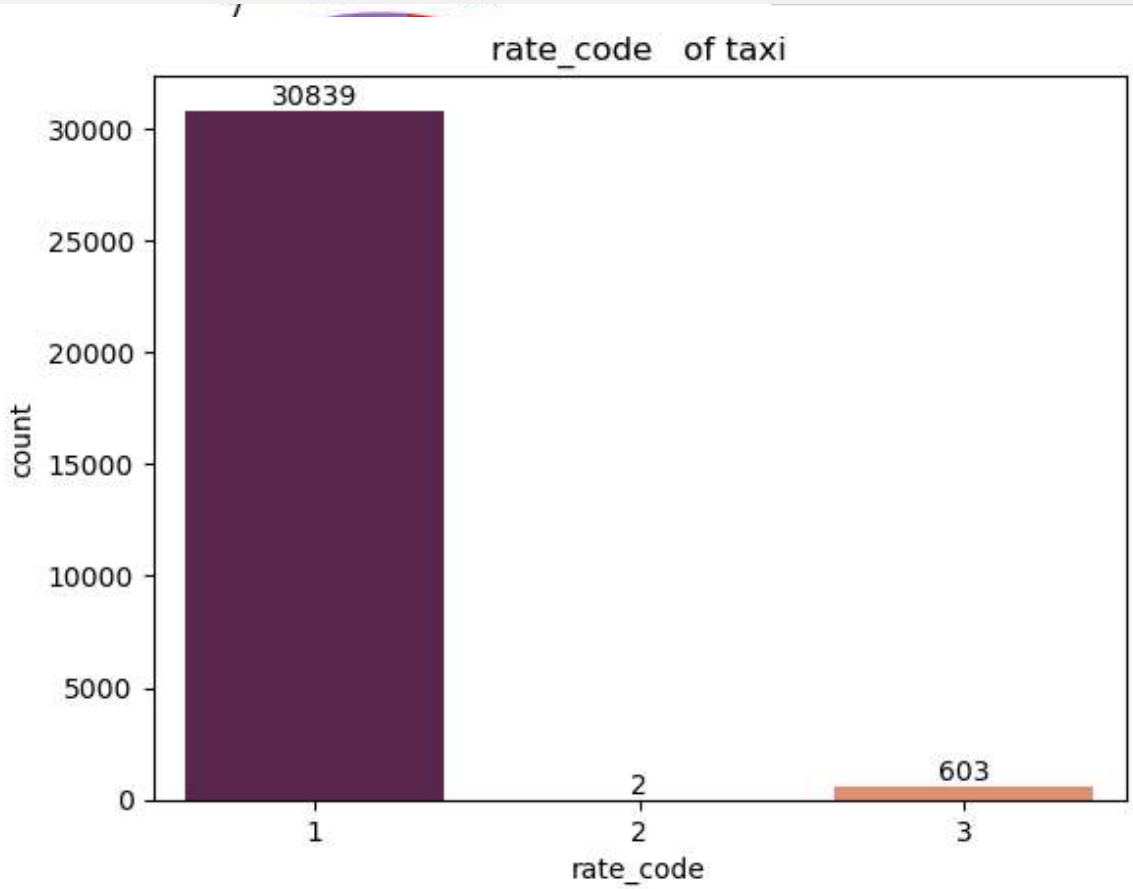

```
inferences of month -
count  of month highest values are-
        month
3   5594
count of month lowest values are-
     month
7   1408
```



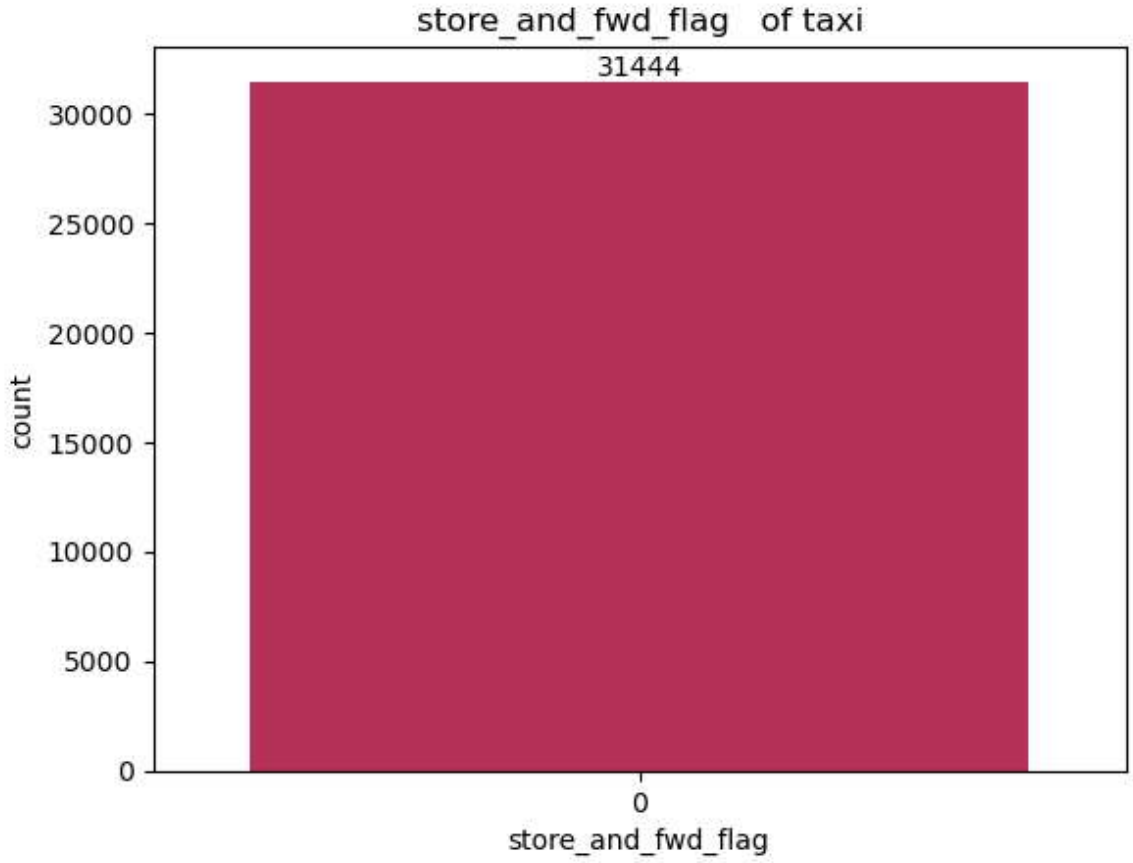

```
inferences of day -
count  of day highest values are-
        day
6  1961
count of day lowest values are-
     day
1  332
```



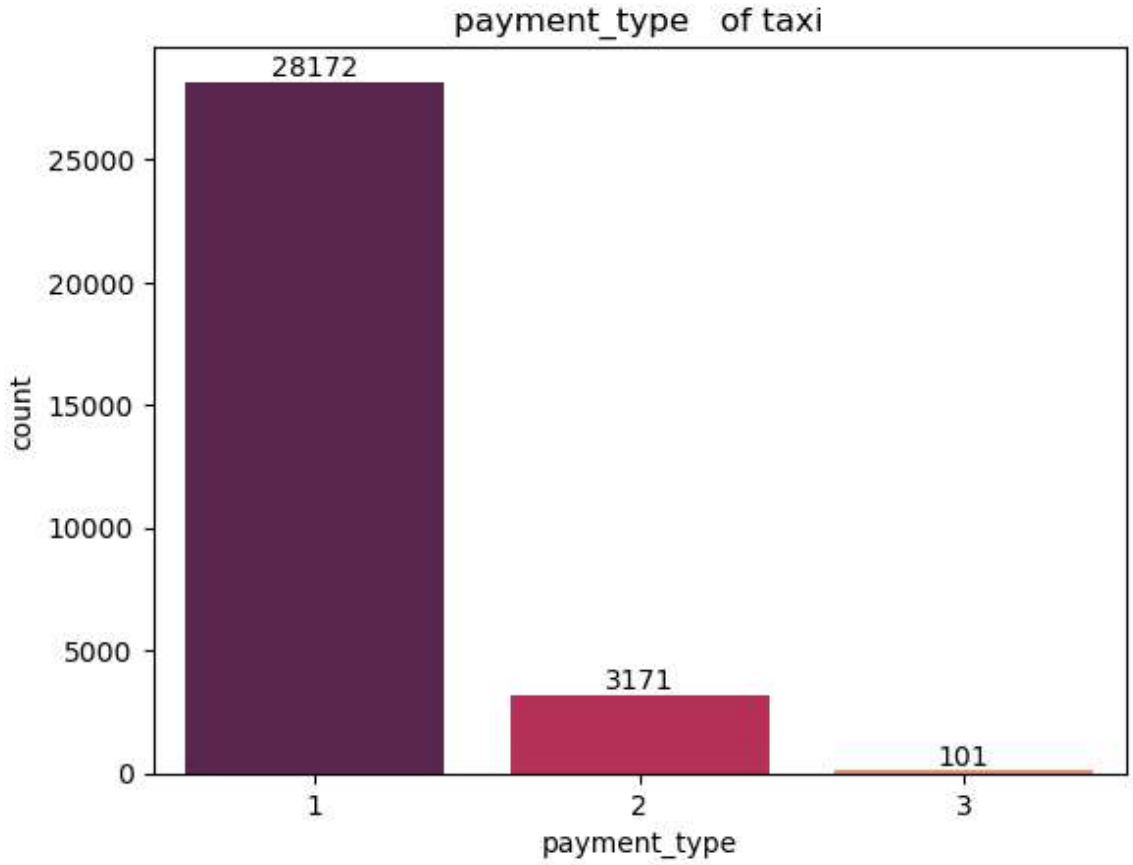
In [26]:
```
for col in taxi.columns:
    plot=sns.countplot(x=col,data=taxi,palette='rocket')
    plt.title(f'{col} of taxi')
    plot.bar_label(plot.containers[0], label_type='edge', fontsize=10, padding=0)
    plt.show()
    print(f'inferences of {col} -\ncount  of {col} highest values are-\n     {pd.DataFram

#By using for loops & plotting bar plot of unique values counts from categorical column
```



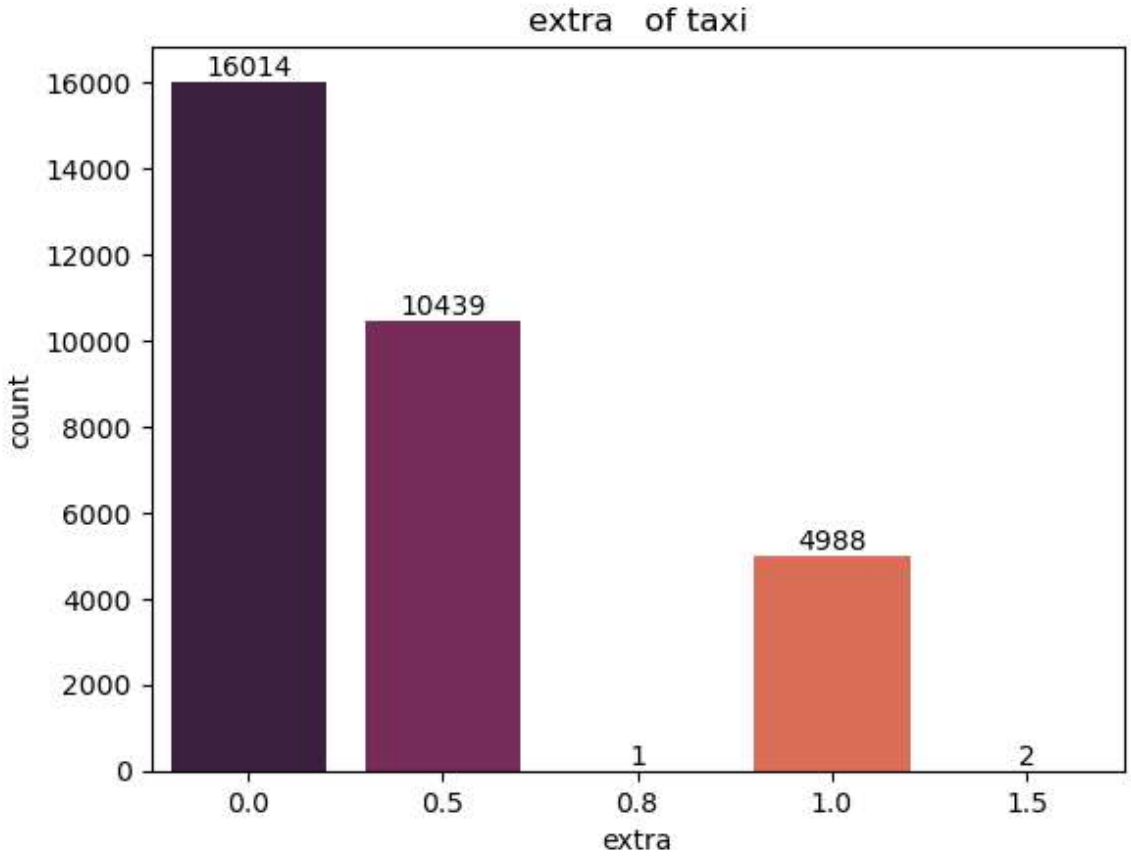

```
     hour_of_day
3            3447
inferences of rate_code -
count  of rate_code highest values are-
        rate_code
1           30839
count of rate_code lowest values are-
     rate_code
2            2
```



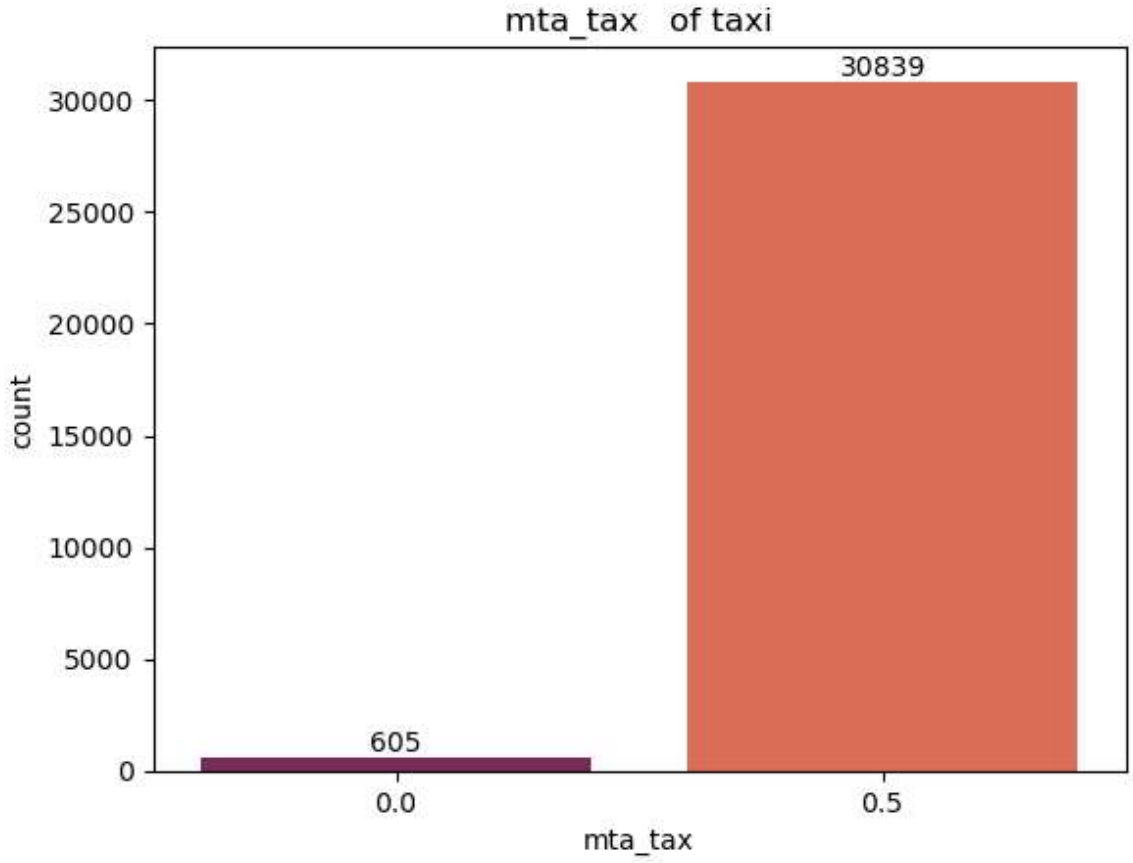

```
inferences of store_and_fwd_flag -
count  of store_and_fwd_flag highest values are-
        store_and_fwd_flag
0                31444
count of store_and_fwd_flag lowest values are-
     store_and_fwd_flag
0                31444
```



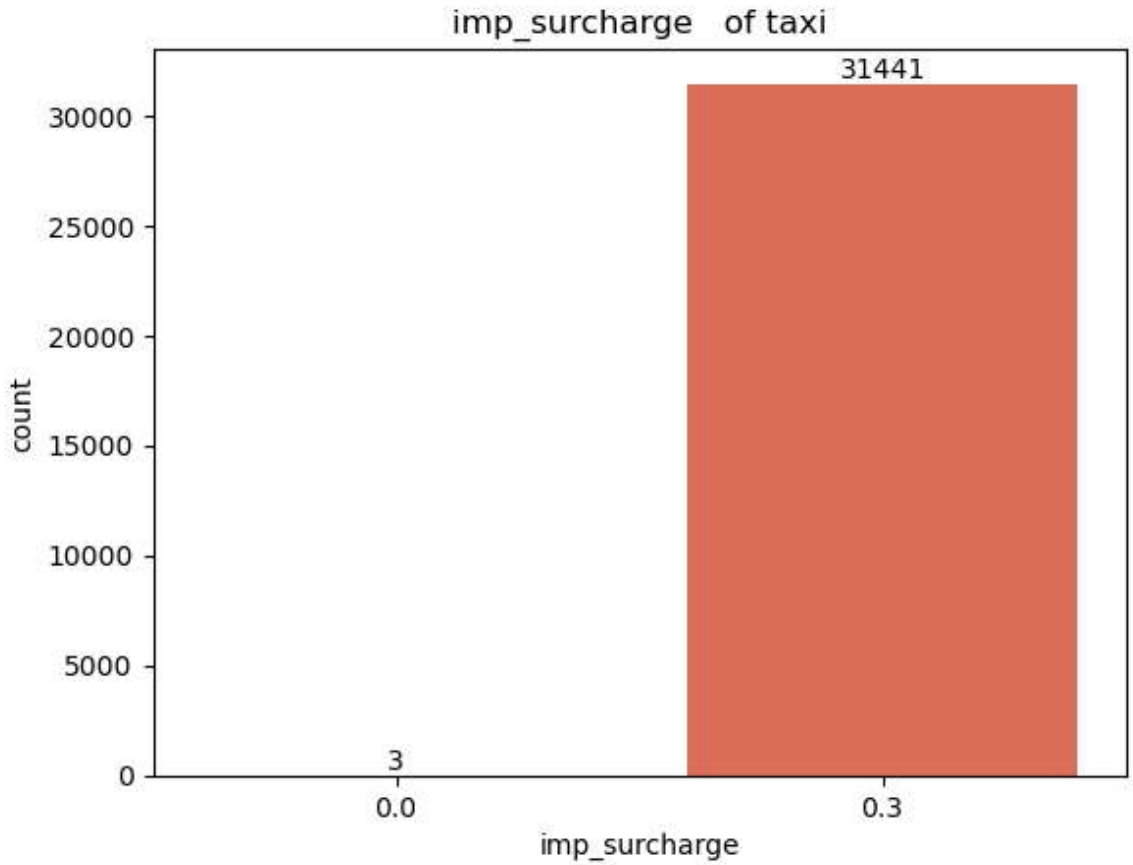
```
inferences of payment_type -
count  of payment_type highest values are-
        payment_type
1          28172
count of payment_type lowest values are-
     payment_type
3            101
```



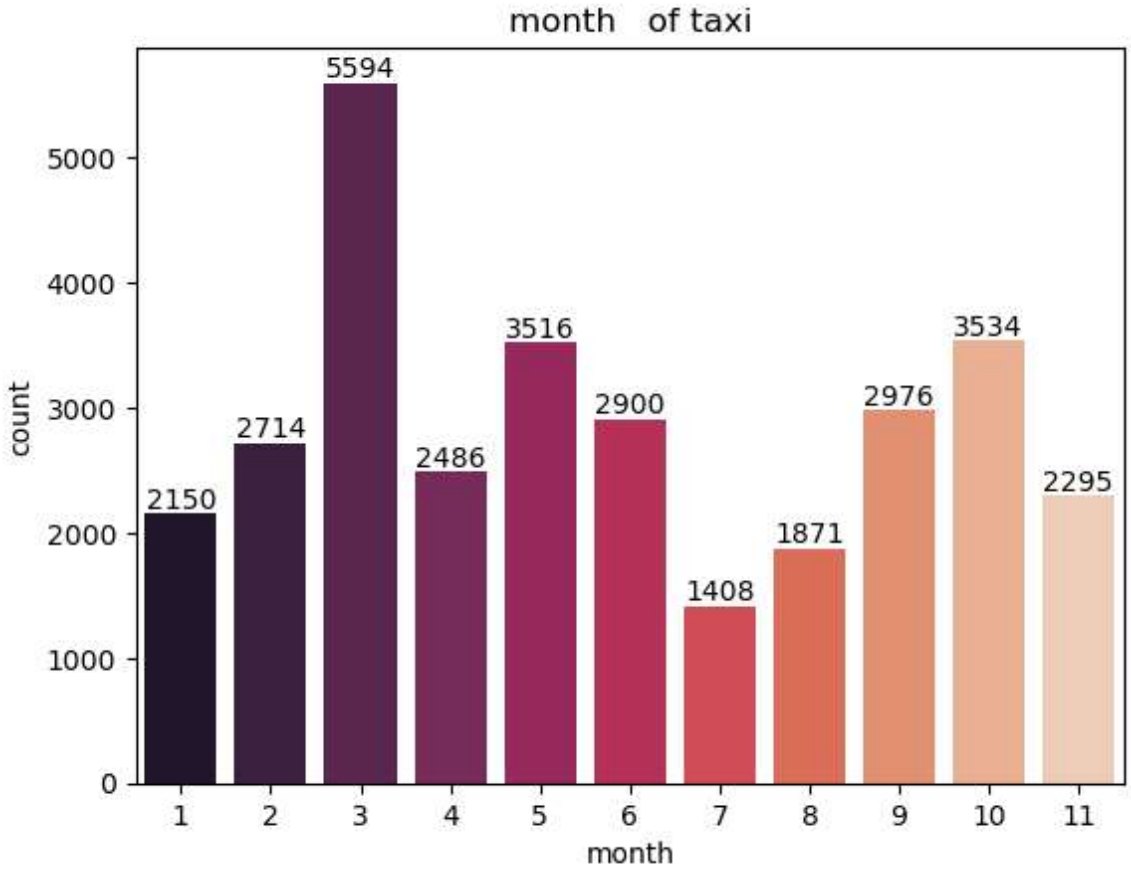

```
inferences of extra -
count  of extra highest values are-
          extra
0.0  16014
count of extra lowest values are-
       extra
0.8        1
```



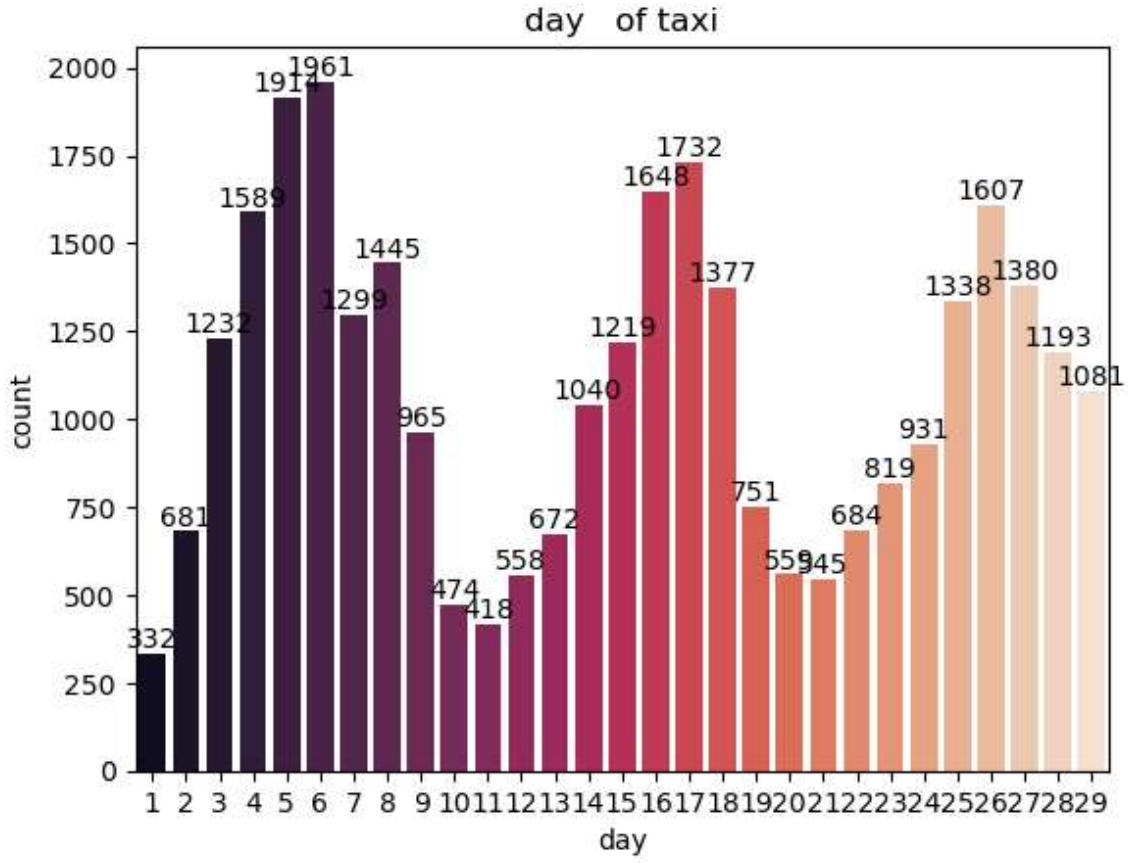

```
inferences of mta_tax -
count  of mta_tax highest values are-
          mta_tax
0.5    30839
count of mta_tax lowest values are-
       mta_tax
0.0      605
```



```
inferences of imp_surcharge -
count  of imp_surcharge highest values are-
          imp_surcharge
0.3          31441
count of imp_surcharge lowest values are-
       imp_surcharge
0.0              3
```



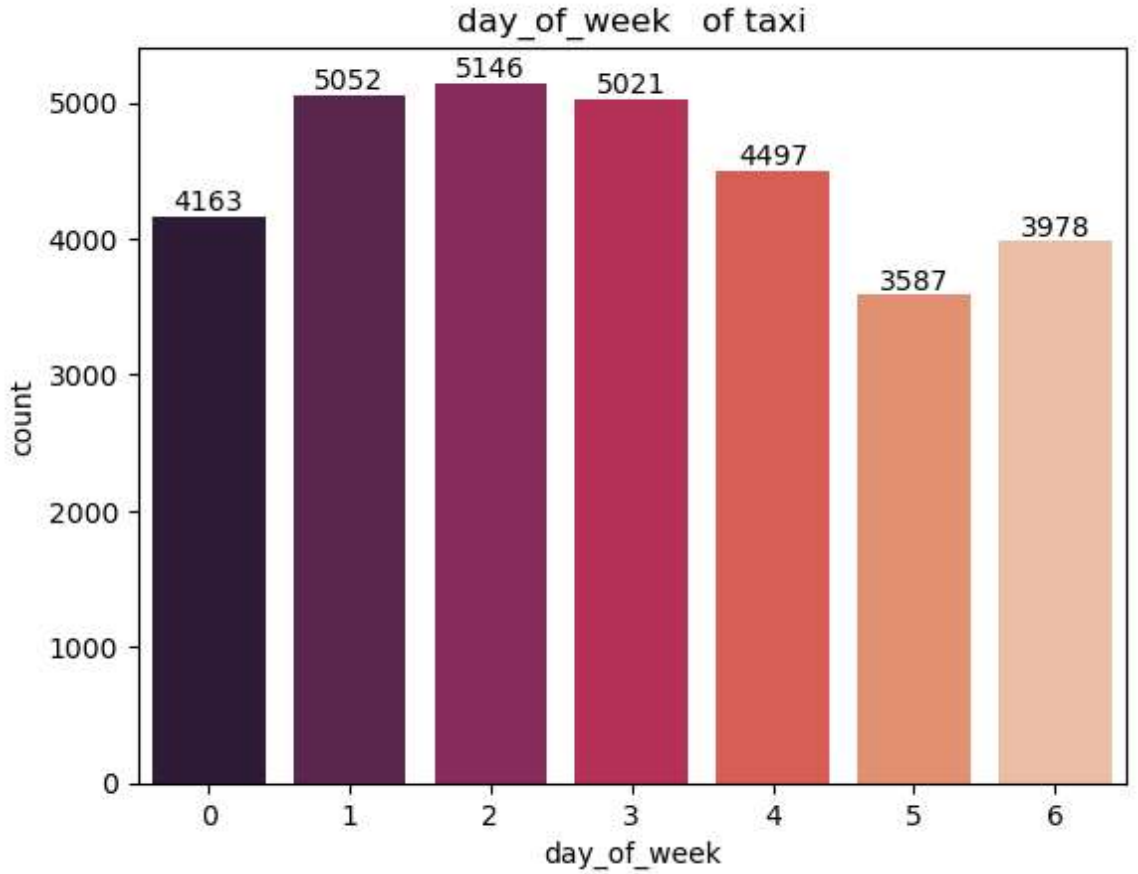

```
inferences of month -
count  of month highest values are-
        month
3   5594
count of month lowest values are-
     month
7   1408
```




```
inferences of day -
count  of day highest values are-
         day
6  1961
count of day lowest values are-
     day
1  332
```

inferences-

1. The majority of trips have a rate code of 1, indicating a standard rate. Only a small number of trips have a rate code of 2, which represents a negotiated fare.
2. All trips in the dataset were flagged as not being stored and forwarded, indicating that they were processed in real-time by the taxi system.
3. The most common payment type is credit card, followed by cash and then no charge.



/ of trips, with

s is the

unt for a

t the tri

inferences of day_of_week -

count of day_of_week highest values are-

day_of_week	
2	5146

count of day_of_week lowest values are-

day_of_week	
5	3587

payment_type:

The most common payment type is 1, which is credit card payment.

There are only 43 trips where payment was made using payment type 4, whi
ch is the lowest count for any payment
type.

extra:

The majority of trips do not have any extra charges.

The lowest count of any extra value is 1, which corresponds to an extra
charge of 0.8.

mta_tax:

The majority of trips have an MTA tax of 0.5, which is the standard tax
rate.

Only 915 trips have an MTA tax of 0, which is the lowest count for any M
TA tax value.

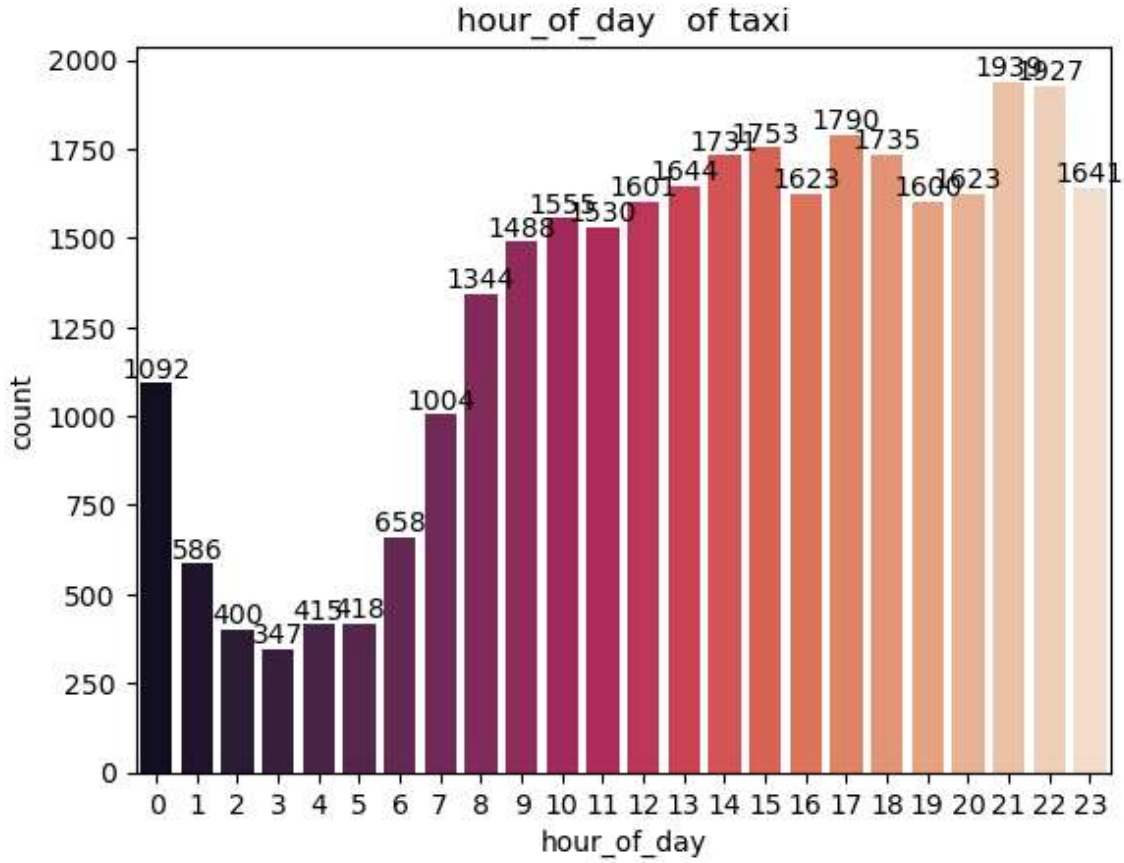
imp_surcharge:

The majority of trips have an improvement surcharge of 0.3.

Only 7 trips have an improvement surcharge of 0, which is the lowest cou
nt for any surcharge value.

month:

trips.



trips.

y (day

ay of the

with 2134

03:00 has the lowest count of any hour of the day with only 388 trips.

inferences of hour_of_day -

count of hour_of_day highest values are-

In [27]:

```
taxi.drop('store_and_fwd_flag',axis=1,inplace=True)
```

count of hour_of_day highest values are-

	hour_of_day
21	1939

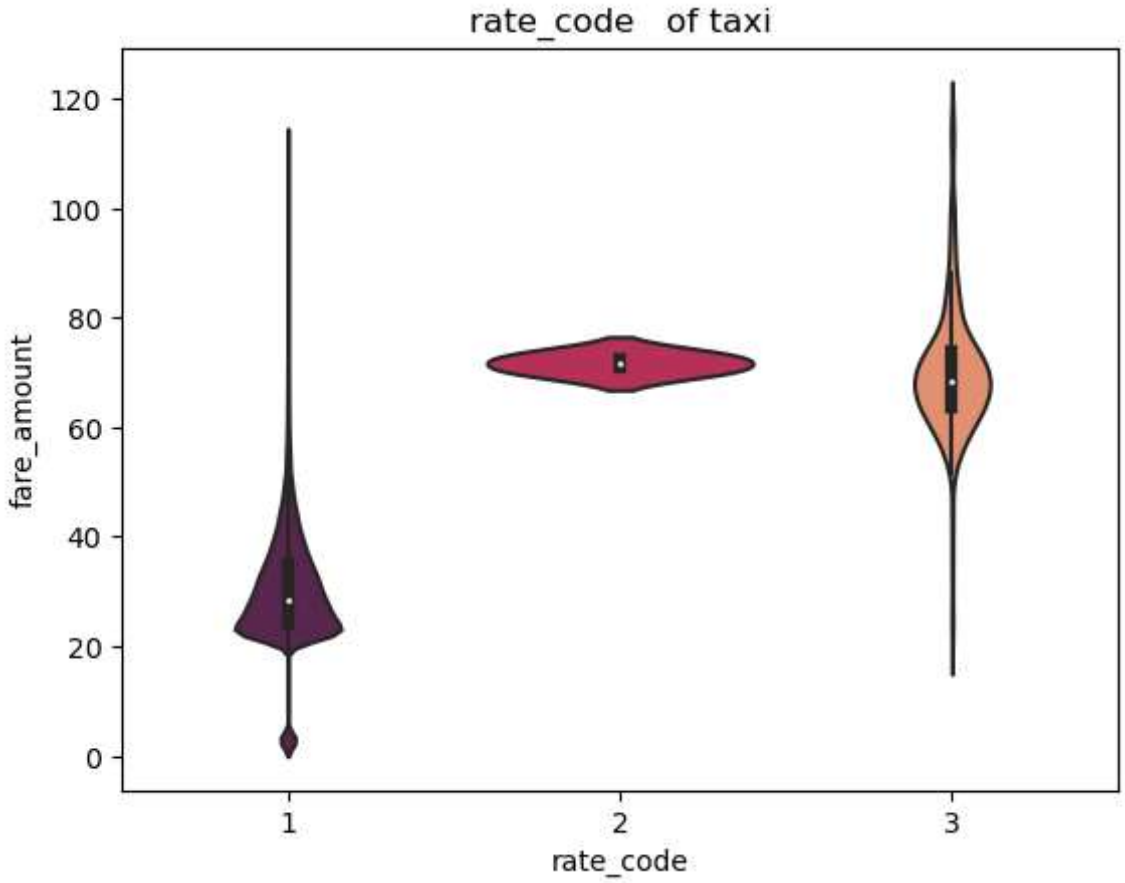
count of hour_of_day lowest values are-

	hour_of_day
3	347

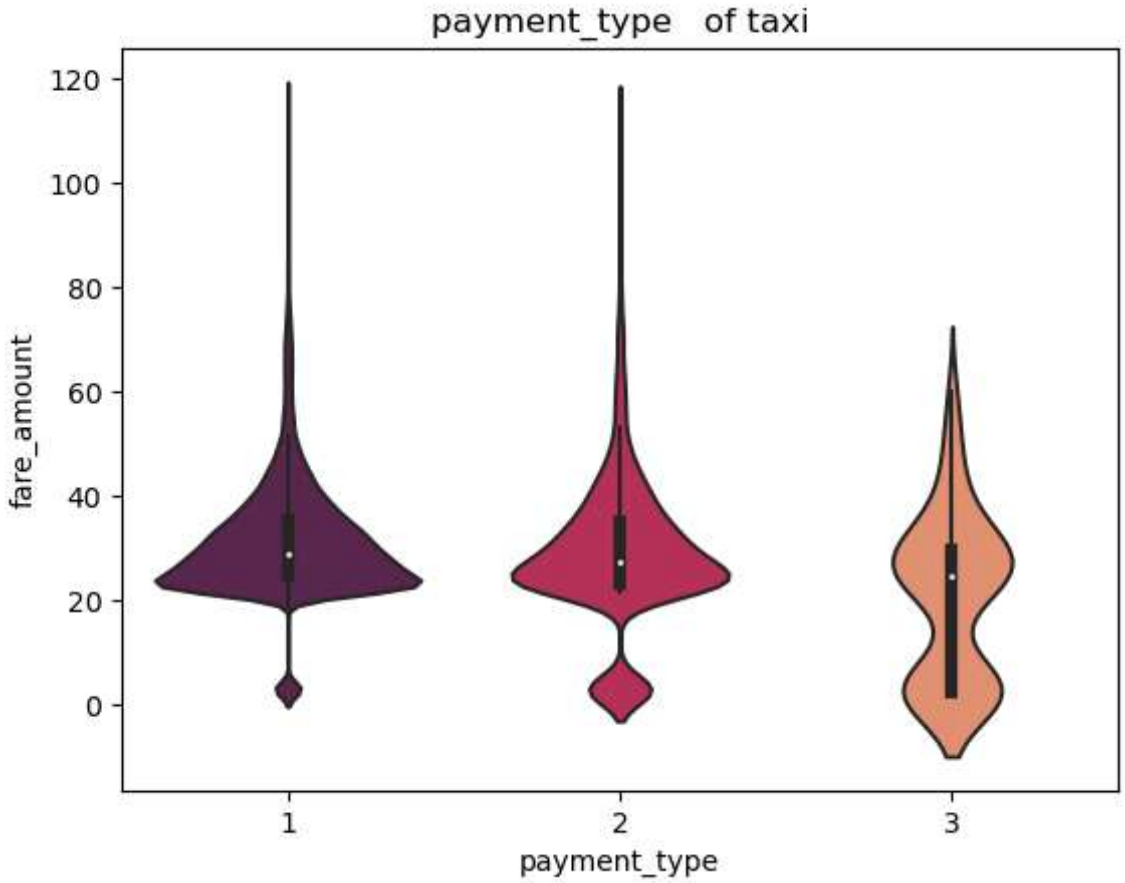
In [28]:

```
for col in taxi.columns:
    if taxi[col].nunique() > 31:
        print(f'{col}  is {taxi[col].nunique()} continues values in column')
    else:
        plot=sns.violinplot(x=col,y='fare_amount',data=taxi,palette='rocket')
        plt.title(f'{col}   of taxi')
        #plot.bar_label(plot.containers[0], label_type='edge', fontsize=10, padding=0)
        plt.show()
    if col=='fare_amount':
        pass
    else:
        grouped = taxi.groupby(col)['fare_amount'].mean().reset_index()
        sorted_groups = grouped.sort_values(by='fare_amount', ascending=False)
        print("Columns with highest average fares: \n"
                ,(sorted_groups.head())
                ,("\n")
                ,("Columns with lowest average fares:\n")
                ,(sorted_groups.tail()))
#by using for loop and if,else condition we are plotting violin plot with fare amount to
#cheack which categorical column will affect the fare amount
```

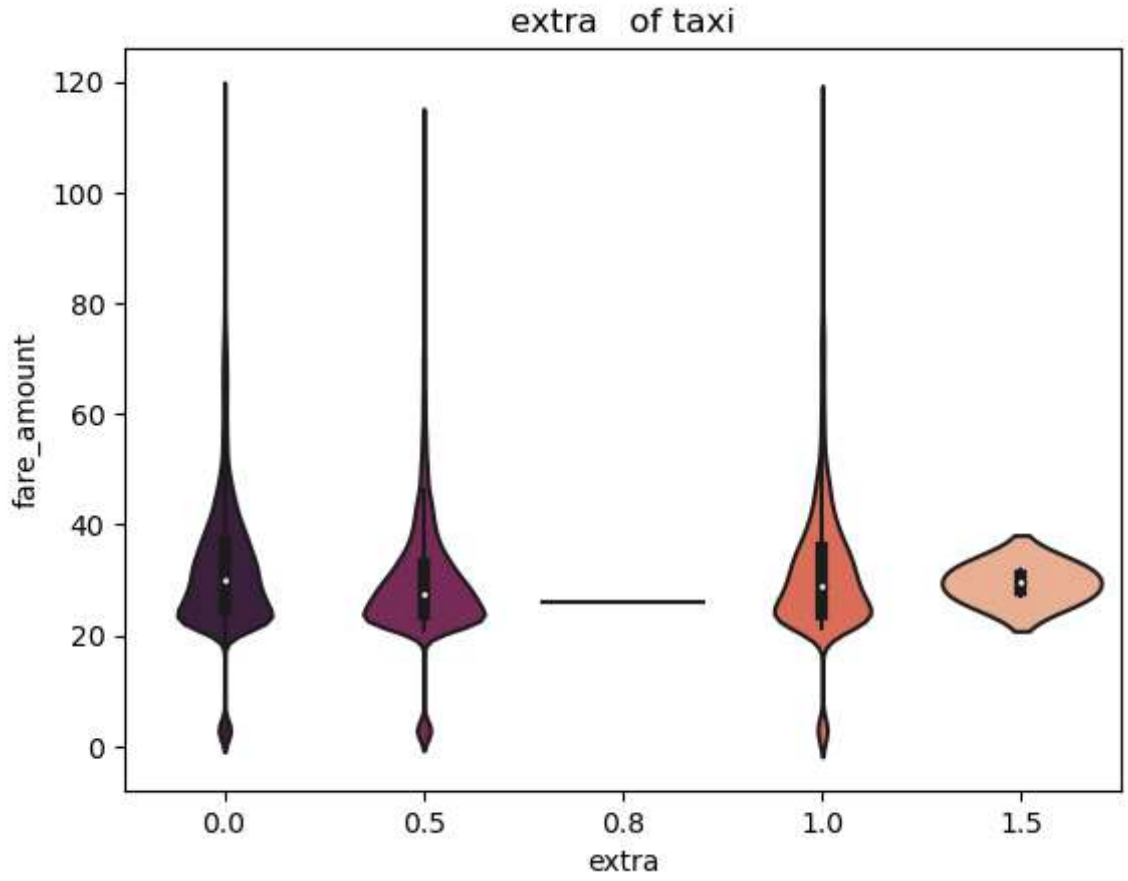
```
trip_distance(km)  is 2139 continues values in column
Columns with highest average fares:
       trip_distance(km)  fare_amount
2137          61.571818        116.5
2135          59.045217        116.0
2136          59.447542        115.5
1963          36.820784        115.0
2123          52.479273        113.5
 Columns with lowest average fares:
     trip_distance(km)  fare_amount
4             0.080465     2.650000
43            1.287440     2.625000
3             0.064372     2.583333
2             0.048279     2.583333
0             0.016093     2.555556
```



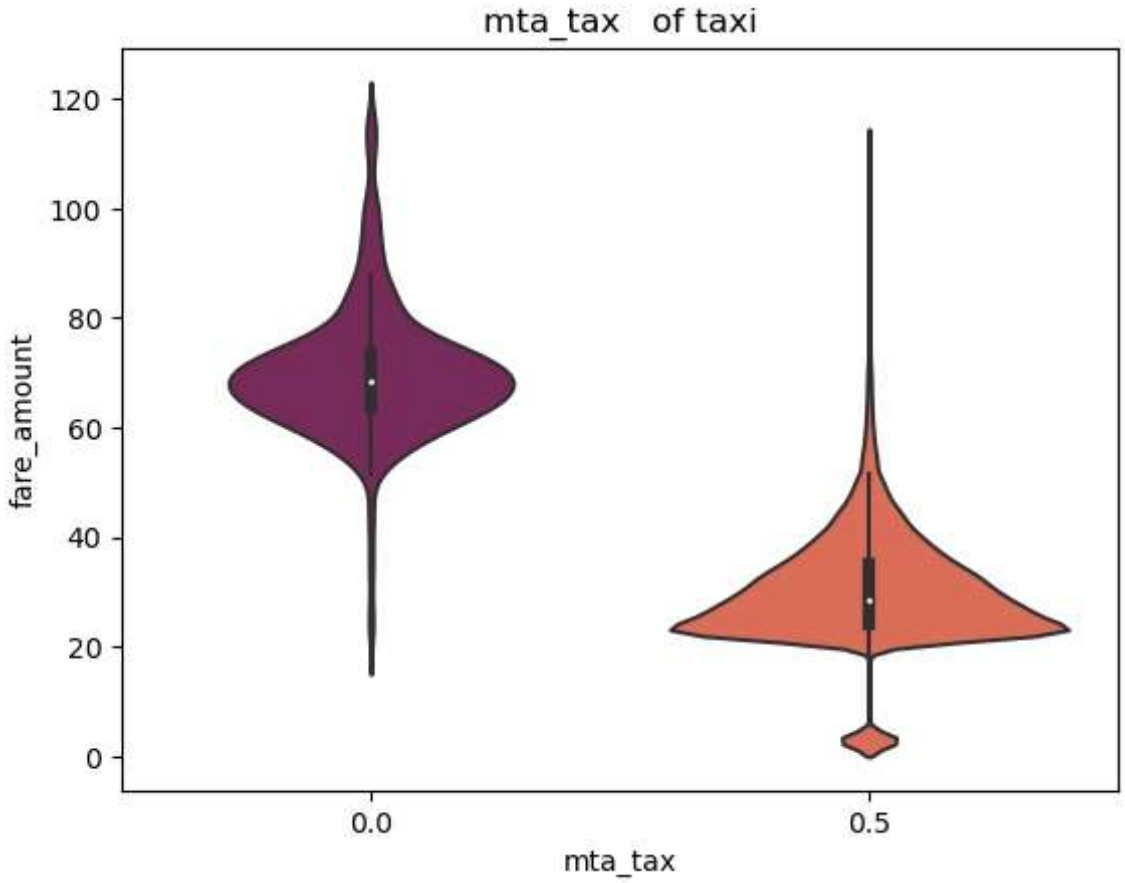

```
Columns with highest average fares:
    rate_code  fare_amount
1           2    71.660000
2           3    69.843284
0           1    30.304279
 Columns with lowest average fares:
    rate_code  fare_amount
1           2    71.660000
2           3    69.843284
0           1    30.304279
```



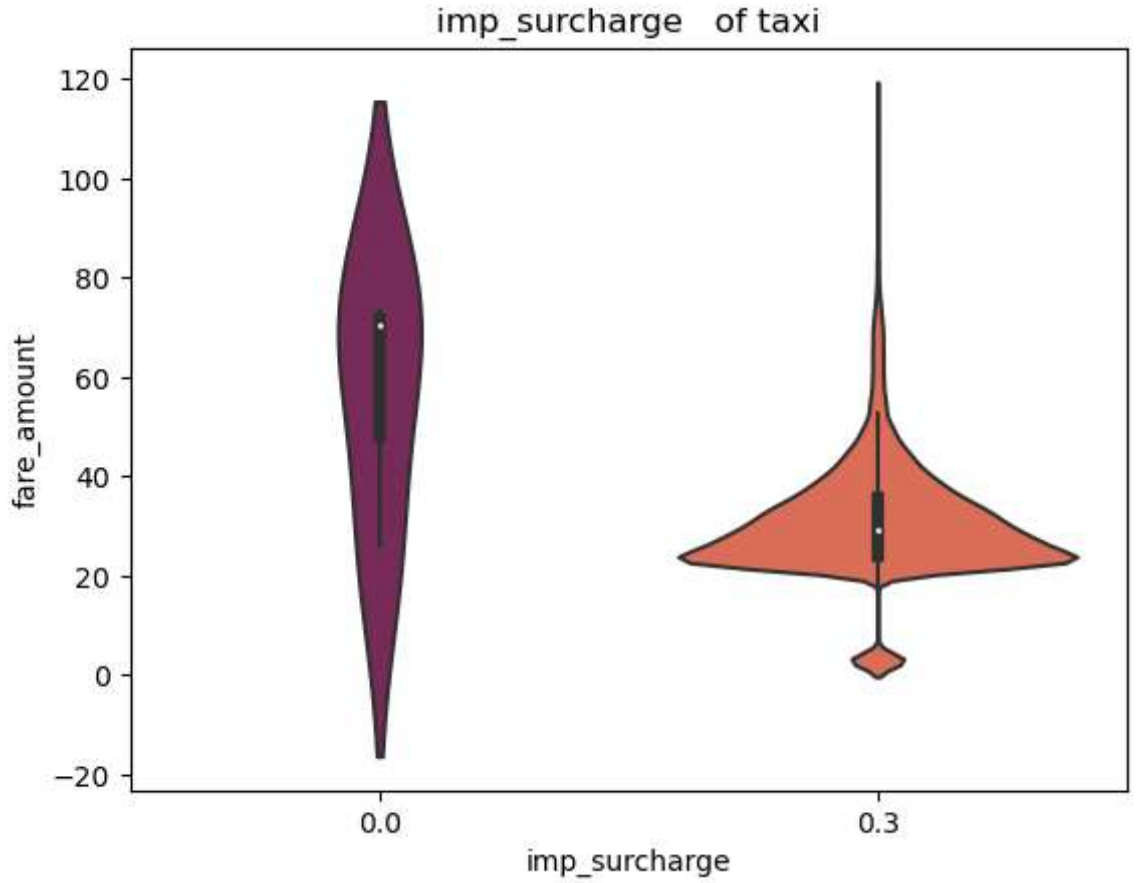

```
Columns with highest average fares:
    payment_type  fare_amount
0              1    31.329120
1              2    29.046515
2              3    20.811881
 Columns with lowest average fares:
    payment_type  fare_amount
0              1    31.329120
1              2    29.046515
2              3    20.811881
fare_amount  is 172 continues values in column
```



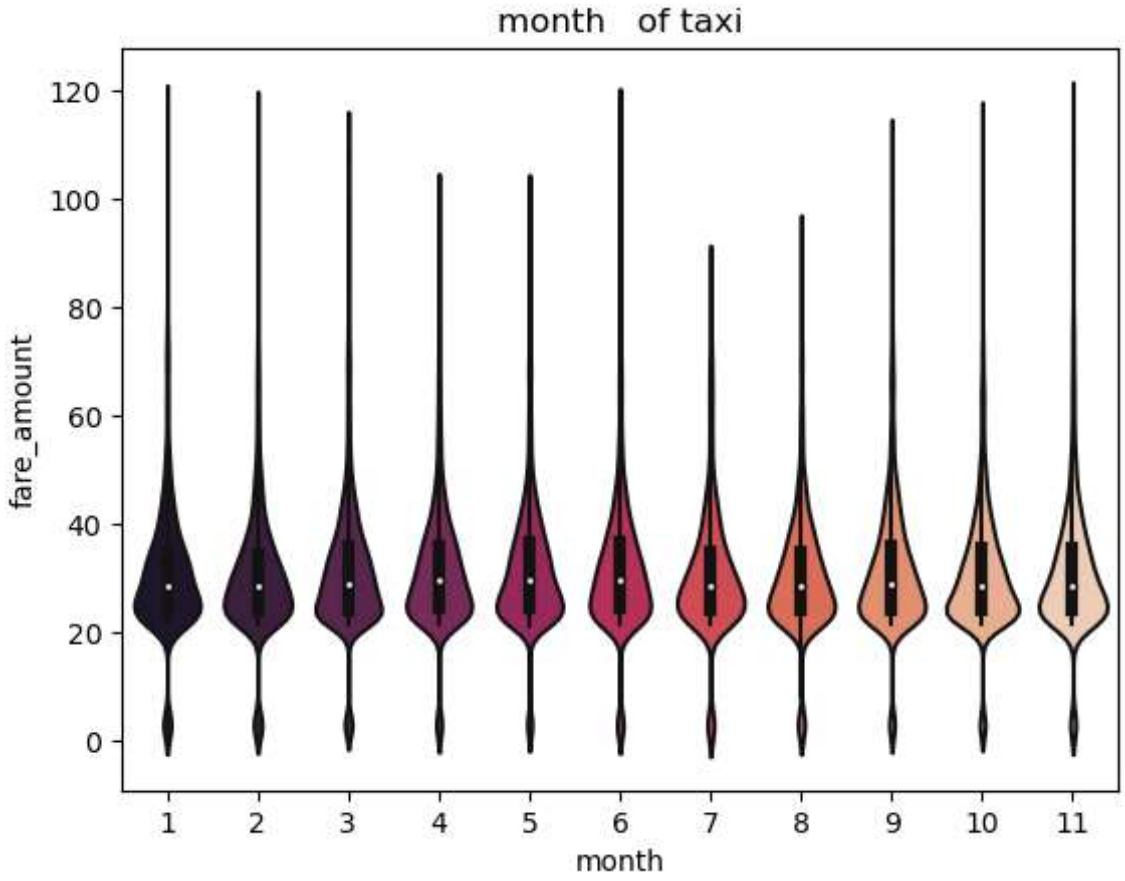

```
Columns with highest average fares:
    extra  fare_amount
0    0.0    31.963273
3    1.0    31.441560
1    0.5    29.508299
4    1.5    29.500000
2    0.8    26.000000
 Columns with lowest average fares:
    extra  fare_amount
0    0.0    31.963273
3    1.0    31.441560
1    0.5    29.508299
4    1.5    29.500000
2    0.8    26.000000
```


mta_tax of taxi
fare_amount
120
100
80
60
40
20
0
0.0
0.5
mta_tax

```
Columns with highest average fares:
    mta_tax  fare_amount
0       0.0    69.849289
1       0.5    30.304279
 Columns with lowest average fares:
    mta_tax  fare_amount
0       0.0    69.849289
1       0.5    30.304279
tip_amount  is 1265 continues values in column
Columns with highest average fares:
       tip_amount  fare_amount
1257       48.25        115.0
1236       25.86        113.5
1237       27.06        112.0
1244       29.65        111.5
1199       22.10        103.5
 Columns with lowest average fares:
       tip_amount  fare_amount
36           0.66          2.5
35           0.65          2.5
52           0.99          2.5
1198       22.00          2.5
1264      116.20          2.5
tolls_amount  is 151 continues values in column
Columns with highest average fares:
      tolls_amount  fare_amount
143          27.02       116.50
142          25.88       116.00
149          44.52       115.00
136          22.02       113.75
147          31.52       113.00
 Columns with lowest average fares:
      tolls_amount  fare_amount
23            5.85         26.0
25            5.94         25.5
58           14.26         25.0
146          31.50         25.0
27            6.56         21.5
```




```
Columns with highest average fares:
    imp_surcharge  fare_amount
0             0.0    56.440000
1             0.3    31.062726
 Columns with lowest average fares:
    imp_surcharge  fare_amount
0             0.0    56.440000
1             0.3    31.062726
total_amount  is 2328 continues values in column
Columns with highest average fares:
       total_amount  fare_amount
2312         143.82        116.5
2324         162.18        116.0
2322         157.82        115.5
2327         209.07        115.0
2320         155.16        113.5
 Columns with lowest average fares:
       total_amount  fare_amount
59             8.91          2.5
55             7.00          2.5
2274         120.00          2.5
50             5.91          2.5
0              3.30          2.5
```




```
Columns with highest average fares:
    month  fare_amount
4       5    31.636630
5       6    31.554310
8       9    31.386929
3       4    31.316573
2       3    31.207365
 Columns with lowest average fares:
    month  fare_amount
9      10    30.868014
6       7    30.615767
0       1    30.532326
7       8    30.481577
1       2    30.282424
```

inferences-

Based on the provided data, we can make the following inferences:

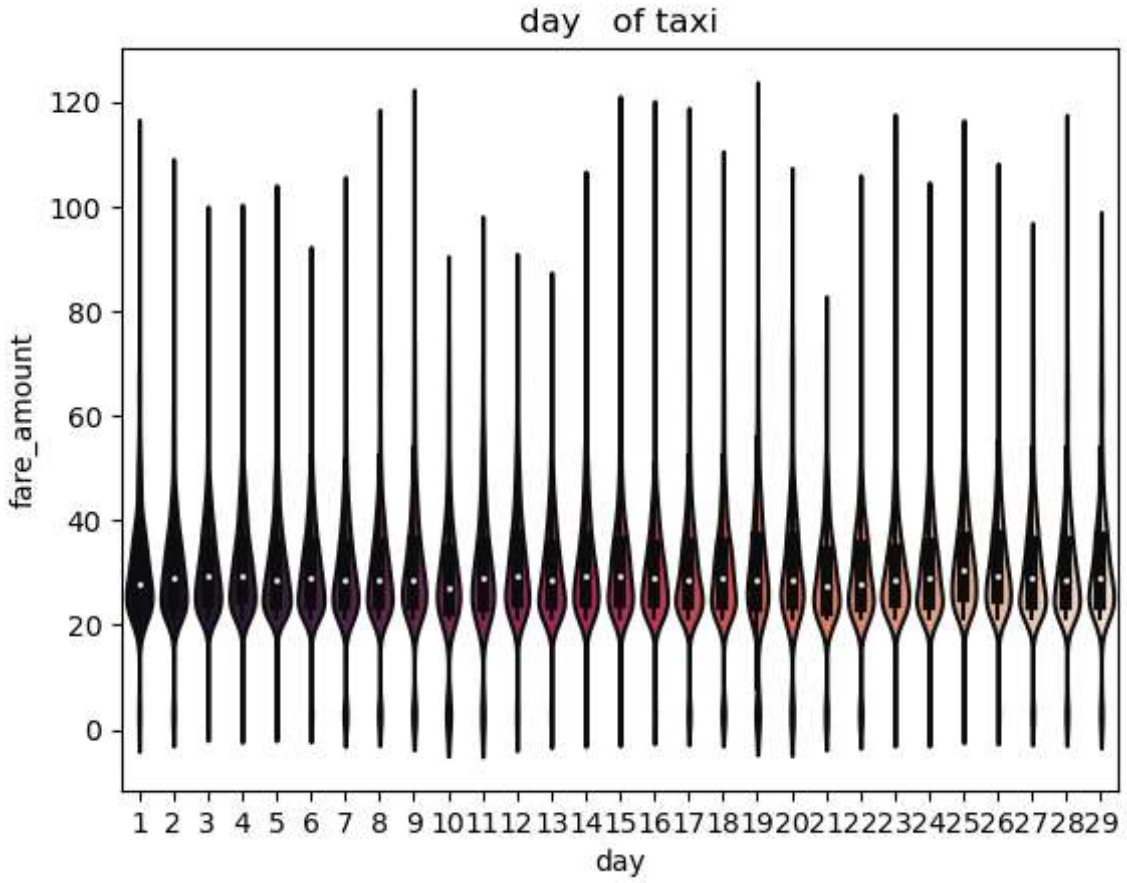
1. Trip distance ranges from 0.01 km to 2139 km with the highest average fare of 61.57 km for a distance of 61.57 km and the lowest average fare of 2.65 for a distance of 0.08 km.
2. Rate code varies from 1 to 3 with the highest average fare of 71.66 for rate code 2 and the lowest average fare of 30.30 for rate code 1.
3. ...
4. Payment type has three values: 1, 2, and 3. The data shows that payment type 1 has the highest average fare of 31.32, and payment type 3 has the lowest average fare of 20.81.
5. Fare amount ranges from 0.01 to 172 with the highest average fare of 31.96 for an extra of 0 and the lowest average fare of 2.55 for a trip distance of 0.01 km.

TA tax value of 0

of 48.25 and

nt of 44.52 and

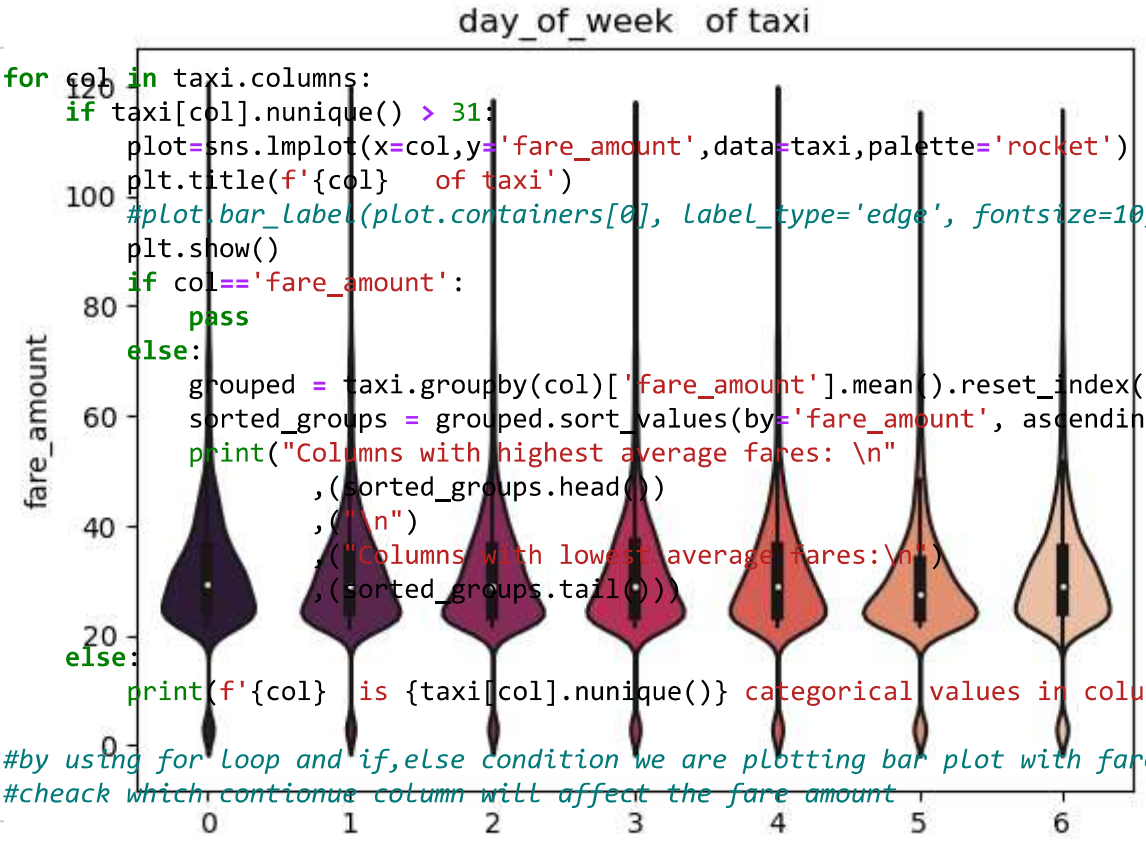
s the highest
).
l amount of

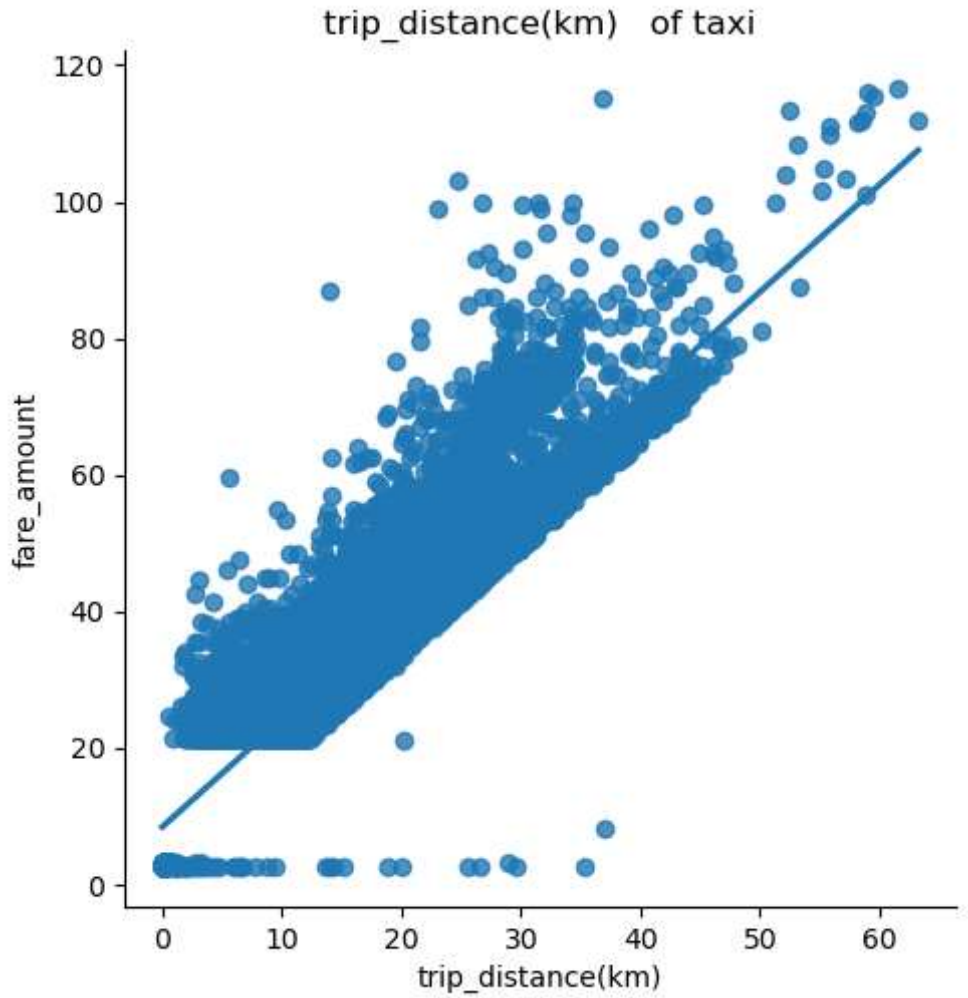


- MTA tax:
  - Highest: mta_tax = 0.0, fare_amount = 73.272852
  - Lowest: mta_tax = 0.5, fare_amount = 30.810833
- Tip amount:
  - Highest: tip_amount = 77.05, fare_amount = 350.5
  - Lowest: tip_amount = 0.66, fare_amount = 2.5
- Tolls amount:
  - Highest: tolls_amount = 89.50, fare_amount = 200.0
  - Lowest: tolls_amount = 3.00, fare_amount = 26.75
- Improvement surcharge:
  - Highest: imp_surcharge = 0.0, fare_amount = 59.625714

```
Columns with highest average fares:
    day   fare_amount
24   25     32.228700
25   26     32.070317
13   14     31.791712
11   12     31.701219
14   15     31.626030
Columns with lowest average fares:
    day   fare_amount
1     2     30.479442
6     7     30.383757
21   22     29.875238
20   21     29.765138
9    10     28.957806
```

```
for col in taxi.columns:
    if taxi[col].nunique() > 31:
        plot=sns.lmplot(x=col,y='fare_amount',data=taxi,palette='rocket')
        plt.title(f'{col}   of taxi')
        #plot.bar_label(plot.containers[0], label_type='edge', fontsize=10, padding=0)
        plt.show()
        if col=='fare_amount':
            pass
        else:
            grouped = taxi.groupby(col)['fare_amount'].mean().reset_index()
            sorted_groups = grouped.sort_values(by='fare_amount', ascending=False)
            print("Columns with highest average fares: \n"
                  ,(sorted_groups.head())
                  ,("\n")
                  ,("Columns with lowest average fares:\n")
                  ,(sorted_groups.tail()))
    else:
        print(f'{col}  is {taxi[col].nunique()} categorical values in column')

#by using for loop and if,else condition we are plotting bar plot with fare amount to
#cheack which continous column will affect the fare amount
```





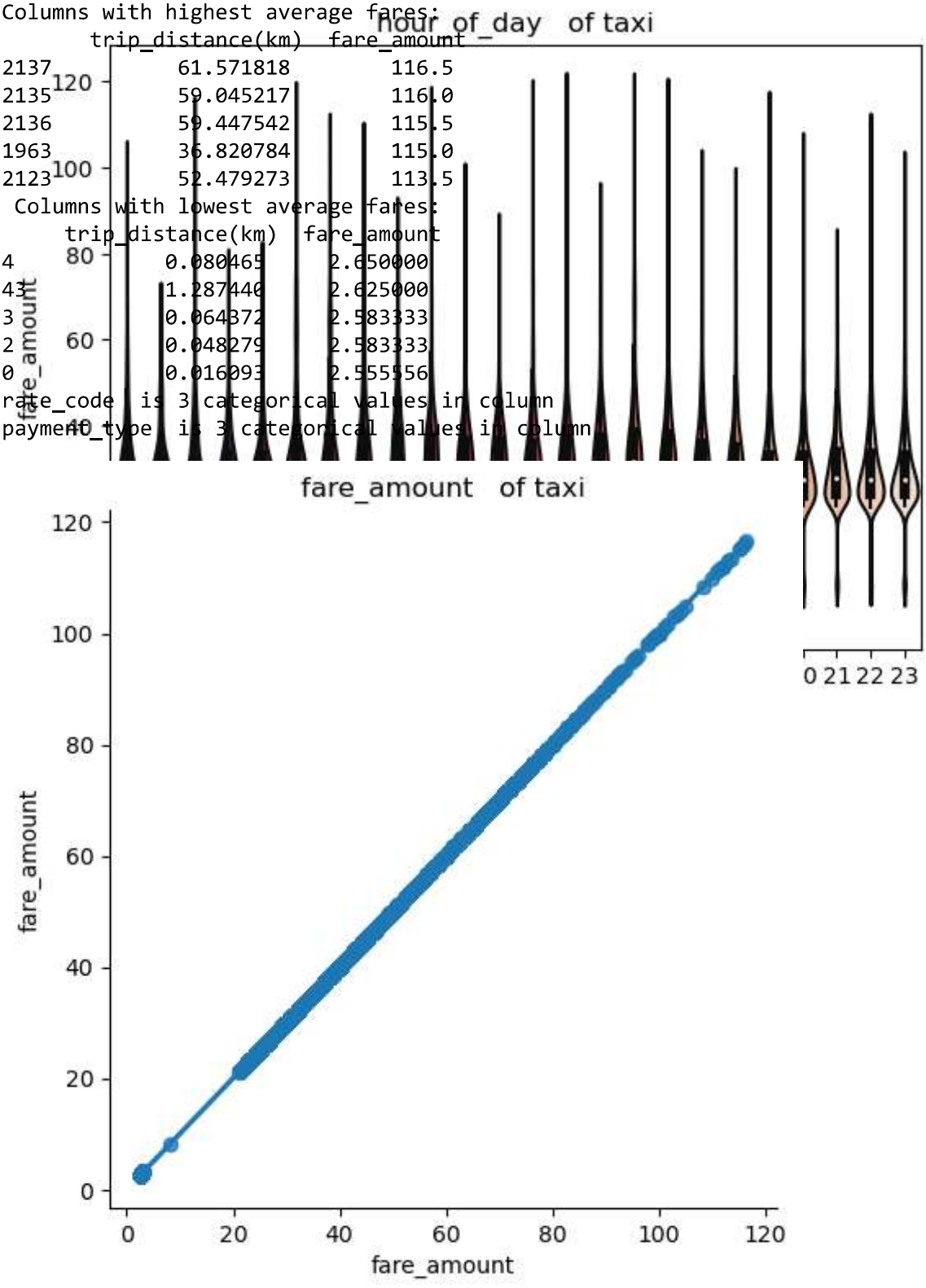
Columns with highest average fares:

	trip_distance(km)	fare_amount
2137	61.571818	116.5
2135	59.045217	116.0
2136	59.447542	115.5
1963	36.820784	115.0
2123	52.479273	113.5

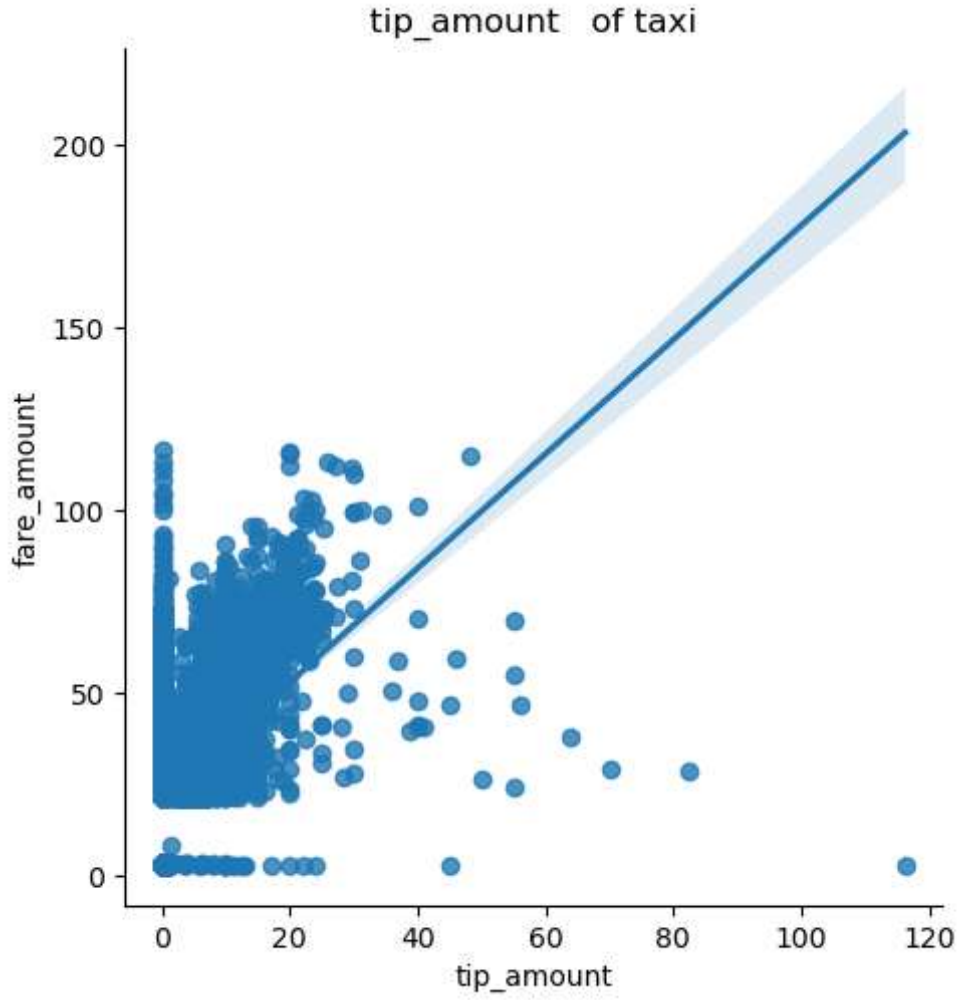
Columns with lowest average fares:

	trip_distance(km)	fare_amount
4	0.080465	2.650000
43	1.287440	2.625000
3	0.064372	2.583333
2	0.048279	2.583333
0	0.016093	2.555556

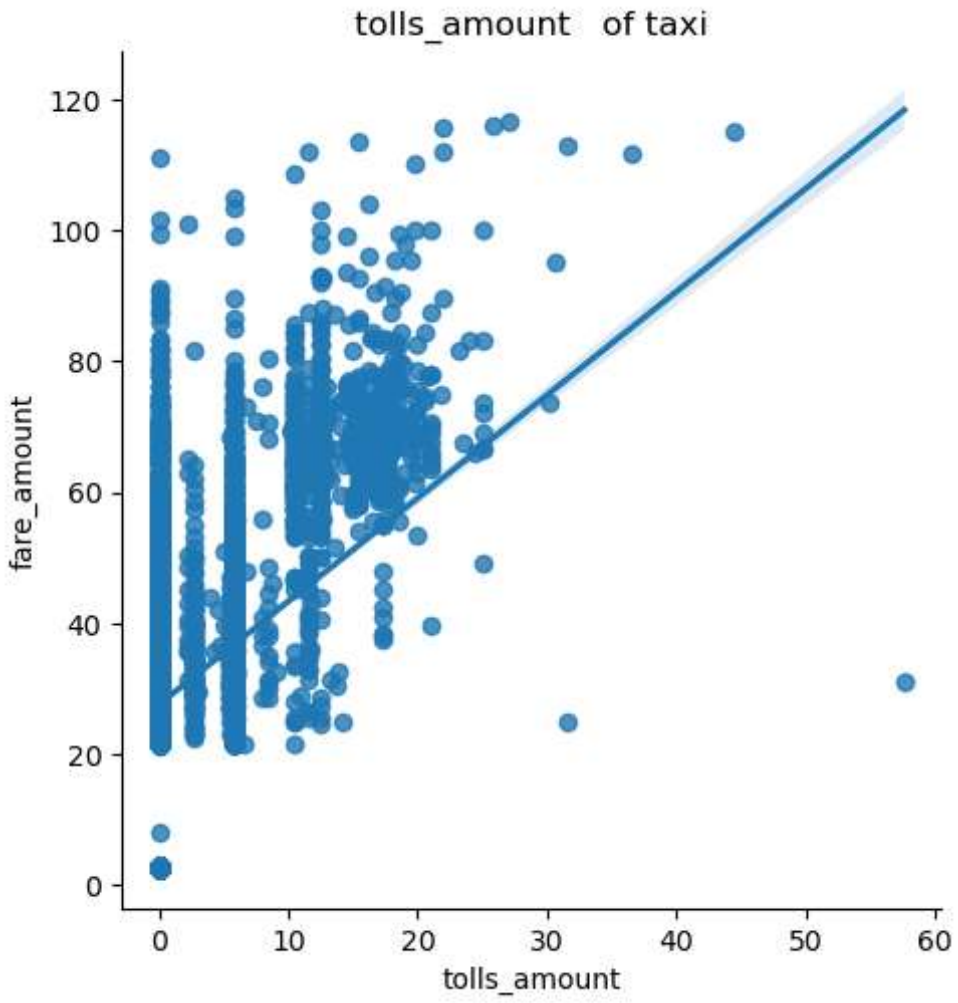
rate_code is 3 categorical values in column
payment_type is 3 categorical values in column



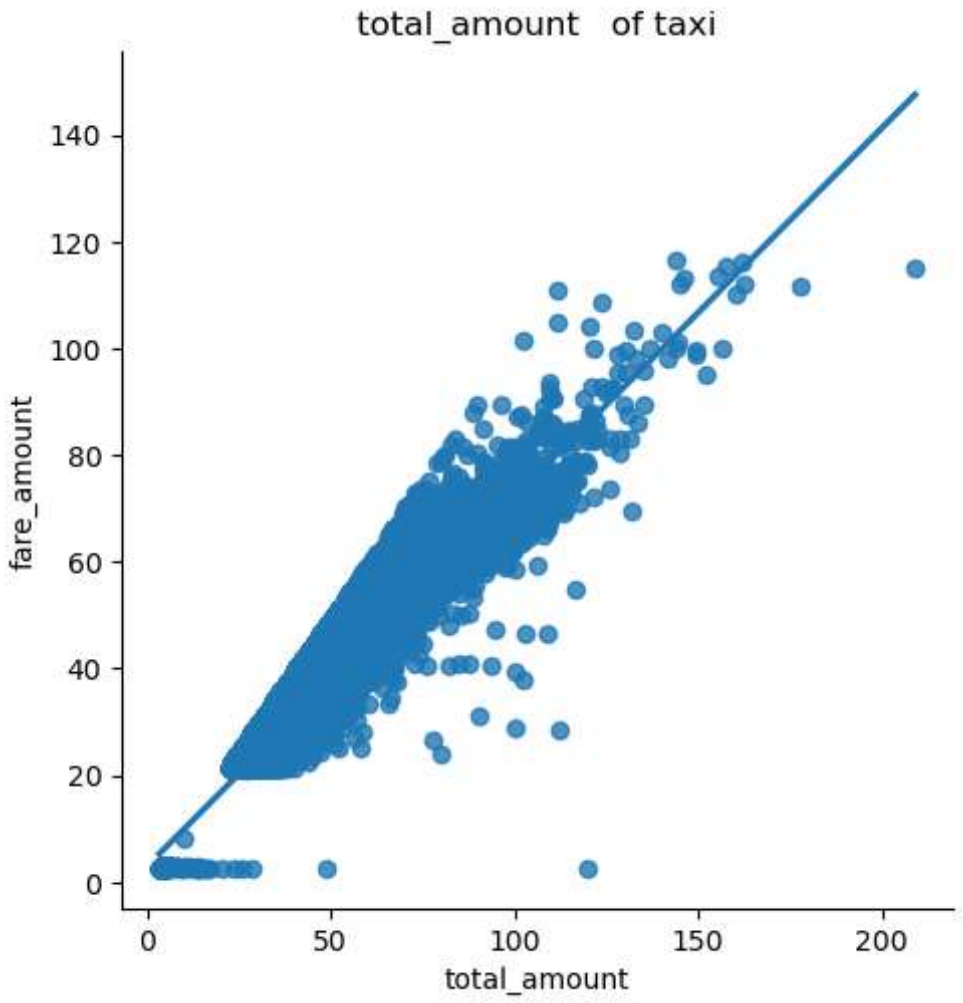
extra is 5 categorical values in column
mta_tax is 2 categorical values in column



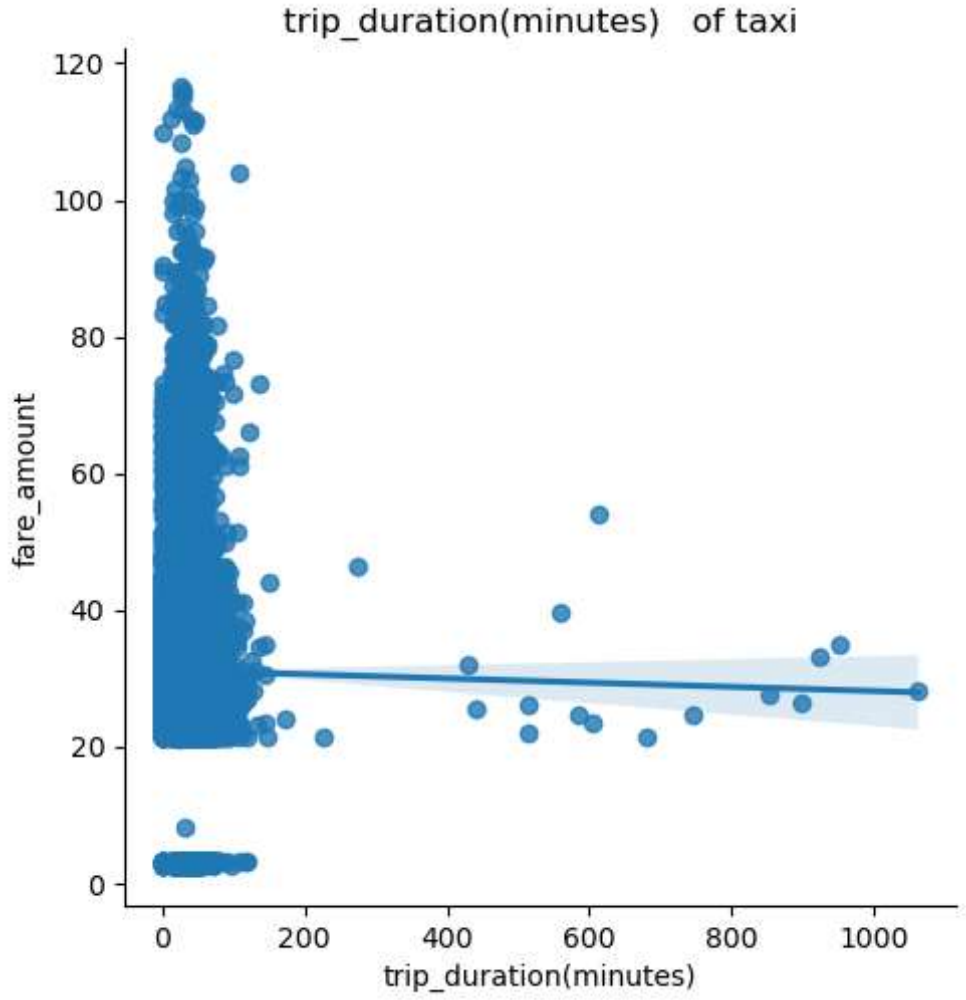

```
Columns with highest average fares:
Columns with highest average fares:
      calculated_total_amount  fare_amount
      tip_amount  fare_amount
448                      55.01        100.0
1257       48.25        115.0
482                      35.67         91.5
1236       25.86        113.5
976                      47.34         89.5
1237       27.06        112.0
682                      40.22         81.0
1244       29.65        111.5
2238                    105.36         80.5
1199       22.10        103.5
 Columns with lowest average fares:
 Columns with lowest average fares:
      calculated_total_amount  fare_amount
      tip_amount  fare_amount
2245                     10.84          3.0
36          0.66         2.5
2126                     97.25          3.0
35          0.65         2.5
1474                     61.74          2.5
52          0.99         2.5
121                      25.09          2.5
1198       22.00         2.5
79                       21.57          2.5
1264      116.20           2.5
```




```
Columns with highest average fares:
      tolls_amount  fare_amount
143         27.02       116.50
142         25.88       116.00
149         44.52       115.00
136         22.02       113.75
147         31.52       113.00
 Columns with lowest average fares:
      tolls_amount  fare_amount
23           5.85         26.0
25           5.94         25.5
58          14.26         25.0
146         31.50         25.0
27           6.56         21.5
imp_surcharge  is 2 categorical values in column
```




```
Columns with highest average fares:
       total_amount  fare_amount
2312        143.82        116.5
2324        162.18        116.0
2322        157.82        115.5
2327        209.07        115.0
2320        155.16        113.5
 Columns with lowest average fares:
       total_amount  fare_amount
59            8.91          2.5
55            7.00          2.5
2274        120.00          2.5
50            5.91          2.5
0             3.30          2.5
month  is 11 categorical values in column
day  is 29 categorical values in column
day_of_week  is 7 categorical values in column
hour_of_day  is 24 categorical values in column
```




```
Columns with highest average fares:
      trip_duration(minutes)  fare_amount
193                13.100000        112.0
3669              108.000000        104.0
205                13.333333         98.0
3488               77.833333         81.5
3119               63.700000         79.0
Columns with lowest average fares:
      trip_duration(minutes)  fare_amount
176                12.600000          3.0
3680              116.566667          3.0
3519               79.633333          3.0
175                12.533333          2.5
3644               96.983333          2.5
```

inferences-

1. Columns with highest and lowest average fares:

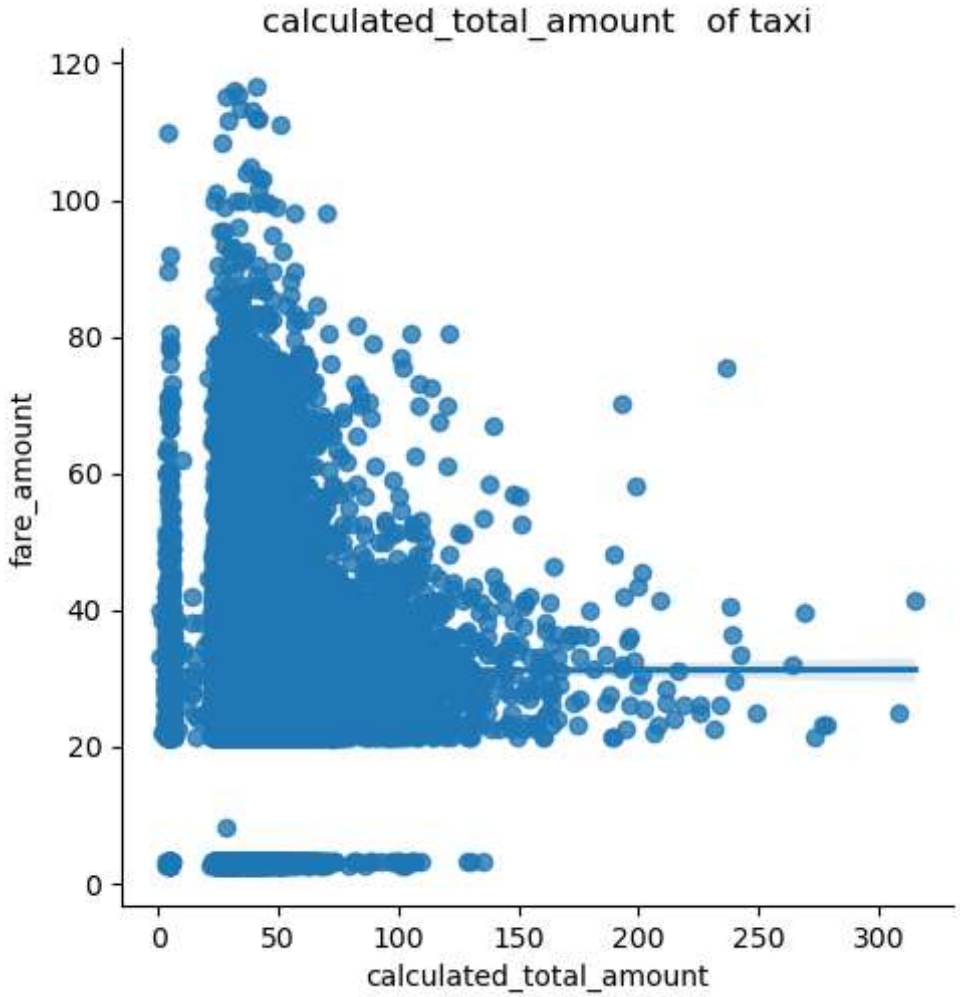
- The highest average fares are observed for trips with long distances. For instance, the trips with the highest average fares have an average distance of over 50 km.
- The trips with the lowest average fares have very short distances, with some trips being less than 100 meters.
- The rate code is a categorical variable that indicates the type of fare being charged, and it has three different values. The store_and_fwd_flag column is also a categorical variable and has only one value. Payment_type column is a categorical variable that indicates the payment method used, and it has three different values.
- The extra column is another categorical variable that shows extra charges applied, and it has five different values. The mta_tax column is another categorical variable that indicates whether or not the Metropolitan Transportation Authority tax was applied, and it has two different values.

2. Columns with highest and lowest average tip amounts:

- The columns with the highest average tip amounts are associated with high fare amounts, with some trips having an average tip amount of over
  $40. – The columns with the lowest average tip amounts are associated with very low fare amounts, with some trips having an average tip amount of less than$
  1.

3. Columns with highest and lowest average toll amounts:

h high fare amounts, with



withverylowfareamounts,

or not the improvement

mounts, with some trips

erylowfareamounts, *withso*

trip, and it has 11 different
ıe month of the trip, and it has
indicates the day of the week
orical variable that indicates

gh fare amounts, with some

y low fare amounts, with

6. Columns with highest and lowest calculated total amounts:

```
Columns with highest average fares:
      calculated_total_amount  fare_amount
448                     105.01        100.0
482                     105.67         91.5
976                      47.34         89.5
682                      40.22         81.0
2238                    105.36         80.5
```

- The columns with the highest calculated total amounts are associated with high fare amounts, with some trips having a calculated total amount of over 100. – *Thecolumnswiththelowestcalculatedtotalamountsareassociatedwithverylowfareamoun*
withsometripshavingacalculatedtotalamountoflessthan

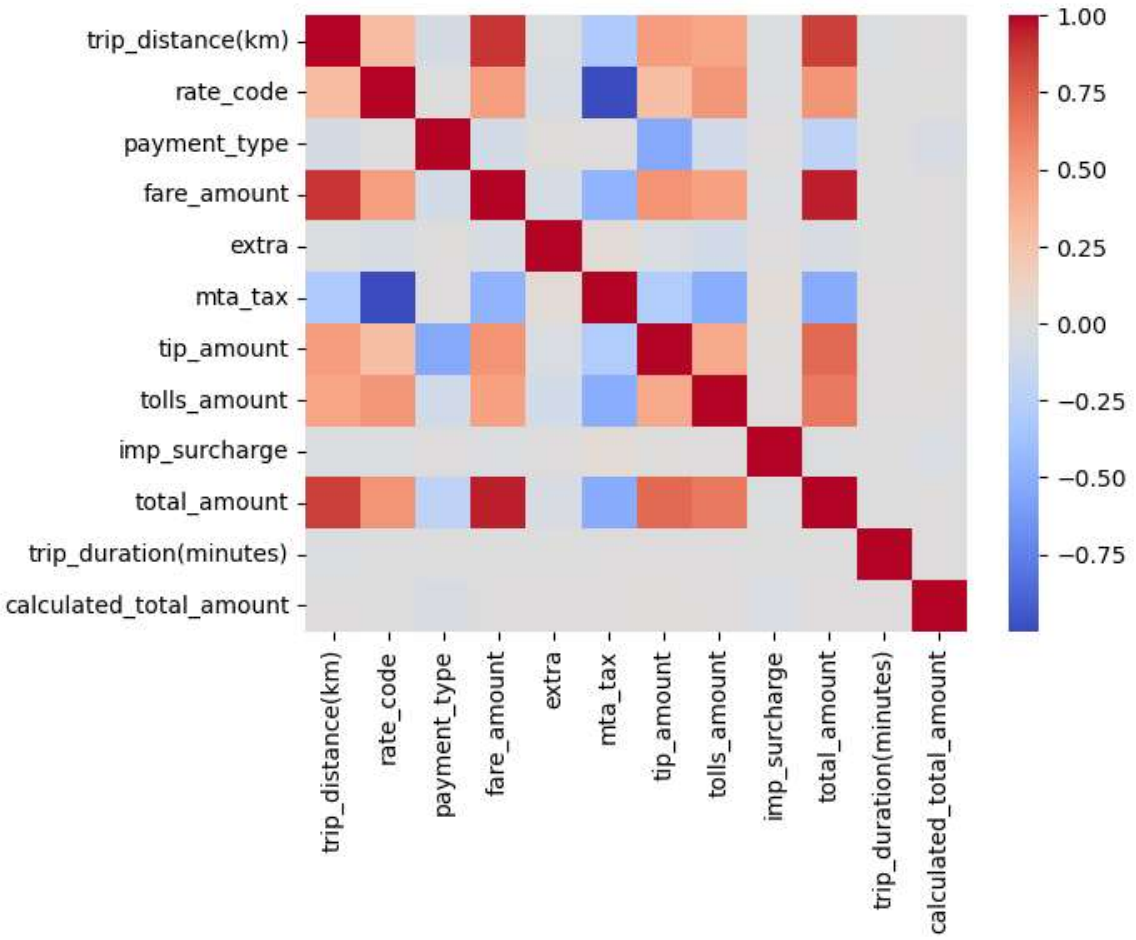
```
Columns with lowest average fares:
      calculated_total_amount  fare_amount
2245                   105.84          3.0
2126                    97.25          3.0
1474                    61.74          2.5
121                     25.09          2.5
79                      21.57          2.5
```

In [41]:

```
sns.heatmap(taxi.corr(),cmap='coolwarm')
```

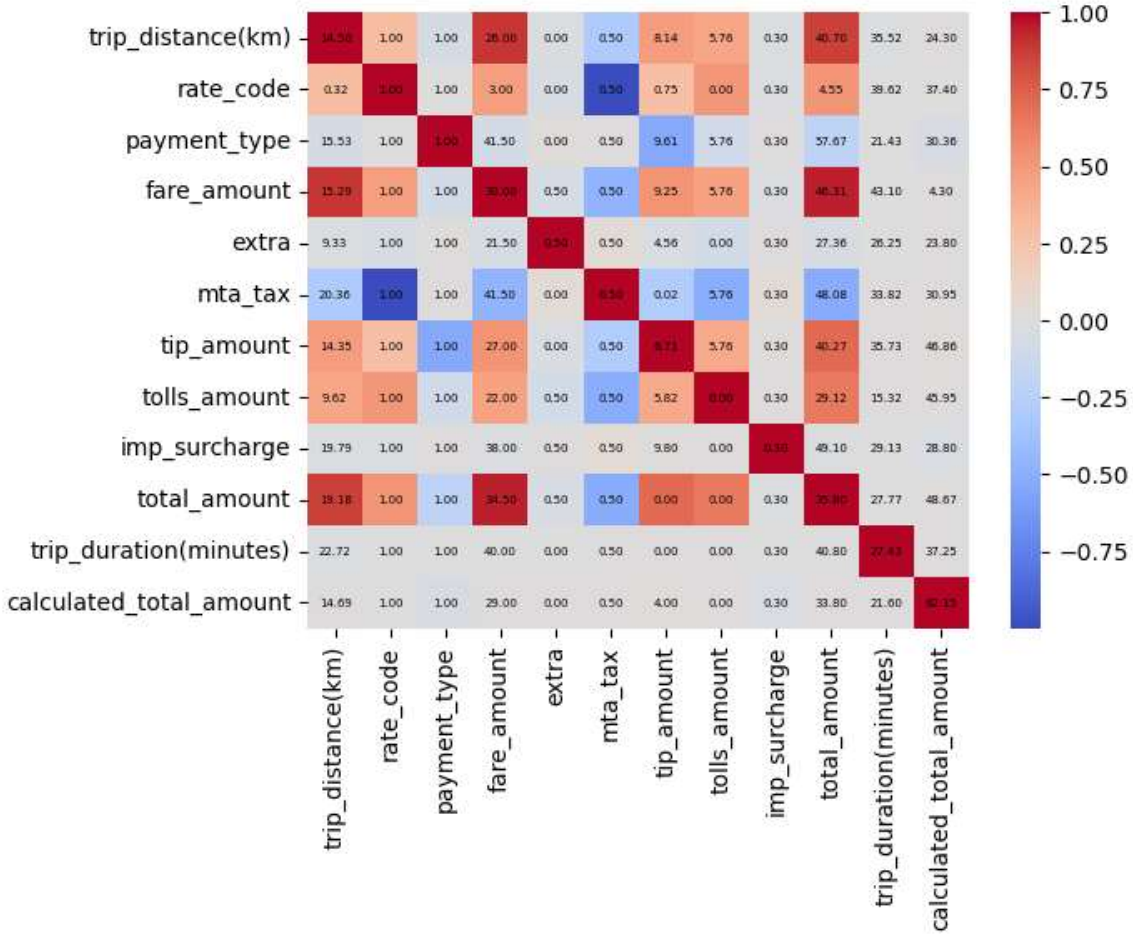
Out[41]:

<AxesSubplot:>



In [44]:

```
sns.heatmap(taxi.corr(),cmap='coolwarm')
for i in range(taxi.corr().shape[0]):
    for j in range(taxi.corr().shape[1]):
        plt.text(j + 0.5, i + 0.5, '{:.2f}'.format(taxi.iloc[i, j]), ha='center', va='cer
```



In [30]:

```
taxi
```

Out[30]:

	trip_distance(km)	rate_code	payment_type	fare_amount	extra	mta_tax	tip_amount
0	14.499793	1	1	26.0	0.0	0.5	8.14
1	0.321860	1	1	3.0	0.0	0.5	0.75
2	15.529745	1	1	41.5	0.0	0.5	9.61
3	15.288350	1	1	30.0	0.5	0.5	9.25
4	9.333940	1	1	21.5	0.5	0.5	4.56
...	...	...	...	...	...	...	...
34995	36.096599	1	1	59.5	0.5	0.5	10.00
34996	14.741188	1	1	30.0	0.0	0.5	6.58
34997	10.911054	1	1	23.0	0.0	0.5	5.95
34998	0.418418	1	2	3.0	0.0	0.5	0.00
34999	29.611120	1	1	53.0	1.0	0.5	10.96

31444 rows × 16 columns

conclusion-

Among the columns with the highest average fares are trip_distance, tip_amount, tolls_amount, and total_amount. These columns show a positive correlation with fare_amount, meaning that as these values increase, so does the fare_amount.

In contrast, the columns with the lowest average fares are trip_distance, tip_amount, tolls_amount, and total_amount but with extremely low values, indicating that these trips may have been short or may not have required additional fees.

Moreover, the duration of the trip and the calculated_total_amount also have a positive correlation with the fare amount, suggesting that longer trips and higher total fees result in higher fare amounts.

Other categorical columns such as payment_type, extra, mta_tax, imp_surcharge, rate_code, store_and_fwd_flag, month, day, day_of_week, and hour_of_day may also affect the fare amount, but we need to analyze them further to draw more specific conclusions.

Therefore, in general, trip_distance, tip_amount, payment_type, tolls_amount, total_amount, duration of the trip, and calculated_total_amount appear to be the columns that affect the fare amount the most.

In [31]:

```
taxi.drop([ 'month', 'day', 'day_of_week', 'hour_of_day'],axis=1,inplace=True)
```

Machine Learning

Type *Markdown* and LaTeX: α^2

In [32]:

```
#assigning x , y for training and testing

x=taxi[['payment_type','trip_distance(km)','rate_code','tolls_amount','tip_amount']]
y=taxi['fare_amount']
```

In [33]:

```
x
```

Out[33]:

	payment_type	trip_distance(km)	rate_code	tolls_amount	tip_amount
0	1	14.499793	1	5.76	8.14
1	1	0.321860	1	0.00	0.75
2	1	15.529745	1	5.76	9.61
3	1	15.288350	1	5.76	9.25
4	1	9.333940	1	0.00	4.56
...	...	...	...	...	...
34995	1	36.096599	1	5.76	10.00
34996	1	14.741188	1	5.76	6.58
34997	1	10.911054	1	0.00	5.95
34998	2	0.418418	1	0.00	0.00
34999	1	29.611120	1	0.00	10.96

31444 rows × 5 columns

In [34]:

```
from sklearn.model_selection import train_test_split
xtrain,xtest,ytrain,ytest = train_test_split(x,y,test_size=0.2,random_state = 142)
```

In [35]:

```
from sklearn.metrics import r2_score,mean_squared_error
```

Linear Regression model

In [36]:

```
from sklearn.linear_model import LinearRegression
model_lr = LinearRegression()
model_lr.fit(xtrain,ytrain)
pp=model_lr.predict(xtest)
r2score=r2_score(ytest,pp)*100
mse = mean_squared_error(ytest, pp)
print("Mean squared error: ", mse)
print('r2_score is',r2score)
```

```
Mean squared error:  18.371590110708173
r2_score is 86.09396303590596
```

Decision Tree Regression model

In [37]:

```
from sklearn.tree import DecisionTreeRegressor
model_dt = DecisionTreeRegressor()
model_dt.fit(xtrain,ytrain)
pp= model_dt.predict(xtest)
r2score=r2_score(ytest,pp)*100
mse = mean_squared_error(ytest, pp)
print("Mean squared error: ", mse)
print('r2_score is',r2score)
```

```
Mean squared error:  17.080942115243055
r2_score is 87.07089527881021
```

Random Tree Forest Regression Model

In [38]:

```
from sklearn.ensemble import RandomForestRegressor
model_rf = RandomForestRegressor()
model_rf.fit(xtrain,ytrain)
pp= model_rf.predict(xtest)
r2score=r2_score(ytest,pp)*100
mse = mean_squared_error(ytest, pp)
print("Mean squared error: ", mse)
print('r2_score is',r2score)
```

```
Mean squared error:  10.981328335006292
r2_score is 91.6878856527262
```

Support Vector Regression Model

In [39]:

```
from sklearn.svm import SVR
model_sv = SVR()
model_sv.fit(xtrain,ytrain)
pp=model_sv.predict(xtest)
r2score=r2_score(ytest,pp)*100
mse = mean_squared_error(ytest, pp)
print("Mean squared error: ", mse)
print('r2_score is',r2score)
```

```
Mean squared error:  16.882428769270255
r2_score is 87.22115630196218
```

K-Neighbors Regression Model

In [40]:

```
from sklearn.neighbors import KNeighborsRegressor
model_kn = KNeighborsRegressor()
model_kn.fit(xtrain,ytrain)
r2score=r2_score(ytest,model_kn.predict(xtest))*100
mse = mean_squared_error(ytest, pp)
print("Mean squared error: ", mse)
print('r2_score is',r2score)
```

```
Mean squared error:  16.882428769270255
r2_score is 90.36188606745571
```

CONCLUSION:

Based on the data exploration that we have done earlier, it is reasonable to use 'trip_distance(km)' as a predictor for the fare amount, as there is a moderate positive correlation between them. 'tolls_amount' and 'tip_amount' are also likely to have an impact on the fare amount, as they are directly added to the fare.

'payment_type' and 'rate_code' could also be potential predictors for the fare amount, as they may reflect the different pricing structures and payment options for different trips. However, as 'payment_type' has only three categorical values and 'rate_code' has only three or five categorical values (depending on which data subset we look at), they may not have a significant impact on the model's accuracy.

It is also worth noting that there may be other factors that affect the fare amount but were not included in the model. For example, time of day, day of week, and month could influence the fare amount due to differences in traffic patterns and demand. Additionally, factors such as passenger count, pickup location, and drop-off location could also have an impact on the fare amount.

Overall, it is great that you have achieved a high accuracy with your model, and it is likely that the selected input features are good predictors for the fare amount. However, there may be other factors that could also

THANK-YOU