Python Portfolio Project - Automatidata

February 27, 2024

0.1 *Automatidata Project*

0.1.1 Project to rationalise the pick and drop-off services of the Automatidata corporation.

[1]:
```
# Importing required libraries

import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import datetime as dt
import seaborn as sns
```

[2]:
```
#importing the dataset collected from the company

df=pd.read_csv('/Users/samantarana/Downloads/2017_Yellow_Taxi_Trip_Data.csv')
```

Heading ahead with 'Data Exploration' and Cleaning

[3]:
```
df.head(10)
```

[3]:
```
   Unnamed: 0  VendorID    tpep_pickup_datetime   tpep_dropoff_datetime  \
0    24870114         2   03/25/2017 8:55:43 AM   03/25/2017 9:09:47 AM
1    35634249         1   04/11/2017 2:53:28 PM   04/11/2017 3:19:58 PM
2   106203690         1   12/15/2017 7:26:56 AM   12/15/2017 7:34:08 AM
3    38942136         2   05/07/2017 1:17:59 PM   05/07/2017 1:48:14 PM
4    30841670         2  04/15/2017 11:32:20 PM  04/15/2017 11:49:03 PM
5    23345809         2   03/25/2017 8:34:11 PM   03/25/2017 8:42:11 PM
6    37660487         2   05/03/2017 7:04:09 PM   05/03/2017 8:03:47 PM
7    69059411         2   08/15/2017 5:41:06 PM   08/15/2017 6:03:05 PM
8     8433159         2   02/04/2017 4:17:07 PM   02/04/2017 4:29:14 PM
9    95294817         1   11/10/2017 3:20:29 PM   11/10/2017 3:40:55 PM

   passenger_count  trip_distance  RatecodeID store_and_fwd_flag  \
0                6           3.34           1                  N
1                1           1.80           1                  N
2                1           1.00           1                  N
3                1           3.70           1                  N
4                1           4.37           1                  N
```

```
5                6         2.30           1                 N
6                1        12.83           1                 N
7                1         2.98           1                 N
8                1         1.20           1                 N
9                1         1.60           1                 N

   PULocationID  DOLocationID  payment_type  fare_amount  extra  mta_tax  \
0           100           231             1         13.0    0.0      0.5
1           186            43             1         16.0    0.0      0.5
2           262           236             1          6.5    0.0      0.5
3           188            97             1         20.5    0.0      0.5
4             4           112             2         16.5    0.5      0.5
5           161           236             1          9.0    0.5      0.5
6            79           241             1         47.5    1.0      0.5
7           237           114             1         16.0    1.0      0.5
8           234           249             2          9.0    0.0      0.5
9           239           237             1         13.0    0.0      0.5

   tip_amount  tolls_amount  improvement_surcharge  total_amount
0        2.76           0.0                    0.3         16.56
1        4.00           0.0                    0.3         20.80
2        1.45           0.0                    0.3          8.75
3        6.39           0.0                    0.3         27.69
4        0.00           0.0                    0.3         17.80
5        2.06           0.0                    0.3         12.36
6        9.86           0.0                    0.3         59.16
7        1.78           0.0                    0.3         19.58
8        0.00           0.0                    0.3          9.80
9        2.75           0.0                    0.3         16.55
```

[4]:
```
df.size
```

[4]: 408582

[5]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 22699 entries, 0 to 22698
Data columns (total 18 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   Unnamed: 0             22699 non-null  int64
 1   VendorID               22699 non-null  int64
 2   tpep_pickup_datetime   22699 non-null  object
 3   tpep_dropoff_datetime  22699 non-null  object
 4   passenger_count        22699 non-null  int64
 5   trip_distance          22699 non-null  float64
 6   RatecodeID             22699 non-null  int64
```

```
 7   store_and_fwd_flag     22699 non-null  object
 8   PULocationID           22699 non-null  int64
 9   DOLocationID           22699 non-null  int64
 10  payment_type           22699 non-null  int64
 11  fare_amount            22699 non-null  float64
 12  extra                  22699 non-null  float64
 13  mta_tax                22699 non-null  float64
 14  tip_amount             22699 non-null  float64
 15  tolls_amount           22699 non-null  float64
 16  improvement_surcharge  22699 non-null  float64
 17  total_amount           22699 non-null  float64
dtypes: float64(8), int64(7), object(3)
memory usage: 3.1+ MB
```

[6]:
```
df.describe()
```

[6]:
```
         Unnamed: 0      VendorID  passenger_count  trip_distance  \
count  2.269900e+04  22699.000000     22699.000000   22699.000000
mean   5.675849e+07      1.556236         1.642319       2.913313
std    3.274493e+07      0.496838         1.285231       3.653171
min    1.212700e+04      1.000000         0.000000       0.000000
25%    2.852056e+07      1.000000         1.000000       0.990000
50%    5.673150e+07      2.000000         1.000000       1.610000
75%    8.537452e+07      2.000000         2.000000       3.060000
max    1.134863e+08      2.000000         6.000000      33.960000

         RatecodeID  PULocationID  DOLocationID  payment_type   fare_amount  \
count  22699.000000  22699.000000  22699.000000  22699.000000  22699.000000
mean       1.043394    162.412353    161.527997      1.336887     13.026629
std        0.708391     66.633373     70.139691      0.496211     13.243791
min        1.000000      1.000000      1.000000      1.000000   -120.000000
25%        1.000000    114.000000    112.000000      1.000000      6.500000
50%        1.000000    162.000000    162.000000      1.000000      9.500000
75%        1.000000    233.000000    233.000000      2.000000     14.500000
max       99.000000    265.000000    265.000000      4.000000    999.990000

              extra       mta_tax    tip_amount  tolls_amount  \
count  22699.000000  22699.000000  22699.000000  22699.000000
mean       0.333275      0.497445      1.835781      0.312542
std        0.463097      0.039465      2.800626      1.399212
min       -1.000000     -0.500000      0.000000      0.000000
25%        0.000000      0.500000      0.000000      0.000000
50%        0.000000      0.500000      1.350000      0.000000
75%        0.500000      0.500000      2.450000      0.000000
max        4.500000      0.500000    200.000000     19.100000

       improvement_surcharge  total_amount
```

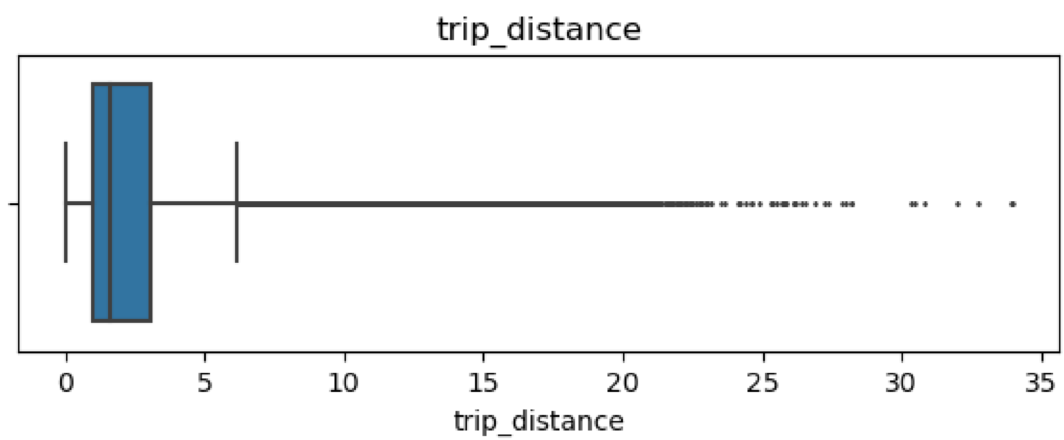
```
count           22699.000000  22699.000000
mean                0.299551     16.310502
std                 0.015673     16.097295
min                -0.300000   -120.300000
25%                 0.300000      8.750000
50%                 0.300000     11.800000
75%                 0.300000     17.800000
max                 0.300000   1200.290000
```

The function info reveals that there in no missing values

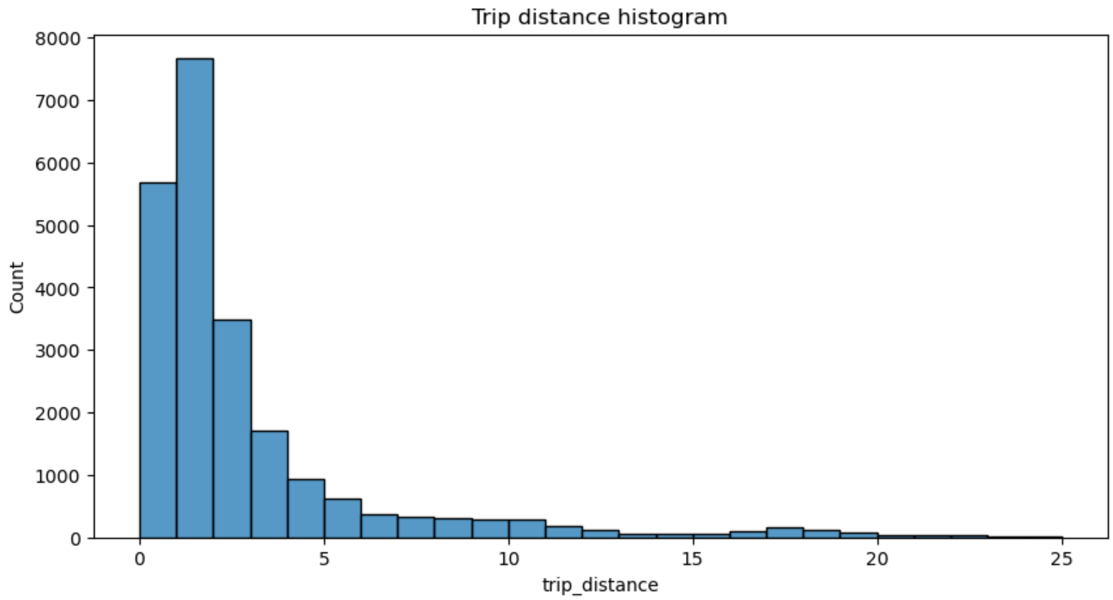
0.1.2 Checking for outliers with the help of Boxplots

[7]:
```
# Convert data columns to datetime
df['tpep_pickup_datetime']=pd.to_datetime(df['tpep_pickup_datetime'])
df['tpep_dropoff_datetime']=pd.to_datetime(df['tpep_dropoff_datetime'])
```

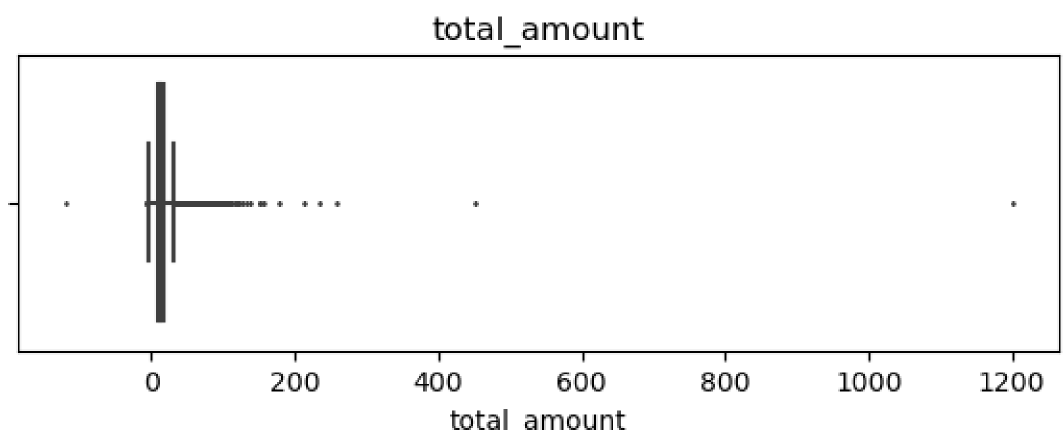
[8]:
```
# Create box plot of trip_distance
plt.figure(figsize=(7,2))
plt.title('trip_distance')
sns.boxplot(data=None, x=df['trip_distance'], fliersize=1);
```



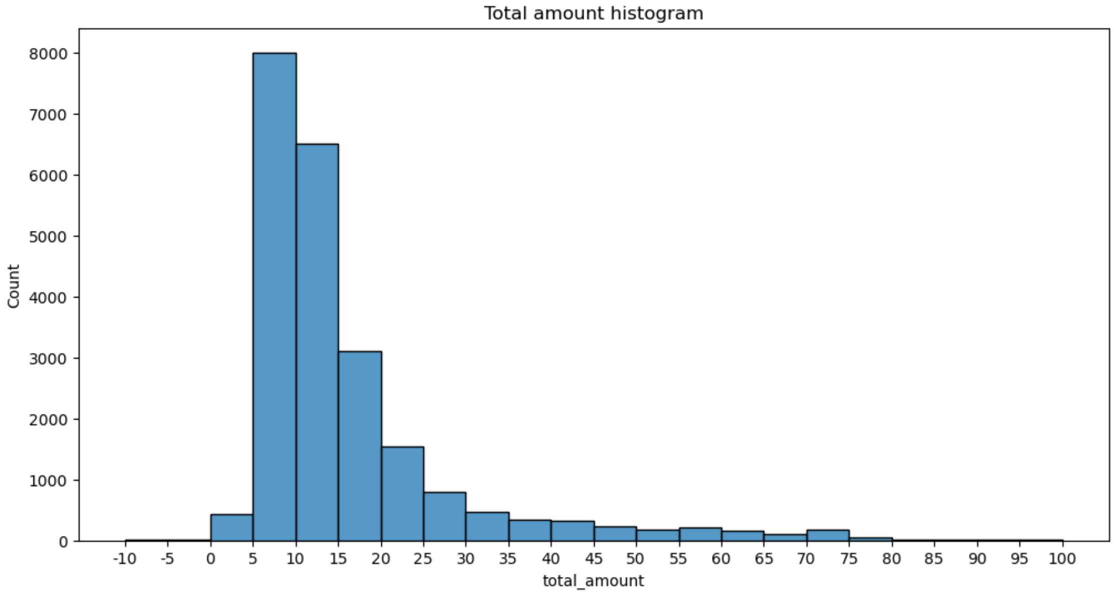
[9]:
```
# Create histogram of trip_distance
plt.figure(figsize=(10,5))
sns.histplot(df['trip_distance'], bins=range(0,26,1))
plt.title('Trip distance histogram');
```



[10]:
```
# Create box plot of total_amount
plt.figure(figsize=(7,2))
plt.title('total_amount')
sns.boxplot(x=df['total_amount'], fliersize=1);
```

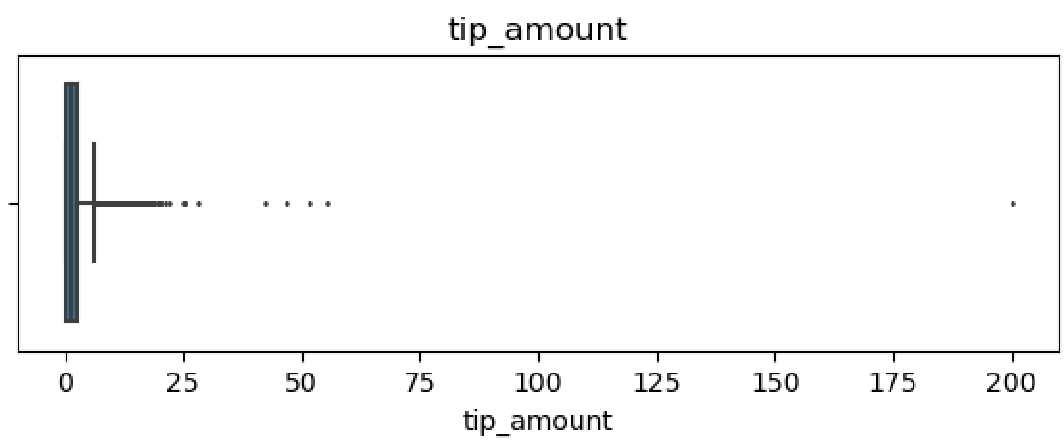


[11]:
```
# Create histogram of total_amount
plt.figure(figsize=(12,6))
ax = sns.histplot(df['total_amount'], bins=range(-10,101,5))
ax.set_xticks(range(-10,101,5))
ax.set_xticklabels(range(-10,101,5))
plt.title('Total amount histogram');
```



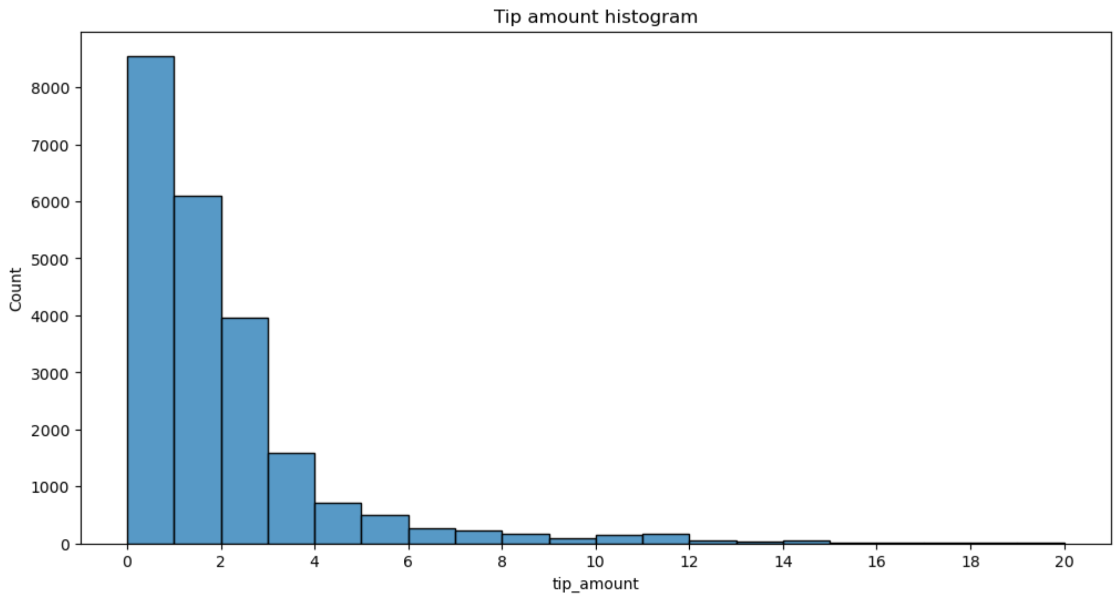
observation : The total cost of each trip also has a distribution that skews right, with most costs falling in the $5-15 range

[12]:
```
# Create box plot of tip_amount
plt.figure(figsize=(7,2))
plt.title('tip_amount')
sns.boxplot(x=df['tip_amount'], fliersize=1);
```



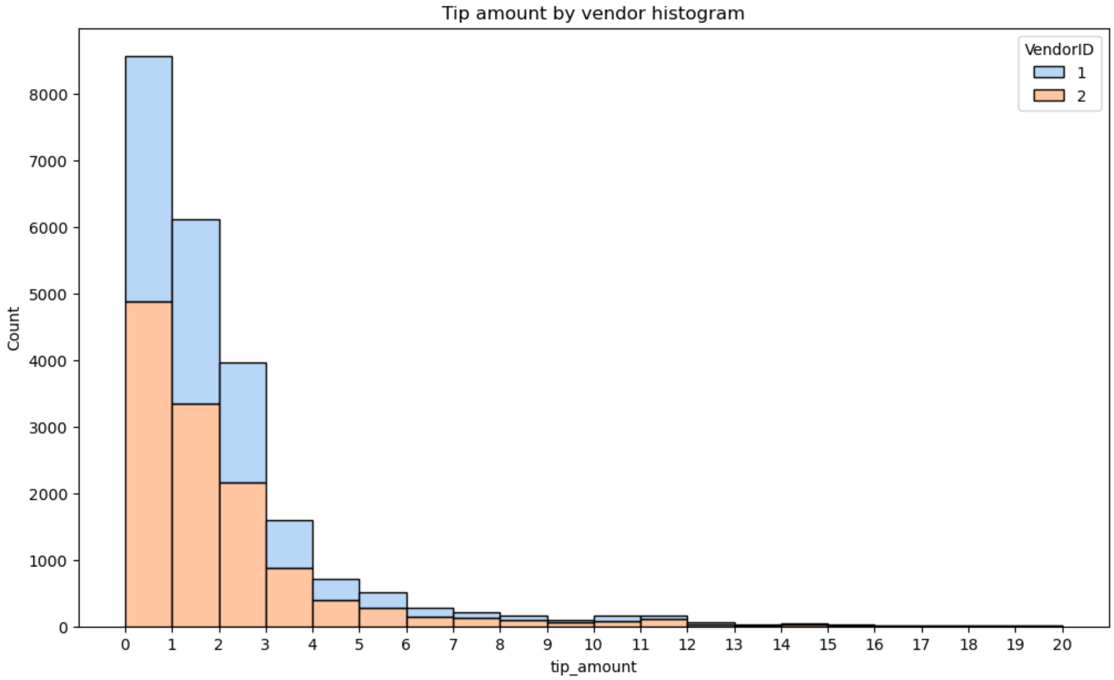
[13]:
```
# Create histogram of tip_amount
plt.figure(figsize=(12,6))
ax = sns.histplot(df['tip_amount'], bins=range(0,21,1))
ax.set_xticks(range(0,21,2))
```

```
ax.set_xticklabels(range(0,21,2))
plt.title('Tip amount histogram');
```



The distribution for tip amount is right-skewed, with nearly all the tips in the $0-3 range.

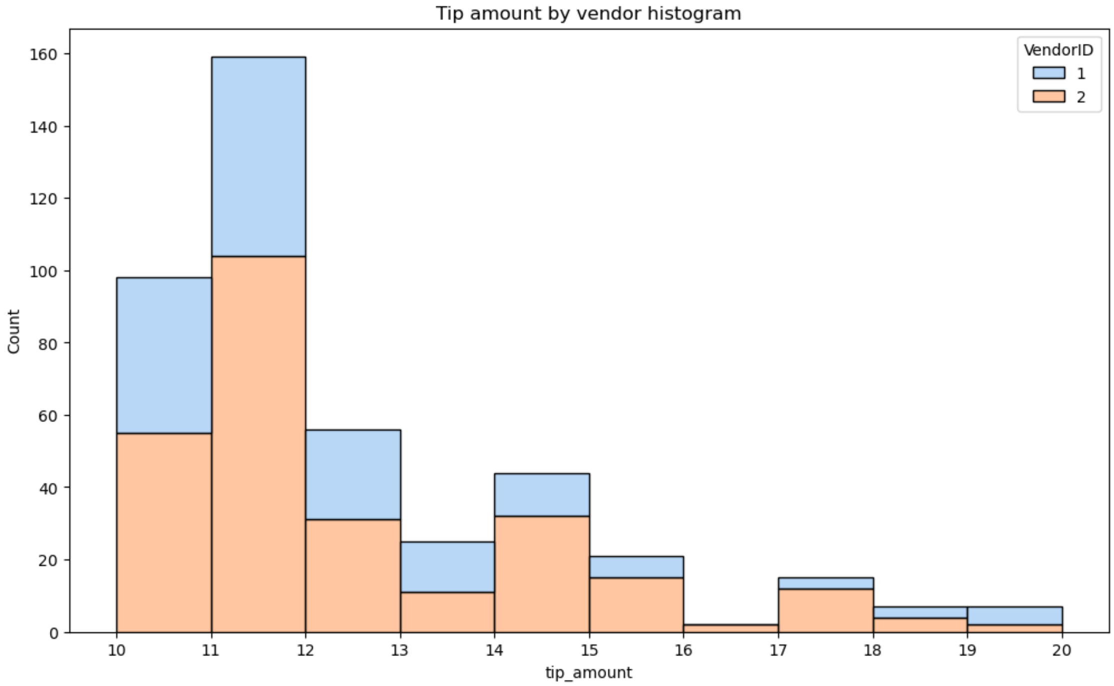
[14]:
```
# Create histogram of tip_amount by vendor
plt.figure(figsize=(12,7))
ax = sns.histplot(data=df, x='tip_amount', bins=range(0,21,1),
                  hue='VendorID',
                  multiple='stack',
                  palette='pastel')
ax.set_xticks(range(0,21,1))
ax.set_xticklabels(range(0,21,1))
plt.title('Tip amount by vendor histogram');
```



observation : Separating the tip amount by vendor reveals that there are no noticeable aberrations in the distribution of tips between the two vendors in the dataset. Vendor two has a slightly higher share of the rides, and this proportion is approximately maintained for all tip amounts.

Next, zoom in on the upper end of the range of tips to check whether vendor one gets noticeably more of the most generous tips.

[15]:
```
# Create histogram of tip_amount by vendor for tips > $10

tips_over_ten = df[df['tip_amount'] > 10]
plt.figure(figsize=(12,7))
ax = sns.histplot(data=tips_over_ten, x='tip_amount', bins=range(10,21,1),
                  hue='VendorID',
                  multiple='stack',
                  palette='pastel')
ax.set_xticks(range(10,21,1))
ax.set_xticklabels(range(10,21,1))
plt.title('Tip amount by vendor histogram');
```



The proportions are maintained even at these higher tip amounts, with the exception being at highest extremity, but this is not noteworthy due to the low sample size at these tip amounts.

[16]:
```
df['passenger_count'].value_counts()
```

[16]:
```
1    16117
2     3305
5     1143
3      953
6      693
4      455
0       33
Name: passenger_count, dtype: int64
```

observation : Nearly two thirds of the rides were single occupancy, though there were still nearly 700 rides with as many as six passengers. Also, there are 33 rides with an occupancy count of zero, which doesn't make sense. These would likely be dropped unless a reasonable explanation can be found for them.

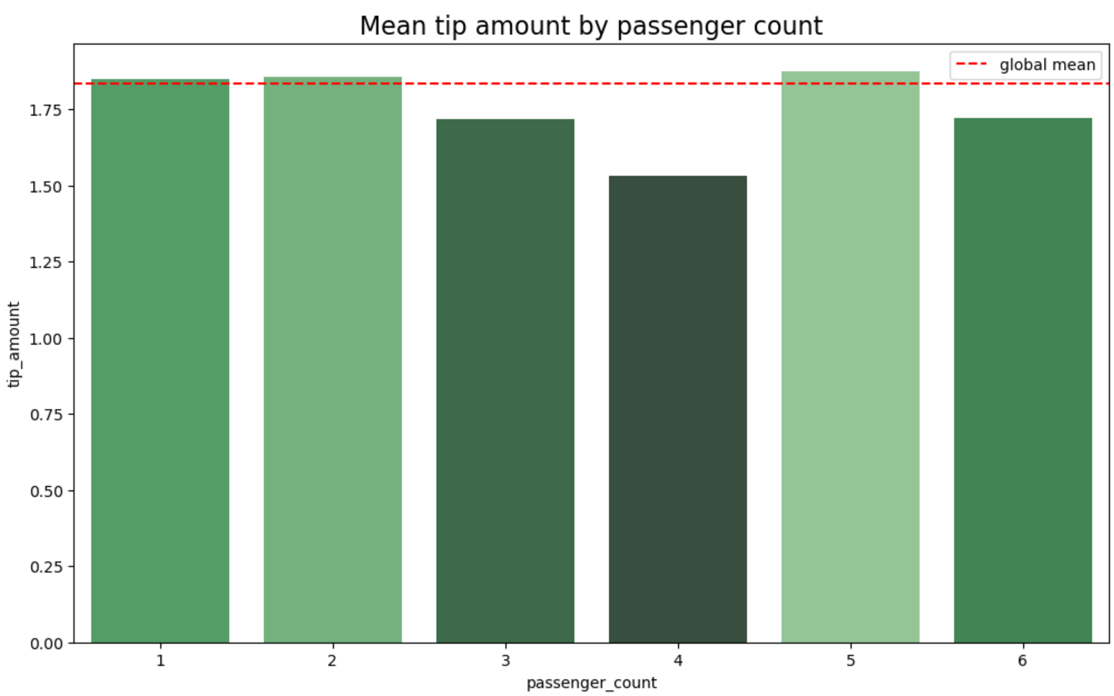
[17]:
```
# Calculate mean tips by passenger_count
mean_tips_by_passenger_count = df.groupby(['passenger_count']).
 ↪mean()[['tip_amount']]
mean_tips_by_passenger_count
```

[17]:

	tip_amount
passenger_count	
0	2.135758
1	1.848920
2	1.856378
3	1.716768
4	1.530264
5	1.873185
6	1.720260

[18]:

```
# Create bar plot for mean tips by passenger count
data = mean_tips_by_passenger_count.tail(-1)
pal = sns.color_palette("Greens_d", len(data))
rank = data['tip_amount'].argsort().argsort()
plt.figure(figsize=(12,7))
ax = sns.barplot(x=data.index,
            y=data['tip_amount'],
            palette=np.array(pal[::-1])[rank])
ax.axhline(df['tip_amount'].mean(), ls='--', color='red', label='global mean')
ax.legend()
plt.title('Mean tip amount by passenger count', fontsize=16);
```



Mean tip amount varies very little by passenger count. Although it does drop noticeably for four-passenger rides, it's expected that there would be a higher degree of fluctuation because rides with four passengers were the least plentiful in the dataset

(aside from rides with zero passengers).

[19]:
```
# Creating a month column
df['month'] = df['tpep_pickup_datetime'].dt.month_name()

# Create a day column
df['day'] = df['tpep_pickup_datetime'].dt.day_name()
```

[20]:
```
# Getting total number of rides for each month

monthly_rides = df['month'].value_counts()
monthly_rides
```

[20]:
```
March        2049
October      2027
April        2019
May          2013
January      1997
June         1964
December     1863
November     1843
February     1769
September    1734
August       1724
July         1697
Name: month, dtype: int64
```

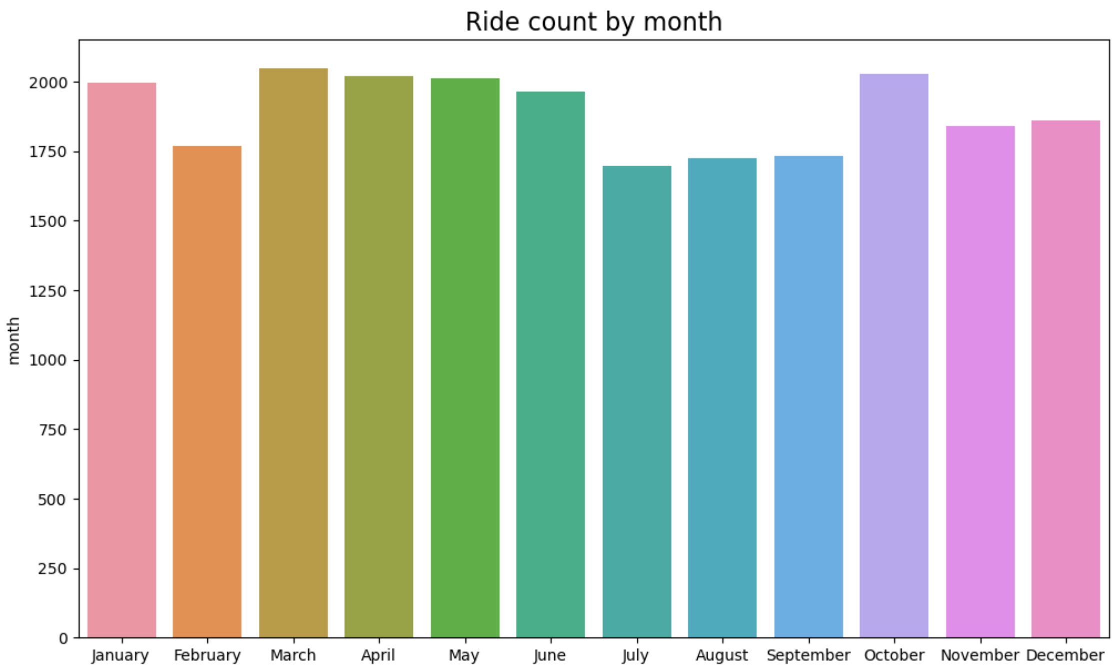
[21]:
```
# Reorder the monthly ride list so months go in order
month_order = ['January', 'February', 'March', 'April', 'May', 'June', 'July',
         'August', 'September', 'October', 'November', 'December']

monthly_rides = monthly_rides.reindex(index=month_order)
monthly_rides
```

[21]:
```
January      1997
February     1769
March        2049
April        2019
May          2013
June         1964
July         1697
August       1724
September    1734
October      2027
November     1843
December     1863
Name: month, dtype: int64
```

[22]:
```
# Show the index

monthly_rides.index
```

[22]:
```
Index(['January', 'February', 'March', 'April', 'May', 'June', 'July',
       'August', 'September', 'October', 'November', 'December'],
      dtype='object')
```

[23]:
```
# Create a bar plot of total rides per month

plt.figure(figsize=(12,7))
ax = sns.barplot(x=monthly_rides.index, y=monthly_rides)
ax.set_xticklabels(month_order)
plt.title('Ride count by month', fontsize=16);
```

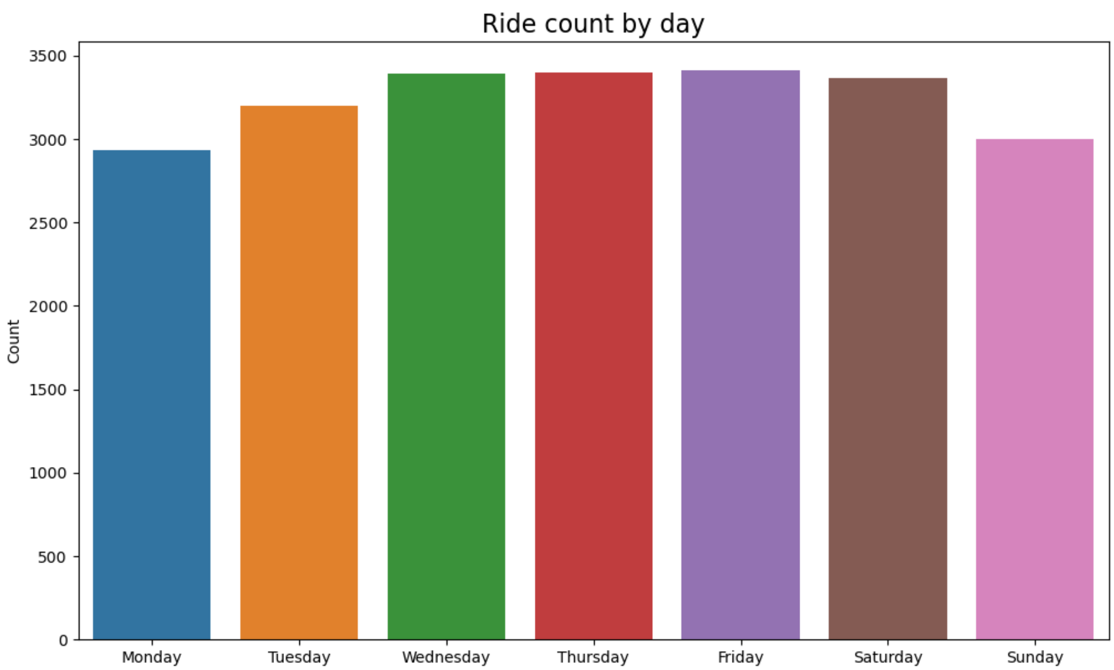


Monthly rides are fairly consistent, with notable dips in the summer months of July, August, and September, and also in February.

[24]:
```
# Repeat the above process, this time for rides by day

daily_rides = df['day'].value_counts()
day_order = ['Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday',␣
↪'Saturday', 'Sunday']
daily_rides = daily_rides.reindex(index=day_order)
daily_rides
```

[24]:
```
Monday       2931
Tuesday      3198
Wednesday    3390
Thursday     3402
Friday       3413
Saturday     3367
Sunday       2998
Name: day, dtype: int64
```

[25]:
```
# Create bar plot for ride count by day

plt.figure(figsize=(12,7))
ax = sns.barplot(x=daily_rides.index, y=daily_rides)
ax.set_xticklabels(day_order)
ax.set_ylabel('Count')
plt.title('Ride count by day', fontsize=16);
```



Suprisingly, Wednesday through Saturday had the highest number of daily rides, while Sunday and Monday had the least.

[26]:
```
# Repeat the process, this time for total revenue by day

day_order = ['Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday',␣
↪'Saturday', 'Sunday']
total_amount_day = df.groupby('day').sum()[['total_amount']]
total_amount_day = total_amount_day.reindex(index=day_order)
```

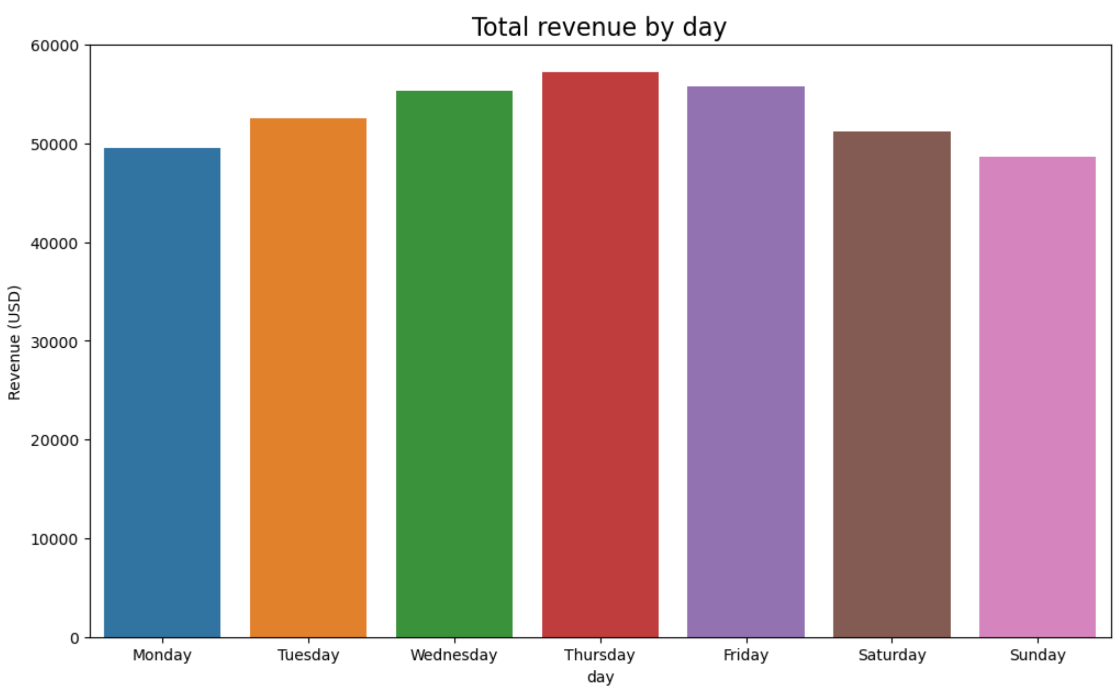
```
total_amount_day
```

[26]:

```
           total_amount
day
Monday         49574.37
Tuesday        52527.14
Wednesday      55310.47
Thursday       57181.91
Friday         55818.74
Saturday       51195.40
Sunday         48624.06
```

[27]:

```
# Create bar plot of total revenue by day

plt.figure(figsize=(12,7))
ax = sns.barplot(x=total_amount_day.index, y=total_amount_day['total_amount'])
ax.set_xticklabels(day_order)
ax.set_ylabel('Revenue (USD)')
plt.title('Total revenue by day', fontsize=16);
```



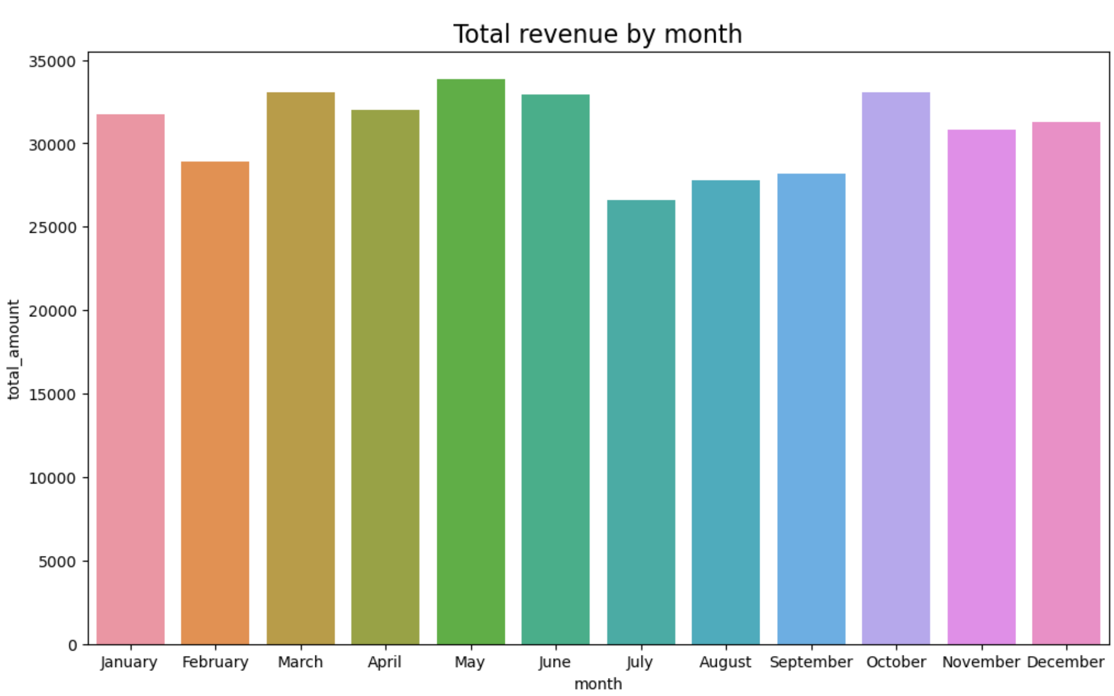
Thursday had the highest gross revenue of all days, and Sunday and Monday had the least. Interestingly, although Saturday had only 35 fewer rides than Thursday, its gross revenue was ~$6,000 less than Thursday's—more than a 10% drop.

[28]:
```python
# Repeat the process, this time for total revenue by month

total_amount_month = df.groupby('month').sum()[['total_amount']]
total_amount_month = total_amount_month.reindex(index=month_order)
total_amount_month
```

[28]:

month	total_amount
January	31735.25
February	28937.89
March	33085.89
April	32012.54
May	33828.58
June	32920.52
July	26617.64
August	27759.56
September	28206.38
October	33065.83
November	30800.44
December	31261.57

[29]:
```python
# Create a bar plot of total revenue by month

plt.figure(figsize=(12,7))
ax = sns.barplot(x=total_amount_month.index,␣
 ↪y=total_amount_month['total_amount'])
plt.title('Total revenue by month', fontsize=16);
```



Monthly revenue generally follows the pattern of monthly rides, with noticeable dips in the summer months of July, August, and September, and also one in February.

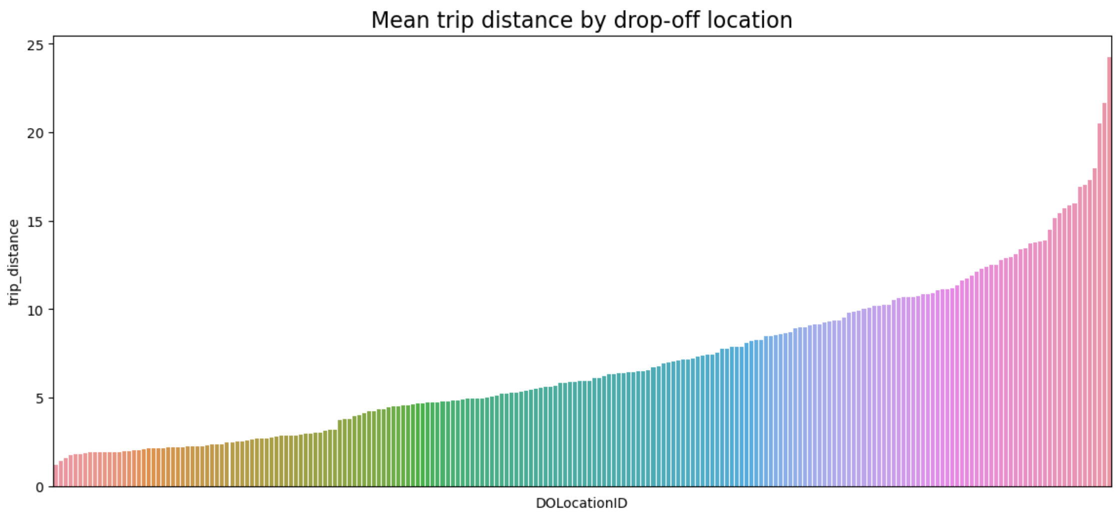
[30]:
```python
# Get number of unique drop-off location IDs

df['DOLocationID'].nunique()
```

[30]: 216

[31]:
```python
# Calculate the mean trip distance for each drop-off location
distance_by_dropoff = df.groupby('DOLocationID').mean()[['trip_distance']]

# Sort the results in descending order by mean trip distance
distance_by_dropoff = distance_by_dropoff.sort_values(by='trip_distance')
distance_by_dropoff
```

[31]:
```
              trip_distance
DOLocationID
207                1.200000
193                1.390556
237                1.555494
234                1.727806
137                1.818852
…                       …
51                17.310000
11                17.945000
210               20.500000
29                21.650000
23                24.275000

[216 rows x 1 columns]
```

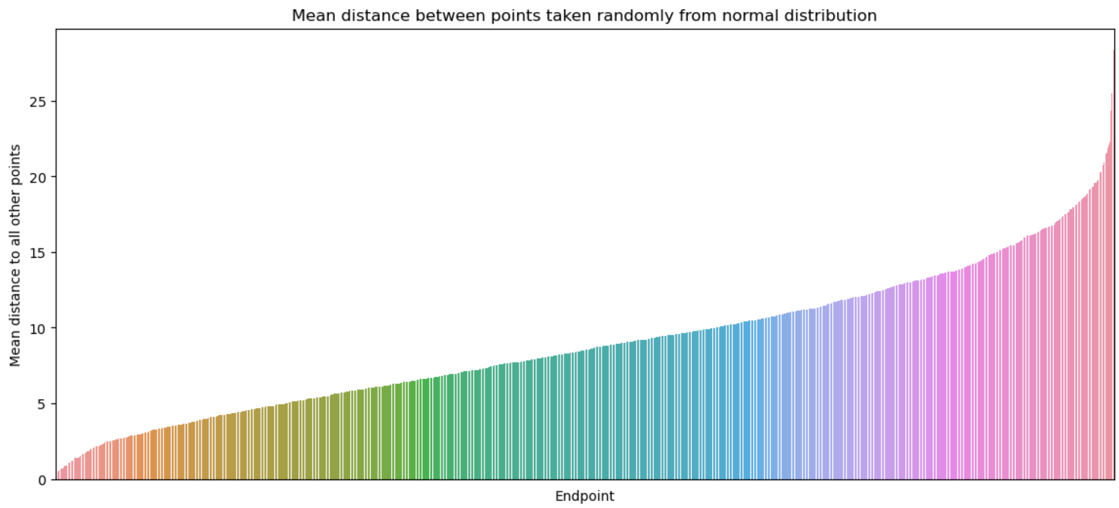
[32]:
```python
# Create a bar plot of mean trip distances by drop-off location in ascending␣
↪order by distance
plt.figure(figsize=(14,6))
ax = sns.barplot(x=distance_by_dropoff.index,
                 y=distance_by_dropoff['trip_distance'],
                 order=distance_by_dropoff.index)
ax.set_xticklabels([])
ax.set_xticks([])
plt.title('Mean trip distance by drop-off location', fontsize=16);
```



This plot presents a characteristic curve related to the cumulative density function of a normal distribution. In other words, it indicates that the drop-off points are relatively evenly distributed over the terrain. This is good to know, because geographic coordinates were not included in this dataset, so there was no obvious way to test for the distibution of locations.

[33]:
```
# 1. Generate random points on a 2D plane from a normal distribution
test = np.round(np.random.normal(10, 5, (3000, 2)), 1)
midway = int(len(test)/2)  # Calculate midpoint of the array of coordinates
start = test[:midway]      # Isolate first half of array ("pick-up locations")
end = test[midway:]        # Isolate second half of array ("drop-off locations")

# 2. Calculate Euclidean distances between points in first half and second half␣
 ↪of array
distances = (start - end)**2
distances = distances.sum(axis=-1)
distances = np.sqrt(distances)

# 3. Group the coordinates by "drop-off location", compute mean distance
test_df = pd.DataFrame({'start': [tuple(x) for x in start.tolist()],
                    'end': [tuple(x) for x in end.tolist()],
                    'distance': distances})
data = test_df[['end', 'distance']].groupby('end').mean()
data = data.sort_values(by='distance')

# 4. Plot the mean distance between each endpoint ("drop-off location") and all␣
 ↪points it connected to
plt.figure(figsize=(14,6))
ax = sns.barplot(x=data.index,
                 y=data['distance'],
```

```
                 order=data.index)
ax.set_xticklabels([])
ax.set_xticks([])
ax.set_xlabel('Endpoint')
ax.set_ylabel('Mean distance to all other points')
ax.set_title('Mean distance between points taken randomly from normal␣
 ↪distribution');
```



The curve described by this graph is nearly identical to that of the mean distance traveled by each taxi ride to each drop-off location. This reveals that the drop-off locations in the taxi dataset are evenly distributed geographically. Note, however, that this does not mean that there was an even distrubtion of rides to each drop-off point. Examining this next.

[34]:
```
# Check if all drop-off locations are consecutively numbered

df['DOLocationID'].max() - len(set(df['DOLocationID']))
```

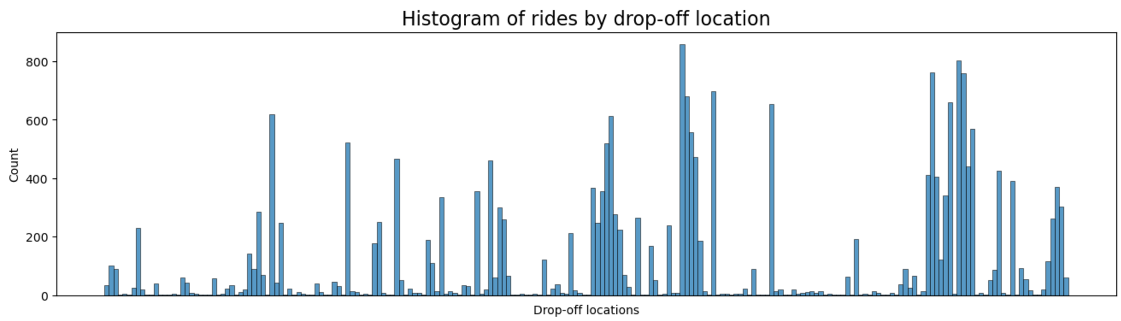
[34]: 49

The above code shows that there are 49 drop-offs locations are not consecutively marked.

Hence, it is required to remove the spaces these 49 locations can introduce in hisotgram.

[35]:
```
plt.figure(figsize=(16,4))
# DOLocationID column is numeric, so sort in ascending order
sorted_dropoffs = df['DOLocationID'].sort_values()
# Convert to string
sorted_dropoffs = sorted_dropoffs.astype('str')
```

```
# Plot
sns.histplot(sorted_dropoffs, bins=range(0, df['DOLocationID'].max()+1, 1))
plt.xticks([])
plt.xlabel('Drop-off locations')
plt.title('Histogram of rides by drop-off location', fontsize=16);
```



Notice that out of the 200+ drop-off locations, a disproportionate number of locations receive the majority of the traffic, while all the rest get relatively few trips. It's likely that these high-traffic locations are near popular tourist attractions like the Empire State Building or Times Square, airports, and train and bus terminals. However, it would be helpful to know the location that each ID corresponds with. Unfortunately, this is not in the data.

```
[ ]:
```