Activity_Course 3 Automatidata project lab

November 21, 2023

1 Course 3 Automatidata project

Course 3 - Go Beyond the Numbers: Translate Data into Insights

You are the newest data professional in a fictional data consulting firm: Automatidata. The team is still early into the project, having only just completed an initial plan of action and some early Python coding work.

Luana Rodriquez, the senior data analyst at Automatidata, is pleased with the work you have already completed and requests your assistance with some EDA and data visualization work for the New York City Taxi and Limousine Commission project (New York City TLC) to get a general understanding of what taxi ridership looks like. The management team is asking for a Python notebook showing data structuring and cleaning, as well as any matplotlib/seaborn visualizations plotted to help understand the data. At the very least, include a box plot of the ride durations and some time series plots, like a breakdown by quarter or month.

Additionally, the management team has recently asked all EDA to include Tableau visualizations. For this taxi data, create a Tableau dashboard showing a New York City map of taxi/limo trips by month. Make sure it is easy to understand to someone who isn't data savvy, and remember that the assistant director at the New York City TLC is a person with visual impairments.

A notebook was structured and prepared to help you in this project. Please complete the following questions.

2 Course 3 End-of-course project: Exploratory data analysis

In this activity, you will examine data provided and prepare it for analysis. You will also design a professional data visualization that tells a story, and will help data-driven decisions for business needs.

Please note that the Tableau visualization activity is optional, and will not affect your completion of the course. Completing the Tableau activity will help you practice planning out and plotting a data visualization based on a specific business need. The structure of this activity is designed to emulate the proposals you will likely be assigned in your career as a data professional. Completing this activity will help prepare you for those career moments.

The purpose of this project is to conduct exploratory data analysis on a provided data set. Your mission is to continue the investigation you began in C2 and perform further EDA on this data with the aim of learning more about the variables.

The goal is to clean data set and create a visualization.
This activity has 4 parts:

Part 1: Imports, links, and loading

Part 2: Data Exploration * Data cleaning

Part 3: Building visualizations

Part 4: Evaluate and share results

Follow the instructions and answer the questions below to complete the activity. Then, you will complete an Executive Summary using the questions listed on the PACE Strategy Document.

Be sure to complete this activity before moving on. The next course item will provide you with a completed exemplar to compare to your own work.

3 Visualize a story in Tableau and Python

4 PACE stages

- `[Plan](#scrollTo=psz51YkZVwtN&line=3&uniqifier=1)`
- `[Analyze](#scrollTo=mA7Mz_SnI8km&line=4&uniqifier=1)`
- `[Construct](#scrollTo=Lca9c8XON8lc&line=2&uniqifier=1)`
- `[Execute](#scrollTo=401PgchTPr4E&line=2&uniqifier=1)`

Throughout these project notebooks, you'll see references to the problem-solving framework PACE. The following notebook components are labeled with the respective PACE stage: Plan, Analyze, Construct, and Execute.

4.1 PACE: Plan

In this stage, consider the following questions where applicable to complete your code response: 1. Identify any outliers:

- What methods are best for identifying outliers?
- How do you make the decision to keep or exclude outliers from any future models?

What methods are best for identifying outliers? * When dealing with data, there are two ways to identify outliers. One way is to plot the data using a Boxplot or Scatterplot, which can provide a visual representation of the data and highlight any outliers. * Another way is to create summary statistics of the data, which can show the maximum and minimum values that may be considered outliers if they fall outside of the normal range.

How do you make the decisions to keep or exclude outliers from any future models? * It is important to consider if the number of outliers is significant compared to the overall number of observations, and whether removing them or keeping them impacts analysis. * The decision to remove outliers or not depends on the nature of the analysis. * It is crucial to determine whether the outliers are

important to the overall analysis or if they are anomalies that will skew the results. * Outliers in the data may simply be a natural variation within the population. Removing them could lead to the loss of valuable information. * There may be instances where outliers have been identified as data entry or measurement errors, and it might be necessary to remove them.

4.1.1 Task 1. Imports, links, and loading

Go to Tableau Public The following link will help you complete this activity. Keep Tableau Public open as you proceed to the next steps.

Link to supporting materials: Tableau Public: https://public.tableau.com/s/

For EDA of the data, import the data and packages that would be most helpful, such as pandas, numpy and matplotlib.

[1]:
```
# Import packages and libraries
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd
```

Note: As shown in this cell, the dataset has been automatically loaded in for you. You do not need to download the .csv file, or provide more code, in order to access the dataset and proceed with this lab. Please continue with this activity by completing the following instructions.

[2]:
```
# Load dataset into dataframe
df = pd.read_csv('2017_Yellow_Taxi_Trip_Data.csv')
```

4.2 PACE: Analyze

Consider the questions in your PACE Strategy Document to reflect on the Analyze stage.

4.2.1 Task 2a. Data exploration and cleaning

Decide which columns are applicable

The first step is to assess your data. Check the Data Source page on Tableau Public to get a sense of the size, shape and makeup of the data set. Then answer these questions to yourself:

Given our scenario, which data columns are most applicable? Which data columns can I eliminate, knowing they won't solve our problem scenario?

Consider functions that help you understand and structure the data.

- head()
- describe()
- info()
- groupby()
- sortby()

What do you do about missing data (if any)?

Are there data outliers? What are they and how might you handle them?

What do the distributions of your variables tell you about the question you're asking or the problem you're trying to solve?

Which data columns are most applicable?

- tpep_pickup_datetime and tpep_dropoff_datetime: Use these to calculate trip length.
- passenger_count: Look for a connection between trip distance/length/price and the number of riders.
- trip_distance: Use this to determine the average price per trip by distance.
- payment_type: Analyze the most popular payment type.
- VendorID: The provider used.
- fare_amount: Determine the average fare by trip distance.
- tip_amount: Use this to determine the average tips from riders, based on trip length, time of day, day of week, etc.

Which data columns can I eliminate?

- The remaining columns appear to have little use for this analysis and can be removed.

What to do about missing data (if any)? When dealing with missing data, there are various approaches you can take depending on the context of your analysis. Here are some considerations to keep in mind:

1. Determine if the missing values are related to variables that are essential for your analysis.
2. If the missing values are not essential, they can be ignored.
3. If the missing values are essential, determine the severity of their impact.
4. Ask yourself questions such as:
    - Are there only a few missing values that won't significantly impact the analysis?
    - If there are many missing values, do you need to contact the data source to obtain the information?
    - Can you safely drop the rows with missing data?

Are there outliers? If so, what are they and how might they be handled? There are noticeable anomalies in the columns of trip_distance, fare_amount, tip_amount, tolls_amount and total_amount.

```
- If these anomalies can be identified as errors, for instance, during data entry or collectio
- It may also be feasible to substitute the median or average values for erroneous data if it
```

What do the distributions of the variables indicate?

- The distribution of variables can indicate skew in the data, informing decisions on what statistical tests to run.

Start by discovering, using head and size.

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

[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

   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

   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

   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
```

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

[4]:
```
408582
```

Use describe...

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

[5]:
```
         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
```

And info.

[6]:
```
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
```

4.2.2 Task 2b. Assess whether dimensions and measures are correct

On the data source page in Tableau, double check the data types for the applicable columns you selected on the previous step. Pay close attention to the dimensions and measures to assure they are correct.

In Python, consider the data types of the columns. *Consider:* Do they make sense?

Review the link provided in the previous activity instructions to create the required Tableau visualization.

4.2.3 Task 2c. Select visualization type(s)

Select data visualization types that will help you understand and explain the data.

Now that you know which data columns you'll use, it is time to decide which data visualization makes the most sense for EDA of the TLC dataset. What type of data visualization(s) would be most helpful?

- Line graph
- Bar chart
- Box plot
- Histogram
- Heat map
- Scatter plot
- A geographic map

- Line Graph: This type of graph is useful when you want to track changes over time. It can help you easily visualize trends and patterns in your data.
- Histogram: A histogram is a chart that shows the distribution of a set of data. It can help you understand how your data is spread out and identify any outliers.
- Scatterplot: A scatterplot is a chart that shows the relationship between two variables. It can help you identify any correlations or patterns in your data.

- Box Plot: A box plot is a chart that shows the distribution of a set of data based on different categories or groups. It can help you compare the distribution of variables across different groups.
- Heatmap: A heatmap is a chart that shows the relationship between multiple variables at once. It can help you identify any patterns or correlations in complex data sets.

4.3 PACE: Construct

Consider the questions in your PACE Strategy Document to reflect on the Construct stage.

4.3.1 Task 3. Data visualization

You've assessed your data, and decided on which data variables are most applicable. It's time to plot your visualization(s)!

4.3.2 Boxplots

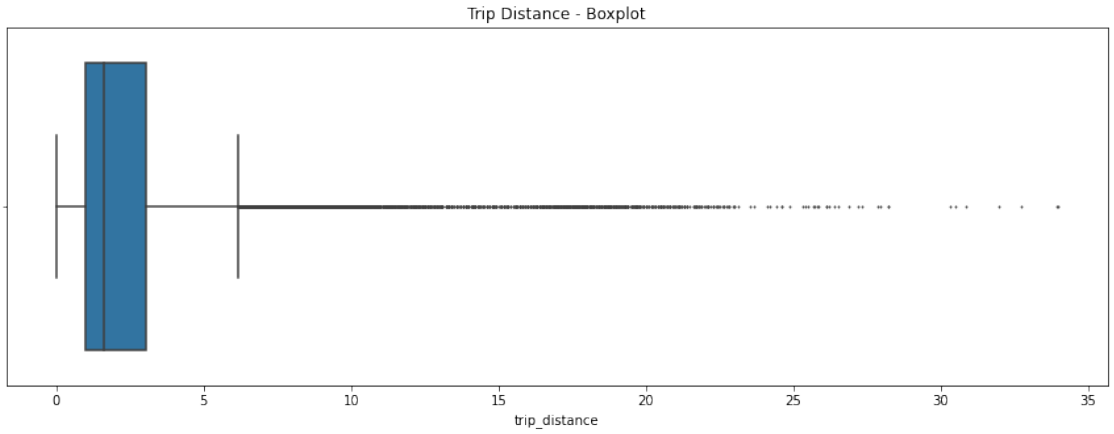
Perform a check for outliers on relevant columns such as trip distance and trip duration. Remember, some of the best ways to identify the presence of outliers in data are box plots and histograms.

Note: Remember to convert your date columns to datetime in order to derive total trip duration.

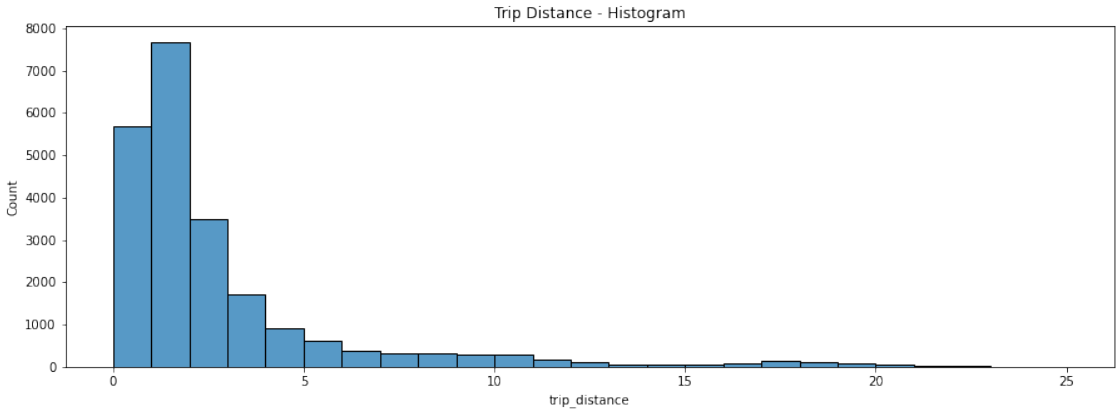
[7]:
```
# Convert data columns to datetime
df['tpep_pickup_datetime'] = pd.to_datetime(df['tpep_pickup_datetime'])
df['tpep_dropoff_datetime'] = pd.to_datetime(df['tpep_dropoff_datetime'])
```

trip distance

[8]:
```
# Create box plot of trip_distance
plt.figure(figsize=(15,5))
plt.title('Trip Distance - Boxplot')
sns.boxplot(x=df['trip_distance'],fliersize=1)
plt.show()
```

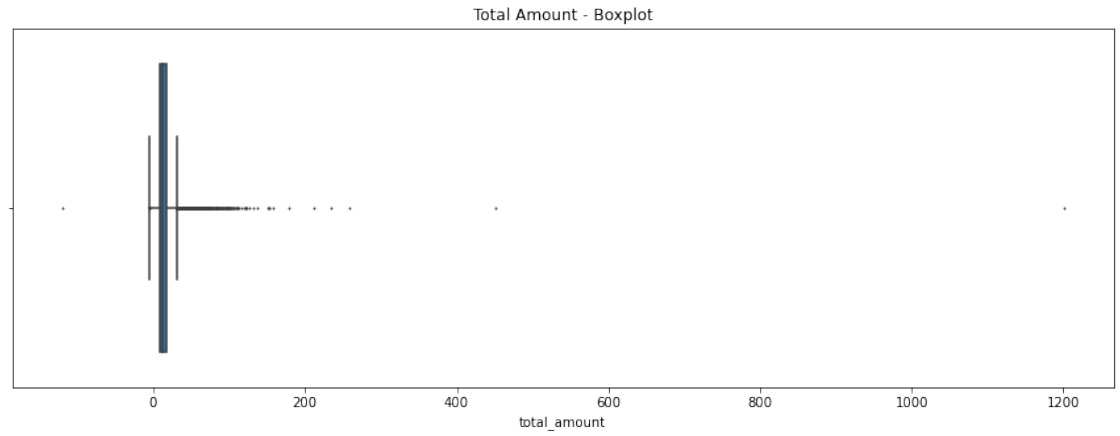


[9]:
```
# Create histogram of trip_distance
plt.figure(figsize=(15,5))
plt.title('Trip Distance - Histogram')
sns.histplot(data=df, x='trip_distance', bins=range(0,26,1))
plt.show()
```

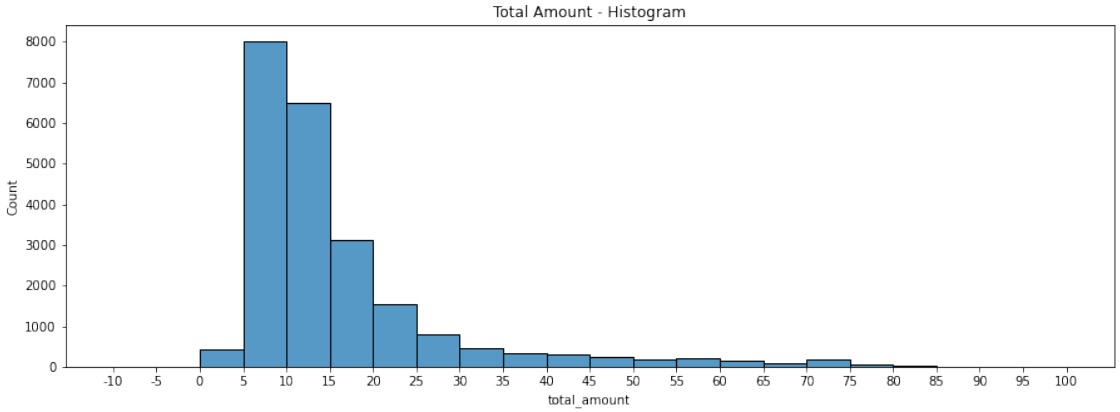


total amount

[10]:
```
# Create box plot of total_amount
plt.figure(figsize=(15,5))
plt.title('Total Amount - Boxplot')
sns.boxplot(x=df['total_amount'],fliersize=1)
plt.show()
```

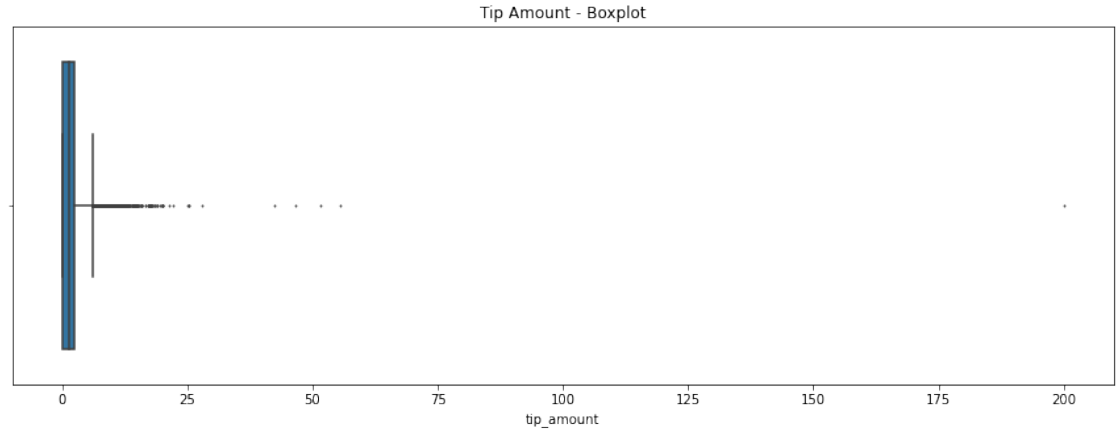


[11]:
```
# Create histogram of total_amount
plt.figure(figsize=(15,5))
ax = sns.histplot(df['total_amount'], bins=range(-10,101,5))
ax.set_xticks(range(-10,101,5))
ax.set_xticklabels(range(-10,101,5))
plt.title('Total Amount - Histogram');
plt.show()
```

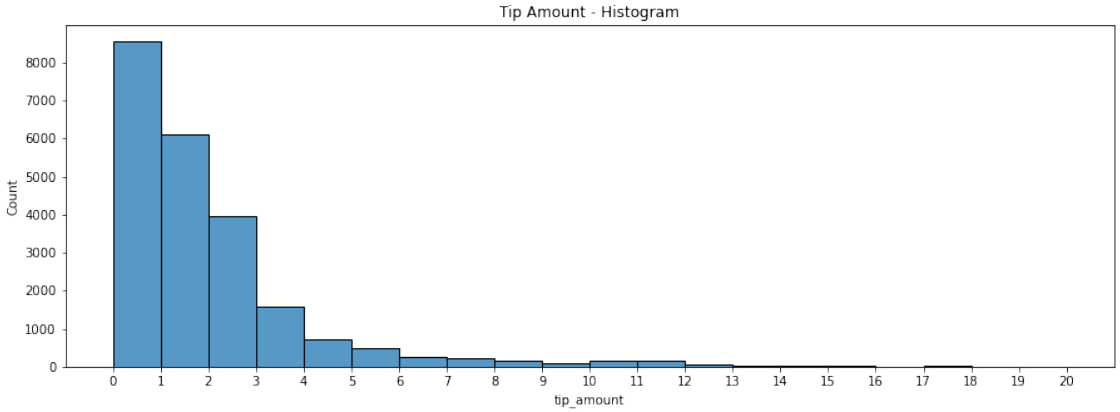


tip amount

[12]:
```
# Create box plot of tip_amount
plt.figure(figsize=(15,5))
plt.title('Tip Amount - Boxplot')
sns.boxplot(x=df['tip_amount'],fliersize=1)
plt.show()
```

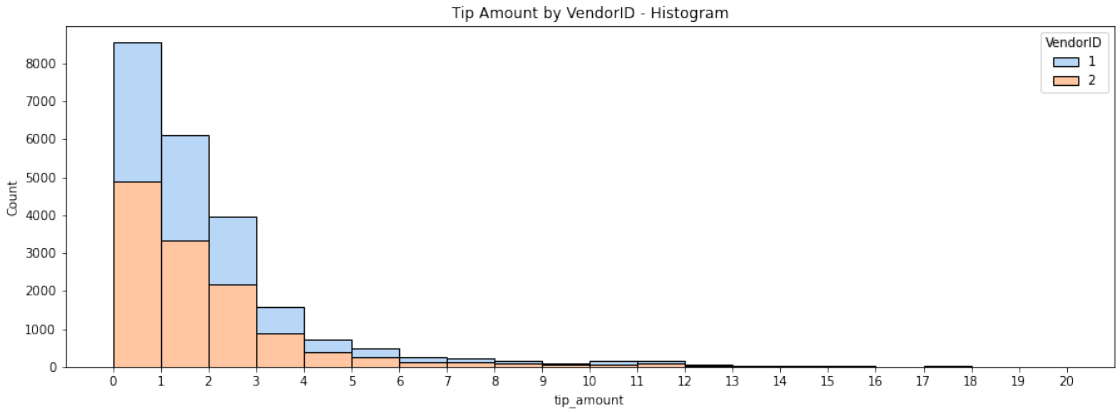


[13]:
```
# Create histogram of tip_amount
plt.figure(figsize=(15,5))
ax = sns.histplot(df['tip_amount'], bins=range(0,21,1))
ax.set_xticks(range(0,21,1))
ax.set_xticklabels(range(0,21,1))
plt.title('Tip Amount - Histogram');
plt.show()
```



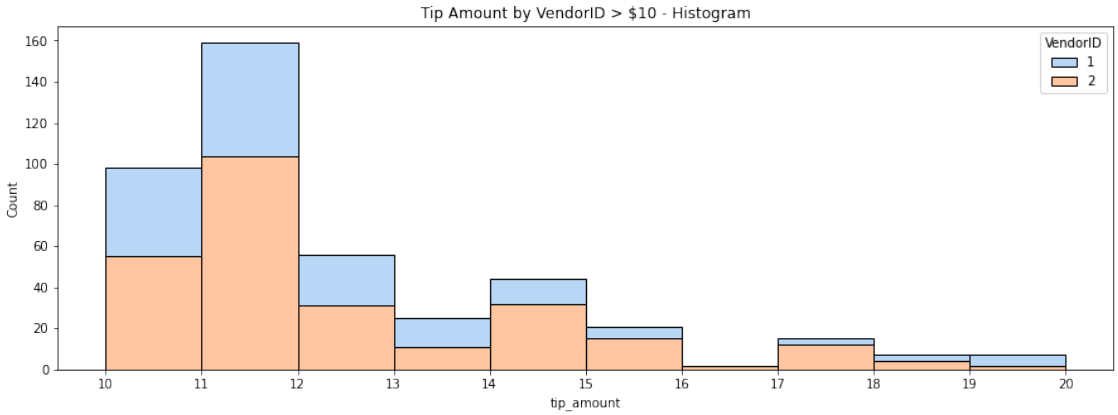
tip_amount by vendor

[14]:
```
# Create histogram of tip_amount by vendor
plt.figure(figsize=(15,5))
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 VendorID - Histogram');
```



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
df_tips_over_ten = df[df['tip_amount'] > 10]

plt.figure(figsize=(15,5))
ax = sns.histplot(data = df_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 VendorID > $10 - Histogram')
plt.show()
```



Mean tips by passenger count

Examine the unique values in the `passenger_count` column.

[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
```

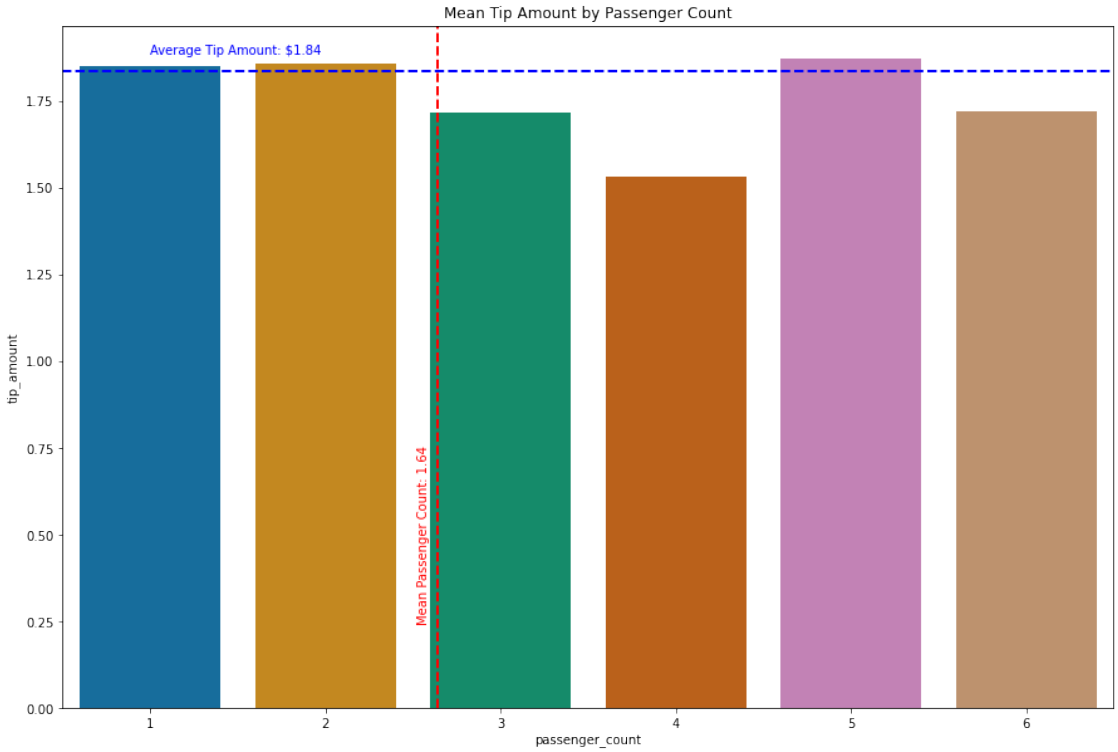
[17]:
```
# Calculate mean tips by passenger_count
mean_tips_by_passenger_count = df.groupby(['passenger_count']).
 ↪mean()[['tip_amount']]
mean_tips_by_passenger_count
```

[17]:

passenger_count	tip_amount
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

# Filter out rows where 'passenger_count' is 0
df_filtered_passenger_count = df[df['passenger_count'] != 0]

# Calculate the mean of all 'passenger_count'
mean_passenger_count = np.mean(df['passenger_count'])

# Calculate the average 'tip_amount' among all 'passenger_count'
average_tip_amount = np.mean(df['tip_amount'])

plt.figure(figsize=(15, 10))

# Use a colorblind-friendly palette
sns.set_palette(sns.color_palette("colorblind"))

sns.barplot(x='passenger_count', y='tip_amount',␣
 ↪data=df_filtered_passenger_count, ci=None)

# Add a line that indicates the mean of all 'passenger_count'
# Increase the line width to make it more visible
mean_line = plt.axvline(x=mean_passenger_count, color='r', linestyle='--',␣
 ↪linewidth=2)

# Add a horizontal line displaying the average 'tip_amount' among all␣
 ↪'passenger_count'
# Increase the line width to make it more visible
average_line = plt.axhline(y=average_tip_amount, color='b', linestyle='--',␣
 ↪linewidth=2)

# Annotate the mean lines with their respective mean values
```

```
plt.text(mean_passenger_count+ -0.12, 0.25, 'Mean Passenger Count: {:.2f}'.
 ↪format(mean_passenger_count), color='r', rotation=90)
plt.text(0, average_tip_amount+ 0.05, 'Average Tip Amount: ${:.2f}'.
 ↪format(average_tip_amount), color='b')

# Add a legend for each of the mean lines
#plt.legend([mean_line, average_line], ['Average Passenger Count', 'Average Tip␣
 ↪Amount'])

plt.title('Mean Tip Amount by Passenger Count')
plt.show()
```



Create month and day columns

[19]:
```
# Create 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()
```

Plot total ride count by month

Begin by calculating total ride count by month.

[20]:
```
# Get 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
```

Reorder the results to put the months in calendar order.

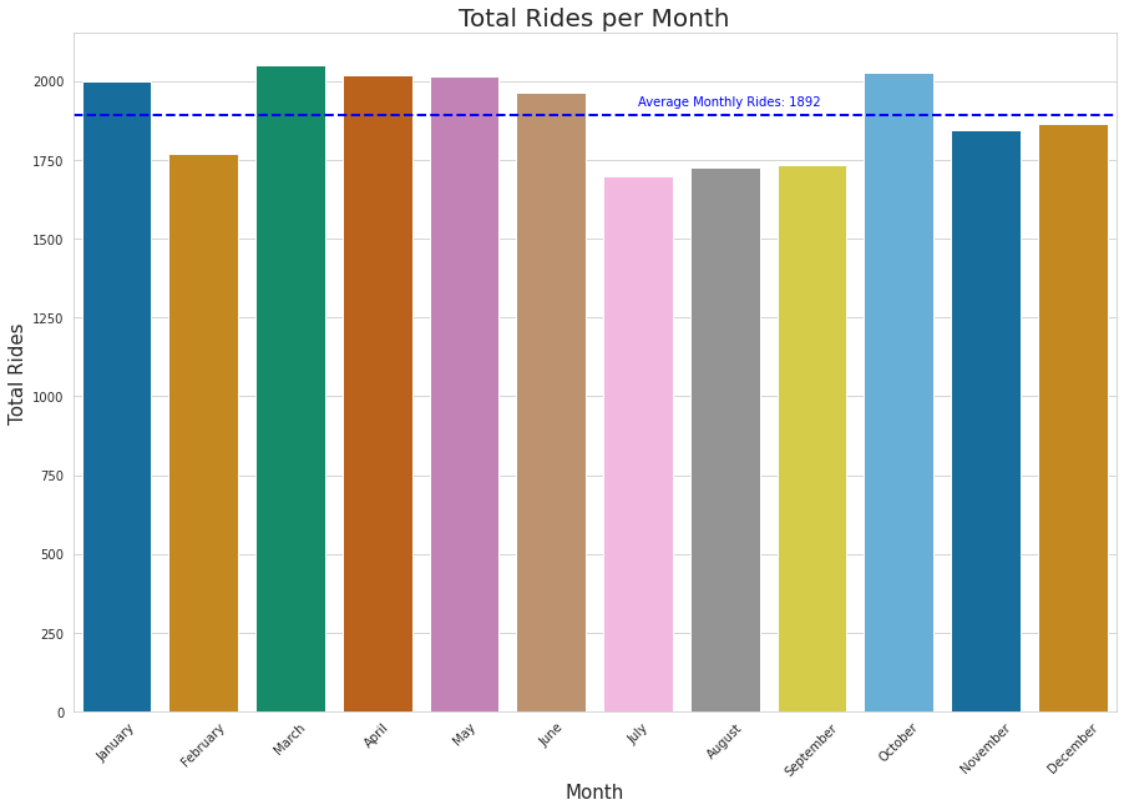
[21]:
```
# Reorder the monthly ride list so months go in order
month_order = ['January', 'February', 'March', 'April', 'May', 'June', 'July',␣
 ↪'August', 'September', 'October', 'November', 'December']
monthly_rides = monthly_rides.reindex(index=month_order)
monthly_rides
```

[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
# Calculate the average of 'monthly_rides'
average_monthly_rides = monthly_rides.mean()

sns.set_style('whitegrid')

plt.figure(figsize=(15,10))
sns.barplot(x=monthly_rides.index, y=monthly_rides, palette='colorblind')

# Add a horizontal line displaying the average 'monthly_rides' across all months
# Increase the line width to make it more visible
average_line = plt.axhline(y=average_monthly_rides, color='b', linestyle='--',␣
 ↪linewidth=2)

# Annotate the average line with the average value
plt.text(6, average_monthly_rides+30, 'Average Monthly Rides: {:.0f}'.
 ↪format(average_monthly_rides), color='b')

# Add a legend for each of the mean lines
#plt.legend([average_line], ['Average Monthly Rides'])

plt.title('Total Rides per Month', fontsize=20)
plt.xlabel('Month', fontsize=15)
plt.ylabel('Total Rides', fontsize=15)
plt.xticks(rotation=45)

plt.show()
```



Plot total ride count by day

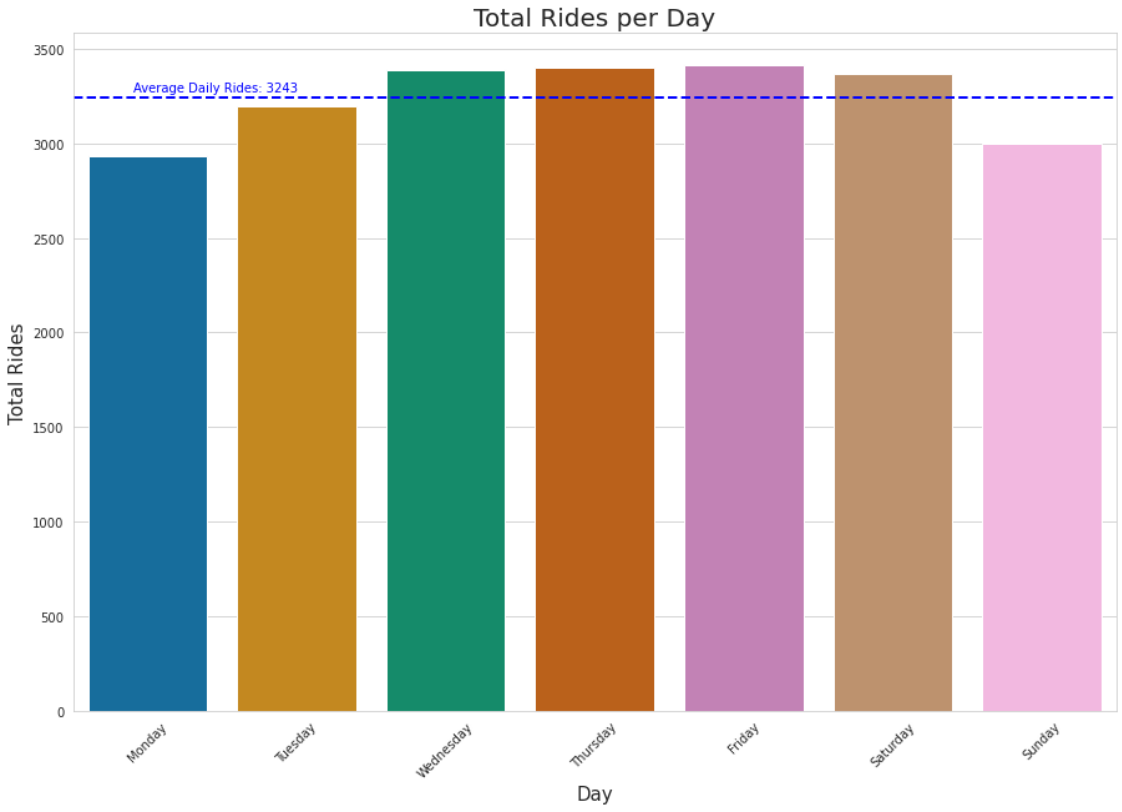
Repeat the above process, but now calculate the total rides by day of the week.

[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
average_daily_rides = daily_rides.mean()
```

```
sns.set_style('whitegrid')
plt.figure(figsize=(15,10))
sns.barplot(x=daily_rides.index, y=daily_rides, palette='colorblind')

# Add a horizontal line displaying the average 'monthly_rides' across all days
# Increase the line width to make it more visible
average_line = plt.axhline(y=average_daily_rides, color='b', linestyle='--',␣
 ↪linewidth=2)

# Annotate the average line with the average value
plt.text(-0.1, average_daily_rides+30, 'Average Daily Rides: {:.0f}'.
 ↪format(average_daily_rides), color='b')

# Add a legend for each of the mean lines
#plt.legend([average_line], ['Average Daily Rides'])

plt.title('Total Rides per Day', fontsize=20)
plt.xlabel('Day', fontsize=15)
plt.ylabel('Total Rides', fontsize=15)
plt.xticks(rotation=45)

plt.show()
```



Plot total revenue by day of the week

Repeat the above process, but now calculate the total revenue by day of the week.

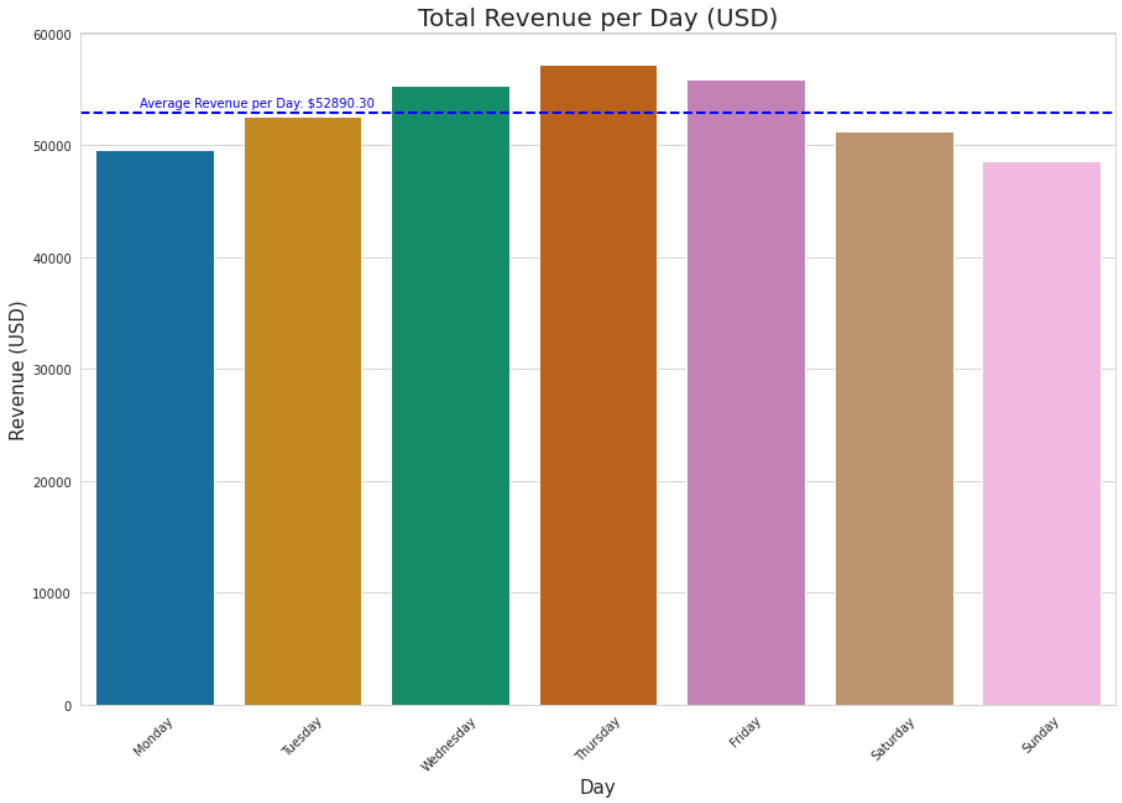
[26]:
```
# Repeat the process, this time for total revenue by day
day_order = ['Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday',␣
 ↪'Saturday', 'Sunday']
total_amount_by_day = df.groupby('day').sum()[['total_amount']]
total_amount_by_day = total_amount_by_day.reindex(index=day_order)
total_amount_by_day
```

[26]:

day	total_amount
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
average_revenue = total_amount_by_day['total_amount'].mean()

sns.set_style('whitegrid')
plt.figure(figsize=(15,10))
sns.barplot(x=total_amount_by_day.index, y=total_amount_by_day['total_amount'],␣
 ↪palette='colorblind')

# Add a horizontal line displaying the average 'average revenue' across all days
# Increase the line width to make it more visible
average_line = plt.axhline(y=average_revenue, color='b', linestyle='--',␣
 ↪linewidth=2)

# Annotate the average line with the average value
plt.text(-0.1, average_revenue+500, 'Average Revenue per Day: ${:.2f}'.
 ↪format(average_revenue), color='b')

# Add a legend for each of the mean lines
#plt.legend([average_line], ['Average Revenue per Day'])

plt.title('Total Revenue per Day (USD)', fontsize=20)
plt.xlabel('Day', fontsize=15)
plt.ylabel('Revenue (USD)', fontsize=15)
plt.xticks(rotation=45)
```

```
plt.show()
```



Plot total revenue by month

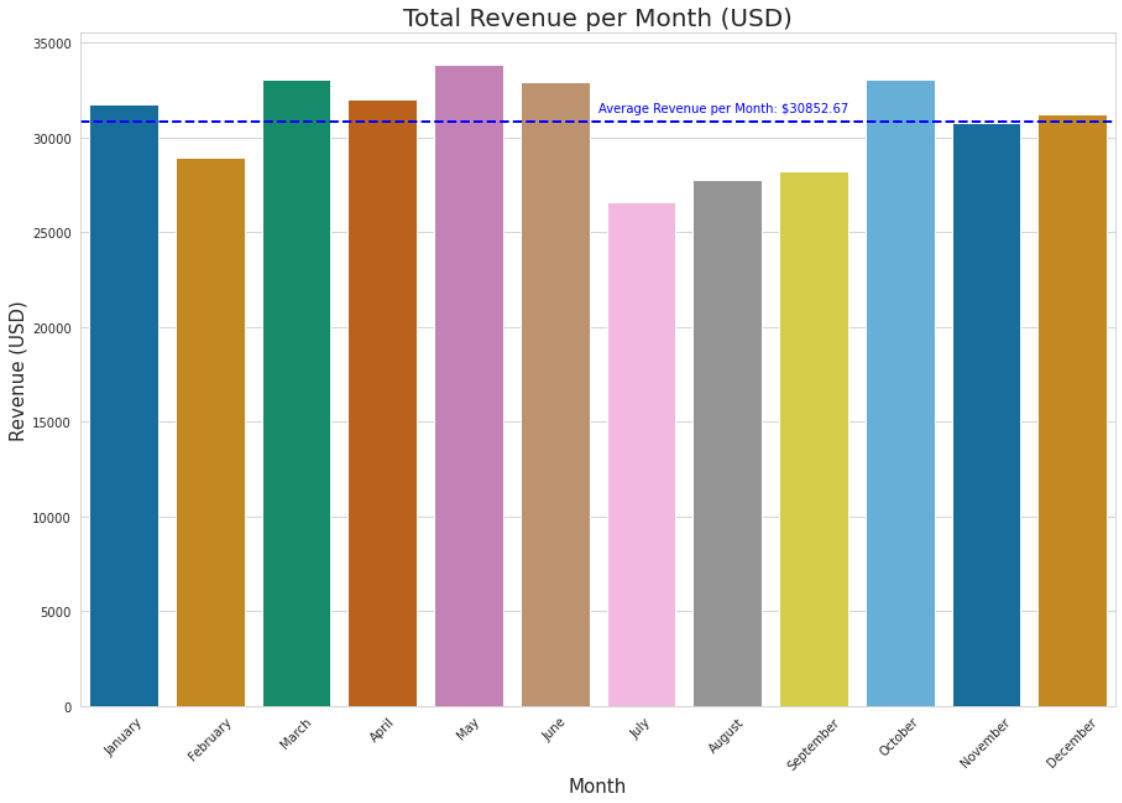
[28]:
```
# Repeat the process, this time for total revenue by month
month_order = ['January', 'February', 'March', 'April', 'May', 'June', 'July',␣
 ↪'August', 'September', 'October', 'November', 'December']
total_amount_by_month = df.groupby('month').sum()[['total_amount']]
total_amount_by_month = total_amount_by_month.reindex(index=month_order)
total_amount_by_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]:
```
# Create a bar plot of total revenue by month
average_revenue = total_amount_by_month['total_amount'].mean()

sns.set_style('whitegrid')
plt.figure(figsize=(15,10))
sns.barplot(x=total_amount_by_month.index,␣
 ↪y=total_amount_by_month['total_amount'], palette='colorblind')

# Add a horizontal line displaying the average 'average revenue' across all␣
 ↪months
# Increase the line width to make it more visible
average_line = plt.axhline(y=average_revenue, color='b', linestyle='--',␣
 ↪linewidth=2)

# Annotate the average line with the average value
plt.text(5.5, average_revenue+500, 'Average Revenue per Month: ${:.2f}'.
 ↪format(average_revenue), color='b')

# Add a legend for each of the mean lines
#plt.legend([average_line], [])

plt.title('Total Revenue per Month (USD)', fontsize=20)
plt.xlabel('Month', fontsize=15)
plt.ylabel('Revenue (USD)', fontsize=15)
plt.xticks(rotation=45)

plt.show()
```



Scatter plot You can create a scatterplot in Tableau Public, which can be easier to manipulate and present. If you'd like step by step instructions, you can review the following link. Those instructions create a scatterplot showing the relationship between total_amount and trip_distance. Consider adding the Tableau visualization to your executive summary, and adding key insights from your findings on those two variables.

Tableau visualization guidelines

Plot mean trip distance by drop-off location

[30]:
```
# Get number of unique drop-off location IDs
df['DOLocationID'].nunique()
```

[30]: 216

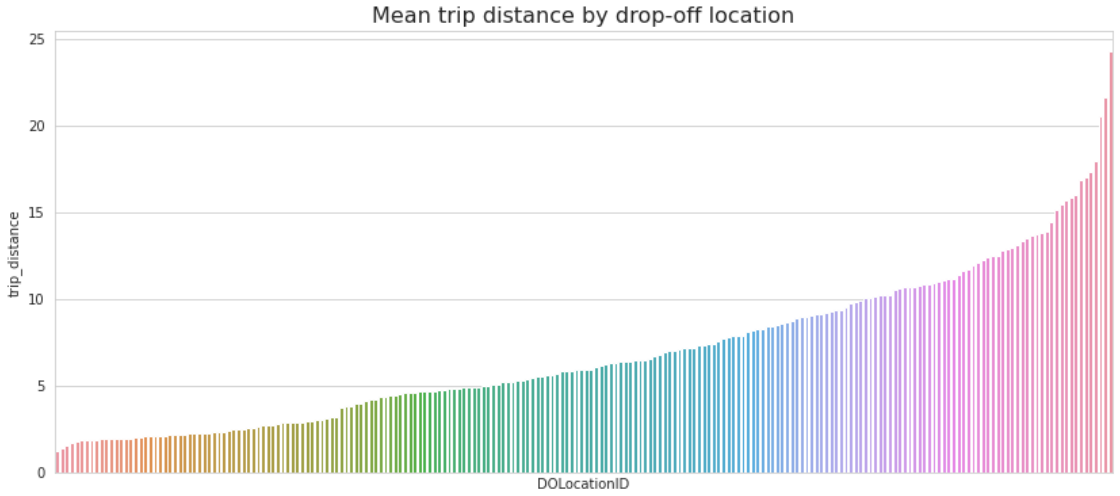
[31]:
```
# Calculate the mean trip distance for each drop-off location
distance_by_dropoff = df.groupby('DOLocationID').mean()[['trip_distance']]

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

[31]:

DOLocationID	trip_distance
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]

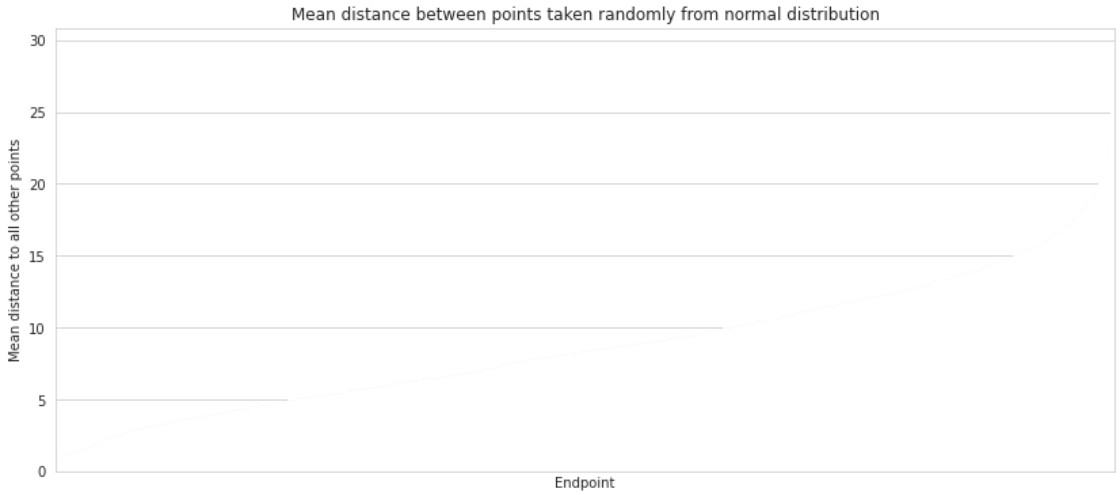
[32]:
```
# Create a bar plot of mean trip distances by drop-off location in ascending␣
 ↪order by distance
# Sort the DataFrame by 'trip_distance' in ascending order

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);
```



4.4 BONUS CONTENT

To confirm your conclusion, consider the following experiment: 1. Create a sample of coordinates from a normal distribution—in this case 1,500 pairs of points from a normal distribution with a mean of 10 and a standard deviation of 5 2. Calculate the distance between each pair of coordinates 3. Group the coordinates by endpoint and calculate the mean distance between that endpoint and all other points it was paired with 4. Plot the mean distance for each unique endpoint

[33]:
```
#BONUS CONTENT

# 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');
```



Histogram of rides by drop-off location

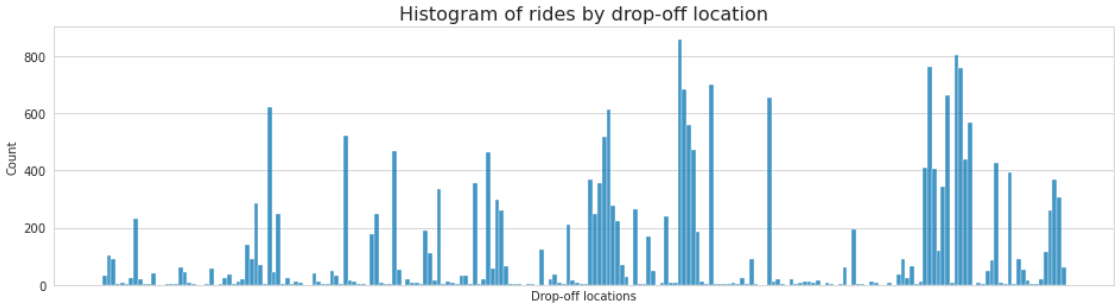
First, check to whether the drop-off locations IDs are consecutively numbered. For instance, does it go 1, 2, 3, 4…, or are some numbers missing (e.g., 1, 3, 4…). If numbers aren't all consecutive, the histogram will look like some locations have very few or no rides when in reality there's no bar because there's no location.

[34]:
```
# Check if all drop-off locations are consecutively numbered
df['DOLocationID'].max() - len(set(df['DOLocationID']))
```

[34]: 49

To eliminate the spaces in the historgram that these missing numbers would create, sort the unique drop-off location values, then convert them to strings. This will make the histplot function display all bars directly next to each other.

[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);
```



4.5 PACE: Execute

Consider the questions in your PACE Strategy Document to reflect on the Execute stage.

4.5.1 Task 4a. Results and evaluation

Having built visualizations in Tableau and in Python, what have you learned about the dataset? What other questions have your visualizations uncovered that you should pursue?

Pro tip: Put yourself in your client's perspective, what would they want to know?

Use the following code fields to pursue any additional EDA based on the visualizations you've already plotted. Also use the space to make sure your visualizations are clean, easily understandable, and accessible.

Ask yourself: Did you consider color, contrast, emphasis, and labeling?

I have learned ….

- Generally:
- That using colors that are appropriate for visually impaired individuals is important.
- That making plots as simple and easy to follow as possible is better than overcomplicating them with too much information. Better to have mutliple plots explaining something than one plot that becomes too busy with information.
- Regarding the clients analysis:
- Vendor2 appears to have a larger proportion of tips.
- The largest distribution of trip distances occurs below 3 miles, with some outliers up to 33 miles.

My other questions are ….

- There are several trips with a distance of 0 miles. Why is this the case, and how will it impact the overall analysis and model?

My client would likely want to know …

- Using the trip pick-up and drop-off times, a trip duration can be derived. Comparing this to the costs of these trips, a model can be established.

[36]:
```
df['trip_duration'] = (df['tpep_dropoff_datetime']-df['tpep_pickup_datetime'])
```

[37]:
```
df.head()
```

[37]:

	Unnamed: 0	VendorID	tpep_pickup_datetime	tpep_dropoff_datetime	passenger_count	trip_distance	RatecodeID	store_and_fwd_flag	PULocationID	DOLocationID	…	fare_amount	extra	mta_tax	tip_amount	tolls_amount	improvement_surcharge	total_amount	month	day	trip_duration
0	24870114	2	2017-03-25 08:55:43	2017-03-25 09:09:47	6	3.34	1	N	100	231	…	13.0	0.0	0.5	2.76	0.0	0.3	16.56	March	Saturday	0 days 00:14:04
1	35634249	1	2017-04-11 14:53:28	2017-04-11 15:19:58	1	1.80	1	N	186	43	…	16.0	0.0	0.5	4.00	0.0	0.3	20.80	April	Tuesday	0 days 00:26:30
2	106203690	1	2017-12-15 07:26:56	2017-12-15 07:34:08	1	1.00	1	N	262	236	…	6.5	0.0	0.5	1.45	0.0	0.3	8.75	December	Friday	0 days 00:07:12
3	38942136	2	2017-05-07 13:17:59	2017-05-07 13:48:14	1	3.70	1	N	188	97	…	20.5	0.0	0.5	6.39	0.0	0.3	27.69	May	Sunday	0 days 00:30:15
4	30841670	2	2017-04-15 23:32:20	2017-04-15 23:49:03	1	4.37	1	N	4	112	…	16.5	0.5	0.5	0.00	0.0	0.3	17.80	April	Saturday	0 days 00:16:43

[5 rows x 21 columns]

4.5.2 Task 4b. Conclusion

Make it professional and presentable

You have visualized the data you need to share with the director now. Remember, the goal of a data visualization is for an audience member to glean the information on the chart in mere seconds.

Questions to ask yourself for reflection: Why is it important to conduct Exploratory Data Analysis? Why are the data visualizations provided in this notebook useful?

EDA is important because …

- EDA is a crucial part of data analysis, as it allows the analyst to understand outliers, handle missing data, and discover additional patterns within it.

Visualizations helped me understand ..

- It was identified that there are outliers in the data that need to be addressed prior to developing a model. The distribution of variables for analysis was also understood, which will inform any required statistical testing methods.

You've now completed professional data visualizations according to a business need. Well done!

Congratulations! You've completed this lab. However, you may not notice a green check mark next to this item on Coursera's platform. Please continue your progress regardless of the check mark. Just click on the "save" icon at the top of this notebook to ensure your work has been logged.