Activity_Course 3 Automatidata project lab

September 24, 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?

Use numpy functions to investigate the mean() and median() of the data and understand range of data values Use a boxplot to visualize the distribution of the data Use histograms to visualize the distribution of the data How do you make the decision to keep or exclude outliers from any future models?

There are three main options for dealing with outliers: keeping them as they are, deleting them, or reassigning them. Whether you keep outliers as they are, delete them, or reassign values is a decision that you make taking into account the nature of the outlying data and the assumptions of the model you are building. To help you make the decision, you can start with these general guidelines:

Delete them: If you are sure the outliers are mistakes, typos, or errors and the dataset will be used for modeling or machine learning, then you are more likely to decide to delete outliers. Of the three choices, you'll use this one the least. Reassign them: If the dataset is small and/or the data will be used for modeling or machine learning, you are more likely to choose a path of deriving new values to replace the outlier values. Leave them: For a dataset that you plan to do EDA/analysis on and nothing else, or for a dataset you are preparing for a model that is resistant to outliers, it is most likely that you are going to leave them in.

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.

[8]:
```
# Import packages and libraries
#==> ENTER YOUR CODE HERE
import numpy as np
import pandas as pd
import datetime as dt
import seaborn as sns
from matplotlib import pyplot as plt
```

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.

[4]:
```
# 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?

==> ENTER YOUR RESPONSE HERE

Start by discovering, using head and size.

[5]:
```
#==> ENTER YOUR CODE HERE
df.head(5)
```

[5]:
```
   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
```

[5]:
```
#==> ENTER YOUR CODE HERE
df.size
```

[5]:
```
408582
```

Use describe...

[6]:
```
#==> ENTER YOUR CODE HERE
df.describe
```

[6]:
```
<bound method NDFrame.describe of        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
…             …       …                      …                       …
22694    14873857         2   02/24/2017 5:37:23 PM   02/24/2017 5:40:39 PM
22695    66632549         2   08/06/2017 4:43:59 PM   08/06/2017 5:24:47 PM
22696    74239933         2   09/04/2017 2:54:14 PM   09/04/2017 2:58:22 PM
22697    60217333         2  07/15/2017 12:56:30 PM   07/15/2017 1:08:26 PM
22698    17208911         1   03/02/2017 1:02:49 PM   03/02/2017 1:16:09 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
…                  …             …         …                 …
22694                3           0.61           1                  N
22695                1          16.71           2                  N
22696                1           0.42           1                  N
22697                1           2.36           1                  N
22698                1           2.10           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
…               …             …             …          …     …      …
22694            48           186             2          4.0    1.0      0.5
```

```
22695         132         164         1       52.0    0.0      0.5
22696         107         234         2        4.5    0.0      0.5
22697          68         144         1       10.5    0.0      0.5
22698         239         236         1       11.0    0.0      0.5

       tip_amount  tolls_amount  improvement_surcharge  total_amount
0            2.76          0.00                    0.3         16.56
1            4.00          0.00                    0.3         20.80
2            1.45          0.00                    0.3          8.75
3            6.39          0.00                    0.3         27.69
4            0.00          0.00                    0.3         17.80
…              …             …                      …            …
22694        0.00          0.00                    0.3          5.80
22695       14.64          5.76                    0.3         73.20
22696        0.00          0.00                    0.3          5.30
22697        1.70          0.00                    0.3         13.00
22698        2.35          0.00                    0.3         14.15

[22699 rows x 18 columns]>
```

And info.

[7]:
```
#==> ENTER YOUR CODE HERE
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

==> ENTER YOUR RESPONSE HERE

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

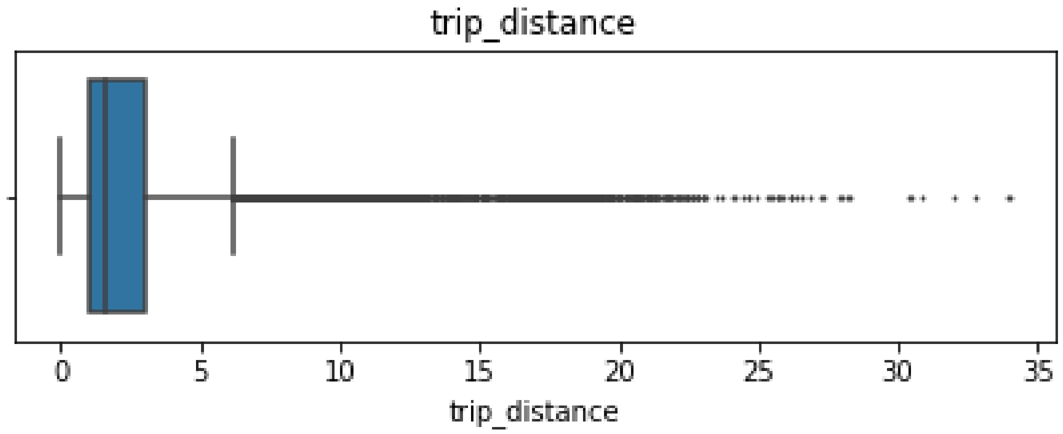
Perform a check for outliers on relevant columns such as trip distance and trip duration. Remember, some of the best ways to identify the presence of outliers in data are box plots and histograms.

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

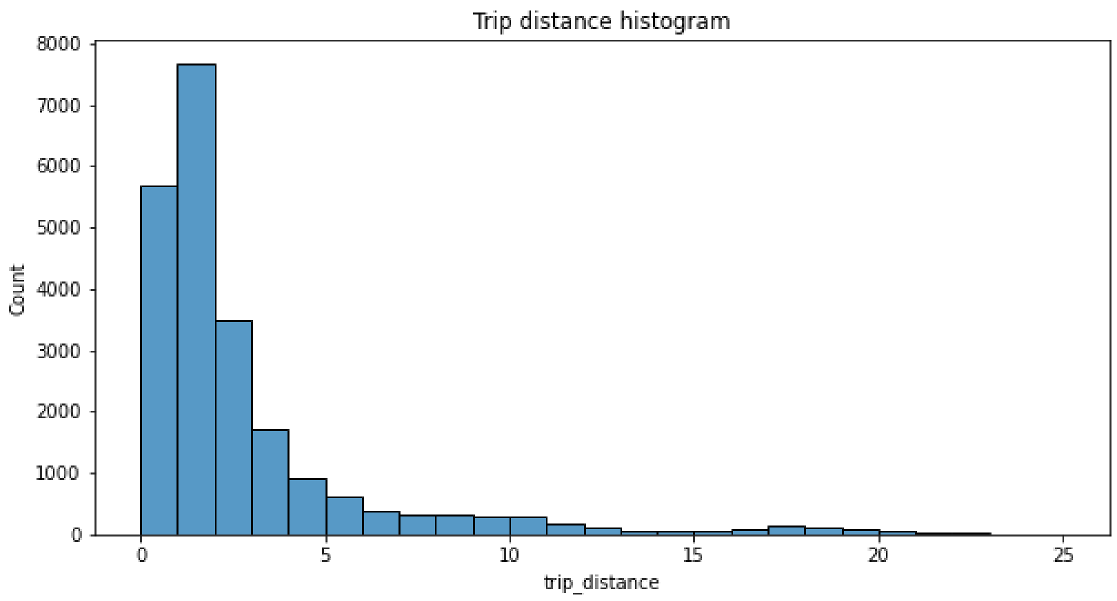
[6]:
```
# Convert data columns to datetime
#==> ENTER YOUR CODE HERE
df["tpep_pickup_datetime"] = pd.to_datetime(df["tpep_pickup_datetime"])
df["tpep_dropoff_datetime"] = pd.to_datetime(df["tpep_dropoff_datetime"])
```

trip distance

[9]:
```
# 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);
```

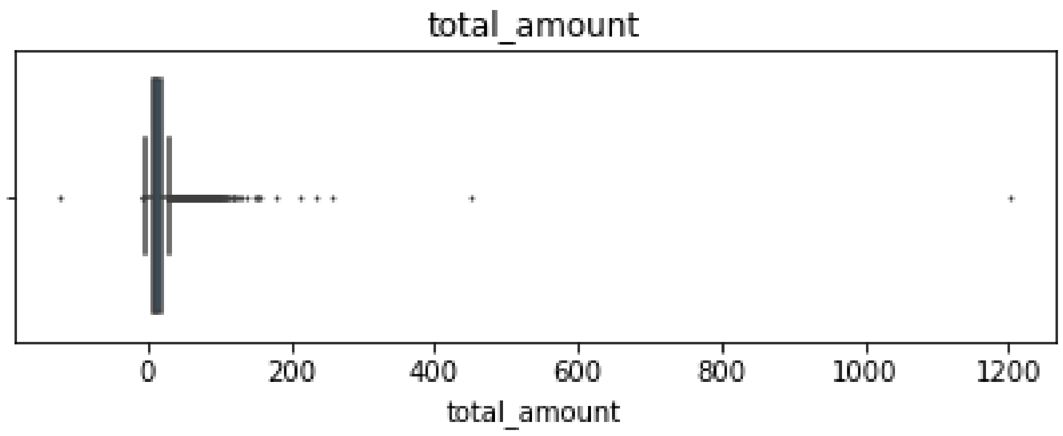


[10]:
```
# Create histogram of trip_distance

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



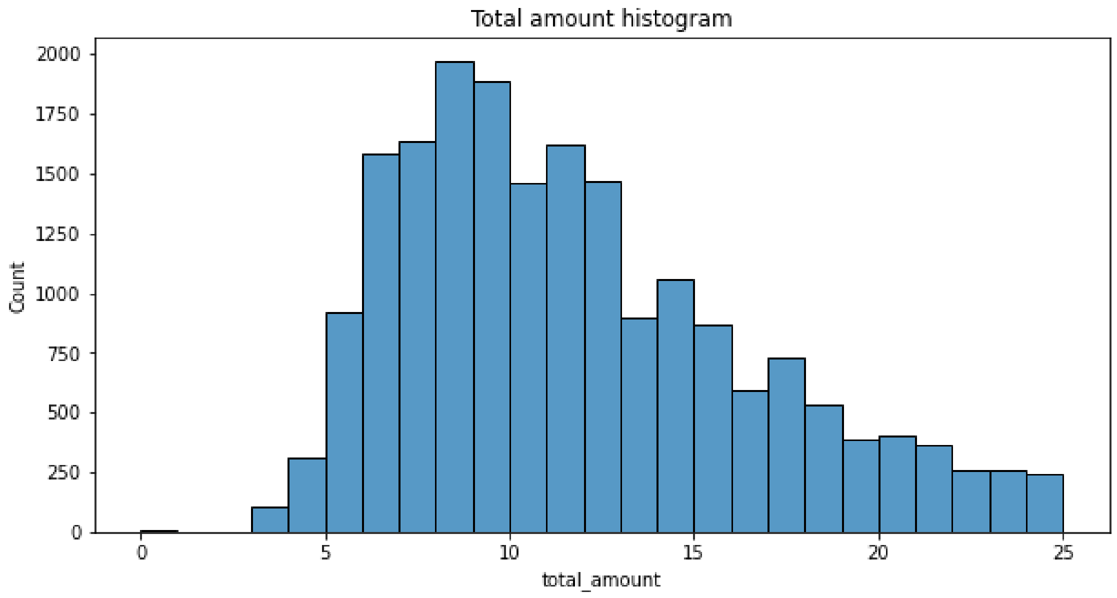
total amount

```
[11]: # Create box plot of total_amount

      plt.figure(figsize=(7,2))
      plt.title('total_amount')
      sns.boxplot(data=None, x=df['total_amount'], fliersize=1);
```



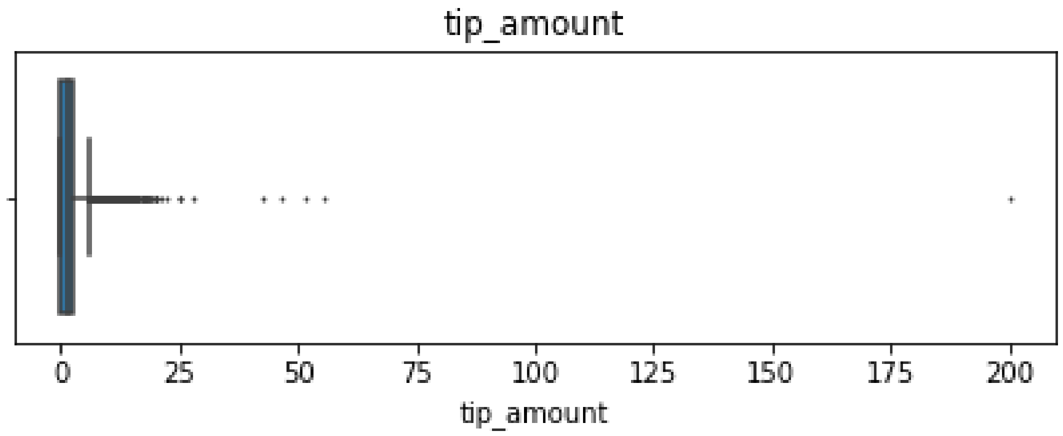
```
[12]: # Create histogram of total_amount

      plt.figure(figsize=(10,5))
      sns.histplot(df['total_amount'], bins=range(0,26,1))
```

```
plt.title('Total amount histogram');
```

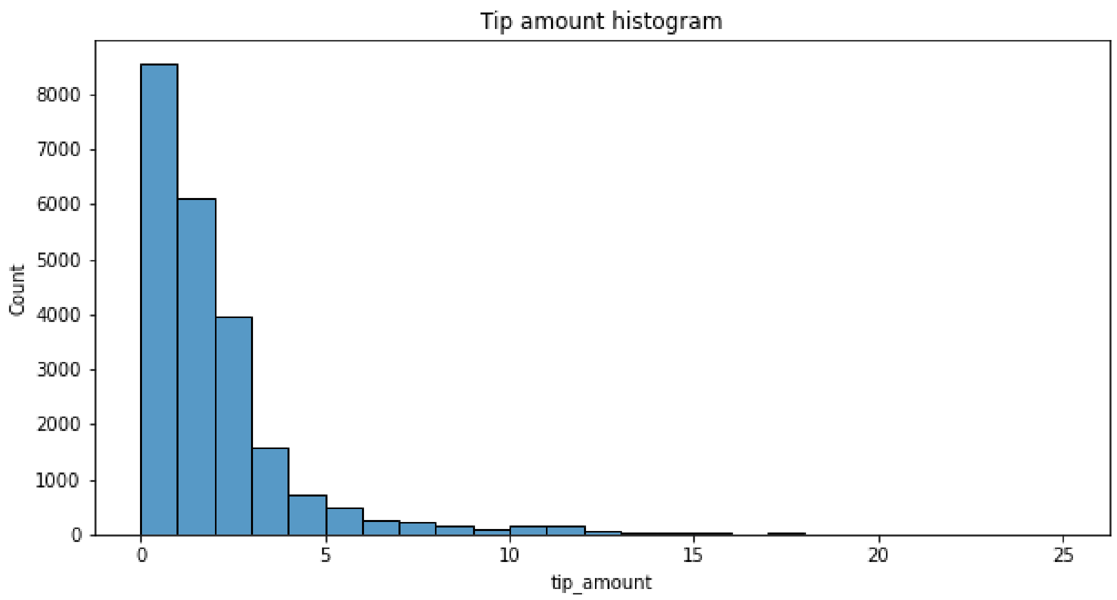


tip amount

[14]:
```
# Create box plot of tip_amount

plt.figure(figsize=(7,2))
plt.title('tip_amount')
sns.boxplot(data=None, x=df['tip_amount'], fliersize=1);
```

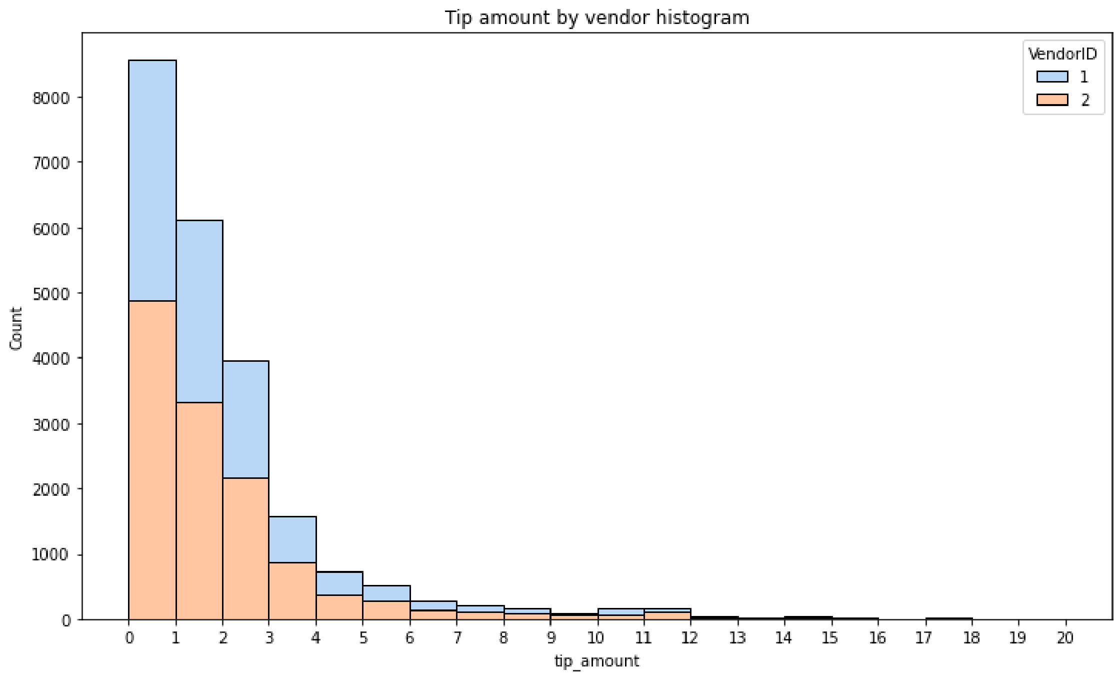


```
[15]: # Create histogram of tip_amount
      plt.figure(figsize=(10,5))
      sns.histplot(df['tip_amount'], bins=range(0,26,1))
      plt.title('Tip amount histogram');
```



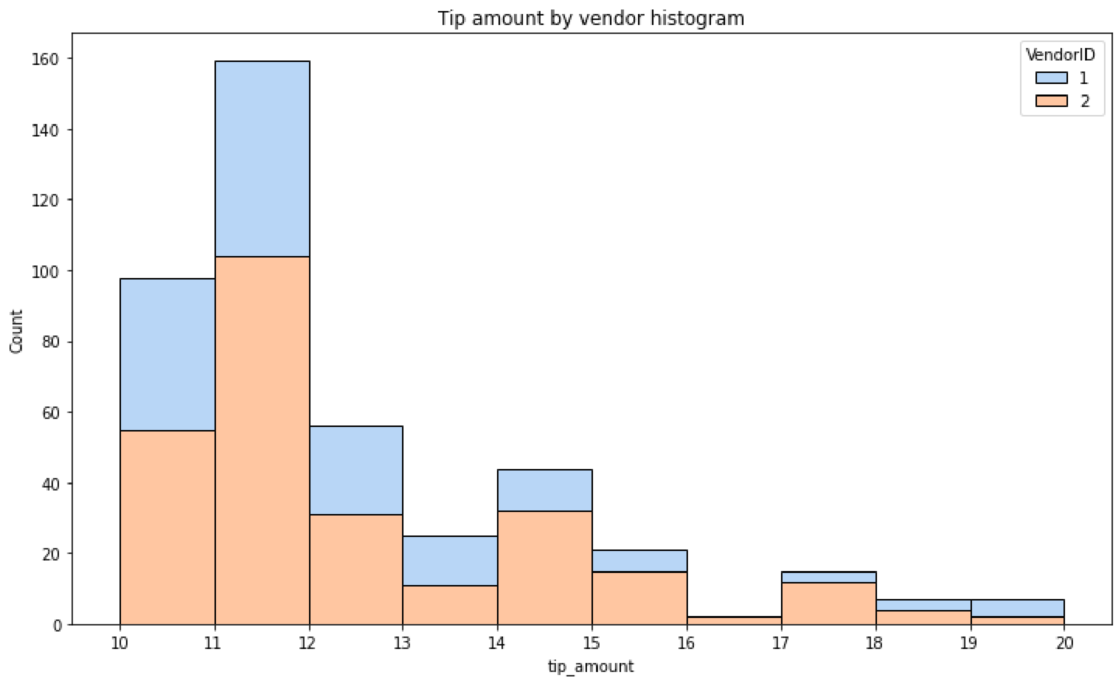
tip__amount by vendor

```
[16]: # 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');
```



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.

[17]:
```
# 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');
```



Mean tips by passenger count

Examine the unique values in the passenger_count column.

[19]:
```
df["passenger_count"].value_counts()
```

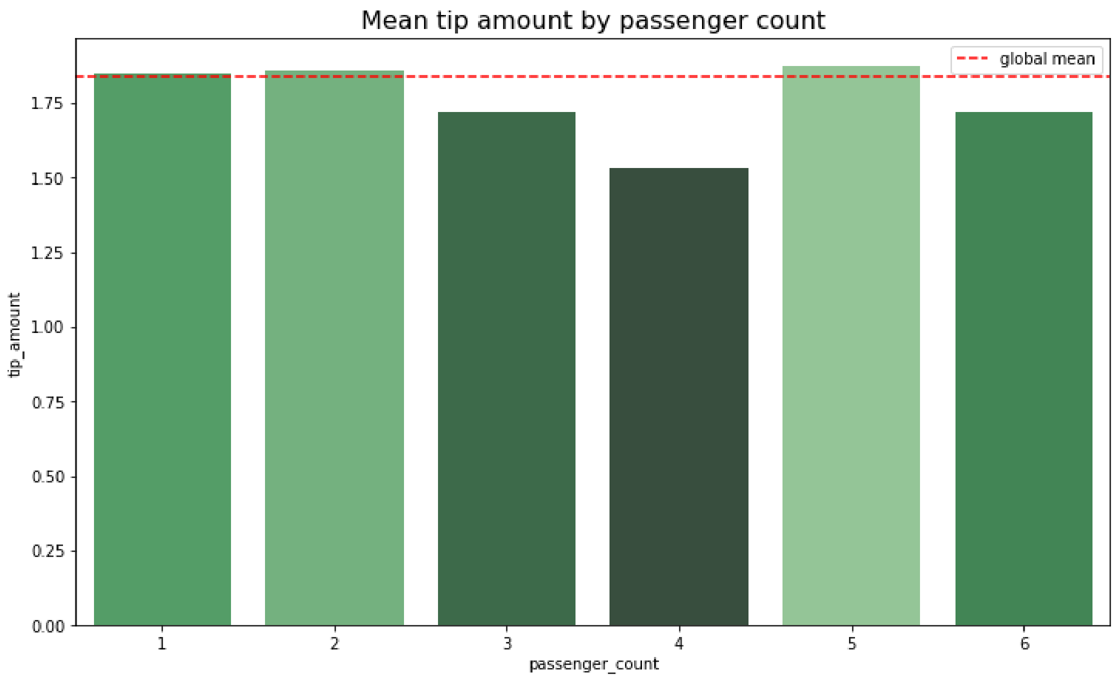
[19]:
```
1    16117
2     3305
5     1143
3      953
6      693
4      455
0       33
Name: passenger_count, dtype: int64
```

[20]:
```
# Calculate mean tips by passenger_count

mean_tips_by_passenger_count = df.groupby(['passenger_count']).
 ↪mean()[['tip_amount']]
mean_tips_by_passenger_count
```

[20]:
```
                 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
```

[21]:
```
# 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);
```



Create month and day columns

[22]:
```
# 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.

```
[23]: # Get total number of rides for each month

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

```
[23]: 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.

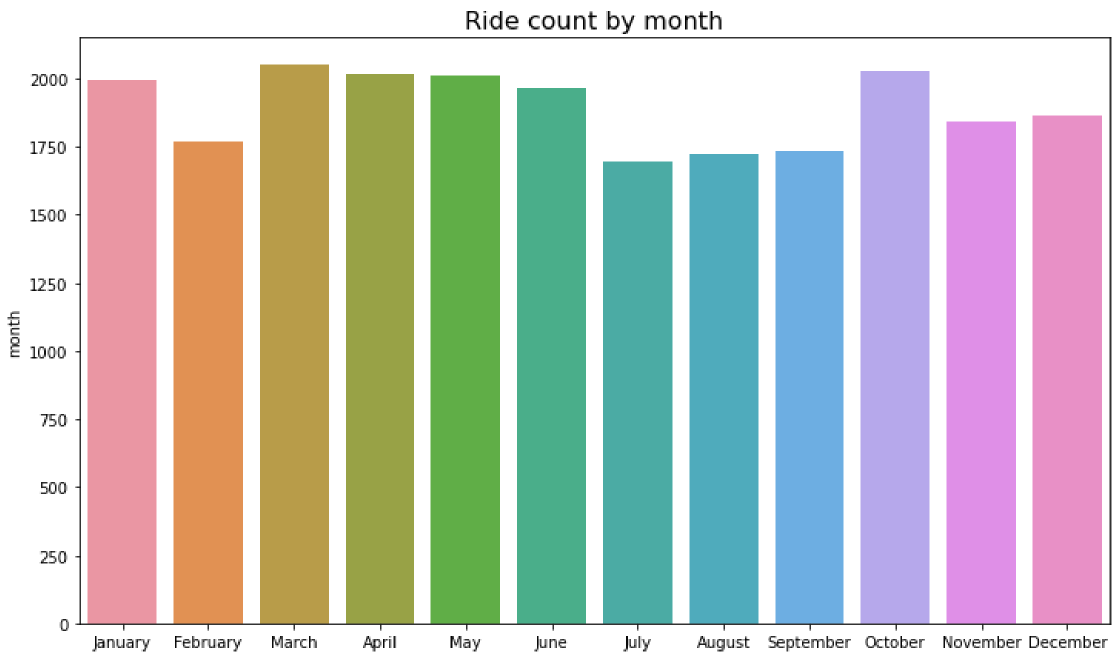
```
[24]: # Reorder the monthly ride list so months go in order

month_order = ['January', 'February', 'March', 'April', 'May', 'June', 'July',
         'August', 'September', 'October', 'November', 'December']

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

```
[24]: 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
```

```
[25]: # Show the index
      monthly_rides.index
```

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

```
[26]: # 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);
```



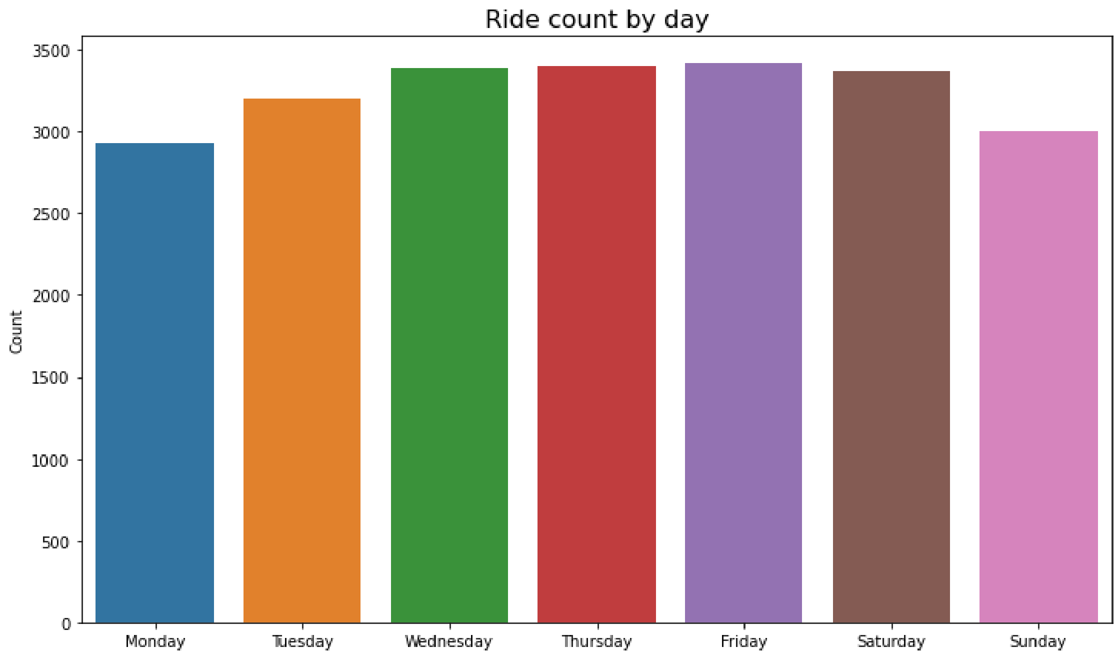
Plot total ride count by day

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

```
[27]: # 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
```

[27]:
```
Monday       2931
Tuesday      3198
Wednesday    3390
Thursday     3402
Friday       3413
Saturday     3367
Sunday       2998
Name: day, dtype: int64
```

[28]:
```
# 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);
```

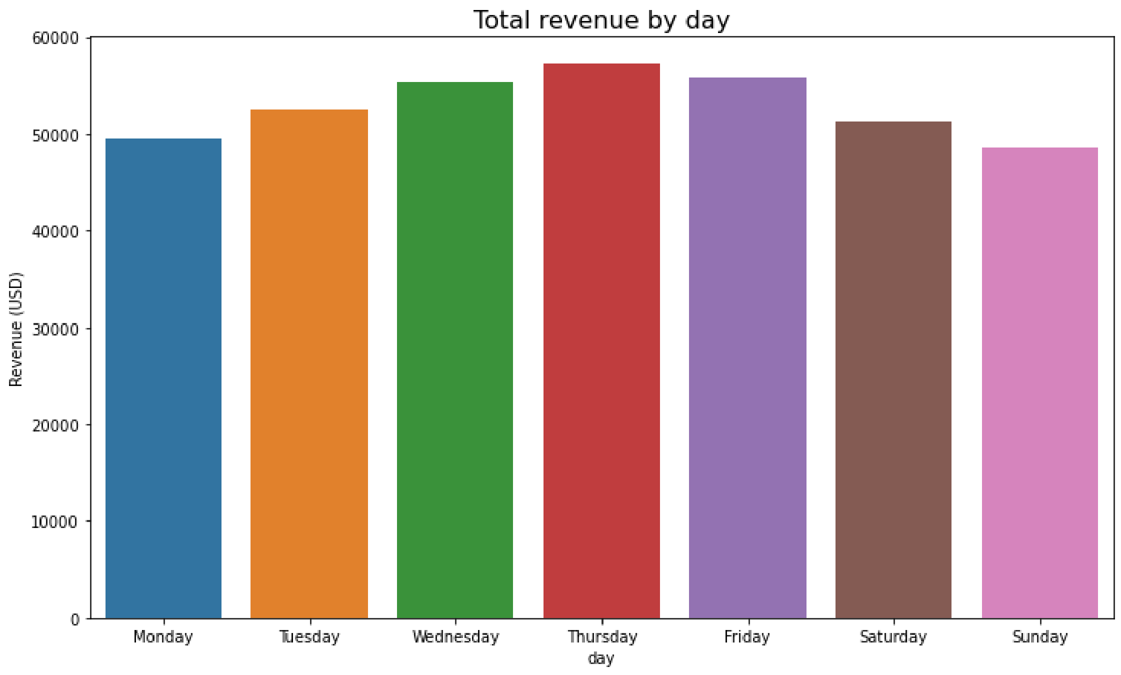


Plot total revenue by day of the week

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

[29]:
```
# 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)
```

[30]:
```
# 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);
```



Plot total revenue by month

[ ]:
```
# Repeat the process, this time for total revenue by month
#==> ENTER YOUR CODE HERE
```

[ ]:
```
# Create a bar plot of total revenue by month
#==> ENTER YOUR CODE HERE
```

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

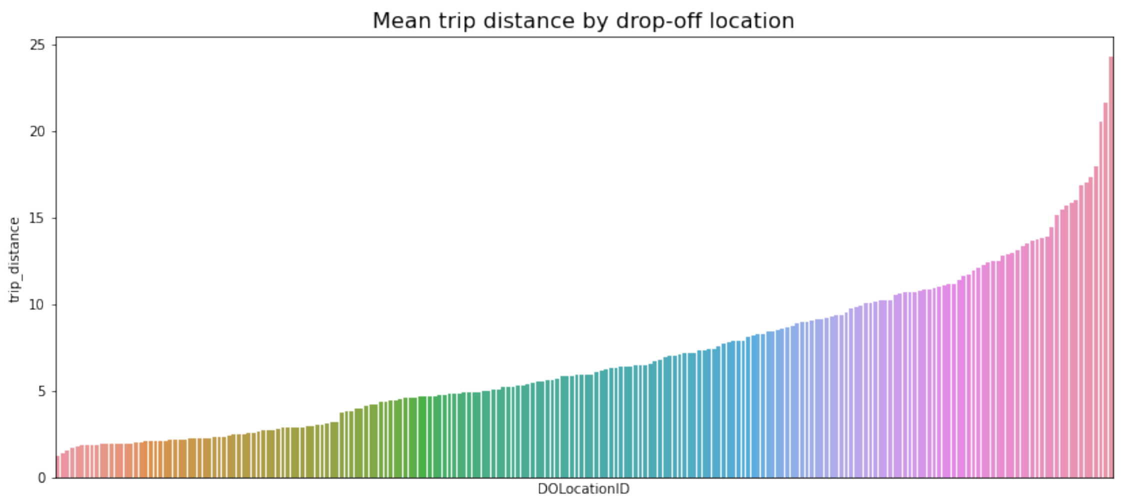
```
[31]: # Get number of unique drop-off location IDs

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

```
[31]: 216
```

```
[32]: # 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
```

```
[32]:               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]
```

```
[33]: # 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);
```

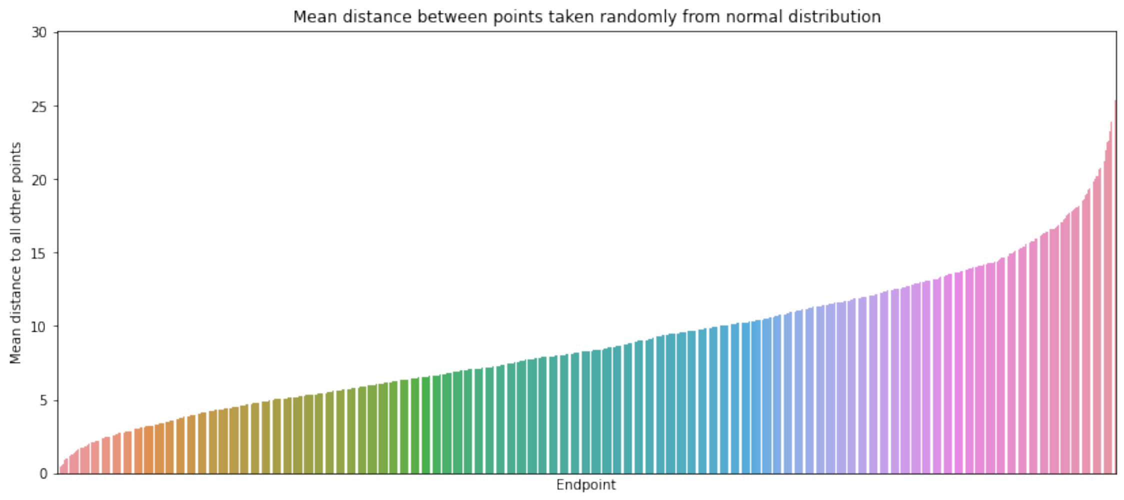


4.4 BONUS CONTENT

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

[34]:
```python
# 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.

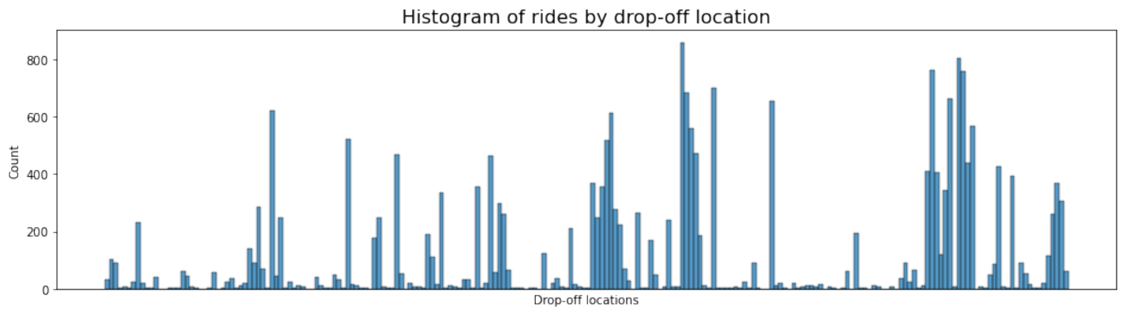
```
[35]: # Check if all drop-off locations are consecutively numbered
      df['DOLocationID'].max() - len(set(df['DOLocationID']))
```

```
[35]: 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.

```
[36]: #==> ENTER YOUR CODE HERE
      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 .... the highest distribution of trip distances are below 5 miles, but there are outliers all the way out to 35 miles. There are no missing values.

My other questions are .... There are several trips that have a trip distance of "0.0." What might those trips be? Will they impact our model?

My client would likely want to know ... that the data includes dropoff and pickup times. We can use that information to derive a trip duration for each line of data. This would likely be something that will help the client with their model.

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

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

```
[38]:    Unnamed: 0  VendorID tpep_pickup_datetime tpep_dropoff_datetime  \
      0    24870114         2  2017-03-25 08:55:43   2017-03-25 09:09:47
      1    35634249         1  2017-04-11 14:53:28   2017-04-11 15:19:58
      2   106203690         1  2017-12-15 07:26:56   2017-12-15 07:34:08
      3    38942136         2  2017-05-07 13:17:59   2017-05-07 13:48:14
      4    30841670         2  2017-04-15 23:32:20   2017-04-15 23:49:03
      5    23345809         2  2017-03-25 20:34:11   2017-03-25 20:42:11
      6    37660487         2  2017-05-03 19:04:09   2017-05-03 20:03:47
      7    69059411         2  2017-08-15 17:41:06   2017-08-15 18:03:05
      8     8433159         2  2017-02-04 16:17:07   2017-02-04 16:29:14
      9    95294817         1  2017-11-10 15:20:29   2017-11-10 15:40:55

         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  …  fare_amount  extra  mta_tax  tip_amount  \
      0           100           231  …         13.0    0.0      0.5        2.76
      1           186            43  …         16.0    0.0      0.5        4.00
      2           262           236  …          6.5    0.0      0.5        1.45
      3           188            97  …         20.5    0.0      0.5        6.39
      4             4           112  …         16.5    0.5      0.5        0.00
      5           161           236  …          9.0    0.5      0.5        2.06
      6            79           241  …         47.5    1.0      0.5        9.86
      7           237           114  …         16.0    1.0      0.5        1.78
      8           234           249  …          9.0    0.0      0.5        0.00
      9           239           237  …         13.0    0.0      0.5        2.75

         tolls_amount  improvement_surcharge  total_amount     month        day  \
      0           0.0                    0.3         16.56     March   Saturday
      1           0.0                    0.3         20.80     April    Tuesday
      2           0.0                    0.3          8.75  December     Friday
      3           0.0                    0.3         27.69       May     Sunday
      4           0.0                    0.3         17.80     April   Saturday
      5           0.0                    0.3         12.36     March   Saturday
      6           0.0                    0.3         59.16       May  Wednesday
      7           0.0                    0.3         19.58    August    Tuesday
```

```
8           0.0                    0.3          9.80  February   Saturday
9           0.0                    0.3         16.55  November     Friday

    trip_duration
0 0 days 00:14:04
1 0 days 00:26:30
2 0 days 00:07:12
3 0 days 00:30:15
4 0 days 00:16:43
5 0 days 00:08:00
6 0 days 00:59:38
7 0 days 00:21:59
8 0 days 00:12:07
9 0 days 00:20:26

[10 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 helps a data professional to get to know the data, understand its outliers, clean its missing values, and prepare it for future modeling. Visualizations helped me understand ..

That this dataset has some outliers that we will need to make decisions on prior to designing a model.

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.