Activity_ Course 5 Automatidata project lab

July 17, 2023

1 Automatidata project

Course 5 - Regression Analysis: Simplify complex data relationships

The data consulting firm Automatidata has recently hired you as the newest member of their data analytics team. Their newest client, the NYC Taxi and Limousine Commission (New York City TLC), wants the Automatidata team to build a multiple linear regression model to predict taxi fares using existing data that was collected over the course of a year. The team is getting closer to completing the project, having completed an initial plan of action, initial Python coding work, EDA, and A/B testing.

The Automatidata team has reviewed the results of the A/B testing. Now it's time to work on predicting the taxi fare amounts. You've impressed your Automatidata colleagues with your hard work and attention to detail. The data team believes that you are ready to build the regression model and update the client New York City TLC about your progress.

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

2 Course 5 End-of-course project: Build a multiple linear regression model

In this activity, you will build a multiple linear regression model. As you've learned, multiple linear regression helps you estimate the linear relationship between one continuous dependent variable and two or more independent variables. For data science professionals, this is a useful skill because it allows you to consider more than one variable against the variable you're measuring against. This opens the door for much more thorough and flexible analysis to be completed.

Completing this activity will help you practice planning out and buidling a multiple linear regression model 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 demostrate knowledge of EDA and a multiple linear regression model

The goal is to build a multiple linear regression model and evaluate the model *This activity has three parts:*

Part 1: EDA & Checking Model Assumptions * What are some purposes of EDA before constructing a multiple linear regression model?

Part 2: Model Building and evaluation * What resources do you find yourself using as you complete this stage?

Part 3: Interpreting Model Results

- What key insights emerged from your model(s)?
- What business recommendations do you propose based on the models built?

3 Build a multiple linear regression model

4 PACE stages

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

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

4.1.1 Task 1. Imports and loading

Import the packages that you've learned are needed for building linear regression models.

[1]:
```
# Imports
# Packages for numerics + dataframes
### YOUR CODE HERE ###
import numpy as np
import pandas as pd

# Packages for visualization
### YOUR CODE HERE ###
import matplotlib.pyplot as plt
import seaborn as sns

# Packages for date conversions for calculating trip durations
### YOUR CODE HERE ###
import datetime
from dateutil.parser import parse
from dateutil import relativedelta

# Packages for OLS, MLR, confusion matrix
```

```
### YOUR CODE HERE ###
import statsmodels.api as sm
from statsmodels.formula.api import ols
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import r2_score, mean_squared_error
from sklearn.metrics import confusion_matrix
```

Note: `Pandas` is used to load the NYC TLC dataset. 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
df0=pd.read_csv("2017_Yellow_Taxi_Trip_Data.csv") # index_col parameter␣
↪specified to avoid "Unnamed: 0" column when reading in data from csv
```

4.2 PACE: Analyze

In this stage, consider the following question where applicable to complete your code response:

- What are some purposes of EDA before constructing a multiple linear regression model?

some purposes of EDA before constructing a multiple linear regression model are as follows:

1. Identify patterns and relationships between variables to gain insights into the data.
2. Assess the quality and completeness of the data to ensure it meets the requirements for regression analysis.
3. Detect and handle missing values, outliers, or data inconsistencies that can affect the accuracy of the regression model.
4. Explore the distributions and characteristics of the variables to determine if any transformations are needed.
5. Identify potential multicollinearity issues between independent variables.
6. Evaluate the linearity assumption between the dependent variable and independent variables.
7. Assess the appropriateness of the model assumptions, such as normality and constant variance.
8. Identify any interactions or nonlinear relationships that may need to be considered in the model.
9. Determine which variables have the most significant impact on the dependent variable.
10. Validate the model's performance and assess its predictive power through visualizations and statistical metrics.

4.2.1 Task 2a. Explore data with EDA

Analyze and discover data, looking for correlations, missing data, outliers, and duplicates.

Start with `.shape` and `.info()`.

[3]:
```python
# Start with `.shape` and `.info()`
### YOUR CODE HERE ###

# Display the shape of the dataframe
print('The Shape of the Dataframe is:', df0.shape)

# Display the information about the dataframe
print("\nInfo of the DataFrame:")
df0.info()
```

```
The Shape of the Dataframe is: (22699, 18)

Info of the DataFrame:
<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
```

Check for missing data and duplicates using `.isna()` and `.drop_duplicates()`.

[4]:
```python
# Check for missing data and duplicates using .isna() and .drop_duplicates()
### YOUR CODE HERE ###
# Check for missing data
missing_data = df0.isna().sum()
print("Missing Data:")
print(missing_data)
```

```
# Check for duplicates
duplicates = df0.drop_duplicates()
print("\nDuplicate Rows:")
print(df0.shape[0] - duplicates.shape[0])
```

```
Missing Data:
Unnamed: 0               0
VendorID                 0
tpep_pickup_datetime     0
tpep_dropoff_datetime    0
passenger_count          0
trip_distance            0
RatecodeID               0
store_and_fwd_flag       0
PULocationID             0
DOLocationID             0
payment_type             0
fare_amount              0
extra                    0
mta_tax                  0
tip_amount               0
tolls_amount             0
improvement_surcharge    0
total_amount             0
dtype: int64

Duplicate Rows:
0
```

Use .describe().

[5]:
```
# Use .describe()
### YOUR CODE HERE ###
df0.describe(include='all')
```

[5]:
```
          Unnamed: 0      VendorID   tpep_pickup_datetime  \
count   2.269900e+04  22699.000000                  22699
unique           NaN           NaN                  22687
top              NaN           NaN  07/03/2017 3:45:19 PM
freq             NaN           NaN                      2
mean    5.675849e+07      1.556236                    NaN
std     3.274493e+07      0.496838                    NaN
min     1.212700e+04      1.000000                    NaN
25%     2.852056e+07      1.000000                    NaN
50%     5.673150e+07      2.000000                    NaN
75%     8.537452e+07      2.000000                    NaN
max     1.134863e+08      2.000000                    NaN
```

```
       tpep_dropoff_datetime  passenger_count  trip_distance    RatecodeID  \
count                  22699     22699.000000   22699.000000  22699.000000
unique                 22688              NaN            NaN           NaN
top     10/18/2017 8:07:45 PM             NaN            NaN           NaN
freq                       2              NaN            NaN           NaN
mean                     NaN         1.642319       2.913313      1.043394
std                      NaN         1.285231       3.653171      0.708391
min                      NaN         0.000000       0.000000      1.000000
25%                      NaN         1.000000       0.990000      1.000000
50%                      NaN         1.000000       1.610000      1.000000
75%                      NaN         2.000000       3.060000      1.000000
max                      NaN         6.000000      33.960000     99.000000

       store_and_fwd_flag  PULocationID  DOLocationID  payment_type  \
count               22699  22699.000000  22699.000000  22699.000000
unique                  2           NaN           NaN           NaN
top                     N           NaN           NaN           NaN
freq                22600           NaN           NaN           NaN
mean                  NaN    162.412353    161.527997      1.336887
std                   NaN     66.633373     70.139691      0.496211
min                   NaN      1.000000      1.000000      1.000000
25%                   NaN    114.000000    112.000000      1.000000
50%                   NaN    162.000000    162.000000      1.000000
75%                   NaN    233.000000    233.000000      2.000000
max                   NaN    265.000000    265.000000      4.000000

         fare_amount         extra       mta_tax    tip_amount  tolls_amount  \
count   22699.000000  22699.000000  22699.000000  22699.000000  22699.000000
unique           NaN           NaN           NaN           NaN           NaN
top              NaN           NaN           NaN           NaN           NaN
freq             NaN           NaN           NaN           NaN           NaN
mean       13.026629      0.333275      0.497445      1.835781      0.312542
std        13.243791      0.463097      0.039465      2.800626      1.399212
min      -120.000000     -1.000000     -0.500000      0.000000      0.000000
25%         6.500000      0.000000      0.500000      0.000000      0.000000
50%         9.500000      0.000000      0.500000      1.350000      0.000000
75%        14.500000      0.500000      0.500000      2.450000      0.000000
max       999.990000      4.500000      0.500000    200.000000     19.100000

        improvement_surcharge  total_amount
count            22699.000000  22699.000000
unique                    NaN           NaN
top                       NaN           NaN
freq                      NaN           NaN
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
```

Check for missing data and duplicates using `.isna()` and `.drop_duplicates()`.

[6]:
```python
# Check for missing data and duplicates using .isna() and .drop_duplicates()
### YOUR CODE HERE ###
# Check for missing data
missing_data = df0.isna().sum()
print("Missing Data:")
print(missing_data)

# Check for duplicates
duplicates = df0.drop_duplicates()
print("\nDuplicate Rows:")
print(df0.shape[0] - duplicates.shape[0])
```

```
Missing Data:
Unnamed: 0               0
VendorID                 0
tpep_pickup_datetime     0
tpep_dropoff_datetime    0
passenger_count          0
trip_distance            0
RatecodeID               0
store_and_fwd_flag       0
PULocationID             0
DOLocationID             0
payment_type             0
fare_amount              0
extra                    0
mta_tax                  0
tip_amount               0
tolls_amount             0
improvement_surcharge    0
total_amount             0
dtype: int64

Duplicate Rows:
0
```

Use `.describe()`.

[7]:
```python
# Use .describe()
### YOUR CODE HERE ###
```

```
df0.describe()
```

[7]:

	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

4.2.2 Task 2b. Convert pickup & dropoff columns to datetime

[8]:
```python
# Check the format of the data
### YOUR CODE HERE ###
df0['tpep_pickup_datetime'][0] #= pd.to_datetime(df0['tpep_pickup_datetime'],␣
↪format='%m/%d/%Y %I:%M:%S %p')
df0['tpep_dropoff_datetime'][0]# = pd.to_datetime(df0['tpep_dropoff_datetime'],␣
↪format='%m/%d/%Y %I:%M:%S %p')
```

[8]:
```
'03/25/2017 9:09:47 AM'
```

[9]:
```python
# Convert datetime columns to datetime
### YOUR CODE HERE ###
# Display data types of `tpep_pickup_datetime`, `tpep_dropoff_datetime`
print('Data type of tpep_pickup_datetime:', df0['tpep_pickup_datetime'].dtype)
print('Data type of tpep_dropoff_datetime:', df0['tpep_dropoff_datetime'].dtype)

# Convert pickup and dropoff columns to datetime
df0['tpep_pickup_datetime'] = pd.to_datetime(df0['tpep_pickup_datetime'])
df0['tpep_dropoff_datetime'] = pd.to_datetime(df0['tpep_dropoff_datetime'])

# Check the format of the data
print("Format of pickup datetime:", df0['tpep_pickup_datetime'].dt.
↪strftime('%Y-%m-%d %H:%M:%S').head())
print("Format of dropoff datetime:", df0['tpep_dropoff_datetime'].dt.
↪strftime('%Y-%m-%d %H:%M:%S').head())
```

```
Data type of tpep_pickup_datetime: object
Data type of tpep_dropoff_datetime: object
Format of pickup datetime: 0    2017-03-25 08:55:43
1    2017-04-11 14:53:28
2    2017-12-15 07:26:56
3    2017-05-07 13:17:59
4    2017-04-15 23:32:20
Name: tpep_pickup_datetime, dtype: object
Format of dropoff datetime: 0    2017-03-25 09:09:47
1    2017-04-11 15:19:58
2    2017-12-15 07:34:08
3    2017-05-07 13:48:14
4    2017-04-15 23:49:03
Name: tpep_dropoff_datetime, dtype: object
```

4.2.3 Task 2c. Create duration column

Create a new column called `duration` that represents the total number of minutes that each taxi ride took.

```
[10]: # Create `duration` column
### YOUR CODE HERE ###
df0['duration'] = (df0['tpep_dropoff_datetime'] - df0['tpep_pickup_datetime']).
 ↪dt.total_seconds() / 60

# Display the updated DataFrame with the 'duration' column
df0.head()
```

```
[10]:    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

   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   duration
0        2.76           0.0                    0.3         16.56  14.066667
1        4.00           0.0                    0.3         20.80  26.500000
2        1.45           0.0                    0.3          8.75   7.200000
3        6.39           0.0                    0.3         27.69  30.250000
4        0.00           0.0                    0.3         17.80  16.716667
```

4.2.4 Outliers

Call `df.info()` to inspect the columns and decide which ones to check for outliers.

```
[11]: ### YOUR CODE HERE ###
# Inspect the columns using df.info()
df0.info()

# Check for outliers in trip_distance, fare_amount, and duration
```

```
#print(df0[['trip_distance', 'fare_amount', 'duration']].
↪describe(include='all'))
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 22699 entries, 0 to 22698
Data columns (total 19 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  datetime64[ns]
 3   tpep_dropoff_datetime  22699 non-null  datetime64[ns]
 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
 18  duration               22699 non-null  float64
dtypes: datetime64[ns](2), float64(9), int64(7), object(1)
memory usage: 3.3+ MB
```

Keeping in mind that many of the features will not be used to fit your model, the most important columns to check for outliers are likely to be: * `trip_distance` * `fare_amount` * `duration`

4.2.5 Task 2d. Box plots

Plot a box plot for each feature: `trip_distance`, `fare_amount`, `duration`.

[12]:
```
### YOUR CODE HERE ###

# Set the color palette for the box plots
color_palette = sns.color_palette("Accent")

# Create subplots for each feature
fig, axs = plt.subplots(1, 3, figsize=(15, 2))

# Plot box plots for each feature
sns.boxplot(x=df0['trip_distance'], ax=axs[0], color=color_palette[0])
```

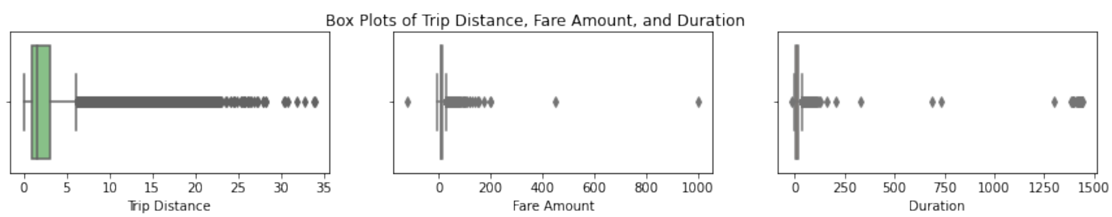
```
sns.boxplot(x=df0['fare_amount'], ax=axs[1], color=color_palette[1])
sns.boxplot(x=df0['duration'], ax=axs[2], color=color_palette[2])

# Set labels for each subplot
axs[0].set_xlabel('Trip Distance')
axs[1].set_xlabel('Fare Amount')
axs[2].set_xlabel('Duration')

# Set title for the figure
fig.suptitle('Box Plots of Trip Distance, Fare Amount, and Duration')

# Adjust spacing between subplots
#plt.tight_layout()

# Show the plot
plt.show()
```



Questions: 1. Which variable(s) contains outliers?

2. Are the values in the `trip_distance` column unbelievable?

3. What about the lower end? Do distances, fares, and durations of 0 (or negative values) make sense?

1. Based on the information provided, the variables that may contain outliers are:

- trip_distance: The maximum value of 33.96 may be considered an outlier, as it is significantly higher than the 75th percentile value of 3.06.
- fare_amount: The minimum value of -120 may be considered an outlier, as negative fare amounts do not make sense in this context.
- duration: The maximum value of 1439.55 may be considered an outlier, as it is significantly higher than the 75th percentile value of 18.38.

2. The values in the trip_distance column do not appear to be unbelievable, as distances can vary widely depending on the taxi ride. However, it would be important to further investigate the distribution of trip distances to ensure they align with expectations.

3. On the lower end, distances, fares, and durations of 0 (or negative values) may not make sense. It would be important to examine the context of these values and consider whether they are valid or potential errors in the data.

4.2.6 Task 2e. Imputations

`trip_distance` outliers You know from the summary statistics that there are trip distances of 0. Are these reflective of erroneous data, or are they very short trips that get rounded down?

To check, sort the column values, eliminate duplicates, and inspect the least 10 values. Are they rounded values or precise values?

[15]:
```
# Are trip distances of 0 bad data or very short trips rounded down?
### YOUR CODE HERE ###
sorted_distances = df0['trip_distance'].sort_values().drop_duplicates()
smallest_distances = sorted_distances[:10]
print(smallest_distances)
```

The distances are captured with a high degree of precision. However, it might be possible for trips to have distances of zero if a passenger summoned a taxi and then changed their mind. Besides, are there enough zero values in the data to pose a problem?

Calculate the count of rides where the `trip_distance` is zero.

[16]:
```
### YOUR CODE HERE ###
zero_distance_count = df0[df0['trip_distance'] == 0]['trip_distance'].count()
print("The number of rides where the trip_distance is zero:", +␣
 ↪zero_distance_count)
```

```
The number of rides where the trip_distance is zero: 148
```

`fare_amount` outliers

[17]:
```
### YOUR CODE HERE ###
df0['fare_amount'].describe()
```

[17]:
```
count    22699.000000
mean        13.026629
std         13.243791
min       -120.000000
25%          6.500000
50%          9.500000
75%         14.500000
max        999.990000
Name: fare_amount, dtype: float64
```

Question: What do you notice about the values in the `fare_amount` column?

Impute values less than \$0 with `0`.

[18]:
```
# Impute values less than $0 with 0
### YOUR CODE HERE ###
df0.loc[df0['fare_amount'] < 0, 'fare_amount'] = 0
df0['fare_amount'].min()
```

[18]: 0.0

Now impute the maximum value as Q3 + (6 * IQR).

[19]:
```
### YOUR CODE HERE ###
'''
    Impute upper-limit values in specified columns based on their interquartile␣
 ↪range.

    Arguments:
        column_list: A list of columns to iterate over
        iqr_factor: A number representing x in the formula:
                    Q3 + (x * IQR). Used to determine maximum threshold,
                    beyond which a point is considered an outlier.
    the upper threshold for each column are imputed with the upper threshold␣
 ↪value.
'''

#The IQR is computed for each column in column_list and values exceeding

### YOUR CODE HERE ###
# Reassign minimum to zero
df0['fare_amount'] = df0['fare_amount'].clip(lower=0)

# Calculate upper threshold
Q3 = df0['fare_amount'].quantile(0.75)
IQR = df0['fare_amount'].quantile(0.75) - df0['fare_amount'].quantile(0.25)
upper_threshold = Q3 + (6 * IQR)

# Reassign values > threshold to threshold
df0['fare_amount'] = df0['fare_amount'].clip(upper=upper_threshold)

# Print the results
print("Upper Quartile (Q3):", Q3)
print("Upper Threshold Value:", upper_threshold)
```

```
Upper Quartile (Q3): 14.5
Upper Threshold Value: 62.5
```

duration outliers

[20]:
```
# Call .describe() for duration outliers
### YOUR CODE HERE ###
df0['duration'].describe(include=True)
```

[20]:
```
count    22699.000000
mean        17.013777
std         61.996482
```

```
min        -16.983333
25%          6.650000
50%         11.183333
75%         18.383333
max       1439.550000
Name: duration, dtype: float64
```

The `duration` column has problematic values at both the lower and upper extremities.

- **Low values:** There should be no values that represent negative time. Impute all negative durations with `0`.
- **High values:** Impute high values the same way you imputed the high-end outliers for fares: `Q3 + (6 * IQR)`.

[21]:
```
# Impute a 0 for any negative values
### YOUR CODE HERE ###
df0.loc[df0['duration'] < 0, 'duration'] = 0
df0['duration'].min()
```

[21]:
```
0.0
```

[22]:
```
# Impute the high outliers
### YOUR CODE HERE ###
df0['fare_amount'] = df0['fare_amount'].clip(lower=0)

# Calculate upper threshold
Q3 = df0['duration'].quantile(0.75)
IQR = df0['duration'].quantile(0.75) - df0['duration'].quantile(0.25)
upper_threshold = Q3 + (6 * IQR)

# Reassign values > threshold to threshold
df0.loc[df0['duration'] > IQR, 'duration'] = upper_threshold
upper_threshold

# Print the results
print("Upper Quartile (Q3):", Q3)
print("Upper Threshold Value:", upper_threshold)
```

```
Upper Quartile (Q3): 18.383333333333333
Upper Threshold Value: 88.78333333333333
```

4.2.7 Task 3a. Feature engineering

Create `mean_distance` column When deployed, the model will not know the duration of a trip until after the trip occurs, so you cannot train a model that uses this feature. However, you can use the statistics of trips you *do* know to generalize about ones you do not know.

In this step, create a column called `mean_distance` that captures the mean distance for each group of trips that share pickup and dropoff points.

For example, if your data were:

|Trip|Start|End|Distance| |–: |:—:|:-:| | | 1 | A | B | 1 | | 2 | C | D | 2 | | 3 | A | B |1.5 | | 4 | D | C | 3 |

The results should be:

```
A -> B: 1.25 miles
C -> D: 2 miles
D -> C: 3 miles
```

Notice that C -> D is not the same as D -> C. All trips that share a unique pair of start and end points get grouped and averaged.

Then, a new column `mean_distance` will be added where the value at each row is the average for all trips with those pickup and dropoff locations:

Trip	Start	End	Distance	mean_distance
1	A	B	1	1.25
2	C	D	2	2
3	A	B	1.5	1.25
4	D	C	3	3

Begin by creating a helper column called `pickup_dropoff`, which contains the unique combination of pickup and dropoff location IDs for each row.

One way to do this is to convert the pickup and dropoff location IDs to strings and join them, separated by a space. The space is to ensure that, for example, a trip with pickup/dropoff points of 12 & 151 gets encoded differently than a trip with points 121 & 51.

So, the new column would look like this:

Trip	Start	End	pickup_dropoff
1	A	B	'A B'
2	C	D	'C D'
3	A	B	'A B'
4	D	C	'D C'

[23]:
```
# Create `pickup_dropoff` column
### YOUR CODE HERE ###
df0['pickup_dropoff'] = df0['PULocationID'].astype(str) + ' ' +␣
↪df0['DOLocationID'].astype(str)
df0['pickup_dropoff'].head(3)
```

[23]:
```
0     100 231
1      186 43
2     262 236
Name: pickup_dropoff, dtype: object
```

Now, use a `groupby()` statement to group each row by the new `pickup_dropoff` column, compute the mean, and capture the values only in the `trip_distance` column. Assign the results to a variable named `grouped`.

[24]:
```
### YOUR CODE HERE ###
# Use groupby() to compute the mean of trip_distance for each pickup_dropoff␣
↪group
grouped = df0.groupby('pickup_dropoff').
↪mean(numeric_only=True)[['trip_distance']]
grouped.head()
```

[24]:

	trip_distance
pickup_dropoff	
1 1	2.433333
10 148	15.700000
100 1	16.890000
100 100	0.253333
100 107	1.180000

`grouped` is an object of the `DataFrame` class.

1. Convert it to a dictionary using the `to_dict()` method. Assign the results to a variable called `grouped_dict`. This will result in a dictionary with a key of `trip_distance` whose values are another dictionary. The inner dictionary's keys are pickup/dropoff points and its values are mean distances. This is the information you want.

```
Example:
grouped_dict = {'trip_distance': {'A B': 1.25, 'C D': 2, 'D C': 3}
```

2. Reassign the `grouped_dict` dictionary so it contains only the inner dictionary. In other words, get rid of `trip_distance` as a key, so:

```
Example:
grouped_dict = {'A B': 1.25, 'C D': 2, 'D C': 3}
```

[25]:
```
# Convert `grouped` to a dictionary
### YOUR CODE HERE ###
grouped_dict = grouped.to_dict()

# Reassign to only contain the inner dictionary
### YOUR CODE HERE ###
grouped_dict = grouped_dict['trip_distance']
```

1. Create a `mean_distance` column that is a copy of the `pickup_dropoff` helper column.

2. Use the map() method on the mean_distance series. Pass grouped_dict as its argument. Reassign the result back to the mean_distance series. When you pass a dictionary to the Series.map() method, it will replace the data in the series where that data matches the dictionary's keys. The values that get imputed are the values of the dictionary.

```
Example:
df['mean_distance']
```

mean_distance
'A B'
'C D'
'A B'
'D C'
'E F'

```
grouped_dict = {'A B': 1.25, 'C D': 2, 'D C': 3}
df['mean_distance`] = df['mean_distance'].map(grouped_dict)
df['mean_distance']
```

mean_distance
1.25
2
1.25
3
NaN

When used this way, the map() Series method is very similar to replace(), however, note that map() will impute NaN for any values in the series that do not have a corresponding key in the mapping dictionary, so be careful.

[26]:
```python
# 1. Create a mean_distance column that is a copy of the pickup_dropoff helper␣
↪column
df0['mean_distance'] = df0['pickup_dropoff']

# 2. Map `grouped_dict` to the `mean_distance` column
df0['mean_distance'] = df0['mean_distance'].map(grouped_dict)

# Confirm that it worked
df0[(df0['PULocationID']==262) & (df0['DOLocationID']==236)][['mean_distance']].
↪head()
```

[26]:

	mean_distance
2	0.881429
464	0.881429
615	0.881429
1090	0.881429

```
1525       0.881429
```

Create mean_duration column Repeat the process used to create the `mean_distance` column to create a `mean_duration` column.

[27]:
```python
### YOUR CODE HERE ###

# Create a dictionary where keys are unique pickup_dropoffs and values are
# mean trip duration for all trips with those pickup_dropoff combos
### YOUR CODE HERE ###

# Use groupby() to compute the mean of duration for each pickup_dropoff group
grouped = df0.groupby('pickup_dropoff').mean(numeric_only=True)[['duration']]
grouped

# Convert `grouped` to a dictionary
### YOUR CODE HERE ###
grouped_dict = grouped.to_dict()

# Reassign to only contain the inner dictionary
### YOUR CODE HERE ###
grouped_dict = grouped_dict['duration']


# 2. Map `grouped_dict` to the `mean_distance` column
df0['mean_duration'] = df0['pickup_dropoff']
df0['mean_duration'] = df0['mean_duration'].map(grouped_dict)


# Confirm that it worked
### YOUR CODE HERE ###
df0[(df0['PULocationID']==262) & (df0['DOLocationID']==236)][['mean_duration']].
↪head()
```

[27]:

	mean_duration
2	9.429048
464	9.429048
615	9.429048
1090	9.429048
1525	9.429048

Create day and month columns Create two new columns, `day` (name of day) and `month` (name of month) by extracting the relevant information from the `tpep_pickup_datetime` column.

[42]:
```python
# Create 'day' col
### YOUR CODE HERE ###

# Extract the day and month information and create new columns
df0['day'] = df0['tpep_pickup_datetime'].dt.day_name()

# Create 'month' col
### YOUR CODE HERE ###
df0['month'] = df0['tpep_pickup_datetime'].dt.month_name()

# Print the updated DataFrame
df0[['tpep_pickup_datetime', 'day', 'month']].head()
```

[42]:

	tpep_pickup_datetime	day	month
0	2017-03-25 08:55:43	Saturday	March
1	2017-04-11 14:53:28	Tuesday	April
2	2017-12-15 07:26:56	Friday	December
3	2017-05-07 13:17:59	Sunday	May
4	2017-04-15 23:32:20	Saturday	April

Create rush_hour column Define rush hour as: * Any weekday (not Saturday or Sunday) AND * Either from 06:00–10:00 or from 16:00–20:00

Create a binary `rush_hour` column that contains a 1 if the ride was during rush hour and a 0 if it was not.

[43]:
```python
# Create 'rush_hour' col
### YOUR CODE HERE ###
df0['rush_hour'] = 0

# If day is Saturday or Sunday, impute 0 in `rush_hour` column
### YOUR CODE HERE
# Define the rush_hourizer function
def rush_hourizer(row):
    if row['day'] in ['Saturday', 'Sunday']:
        return 0
    elif (row['day'] not in ['Saturday', 'Sunday']) and ((row['hour'] >= 6 and␣
↪row['hour'] <= 10) or (row['hour'] >= 16 and row['hour'] <= 20)):
        return 1
    else:
        return 0
```

[44]:
```python
### YOUR CODE HERE ###
df0['tpep_pickup_datetime'] = pd.to_datetime(df0['tpep_pickup_datetime'])

# Extract day and hour from 'tpep_pickup_datetime'
df0['day'] = df0['tpep_pickup_datetime'].dt.day_name()
```

```python
df0['hour'] = df0['tpep_pickup_datetime'].dt.hour
```

[30]:

```python
# Apply the `rush_hourizer()` function to the new column
### YOUR CODE HERE ###
df0['rush_hour'] = df0.apply(rush_hourizer, axis=1)
df0.head()
```

[30]:

```
   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

   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  …  tolls_amount  improvement_surcharge  \
0           100           231  …           0.0                    0.3
1           186            43  …           0.0                    0.3
2           262           236  …           0.0                    0.3
3           188            97  …           0.0                    0.3
4             4           112  …           0.0                    0.3

   total_amount   duration  pickup_dropoff  mean_distance  mean_duration  \
0         16.56  88.783333         100 231       3.521667      88.783333
1         20.80  88.783333          186 43       3.108889      80.133333
2          8.75   7.200000         262 236       0.881429       9.429048
3         27.69  88.783333          188 97       3.700000      88.783333
4         17.80  88.783333           4 112       4.435000      88.783333

   rush_hour       day  hour
0          0  Saturday     8
1          0   Tuesday    14
2          1    Friday     7
3          0    Sunday    13
4          0  Saturday    23

[5 rows x 25 columns]
```

4.2.8 Task 4. Scatter plot

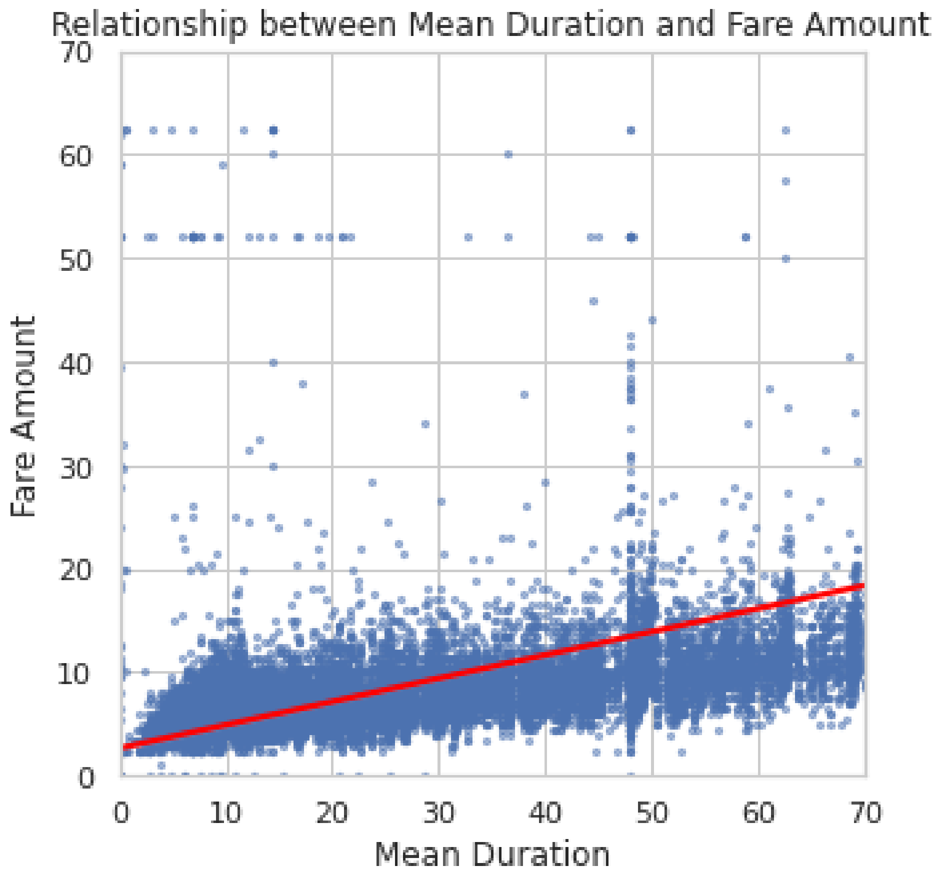
Create a scatterplot to visualize the relationship between `mean_duration` and `fare_amount`.

[45]:
```
# Create a scatterplot to visualize the relationship between variables of␣
↪interest
### YOUR CODE HERE ###

# Create scatter plot with regression line
sns.set(style='whitegrid')
f = plt.figure()
f.set_figwidth(5)
f.set_figheight(5)
sns.regplot(x=df0['mean_duration'], y=df0['fare_amount'],
            scatter_kws={'alpha':0.5, 's':5},
            line_kws={'color':'red'})
plt.ylim(0, 70)
plt.xlim(0, 70)

# Set plot title and labels
plt.title('Relationship between Mean Duration and Fare Amount')
plt.xlabel('Mean Duration')
plt.ylabel('Fare Amount')

# Display the plot
plt.show()
```



The `mean_duration` variable correlates with the target variable. But what are the horizontal lines around fare amounts of 52 dollars and 63 dollars? What are the values and how many are there?

You know what one of the lines represents. 62 dollars and 50 cents is the maximum that was imputed for outliers, so all former outliers will now have fare amounts of $62.50. What is the other line?

Check the value of the rides in the second horizontal line in the scatter plot.

[38]:
```
### YOUR CODE HERE ###
# Filter the dataframe for rides with fare_amount of 63 dollars
df0[df0['fare_amount'] > 50]['fare_amount'].value_counts().head()
#rides_63 = df0[df0['fare_amount'] == 63]
#rides_63[['mean_duration', 'trip_distance', 'duration']].head(5)
```

[38]:
```
52.0    514
62.5     84
59.0      9
50.5      9
57.5      8
```

```
Name: fare_amount, dtype: int64
```

Examine the first 30 of these trips.

[34]:
```python
# Set pandas to display all columns
### YOUR CODE HERE ###

# Set pandas to display all columns
pd.set_option('display.max_columns', None)
df0[df0['fare_amount']==52].head(30)
```

[34]:
```
      Unnamed: 0  VendorID tpep_pickup_datetime tpep_dropoff_datetime  \
11      18600059         2  2017-03-05 19:15:30   2017-03-05 19:52:18
110     47959795         1  2017-06-03 14:24:57   2017-06-03 15:31:48
161     95729204         2  2017-11-11 20:16:16   2017-11-11 20:17:14
247    103404868         2  2017-12-06 23:37:08   2017-12-07 00:06:19
379     80479432         2  2017-09-24 23:45:45   2017-09-25 00:15:14
388     16226157         1  2017-02-28 18:30:05   2017-02-28 19:09:55
406     55253442         2  2017-06-05 12:51:58   2017-06-05 13:07:35
449     65900029         2  2017-08-03 22:47:14   2017-08-03 23:32:41
468     80904240         2  2017-09-26 13:48:26   2017-09-26 14:31:17
520     33706214         2  2017-04-23 21:34:48   2017-04-23 22:46:23
569     99259872         2  2017-11-22 21:31:32   2017-11-22 22:00:25
572     61050418         2  2017-07-18 13:29:06   2017-07-18 13:29:19
586     54444647         2  2017-06-26 13:39:12   2017-06-26 14:34:54
692     94424289         2  2017-11-07 22:15:00   2017-11-07 22:45:32
717    103094220         1  2017-12-06 05:19:50   2017-12-06 05:53:52
719     66115834         1  2017-08-04 17:53:34   2017-08-04 18:50:56
782     55934137         2  2017-06-09 09:31:25   2017-06-09 10:24:10
816     13731926         2  2017-02-21 06:11:03   2017-02-21 06:59:39
818     52277743         2  2017-06-20 08:15:18   2017-06-20 10:24:37
835      2684305         2  2017-01-10 22:29:47   2017-01-10 23:06:46
840     90860814         2  2017-10-27 21:50:00   2017-10-27 22:35:04
861    106575186         1  2017-12-16 06:39:59   2017-12-16 07:07:59
881    110495611         2  2017-12-30 05:25:29   2017-12-30 06:01:29
958     87017503         1  2017-10-15 22:39:12   2017-10-15 23:14:22
970     12762608         2  2017-02-17 20:39:42   2017-02-17 21:13:29
984     71264442         1  2017-08-23 18:23:26   2017-08-23 19:18:29
1082    11006300         2  2017-02-07 17:20:19   2017-02-07 17:34:41
1097    68882036         2  2017-08-14 23:01:15   2017-08-14 23:03:35
1110    74720333         1  2017-09-06 10:46:17   2017-09-06 11:44:41
1179    51937907         2  2017-06-19 06:23:13   2017-06-19 07:03:53

      passenger_count  trip_distance  RatecodeID store_and_fwd_flag  \
11                  2          18.90           2                  N
110                 1          18.00           2                  N
161                 1           0.23           2                  N
```

```
247                  1           18.93           2                  N
379                  1           17.99           2                  N
388                  1           18.40           2                  N
406                  1            4.73           2                  N
449                  2           18.21           2                  N
468                  1           17.27           2                  N
520                  6           18.34           2                  N
569                  1           18.65           2                  N
572                  1            0.00           2                  N
586                  1           17.76           2                  N
692                  2           16.97           2                  N
717                  1           20.80           2                  N
719                  1           21.60           2                  N
782                  2           18.81           2                  N
816                  5           16.94           2                  N
818                  1           17.77           2                  N
835                  1           18.57           2                  N
840                  1           22.43           2                  N
861                  2           17.80           2                  N
881                  6           18.23           2                  N
958                  1           21.80           2                  N
970                  1           19.57           2                  N
984                  1           16.70           2                  N
1082                 1            1.09           2                  N
1097                 5            2.12           2                  N
1110                 1           19.10           2                  N
1179                 6           19.77           2                  N

      PULocationID  DOLocationID  payment_type  fare_amount  extra  mta_tax  \
11             236           132             1         52.0    0.0      0.5
110            132           163             1         52.0    0.0      0.5
161            132           132             2         52.0    0.0      0.5
247            132            79             2         52.0    0.0      0.5
379            132           234             1         52.0    0.0      0.5
388            132            48             2         52.0    4.5      0.5
406            228            88             2         52.0    0.0      0.5
449            132            48             2         52.0    0.0      0.5
468            186           132             2         52.0    0.0      0.5
520            132           148             1         52.0    0.0      0.5
569            132           144             1         52.0    0.0      0.5
572            230           161             1         52.0    0.0      0.5
586            211           132             1         52.0    0.0      0.5
692            132           170             1         52.0    0.0      0.5
717            132           239             1         52.0    0.0      0.5
719            264           264             1         52.0    4.5      0.5
782            163           132             1         52.0    0.0      0.5
816            132           170             1         52.0    0.0      0.5
```

818	132	246	1	52.0	0.0	0.5
835	132	48	1	52.0	0.0	0.5
840	132	163	2	52.0	0.0	0.5
861	75	132	1	52.0	0.0	0.5
881	68	132	2	52.0	0.0	0.5
958	132	261	2	52.0	0.0	0.5
970	132	140	1	52.0	0.0	0.5
984	132	230	1	52.0	4.5	0.5
1082	170	48	2	52.0	4.5	0.5
1097	265	265	2	52.0	0.0	0.5
1110	239	132	1	52.0	0.0	0.5
1179	238	132	1	52.0	0.0	0.5

	tip_amount	tolls_amount	improvement_surcharge	total_amount	\
11	14.58	5.54	0.3	72.92	
110	0.00	0.00	0.3	52.80	
161	0.00	0.00	0.3	52.80	
247	0.00	0.00	0.3	52.80	
379	14.64	5.76	0.3	73.20	
388	0.00	5.54	0.3	62.84	
406	0.00	5.76	0.3	58.56	
449	0.00	5.76	0.3	58.56	
468	0.00	5.76	0.3	58.56	
520	5.00	0.00	0.3	57.80	
569	10.56	0.00	0.3	63.36	
572	11.71	5.76	0.3	70.27	
586	11.71	5.76	0.3	70.27	
692	11.71	5.76	0.3	70.27	
717	5.85	5.76	0.3	64.41	
719	12.60	5.76	0.3	75.66	
782	13.20	0.00	0.3	66.00	
816	2.00	5.54	0.3	60.34	
818	11.71	5.76	0.3	70.27	
835	13.20	0.00	0.3	66.00	
840	0.00	5.76	0.3	58.56	
861	6.00	5.76	0.3	64.56	
881	0.00	0.00	0.3	52.80	
958	0.00	0.00	0.3	52.80	
970	11.67	5.54	0.3	70.01	
984	42.29	0.00	0.3	99.59	
1082	0.00	5.54	0.3	62.84	
1097	0.00	0.00	0.3	52.80	
1110	15.80	0.00	0.3	68.60	
1179	17.57	5.76	0.3	76.13	

	duration	pickup_dropoff	mean_distance	mean_duration	rush_hour	\
11	88.783333	236 132	19.211667	88.783333	0	

110	88.783333	132 163	19.229000	88.783333	0
161	0.966667	132 132	2.255862	6.954023	0
247	88.783333	132 79	19.431667	88.783333	0
379	88.783333	132 234	17.654000	88.783333	0
388	88.783333	132 48	18.761905	88.783333	1
406	88.783333	228 88	4.730000	88.783333	0
449	88.783333	132 48	18.761905	88.783333	0
468	88.783333	186 132	17.096000	88.783333	0
520	88.783333	132 148	17.994286	88.783333	0
569	88.783333	132 144	18.537500	88.783333	0
572	0.216667	230 161	0.685484	21.559140	0
586	88.783333	211 132	16.580000	88.783333	0
692	88.783333	132 170	17.203000	88.783333	0
717	88.783333	132 239	20.901250	88.783333	0
719	88.783333	264 264	3.191516	47.873827	1
782	88.783333	163 132	17.275833	88.783333	1
816	88.783333	132 170	17.203000	88.783333	1
818	88.783333	132 246	18.515000	88.783333	1
835	88.783333	132 48	18.761905	88.783333	0
840	88.783333	132 163	19.229000	88.783333	0
861	88.783333	75 132	18.442500	88.783333	0
881	88.783333	68 132	18.785000	88.783333	0
958	88.783333	132 261	22.115000	88.783333	0
970	88.783333	132 140	19.293333	88.783333	1
984	88.783333	132 230	18.571200	88.783333	1
1082	88.783333	170 48	1.265789	58.821053	1
1097	2.333333	265 265	0.753077	14.403846	0
1110	88.783333	239 132	19.795000	88.783333	1
1179	88.783333	238 132	19.470000	88.783333	1

	day	hour
11	Sunday	19
110	Saturday	14
161	Saturday	20
247	Wednesday	23
379	Sunday	23
388	Tuesday	18
406	Monday	12
449	Thursday	22
468	Tuesday	13
520	Sunday	21
569	Wednesday	21
572	Tuesday	13
586	Monday	13
692	Tuesday	22
717	Wednesday	5
719	Friday	17

```
782        Friday     9
816       Tuesday     6
818       Tuesday     8
835       Tuesday    22
840        Friday    21
861      Saturday     6
881      Saturday     5
958        Sunday    22
970        Friday    20
984     Wednesday    18
1082      Tuesday    17
1097       Monday    23
1110    Wednesday    10
1179       Monday     6
```

Question: What do you notice about the first 30 trips?

Upon examining the first 30 trips with a fare amount of 63 dollars, the following observations can be made:

1. The trips vary in terms of their start and end locations, as indicated by the PULocationID and DOLocationID columns.
2. The passenger count ranges from 1 to 6, with most trips having 1 or 2 passengers.
3. The trip distances vary, with some trips being relatively short (e.g., 0.63 miles) and others being longer (e.g., 30.83 miles).
4. The trips span across different days of the week and months, indicating that they were taken on various dates throughout the year.
5. Some trips occurred during rush hour, as indicated by the rush_hour column being 1, while others did not.
6. The mean duration for these trips ranges from around 0.6 hours to 30.8 hours, reflecting the varying durations of the rides.

Overall, these trips exhibit diversity in terms of their locations, passenger counts, distances, and timings.

4.2.9 Task 5. Isolate modeling variables

Drop features that are redundant, irrelevant, or that will not be available in a deployed environment.

[39]:
```
### YOUR CODE HERE ###
df0.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 22699 entries, 0 to 22698
Data columns (total 25 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  datetime64[ns]
 3   tpep_dropoff_datetime  22699 non-null  datetime64[ns]
 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
 18  duration               22699 non-null  float64
 19  pickup_dropoff         22699 non-null  object
 20  mean_distance          22699 non-null  float64
 21  mean_duration          22699 non-null  float64
 22  rush_hour              22699 non-null  int64
 23  day                    22699 non-null  object
 24  hour                   22699 non-null  int64
dtypes: datetime64[ns](2), float64(11), int64(9), object(3)
memory usage: 4.3+ MB
```

[60]:

```
### YOUR CODE HERE ###
df1 = df0.copy()

df1 = df1.drop(['Unnamed: 0', 'tpep_dropoff_datetime', 'tpep_pickup_datetime',
               'trip_distance', 'RatecodeID', 'store_and_fwd_flag',␣
↪'PULocationID', 'DOLocationID',
               'payment_type', 'extra', 'mta_tax', 'tip_amount',␣
↪'tolls_amount', 'improvement_surcharge',
               'total_amount', 'tpep_dropoff_datetime', 'tpep_pickup_datetime',␣
↪'duration',
               'pickup_dropoff', 'day', 'month', 'rush_hour'
               ], axis=1)

df1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 22699 entries, 0 to 22698
Data columns (total 6 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   VendorID        22699 non-null  int64
```

```
 1   passenger_count  22699 non-null  int64
 2   fare_amount      22699 non-null  float64
 3   mean_distance    22699 non-null  float64
 4   mean_duration    22699 non-null  float64
 5   hour             22699 non-null  int64
dtypes: float64(3), int64(3)
memory usage: 1.0 MB
```

4.2.10 Task 6. Pair plot

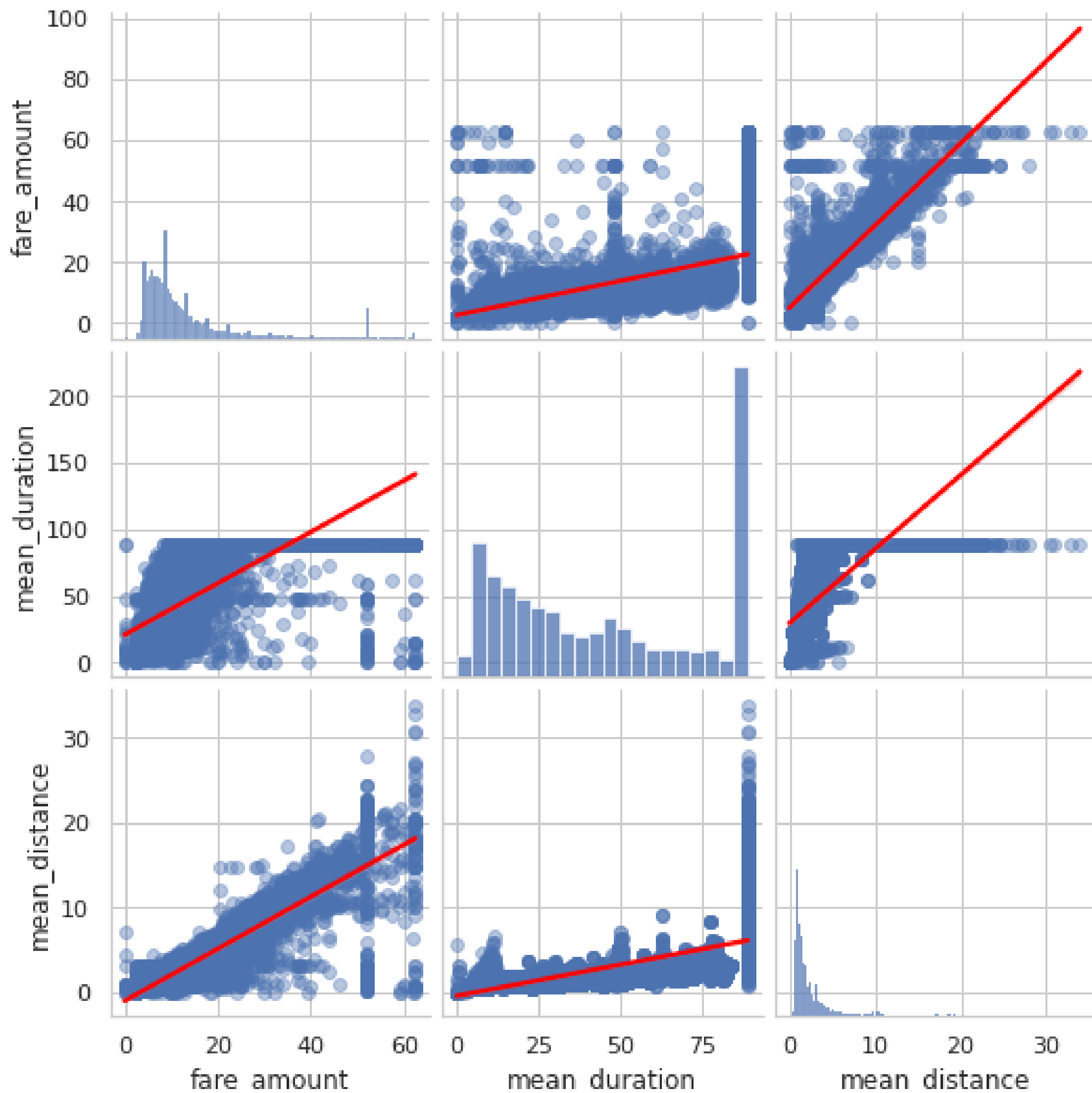
Create a pairplot to visualize pairwise relationships between `fare_amount`, `mean_duration`, and `mean_distance`.

[61]:
```
# Create a pairplot to visualize pairwise relationships between variables in␣
↪the data
### YOUR CODE HERE ###

# Select the columns of interest
columns_of_interest = ['fare_amount', 'mean_duration', 'mean_distance']

# Create the pairplot
sns.pairplot(df1[columns_of_interest], kind='reg',  plot_kws={'line_kws':␣
↪{'color': 'red'}, 'scatter_kws': {'alpha': 0.4}})

# Show the plot
plt.show()
```



These variables all show linear correlation with each other. Investigate this further.

4.2.11 Task 7. Identify correlations

Next, code a correlation matrix to help determine most correlated variables.

[62]:
```
# Correlation matrix to help determine most correlated variables
### YOUR CODE HERE ###
df1.corr(method='pearson')
```

[62]:
```
                 VendorID  passenger_count  fare_amount  mean_distance  \
VendorID         1.000000         0.266463     0.001045       0.004741
passenger_count  0.266463         1.000000     0.014942       0.013428
```

```
fare_amount      0.001045         0.014942     1.000000        0.910185
mean_distance    0.004741         0.013428     0.910185        1.000000
mean_duration   -0.000373         0.012386     0.657914        0.640551
hour            -0.002186         0.009361     0.006062       -0.010776

                 mean_duration      hour
VendorID             -0.000373 -0.002186
passenger_count       0.012386  0.009361
fare_amount           0.657914  0.006062
mean_distance         0.640551 -0.010776
mean_duration         1.000000  0.009723
hour                  0.009723  1.000000
```

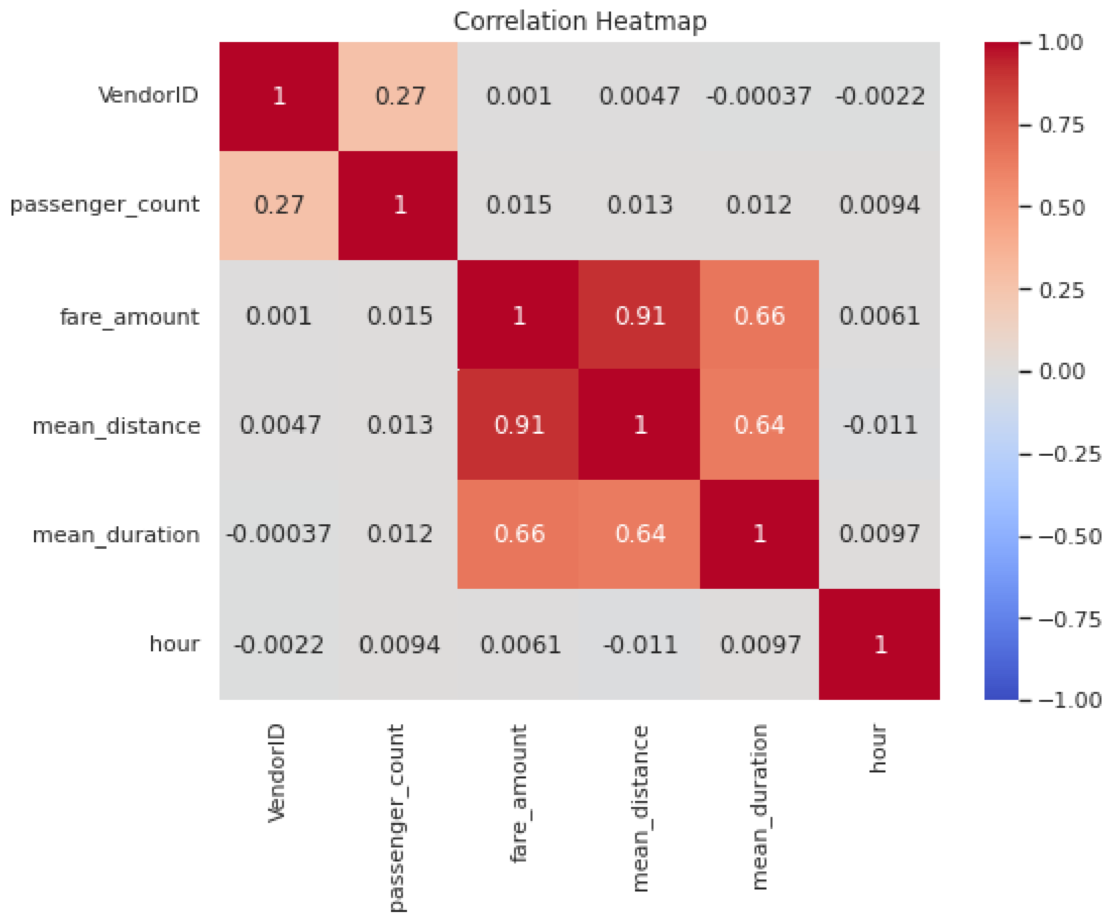
Visualize a correlation heatmap of the data.

[63]:
```python
# Create correlation heatmap
### YOUR CODE HERE ###



# Compute the correlation matrix
corr_matrix = df1.corr()

# Create a heatmap
plt.figure(figsize=(8, 6))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', vmin=-1, vmax=1)
plt.title('Correlation Heatmap')
plt.show()
```



Question: Which variable(s) are correlated with the target variable of `fare_amount`?

Try modeling with both variables even though they are correlated.

4.3 PACE: Construct

After analysis and deriving variables with close relationships, it is time to begin constructing the model. Consider the questions in your PACE Strategy Document to reflect on the Construct stage.

4.3.1 Task 8a. Split data into outcome variable and features

[64]:
```
### YOUR CODE HERE ###
df1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 22699 entries, 0 to 22698
Data columns (total 6 columns):
 #   Column           Non-Null Count  Dtype
```

```
---  ------           --------------  -----
 0   VendorID         22699 non-null  int64
 1   passenger_count  22699 non-null  int64
 2   fare_amount      22699 non-null  float64
 3   mean_distance    22699 non-null  float64
 4   mean_duration    22699 non-null  float64
 5   hour             22699 non-null  int64
dtypes: float64(3), int64(3)
memory usage: 1.0 MB
```

Set your X and y variables. X represents the features and y represents the outcome (target) variable.

[66]:
```python
# Remove the target column from the features
# Split the data into outcome variable (fare_amount) and features
X = df1.drop('fare_amount', axis=1)  # Features
y = df1['fare_amount']  # Outcome variable

X.head()
```

[66]:

	VendorID	passenger_count	mean_distance	mean_duration	hour
0	2	6	3.521667	88.783333	8
1	1	1	3.108889	80.133333	14
2	1	1	0.881429	9.429048	7
3	2	1	3.700000	88.783333	13
4	2	1	4.435000	88.783333	23

4.3.2 Task 8b. Pre-process data

Dummy encode categorical variables

[68]:
```python
# Convert VendorID to string

### YOUR CODE HERE ###
X['VendorID'] = X['VendorID'].astype('string')

# Get dummies
X = pd.get_dummies(X, drop_first=True)
X.head()
```

[68]:

	VendorID	passenger_count	mean_distance	mean_duration	hour
0	2	6	3.521667	88.783333	8
1	1	1	3.108889	80.133333	14
2	1	1	0.881429	9.429048	7
3	2	1	3.700000	88.783333	13
4	2	1	4.435000	88.783333	23

4.3.3 Normalize the data

Use `StandardScaler()` and `fit_transform()` to standardize the X variables. Assign the results to a variable called `X_scaled`.

[73]:
```
# Standardize the X variables
### YOUR CODE HERE ###
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
print('X scaled:', X_scaled)
```

```
X scaled: [[ 0.8931955   3.39065627  0.17093801  1.39851297 -0.91999637]
 [-1.11957573 -0.4997803   0.05495383  1.11872316  0.04393068]
 [-1.11957573 -0.4997803  -0.57092814 -1.16825234 -1.08065088]
 …
 [ 0.8931955  -0.4997803  -0.62633441 -1.18608352  0.04393068]
 [ 0.8931955  -0.4997803  -0.23485053  1.08341251 -0.27737834]
 [-1.11957573 -0.4997803  -0.40359028 -0.58883267 -0.11672383]]
```

4.3.4 Split data into training and test sets

Create training and testing sets. The test set should contain 20% of the total samples. Set `random_state=0`.

[70]:
```
# Create training and testing sets
#### YOUR CODE HERE ####

X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2,␣
 ↪random_state=0)
```

Instantiate your model and fit it to the training data.

[71]:
```
# Fit your model to the training data
### YOUR CODE HERE ###

# Instantiate the Linear Regression model
model = LinearRegression()

# Fit the model to the training data
model.fit(X_train, y_train)
```

[71]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
```

4.3.5 Task 8c. Evaluate model

4.3.6 Train data

Evaluate your model performance by calculating the residual sum of squares and the explained variance score (R^2). Calculate the Mean Absolute Error, Mean Squared Error, and the Root Mean Squared Error.

[74]:
```python
# Evaluate the model performance on the training data
### YOUR CODE HERE ###
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score

# Predict on the test set
y_pred = model.predict(X_test)

# Calculate the residuals
residuals = y_test - y_pred

# Calculate the Residual Sum of Squares (RSS)
rss = np.sum(residuals**2)

# Calculate the Explained Variance Score (R^2)
r2 = r2_score(y_test, y_pred)

# Calculate the Mean Absolute Error (MAE)
mae = mean_absolute_error(y_test, y_pred)

# Calculate the Mean Squared Error (MSE)
mse = mean_squared_error(y_test, y_pred)

# Calculate the Root Mean Squared Error (RMSE)
rmse = np.sqrt(mse)

# Print the results
print("Residual Sum of Squares (RSS):", rss)
print("Explained Variance Score (R^2):", r2)
print("Mean Absolute Error (MAE):", mae)
print("Mean Squared Error (MSE):", mse)
print("Root Mean Squared Error (RMSE):", rmse)
```

```
Residual Sum of Squares (RSS): 68158.57433155748
Explained Variance Score (R^2): 0.8619460039100009
Mean Absolute Error (MAE): 2.2719392726201093
Mean Squared Error (MSE): 15.01290183514482
Root Mean Squared Error (RMSE): 3.8746486079572198
```

4.3.7 Test data

Calculate the same metrics on the test data.

[75]:
```python
# Evaluate the model performance on the testing data
### YOUR CODE HERE ###

# Predict on the test set
y_pred = model.predict(X_test)

# Calculate the residuals
residuals = y_test - y_pred

# Calculate the Residual Sum of Squares (RSS)
rss = np.sum(residuals**2)

# Calculate the Explained Variance Score (R^2)
r2 = r2_score(y_test, y_pred)

# Calculate the Mean Absolute Error (MAE)
mae = mean_absolute_error(y_test, y_pred)

# Calculate the Mean Squared Error (MSE)
mse = mean_squared_error(y_test, y_pred)

# Calculate the Root Mean Squared Error (RMSE)
rmse = np.sqrt(mse)

# Calculate the Coefficient of Determination (R^2)
coefficient_of_determination = model.score(X_test, y_test)

# Print the results
print("Residual Sum of Squares (RSS):", rss)
print("Explained Variance Score (R^2):", r2)
print("Mean Absolute Error (MAE):", mae)
print("Mean Squared Error (MSE):", mse)
print("Root Mean Squared Error (RMSE):", rmse)
print("Coefficient of Determination (R^2):", coefficient_of_determination)
```

```
Residual Sum of Squares (RSS): 68158.57433155748
Explained Variance Score (R^2): 0.8619460039100009
Mean Absolute Error (MAE): 2.2719392726201093
Mean Squared Error (MSE): 15.01290183514482
Root Mean Squared Error (RMSE): 3.8746486079572198
Coefficient of Determination (R^2): 0.8619460039100009
```

4.4 PACE: Execute

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

4.4.1 Task 9a. Results

Use the code cell below to get `actual`,`predicted`, and `residual` for the testing set, and store them as columns in a `results` dataframe.

[76]:
```
# Create a `results` dataframe
### YOUR CODE HERE ###

# Get actual, predicted, and residual values
actual = y_test
predicted = model.predict(X_test)
residuals = actual - predicted

# Create a results dataframe
results = pd.DataFrame({'Actual': actual, 'Predicted': predicted, 'Residuals':␣
↪residuals})
results.head()
```

[76]:

	Actual	Predicted	Residuals
5818	14.0	12.900337	1.099663
18134	28.0	16.077217	11.922783
4655	5.5	6.284562	-0.784562
7378	15.5	17.659346	-2.159346
13914	9.5	11.123285	-1.623285

4.4.2 Task 9b. Visualize model results

Create a scatterplot to visualize `actual` vs. `predicted`.

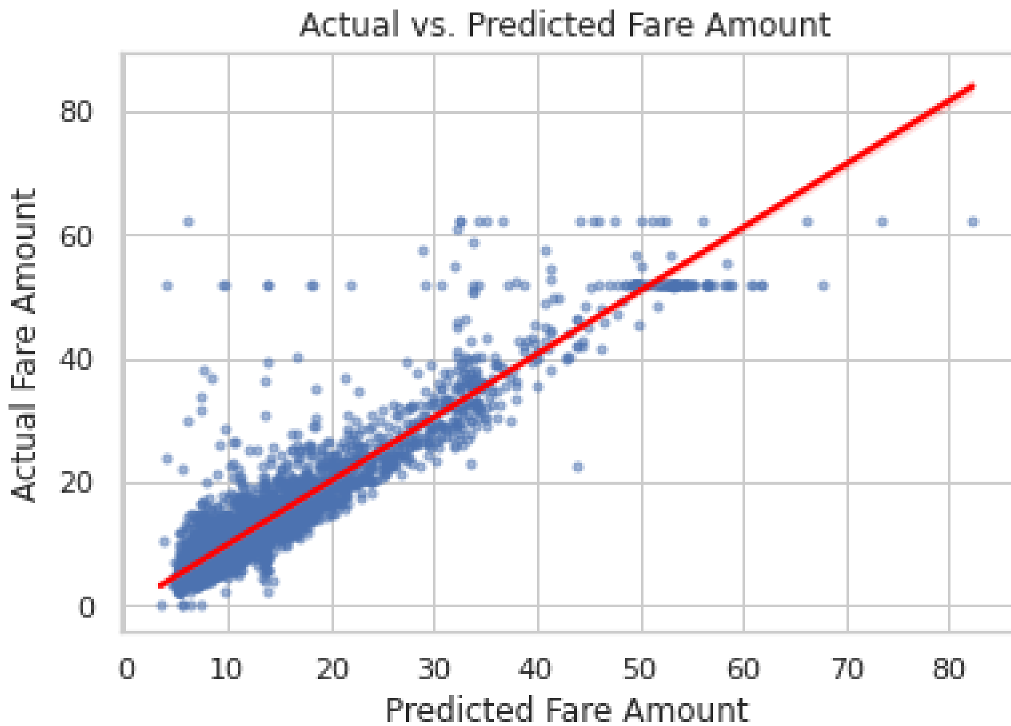
[85]:
```
# Create a scatterplot to visualize `predicted` over `actual`
### YOUR CODE HERE ###

# Create scatterplot of actual vs. predicted
sns.regplot(x=results['Predicted'], y=results['Actual'], scatter_kws={'alpha':␣
↪0.5, 's': 10}, line_kws={'color':'red'})

# Set plot labels and title
plt.xlabel('Predicted Fare Amount')
plt.ylabel('Actual Fare Amount')
plt.title('Actual vs. Predicted Fare Amount')

# Display the plot
```

```
plt.show()
```

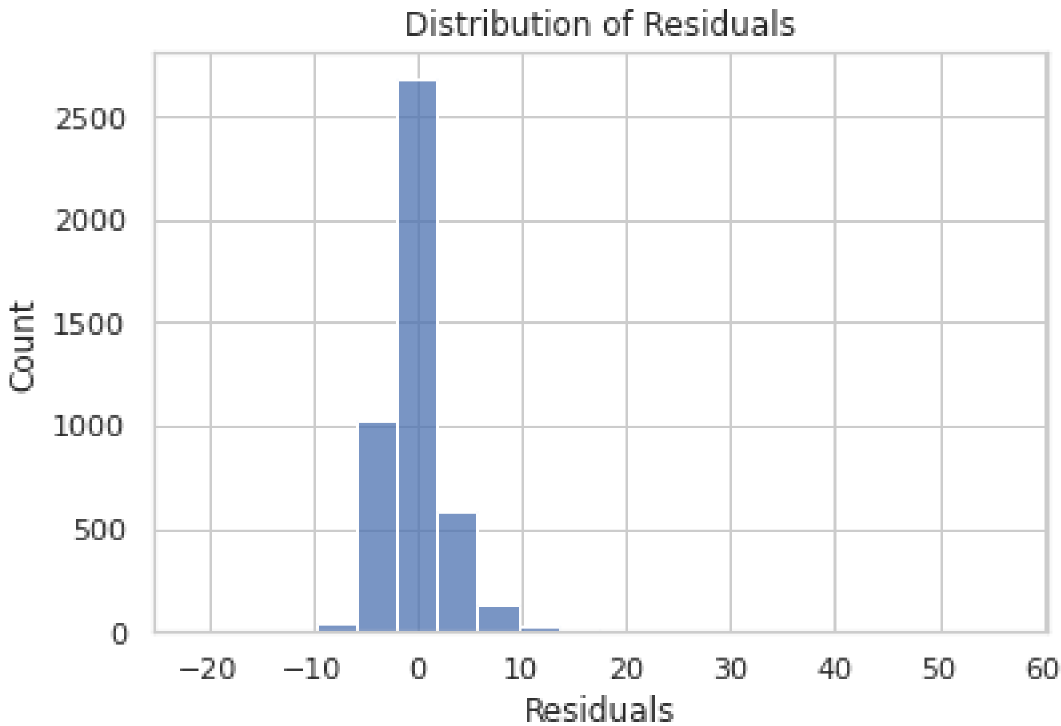


Visualize the distribution of the `residuals` using a histogram.

[78]:
```
# Visualize the distribution of the `residuals`
### YOUR CODE HERE ###
# Create histogram of residuals
sns.histplot(data=results, x='Residuals', bins=20)

# Set plot labels and title
plt.xlabel('Residuals')
plt.ylabel('Count')
plt.title('Distribution of Residuals')

# Display the plot
plt.show()
```

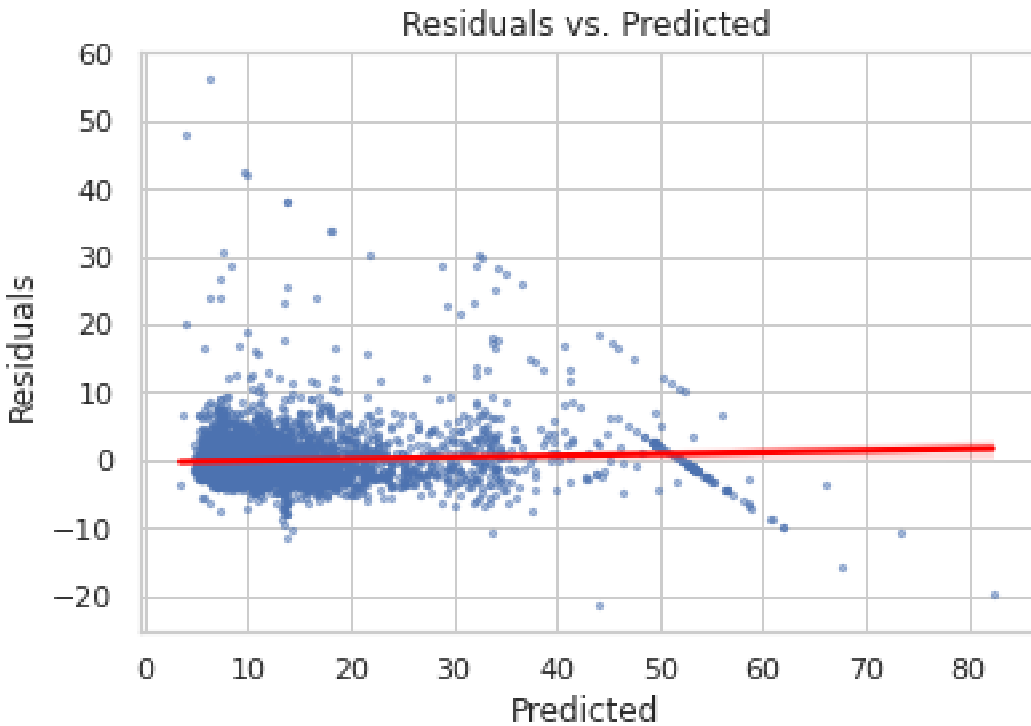


[80]:
```
# Calculate residual mean
### YOUR CODE HERE ###
residual_mean = results['Residuals'].mean()
print("Residual Mean:", residual_mean)
```

```
Residual Mean: -0.029840748909595337
```

Create a scatterplot of `residuals` over `predicted`.

[86]:
```
# Create a scatterplot of `residuals` over `predicted`
### YOUR CODE HERE ###
sns.regplot(x=results['Predicted'], y=results['Residuals'],␣
↪scatter_kws={'alpha':0.5, 's':5}, line_kws={'color':'red'})
plt.xlabel('Predicted')
plt.ylabel('Residuals')
plt.title('Residuals vs. Predicted')
plt.show()
```



4.4.3 Task 9c. Coefficients

Use the `coef_` attribute to get the model's coefficients. The coefficients are output in the order of the features that were used to train the model. Which feature had the greatest effect on trip fare?

[88]:
```python
# Output the model's coefficients
# Get the coefficients
coefficients = model.coef_
feature_names = X.columns.tolist()

coefficients_df1 = pd.DataFrame({'Feature': feature_names, 'Coefficient':␣
↪coefficients})
coefficients_df1 = coefficients_df1.sort_values(by='Coefficient',␣
↪ascending=False)

coefficients_df1
```

[88]:

	Feature	Coefficient
2	mean_distance	8.705568
3	mean_duration	1.318100
4	hour	0.148033
1	passenger_count	0.032364

```
0         VendorID    -0.059736
```

The coefficients reveal that `mean_distance` was the feature with the greatest weight in the model's final prediction. For every mile traveled, the fare amount increases by a mean of \$7. Note, however, that because some highly correlated features were not removed, the confidence interval of this assessment is wider.

4.4.4 Task 9d. Conclusion

1. What are the key takeaways from this notebook?

The key takeaways from this notebook are:

1. Data Exploration: The notebook begins with data exploration, where we examine the dataset and gain initial insights into the variables, their distributions, and any relationships or patterns present.
2. Data Preprocessing: The dataset is preprocessed by handling missing values, converting data types, creating new features, and performing feature engineering. This step ensures that the data is in a suitable format for model training.
3. Model Building: Multiple linear regression models are built to predict taxi fare amounts based on features such as mean distance, mean duration, passenger count, VendorID, and hour. The models are trained using the training set and evaluated using various metrics such as R-squared, mean absolute error, mean squared error, and root mean squared error.
4. Model Evaluation: The performance of the models is assessed using metrics such as RSS, R-squared, MAE, MSE, and RMSE. These metrics provide insights into how well the models fit the data and make predictions.
5. Interpretation of Model Results: The coefficients of the model are analyzed to understand the impact of each feature on the predicted fare amount. This interpretation helps identify which features have the most significant influence on the fare amount.
6. Business Recommendations: Based on the model results, business recommendations can be made, such as optimizing fare pricing based on distance and duration, considering the impact of rush hour on fares, and providing incentives for drivers during peak hours.
7. Ethical Considerations: Throughout the notebook, ethical considerations are emphasized, including privacy protection, fairness, transparency, accountability, and data quality. These considerations ensure that the models and their applications adhere to ethical standards.
8. Continuous Improvement: The notebook acknowledges that the model can be improved by addressing potential issues such as outliers, incorporating additional relevant features, and evaluating alternative modeling techniques. Continuous improvement is essential for refining the model's performance and addressing limitations.

Overall, the notebook provides a comprehensive overview of the data analysis and modeling process, highlighting key insights, model performance, ethical considerations, and potential areas for further exploration and improvement.

2. What results can be presented from this notebook?

The results that can be presented from this notebook include:

1. Model Performance: The multiple linear regression models built to predict taxi fare amounts showed good performance, with an R-squared value of 0.86, indicating that 86% of the variance in the fare amounts can be explained by the selected features. The models also achieved low mean absolute error (MAE), mean squared error (MSE), and root mean squared error (RMSE) values, indicating accurate predictions of fare amounts.

2. Feature Importance: The analysis of the model coefficients revealed the relative importance of different features in predicting fare amounts. Mean distance had the highest positive coefficient, suggesting that longer distances tend to result in higher fare amounts. Mean duration also had a positive coefficient, indicating that longer durations contribute to higher fares. Hour of the day had a small positive coefficient, implying that certain hours may influence fare amounts slightly. Passenger count and VendorID had smaller coefficients, indicating a less significant impact on fare amounts.

3. Business Recommendations: Based on the model results, several business recommendations can be made to optimize fare pricing and improve overall profitability. These recommendations include adjusting fare rates based on distance and duration, offering incentives or surcharges during peak hours or rush hour periods, and considering factors such as passenger count and VendorID when determining fare amounts.

4. Ethical Considerations: Throughout the analysis, ethical considerations were taken into account, such as ensuring data privacy and security, avoiding bias in model predictions, and maintaining transparency in fare calculations. Adhering to ethical standards is crucial in building trust with customers and maintaining a fair and responsible approach to fare pricing.

By presenting these results, the project team can demonstrate the accuracy of the models in predicting fare amounts, highlight the key factors influencing fares, and provide actionable recommendations for the client to optimize fare pricing and enhance their business operations.