DMT Project Group Primrose

December 10, 2024

1 Rideshare Service Price Analysis and Prediction

1.1 Group Primrose

1.1.1 Group Members:

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1.1.5 Import Libraries

[1]:
```
# Import necessary libraries
import pandas as pd
import seaborn as sns
from sklearn import preprocessing
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor
from sklearn.tree import DecisionTreeRegressor
from sklearn.tree import plot_tree
import matplotlib.pyplot as plt
from sklearn.metrics import mean_absolute_error, mean_squared_error,␣
↪r2_score,mean_absolute_percentage_error
pd.set_option("future.no_silent_downcasting", True)
```

1.1.6 Import Data

[2]:
```
file_path="data/rideshare_kaggle.csv"
cab_rides_data=pd.read_csv(file_path)
```

[3]:
```
# Display the first few rows of the dataset
cab_rides_data.head()
```

[3]:

	id	timestamp	hour	day	month	\
0	424553bb-7174-41ea-aeb4-fe06d4f4b9d7	1.544953e+09	9	16	12	
1	4bd23055-6827-41c6-b23b-3c491f24e74d	1.543284e+09	2	27	11	
2	981a3613-77af-4620-a42a-0c0866077d1e	1.543367e+09	1	28	11	

```
3  c2d88af2-d278-4bfd-a8d0-29ca77cc5512  1.543554e+09     4   30     11
4  e0126e1f-8ca9-4f2e-82b3-50505a09db9a  1.543463e+09     3   29     11

              datetime          timezone            source    destination  \
0  2018-12-16 09:30:07  America/New_York  Haymarket Square  North Station
1  2018-11-27 02:00:23  America/New_York  Haymarket Square  North Station
2  2018-11-28 01:00:22  America/New_York  Haymarket Square  North Station
3  2018-11-30 04:53:02  America/New_York  Haymarket Square  North Station
4  2018-11-29 03:49:20  America/New_York  Haymarket Square  North Station

  cab_type  … precipIntensityMax uvIndexTime  temperatureMin  \
0     Lyft  …              0.1276  1544979600           39.89
1     Lyft  …              0.1300  1543251600           40.49
2     Lyft  …              0.1064  1543338000           35.36
3     Lyft  …              0.0000  1543507200           34.67
4     Lyft  …              0.0001  1543420800           33.10

   temperatureMinTime  temperatureMax  temperatureMaxTime  \
0          1545012000           43.68          1544968800
1          1543233600           47.30          1543251600
2          1543377600           47.55          1543320000
3          1543550400           45.03          1543510800
4          1543402800           42.18          1543420800

   apparentTemperatureMin  apparentTemperatureMinTime  apparentTemperatureMax  \
0                   33.73                  1545012000                   38.07
1                   36.20                  1543291200                   43.92
2                   31.04                  1543377600                   44.12
3                   30.30                  1543550400                   38.53
4                   29.11                  1543392000                   35.75

  apparentTemperatureMaxTime
0                 1544958000
1                 1543251600
2                 1543320000
3                 1543510800
4                 1543420800

[5 rows x 57 columns]
```

[4]:
```
# Display the information about the dataset including the data types of the␣
↪columns
cab_rides_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 693071 entries, 0 to 693070
Data columns (total 57 columns):
 #   Column                       Non-Null Count   Dtype
```

| --- | ------ | -------------- | ----- |
0	id	693071 non-null	object
1	timestamp	693071 non-null	float64
2	hour	693071 non-null	int64
3	day	693071 non-null	int64
4	month	693071 non-null	int64
5	datetime	693071 non-null	object
6	timezone	693071 non-null	object
7	source	693071 non-null	object
8	destination	693071 non-null	object
9	cab_type	693071 non-null	object
10	product_id	693071 non-null	object
11	name	693071 non-null	object
12	price	637976 non-null	float64
13	distance	693071 non-null	float64
14	surge_multiplier	693071 non-null	float64
15	latitude	693071 non-null	float64
16	longitude	693071 non-null	float64
17	temperature	693071 non-null	float64
18	apparentTemperature	693071 non-null	float64
19	short_summary	693071 non-null	object
20	long_summary	693071 non-null	object
21	precipIntensity	693071 non-null	float64
22	precipProbability	693071 non-null	float64
23	humidity	693071 non-null	float64
24	windSpeed	693071 non-null	float64
25	windGust	693071 non-null	float64
26	windGustTime	693071 non-null	int64
27	visibility	693071 non-null	float64
28	temperatureHigh	693071 non-null	float64
29	temperatureHighTime	693071 non-null	int64
30	temperatureLow	693071 non-null	float64
31	temperatureLowTime	693071 non-null	int64
32	apparentTemperatureHigh	693071 non-null	float64
33	apparentTemperatureHighTime	693071 non-null	int64
34	apparentTemperatureLow	693071 non-null	float64
35	apparentTemperatureLowTime	693071 non-null	int64
36	icon	693071 non-null	object
37	dewPoint	693071 non-null	float64
38	pressure	693071 non-null	float64
39	windBearing	693071 non-null	int64
40	cloudCover	693071 non-null	float64
41	uvIndex	693071 non-null	int64
42	visibility.1	693071 non-null	float64
43	ozone	693071 non-null	float64
44	sunriseTime	693071 non-null	int64
45	sunsetTime	693071 non-null	int64
46	moonPhase	693071 non-null	float64

```
 47  precipIntensityMax           693071 non-null  float64
 48  uvIndexTime                  693071 non-null  int64
 49  temperatureMin               693071 non-null  float64
 50  temperatureMinTime           693071 non-null  int64
 51  temperatureMax               693071 non-null  float64
 52  temperatureMaxTime           693071 non-null  int64
 53  apparentTemperatureMin       693071 non-null  float64
 54  apparentTemperatureMinTime   693071 non-null  int64
 55  apparentTemperatureMax       693071 non-null  float64
 56  apparentTemperatureMaxTime   693071 non-null  int64
dtypes: float64(29), int64(17), object(11)
memory usage: 301.4+ MB
```

1.1.7 Basic Data Validation Checks

[5]:
```
# Find the number of missing values in each column of the dataset and the␣
 ↪percentage of missing values in each column
missing_values = cab_rides_data.isnull().sum()
missing_percentage = (missing_values / len(cab_rides_data)) * 100

missing_info = pd.DataFrame({
    'Missing Values': missing_values,
    'Percentage': missing_percentage
})

print("Missing Values Report:")
print(missing_info[missing_info['Missing Values'] > 0].sort_values(by='Missing␣
 ↪Values', ascending=False))
```

```
Missing Values Report:
       Missing Values  Percentage
price           55095    7.949402
```

[6]:
```
# Find the missing values in the 'price' column for each cab company.
missing_values_per_cab_type = cab_rides_data.groupby('cab_type')['price'].
 ↪apply(lambda x: x.isnull().sum())

print("Missing Values for 'price' by Cab Type:")
print(missing_values_per_cab_type)
```

```
Missing Values for 'price' by Cab Type:
cab_type
Lyft        0
Uber    55095
Name: price, dtype: int64
```

[7]:
```
# To  substitute the missing values in the 'price' column with the mean price␣
 ↪for that cab type
```

```
cab_rides_data['time_slot'] = (cab_rides_data['hour'] // 2) * 2  # e.g., 0-1␣
 ↪becomes 0, 2-3 becomes 2

# Calculate the mean price for each 2-hour time slot
slot_mean_price = cab_rides_data.groupby(['time_slot','cab_type'])['price'].
 ↪mean()

# Impute missing prices with the mean price of their respective time slot
cab_rides_data['price'] = cab_rides_data.apply(
    lambda row: slot_mean_price.get((row['time_slot'], row['cab_type']),␣
 ↪row['price'])
    if pd.isnull(row['price']) else row['price'],
    axis=1
)
cab_rides_data
```

[7]:

	id	timestamp	hour	day	month	\
0	424553bb-7174-41ea-aeb4-fe06d4f4b9d7	1.544953e+09	9	16	12	
1	4bd23055-6827-41c6-b23b-3c491f24e74d	1.543284e+09	2	27	11	
2	981a3613-77af-4620-a42a-0c0866077d1e	1.543367e+09	1	28	11	
3	c2d88af2-d278-4bfd-a8d0-29ca77cc5512	1.543554e+09	4	30	11	
4	e0126e1f-8ca9-4f2e-82b3-50505a09db9a	1.543463e+09	3	29	11	
…	…	…	…	…	…	
693066	616d3611-1820-450a-9845-a9ff304a4842	1.543708e+09	23	1	12	
693067	633a3fc3-1f86-4b9e-9d48-2b7132112341	1.543708e+09	23	1	12	
693068	64d451d0-639f-47a4-9b7c-6fd92fbd264f	1.543708e+09	23	1	12	
693069	727e5f07-a96b-4ad1-a2c7-9abc3ad55b4e	1.543708e+09	23	1	12	
693070	e7fdc087-fe86-40a5-a3c3-3b2a8badcbda	1.543708e+09	23	1	12	

	datetime	timezone	source	\
0	2018-12-16 09:30:07	America/New_York	Haymarket Square	
1	2018-11-27 02:00:23	America/New_York	Haymarket Square	
2	2018-11-28 01:00:22	America/New_York	Haymarket Square	
3	2018-11-30 04:53:02	America/New_York	Haymarket Square	
4	2018-11-29 03:49:20	America/New_York	Haymarket Square	
…	…	…	…	
693066	2018-12-01 23:53:05	America/New_York	West End	
693067	2018-12-01 23:53:05	America/New_York	West End	
693068	2018-12-01 23:53:05	America/New_York	West End	
693069	2018-12-01 23:53:05	America/New_York	West End	
693070	2018-12-01 23:53:05	America/New_York	West End	

	destination	cab_type	…	uvIndexTime	temperatureMin	\
0	North Station	Lyft	…	1544979600	39.89	
1	North Station	Lyft	…	1543251600	40.49	
2	North Station	Lyft	…	1543338000	35.36	
3	North Station	Lyft	…	1543507200	34.67	

```
4       North Station     Lyft  …  1543420800          33.10
…               …       …  …   …            …
693066      North End     Uber  …  1543683600          31.42
693067      North End     Uber  …  1543683600          31.42
693068      North End     Uber  …  1543683600          31.42
693069      North End     Uber  …  1543683600          31.42
693070      North End     Uber  …  1543683600          31.42

        temperatureMinTime  temperatureMax  temperatureMaxTime  \
0               1545012000           43.68          1544968800
1               1543233600           47.30          1543251600
2               1543377600           47.55          1543320000
3               1543550400           45.03          1543510800
4               1543402800           42.18          1543420800
…                    …              …                   …
693066          1543658400           44.76          1543690800
693067          1543658400           44.76          1543690800
693068          1543658400           44.76          1543690800
693069          1543658400           44.76          1543690800
693070          1543658400           44.76          1543690800

        apparentTemperatureMin  apparentTemperatureMinTime  \
0                        33.73                  1545012000
1                        36.20                  1543291200
2                        31.04                  1543377600
3                        30.30                  1543550400
4                        29.11                  1543392000
…                        …                         …
693066                   27.77                  1543658400
693067                   27.77                  1543658400
693068                   27.77                  1543658400
693069                   27.77                  1543658400
693070                   27.77                  1543658400

        apparentTemperatureMax  apparentTemperatureMaxTime time_slot
0                        38.07                  1544958000         8
1                        43.92                  1543251600         2
2                        44.12                  1543320000         0
3                        38.53                  1543510800         4
4                        35.75                  1543420800         2
…                        …                         …       …
693066                   44.09                  1543690800        22
693067                   44.09                  1543690800        22
693068                   44.09                  1543690800        22
693069                   44.09                  1543690800        22
693070                   44.09                  1543690800        22
```

```
[693071 rows x 58 columns]
```

[8]:
```
missing_values_per_cab_type=cab_rides_data.groupby('cab_type')['price'].
 ↪apply(lambda x:x.isnull().sum())
missing_values_per_cab_type
```

[8]:
```
cab_type
Lyft    0
Uber    0
Name: price, dtype: int64
```

1.1.8 Formatting Data

[9]:
```
# Create a new column 'is_rain' that indicates whether it was raining or not␣
 ↪during the ride
cab_rides_data['is_rain'] = cab_rides_data['short_summary'].str.
 ↪contains('rain', case=False).astype(int)
```

[10]:
```
#sorting by datetime column
cab_rides_data = cab_rides_data.sort_values(by='datetime')
```

[11]:
```
# Format datetime
cab_rides_data['datetime'] = pd.to_datetime(cab_rides_data['datetime'],␣
 ↪format='%Y-%m-%d %H:%M:%S')
```

[12]:
```
# Split Date and Time
cab_rides_data['date'] = cab_rides_data['datetime'].dt.date
cab_rides_data['time'] = cab_rides_data['datetime'].dt.time
cab_rides_data.head()
```

[12]:
```
                                     id     timestamp  hour  day  month  \
66422   a7b50600-c6c5-4e6c-bea9-4487344196d4  1.543204e+09     3   26     11
446073  9962f244-8fce-4ae9-a583-139d5d7522e1  1.543204e+09     3   26     11
184332  4aa68a5d-abc0-4fdf-a47f-0003617afbae  1.543204e+09     3   26     11
167114  ef8b695c-c24d-4ac1-b3fe-4aa1a7ed79f4  1.543204e+09     3   26     11
184333  89f35ef7-7129-483d-b3e6-d89afdf6946d  1.543204e+09     3   26     11

                  datetime          timezone             source  \
66422  2018-11-26 03:40:46  America/New_York      North Station
446073 2018-11-26 03:40:46  America/New_York   Theatre District
184332 2018-11-26 03:40:46  America/New_York          North End
167114 2018-11-26 03:40:46  America/New_York  Boston University
184333 2018-11-26 03:40:46  America/New_York          North End

             destination cab_type  … temperatureMax temperatureMaxTime  \
66422   Haymarket Square     Uber  …          46.15         1543154400
446073         North End     Uber  …          46.15         1543154400
```

```
184332          West End     Lyft  …          46.15         1543154400
167114       Beacon Hill     Lyft  …          46.15         1543154400
184333          West End     Lyft  …          46.15         1543154400

        apparentTemperatureMin  apparentTemperatureMinTime  \
66422                    38.23                  1543136400
446073                   38.23                  1543136400
184332                   38.23                  1543136400
167114                   38.23                  1543136400
184333                   38.23                  1543136400

        apparentTemperatureMax  apparentTemperatureMaxTime  time_slot  \
66422                    43.17                  1543186800          2
446073                   43.17                  1543186800          2
184332                   43.17                  1543186800          2
167114                   43.17                  1543186800          2
184333                   43.17                  1543186800          2

        is_rain        date      time
66422         0  2018-11-26  03:40:46
446073        0  2018-11-26  03:40:46
184332        0  2018-11-26  03:40:46
167114        0  2018-11-26  03:40:46
184333        0  2018-11-26  03:40:46

[5 rows x 61 columns]
```

[13]:
```
# Create "odd_time" column
cab_rides_data['odd_time'] = cab_rides_data['time'].apply(lambda x: 1 if x.hour␣
 ↪< 6 else 0)

# Create "peak_time" column
cab_rides_data['peak_time'] = cab_rides_data['time'].apply(lambda x: 1 if (8 <=␣
 ↪x.hour <= 10) or (
            16 <= x.hour <= 19) else 0)

# Print the updated dataframe
cab_rides_data.head()
```

[13]:
```
                                     id     timestamp  hour  day  month  \
66422   a7b50600-c6c5-4e6c-bea9-4487344196d4  1.543204e+09     3   26     11
446073  9962f244-8fce-4ae9-a583-139d5d7522e1  1.543204e+09     3   26     11
184332  4aa68a5d-abc0-4fdf-a47f-0003617afbae  1.543204e+09     3   26     11
167114  ef8b695c-c24d-4ac1-b3fe-4aa1a7ed79f4  1.543204e+09     3   26     11
184333  89f35ef7-7129-483d-b3e6-d89afdf6946d  1.543204e+09     3   26     11

                datetime          timezone             source  \
```

```
66422  2018-11-26 03:40:46  America/New_York      North Station
446073 2018-11-26 03:40:46  America/New_York   Theatre District
184332 2018-11-26 03:40:46  America/New_York          North End
167114 2018-11-26 03:40:46  America/New_York  Boston University
184333 2018-11-26 03:40:46  America/New_York          North End

            destination cab_type  … apparentTemperatureMin  \
66422   Haymarket Square     Uber  …                  38.23
446073         North End     Uber  …                  38.23
184332          West End     Lyft  …                  38.23
167114       Beacon Hill     Lyft  …                  38.23
184333          West End     Lyft  …                  38.23

       apparentTemperatureMinTime  apparentTemperatureMax  \
66422                  1543136400                   43.17
446073                 1543136400                   43.17
184332                 1543136400                   43.17
167114                 1543136400                   43.17
184333                 1543136400                   43.17

        apparentTemperatureMaxTime  time_slot  is_rain        date      time  \
66422                   1543186800          2        0  2018-11-26  03:40:46
446073                  1543186800          2        0  2018-11-26  03:40:46
184332                  1543186800          2        0  2018-11-26  03:40:46
167114                  1543186800          2        0  2018-11-26  03:40:46
184333                  1543186800          2        0  2018-11-26  03:40:46

        odd_time peak_time
66422          1         0
446073         1         0
184332         1         0
167114         1         0
184333         1         0

[5 rows x 63 columns]
```

[14]:
```
# Add a column which stores was the ride taken in day or night
cab_rides_data['is_night'] = cab_rides_data.apply(
    lambda row: not (row['sunriseTime'] <= row['datetime'].timestamp() <=␣
 ↪row['sunsetTime']),
    axis=1
)

# Print the updated DataFrame
cab_rides_data.head()
```

[14]:
```
                                       id     timestamp  hour  day  month  \
66422   a7b50600-c6c5-4e6c-bea9-4487344196d4  1.543204e+09     3   26     11
446073  9962f244-8fce-4ae9-a583-139d5d7522e1  1.543204e+09     3   26     11
184332  4aa68a5d-abc0-4fdf-a47f-0003617afbae  1.543204e+09     3   26     11
167114  ef8b695c-c24d-4ac1-b3fe-4aa1a7ed79f4  1.543204e+09     3   26     11
184333  89f35ef7-7129-483d-b3e6-d89afdf6946d  1.543204e+09     3   26     11

                  datetime          timezone             source  \
66422  2018-11-26 03:40:46  America/New_York      North Station
446073 2018-11-26 03:40:46  America/New_York   Theatre District
184332 2018-11-26 03:40:46  America/New_York          North End
167114 2018-11-26 03:40:46  America/New_York  Boston University
184333 2018-11-26 03:40:46  America/New_York          North End

            destination cab_type  … apparentTemperatureMinTime  \
66422   Haymarket Square     Uber  …                 1543136400
446073         North End     Uber  …                 1543136400
184332          West End     Lyft  …                 1543136400
167114       Beacon Hill     Lyft  …                 1543136400
184333          West End     Lyft  …                 1543136400

       apparentTemperatureMax  apparentTemperatureMaxTime  time_slot  is_rain  \
66422                   43.17                  1543186800          2        0
446073                  43.17                  1543186800          2        0
184332                  43.17                  1543186800          2        0
167114                  43.17                  1543186800          2        0
184333                  43.17                  1543186800          2        0

              date      time  odd_time  peak_time is_night
66422   2018-11-26  03:40:46         1          0     True
446073  2018-11-26  03:40:46         1          0     True
184332  2018-11-26  03:40:46         1          0     True
167114  2018-11-26  03:40:46         1          0     True
184333  2018-11-26  03:40:46         1          0     True

[5 rows x 64 columns]
```

[15]:
```
# Rename column 'cab_type' to 'cab_company', 'name' to 'cab_type', 'odd_time'␣
 ↪to 'odd_time_of_travel' of cab_rides_data
cab_rides_data.rename(columns={
    'cab_type': 'cab_company',
    'odd_time': 'odd_time_of_travel'
}, inplace=True)

cab_rides_data.rename(columns={
    'name': 'cab_type'
}, inplace=True)
```

```
# Display the first few rows of the dataset
cab_rides_data.head()
```

[15]:
```
                                      id     timestamp  hour  day  month  \
66422   a7b50600-c6c5-4e6c-bea9-4487344196d4  1.543204e+09     3   26     11
446073  9962f244-8fce-4ae9-a583-139d5d7522e1  1.543204e+09     3   26     11
184332  4aa68a5d-abc0-4fdf-a47f-0003617afbae  1.543204e+09     3   26     11
167114  ef8b695c-c24d-4ac1-b3fe-4aa1a7ed79f4  1.543204e+09     3   26     11
184333  89f35ef7-7129-483d-b3e6-d89afdf6946d  1.543204e+09     3   26     11

                 datetime          timezone             source  \
66422  2018-11-26 03:40:46  America/New_York      North Station
446073 2018-11-26 03:40:46  America/New_York   Theatre District
184332 2018-11-26 03:40:46  America/New_York          North End
167114 2018-11-26 03:40:46  America/New_York  Boston University
184333 2018-11-26 03:40:46  America/New_York          North End

            destination cab_company  … apparentTemperatureMinTime  \
66422   Haymarket Square        Uber  …                 1543136400
446073         North End        Uber  …                 1543136400
184332          West End        Lyft  …                 1543136400
167114       Beacon Hill        Lyft  …                 1543136400
184333          West End        Lyft  …                 1543136400

       apparentTemperatureMax  apparentTemperatureMaxTime  time_slot  is_rain  \
66422                   43.17                  1543186800          2        0
446073                  43.17                  1543186800          2        0
184332                  43.17                  1543186800          2        0
167114                  43.17                  1543186800          2        0
184333                  43.17                  1543186800          2        0

             date      time  odd_time_of_travel  peak_time is_night
66422   2018-11-26  03:40:46                   1          0     True
446073  2018-11-26  03:40:46                   1          0     True
184332  2018-11-26  03:40:46                   1          0     True
167114  2018-11-26  03:40:46                   1          0     True
184333  2018-11-26  03:40:46                   1          0     True

[5 rows x 64 columns]
```

[16]:
```
# Create a new column 'day_of_week' that indicates the day of the week for each␣
 ↪ride
cab_rides_data['day_of_week'] = cab_rides_data['datetime'].dt.day_name()
```

[17]:
```
# Create "is_weekend" column that indicates whether the ride was on a weekend␣
 ↪or not
```

```
cab_rides_data['is_weekend'] = cab_rides_data['day_of_week'].apply(lambda x: 1␣
 ↪if x=="Saturday" or x=="Sunday" else 0)
cab_rides_data.head()
```

[17]:

```
                                       id     timestamp  hour  day  month  \
66422   a7b50600-c6c5-4e6c-bea9-4487344196d4  1.543204e+09     3   26     11
446073  9962f244-8fce-4ae9-a583-139d5d7522e1  1.543204e+09     3   26     11
184332  4aa68a5d-abc0-4fdf-a47f-0003617afbae  1.543204e+09     3   26     11
167114  ef8b695c-c24d-4ac1-b3fe-4aa1a7ed79f4  1.543204e+09     3   26     11
184333  89f35ef7-7129-483d-b3e6-d89afdf6946d  1.543204e+09     3   26     11

                  datetime          timezone             source  \
66422  2018-11-26 03:40:46  America/New_York      North Station
446073 2018-11-26 03:40:46  America/New_York   Theatre District
184332 2018-11-26 03:40:46  America/New_York          North End
167114 2018-11-26 03:40:46  America/New_York  Boston University
184333 2018-11-26 03:40:46  America/New_York          North End

            destination cab_company  … apparentTemperatureMaxTime  \
66422   Haymarket Square        Uber  …                 1543186800
446073         North End        Uber  …                 1543186800
184332          West End        Lyft  …                 1543186800
167114       Beacon Hill        Lyft  …                 1543186800
184333          West End        Lyft  …                 1543186800

       time_slot  is_rain        date      time  odd_time_of_travel  \
66422          2        0  2018-11-26  03:40:46                   1
446073         2        0  2018-11-26  03:40:46                   1
184332         2        0  2018-11-26  03:40:46                   1
167114         2        0  2018-11-26  03:40:46                   1
184333         2        0  2018-11-26  03:40:46                   1

        peak_time  is_night  day_of_week is_weekend
66422           0      True       Monday          0
446073          0      True       Monday          0
184332          0      True       Monday          0
167114          0      True       Monday          0
184333          0      True       Monday          0

[5 rows x 66 columns]
```

[18]:

```
# Convert 0 to False and 1 to True in the specified columns
columns_to_convert = ['peak_time', 'is_weekend', 'odd_time_of_travel',␣
 ↪'is_rain']

cab_rides_data[columns_to_convert] = cab_rides_data[columns_to_convert].apply(
    lambda col: col.replace({0: False, 1: True}).astype(bool)
```

```
)

cab_rides_data.head()
```

[18]:
```
                                     id     timestamp  hour  day  month  \
66422   a7b50600-c6c5-4e6c-bea9-4487344196d4  1.543204e+09     3   26     11
446073  9962f244-8fce-4ae9-a583-139d5d7522e1  1.543204e+09     3   26     11
184332  4aa68a5d-abc0-4fdf-a47f-0003617afbae  1.543204e+09     3   26     11
167114  ef8b695c-c24d-4ac1-b3fe-4aa1a7ed79f4  1.543204e+09     3   26     11
184333  89f35ef7-7129-483d-b3e6-d89afdf6946d  1.543204e+09     3   26     11

                  datetime          timezone             source  \
66422  2018-11-26 03:40:46  America/New_York      North Station
446073 2018-11-26 03:40:46  America/New_York   Theatre District
184332 2018-11-26 03:40:46  America/New_York          North End
167114 2018-11-26 03:40:46  America/New_York  Boston University
184333 2018-11-26 03:40:46  America/New_York          North End

            destination cab_company  … apparentTemperatureMaxTime  \
66422   Haymarket Square        Uber  …                 1543186800
446073         North End        Uber  …                 1543186800
184332          West End        Lyft  …                 1543186800
167114       Beacon Hill        Lyft  …                 1543186800
184333          West End        Lyft  …                 1543186800

       time_slot  is_rain        date      time  odd_time_of_travel  \
66422          2    False  2018-11-26  03:40:46                True
446073         2    False  2018-11-26  03:40:46                True
184332         2    False  2018-11-26  03:40:46                True
167114         2    False  2018-11-26  03:40:46                True
184333         2    False  2018-11-26  03:40:46                True

        peak_time  is_night  day_of_week is_weekend
66422       False      True       Monday      False
446073      False      True       Monday      False
184332      False      True       Monday      False
167114      False      True       Monday      False
184333      False      True       Monday      False

[5 rows x 66 columns]
```

[19]:
```
# Cleanup before selecting data
cab_rides_data['year'] = cab_rides_data['datetime'].dt.year
cab_rides_data['month'] = cab_rides_data['datetime'].dt.month
cab_rides_data['day'] = cab_rides_data['datetime'].dt.day
cab_rides_data['hour'] = cab_rides_data['datetime'].dt.hour
cab_rides_data['minute'] = cab_rides_data['datetime'].dt.minute
```

```
cab_rides_data['weekday'] = cab_rides_data['datetime'].dt.weekday

# Ensure boolean columns are explicitly cast to boolean type
cab_rides_data['is_night'] = cab_rides_data['is_night'].astype(bool)
cab_rides_data['is_rain'] = cab_rides_data['is_rain'].astype(bool)
cab_rides_data['is_weekend'] = cab_rides_data['is_weekend'].astype(bool)

cab_rides_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 693071 entries, 66422 to 166551
Data columns (total 69 columns):
 #   Column                      Non-Null Count   Dtype
---  ------                      --------------   -----
 0   id                          693071 non-null  object
 1   timestamp                   693071 non-null  float64
 2   hour                        693071 non-null  int32
 3   day                         693071 non-null  int32
 4   month                       693071 non-null  int32
 5   datetime                    693071 non-null  datetime64[ns]
 6   timezone                    693071 non-null  object
 7   source                      693071 non-null  object
 8   destination                 693071 non-null  object
 9   cab_company                 693071 non-null  object
 10  product_id                  693071 non-null  object
 11  cab_type                    693071 non-null  object
 12  price                       693071 non-null  float64
 13  distance                    693071 non-null  float64
 14  surge_multiplier            693071 non-null  float64
 15  latitude                    693071 non-null  float64
 16  longitude                   693071 non-null  float64
 17  temperature                 693071 non-null  float64
 18  apparentTemperature         693071 non-null  float64
 19  short_summary               693071 non-null  object
 20  long_summary                693071 non-null  object
 21  precipIntensity             693071 non-null  float64
 22  precipProbability           693071 non-null  float64
 23  humidity                    693071 non-null  float64
 24  windSpeed                   693071 non-null  float64
 25  windGust                    693071 non-null  float64
 26  windGustTime                693071 non-null  int64
 27  visibility                  693071 non-null  float64
 28  temperatureHigh             693071 non-null  float64
 29  temperatureHighTime         693071 non-null  int64
 30  temperatureLow              693071 non-null  float64
 31  temperatureLowTime          693071 non-null  int64
 32  apparentTemperatureHigh     693071 non-null  float64
 33  apparentTemperatureHighTime 693071 non-null  int64
```

```
 34  apparentTemperatureLow       693071 non-null  float64
 35  apparentTemperatureLowTime   693071 non-null  int64
 36  icon                         693071 non-null  object
 37  dewPoint                     693071 non-null  float64
 38  pressure                     693071 non-null  float64
 39  windBearing                  693071 non-null  int64
 40  cloudCover                   693071 non-null  float64
 41  uvIndex                      693071 non-null  int64
 42  visibility.1                 693071 non-null  float64
 43  ozone                        693071 non-null  float64
 44  sunriseTime                  693071 non-null  int64
 45  sunsetTime                   693071 non-null  int64
 46  moonPhase                    693071 non-null  float64
 47  precipIntensityMax           693071 non-null  float64
 48  uvIndexTime                  693071 non-null  int64
 49  temperatureMin               693071 non-null  float64
 50  temperatureMinTime           693071 non-null  int64
 51  temperatureMax               693071 non-null  float64
 52  temperatureMaxTime           693071 non-null  int64
 53  apparentTemperatureMin       693071 non-null  float64
 54  apparentTemperatureMinTime   693071 non-null  int64
 55  apparentTemperatureMax       693071 non-null  float64
 56  apparentTemperatureMaxTime   693071 non-null  int64
 57  time_slot                    693071 non-null  int64
 58  is_rain                      693071 non-null  bool
 59  date                         693071 non-null  object
 60  time                         693071 non-null  object
 61  odd_time_of_travel           693071 non-null  bool
 62  peak_time                    693071 non-null  bool
 63  is_night                     693071 non-null  bool
 64  day_of_week                  693071 non-null  object
 65  is_weekend                   693071 non-null  bool
 66  year                         693071 non-null  int32
 67  minute                       693071 non-null  int32
 68  weekday                      693071 non-null  int32
dtypes: bool(5), datetime64[ns](1), float64(29), int32(6), int64(15), object(13)
memory usage: 331.1+ MB
```

1.1.9 Visualization

[20]:
```
# Create a deep copy of the dataset for visualisation
cab_rides_data_for_visualisation =cab_rides_data.copy(deep=True)
cab_rides_data_for_visualisation.head()
```

[20]:

	id	timestamp	hour	day	month	\
66422	a7b50600-c6c5-4e6c-bea9-4487344196d4	1.543204e+09	3	26	11	
446073	9962f244-8fce-4ae9-a583-139d5d7522e1	1.543204e+09	3	26	11	
184332	4aa68a5d-abc0-4fdf-a47f-0003617afbae	1.543204e+09	3	26	11	

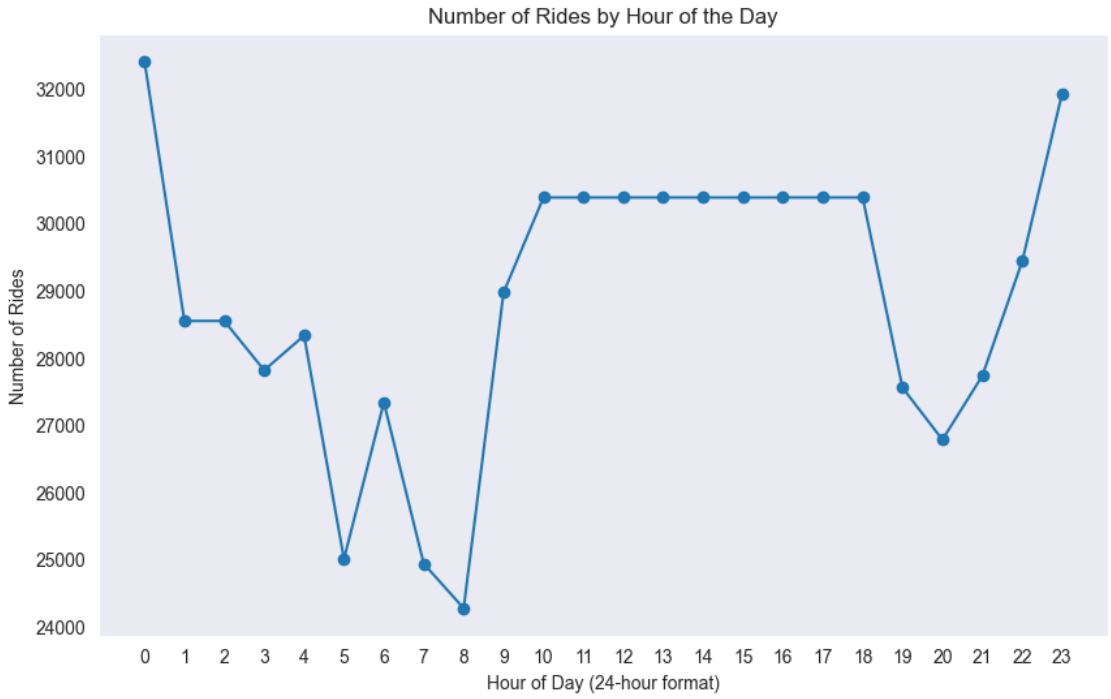
```
167114  ef8b695c-c24d-4ac1-b3fe-4aa1a7ed79f4  1.543204e+09     3   26     11
184333  89f35ef7-7129-483d-b3e6-d89afdf6946d  1.543204e+09     3   26     11

                  datetime          timezone             source  \
66422  2018-11-26 03:40:46  America/New_York      North Station
446073 2018-11-26 03:40:46  America/New_York   Theatre District
184332 2018-11-26 03:40:46  America/New_York          North End
167114 2018-11-26 03:40:46  America/New_York  Boston University
184333 2018-11-26 03:40:46  America/New_York          North End

             destination cab_company  …        date      time  \
66422   Haymarket Square        Uber  …  2018-11-26  03:40:46
446073         North End        Uber  …  2018-11-26  03:40:46
184332          West End        Lyft  …  2018-11-26  03:40:46
167114       Beacon Hill        Lyft  …  2018-11-26  03:40:46
184333          West End        Lyft  …  2018-11-26  03:40:46

        odd_time_of_travel  peak_time  is_night  day_of_week  is_weekend  \
66422                 True      False      True       Monday       False
446073                True      False      True       Monday       False
184332                True      False      True       Monday       False
167114                True      False      True       Monday       False
184333                True      False      True       Monday       False

        year  minute weekday
66422   2018      40       0
446073  2018      40       0
184332  2018      40       0
167114  2018      40       0
184333  2018      40       0

[5 rows x 69 columns]
```

[21]:
```python
# Extract hour of the day for grouping
cab_rides_data['hour_of_day'] = cab_rides_data_for_visualisation['datetime'].dt.
 ↪hour

# Group by hour of day and calculate the total rides
rides_per_hour_of_day = cab_rides_data.groupby('hour_of_day').size().
 ↪reset_index(name='rides_count')

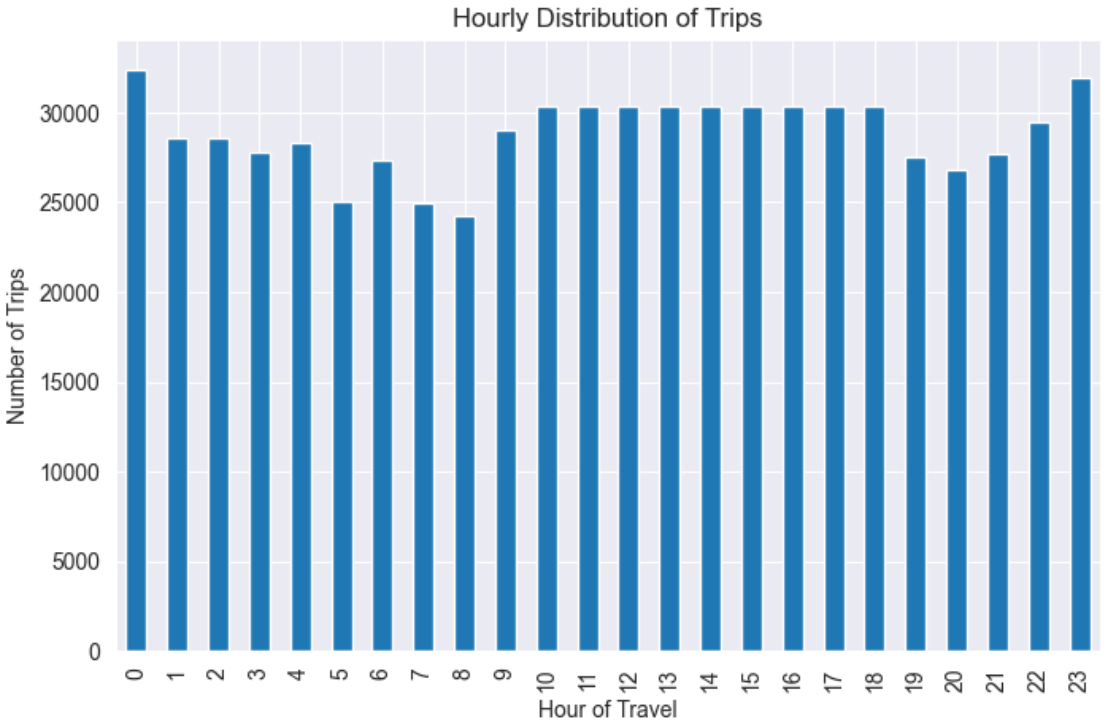
# Plot the number of rides per hour of the day
plt.figure(figsize=(10, 6))
plt.plot(rides_per_hour_of_day['hour_of_day'],␣
 ↪rides_per_hour_of_day['rides_count'], marker='o')
plt.title('Number of Rides by Hour of the Day')
plt.xlabel('Hour of Day (24-hour format)')
```

```
plt.ylabel('Number of Rides')
plt.grid()
plt.xticks(range(0, 24))
plt.show()
```



[22]:
```
# Hourly Distribution of Trips by Hour of Travel
hourly_counts = cab_rides_data_for_visualisation['hour'].value_counts().
 ↪sort_index()

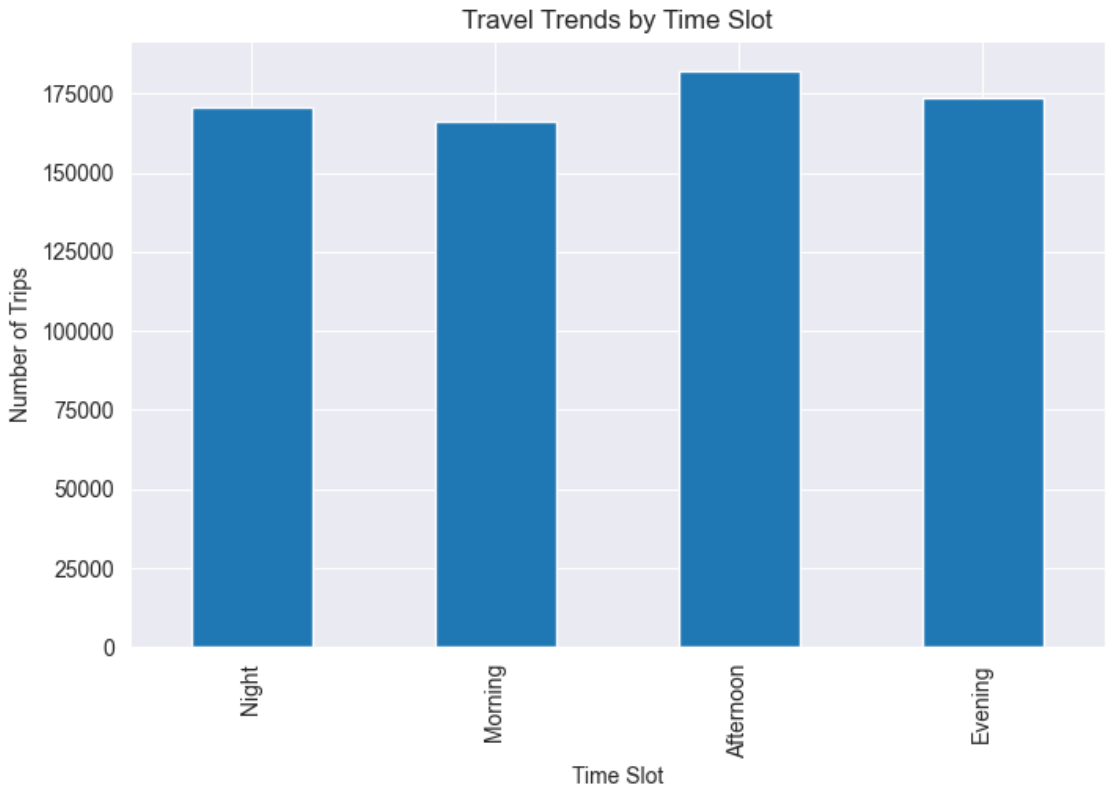
plt.figure(figsize=(8, 5))
hourly_counts.plot(kind='bar', title='Hourly Distribution of Trips')
plt.xlabel('Hour of Travel')
plt.ylabel('Number of Trips')
plt.show()
```



[23]:
```
# Create a graph to visualize the distribution of rides

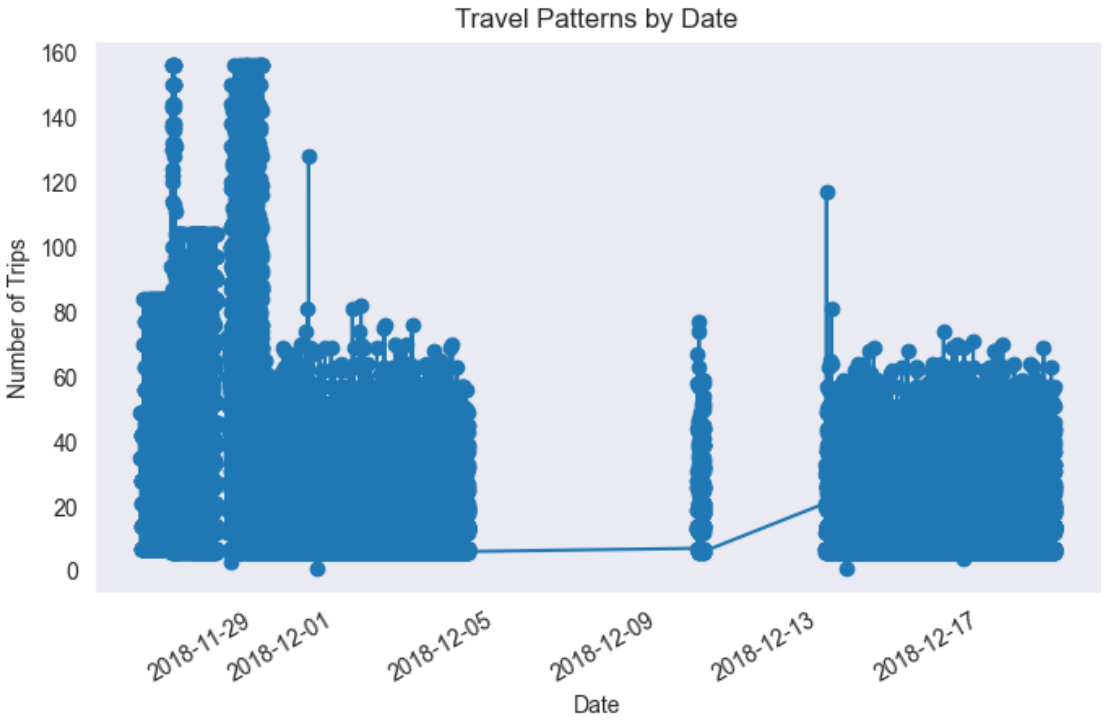
cab_rides_data_for_visualisation['time_slot'] = pd.
 ↪cut(cab_rides_data_for_visualisation['hour'], bins=[0, 6, 12, 18, 24],␣
 ↪labels=['Night', 'Morning', 'Afternoon', 'Evening'], right=False)
time_slot_counts = cab_rides_data_for_visualisation['time_slot'].value_counts().
 ↪sort_index()

plt.figure(figsize=(8, 5))
time_slot_counts.plot(kind='bar', title='Travel Trends by Time Slot')
plt.xlabel('Time Slot')
plt.ylabel('Number of Trips')
plt.show()
```



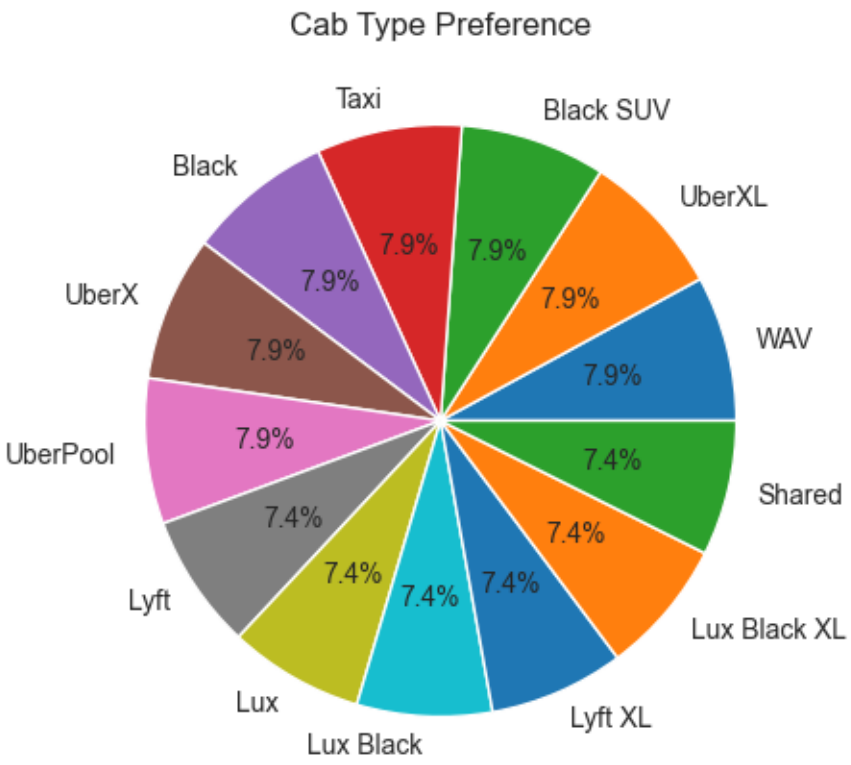
[24]:
```
# Plot Travel Patterns
date_counts = cab_rides_data_for_visualisation['datetime'].value_counts().
 ↪sort_index()

plt.figure(figsize=(8, 5))
date_counts.plot(kind='line', marker='o', title='Travel Patterns by Date')
plt.xlabel('Date')
plt.ylabel('Number of Trips')
plt.grid()
plt.show()
```



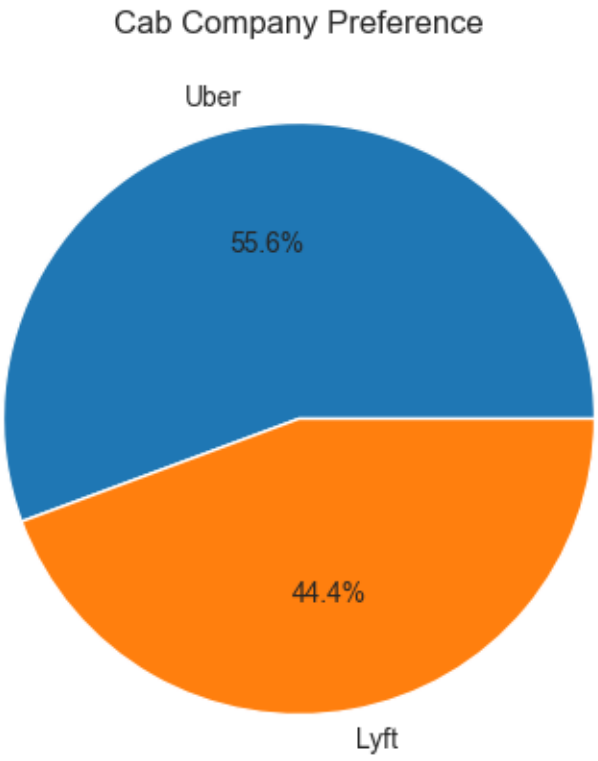
[25]:
```
# Create a graph to visualize the distribution of rides by cab type
cab_type_counts = cab_rides_data_for_visualisation['cab_type'].value_counts()

plt.figure(figsize=(8, 5))
cab_type_counts.plot(kind='pie', autopct='%1.1f%%', title='Cab Type Preference')
plt.ylabel('')
plt.show()
```



[26]:
```
# Create a graph to visualize the distribution of rides by cab company
cab_company_counts = cab_rides_data_for_visualisation['cab_company'].
 ↪value_counts()

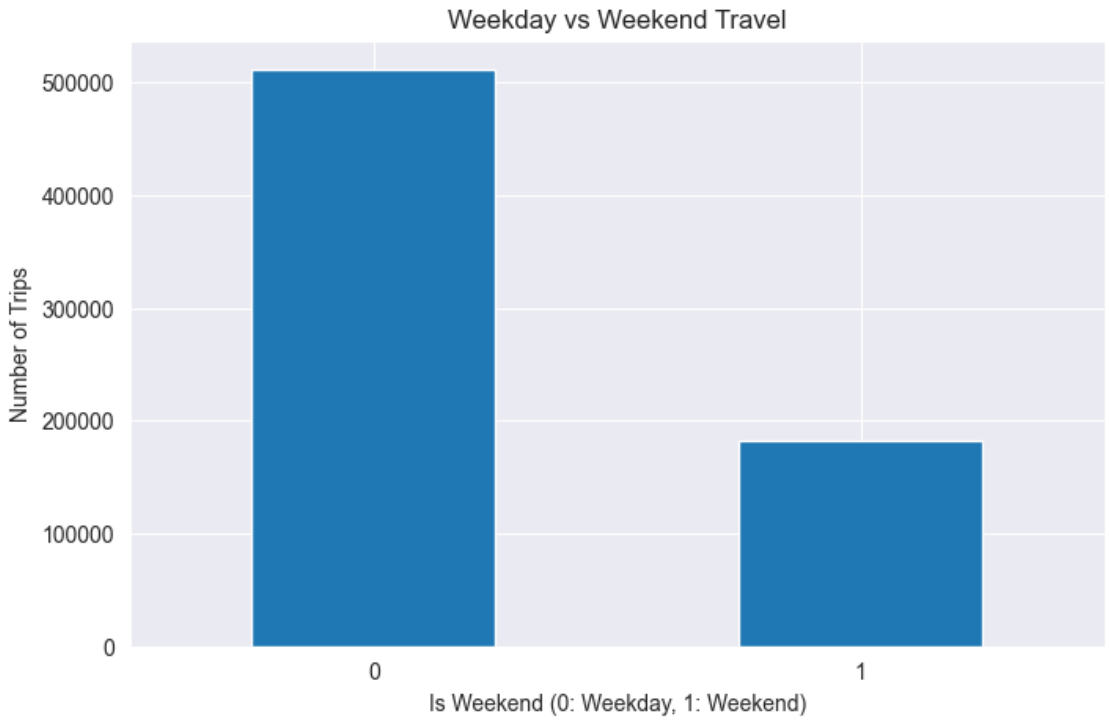
plt.figure(figsize=(8, 5))
cab_company_counts.plot(kind='pie', autopct='%1.1f%%', title='Cab Company␣
 ↪Preference')
plt.ylabel('')
plt.show()
```



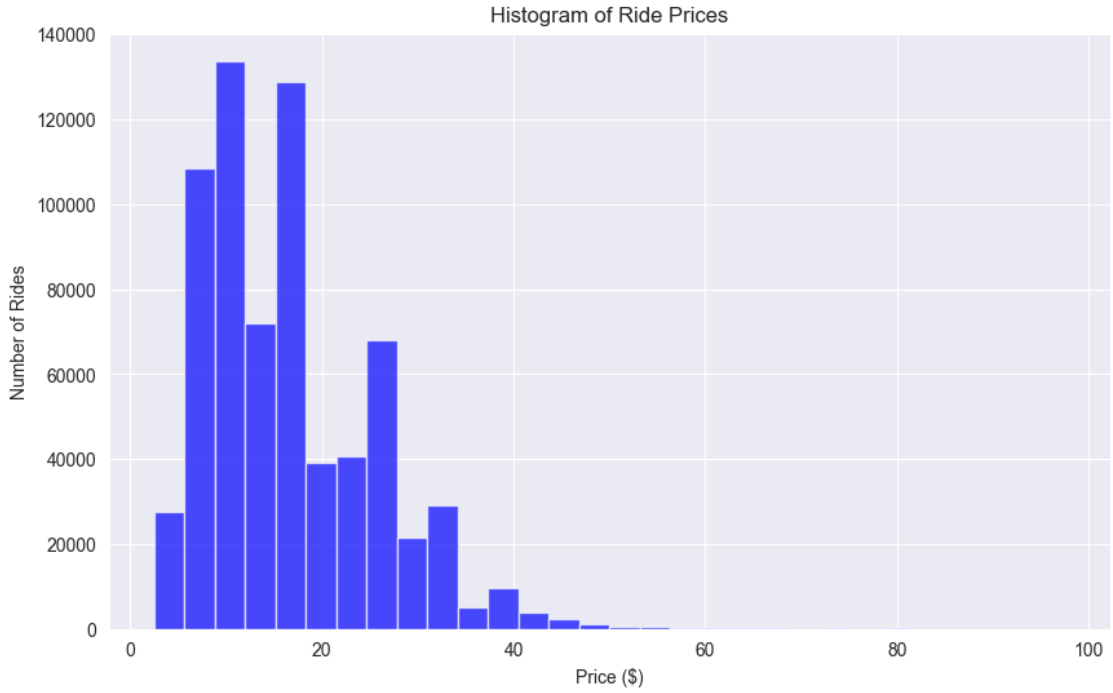
[27]:
```
# Visualize the distribution of rides by the week or weekend

cab_rides_data_for_visualisation['weekday'] = pd.
 ↪to_datetime(cab_rides_data_for_visualisation['date']).dt.dayofweek
cab_rides_data_for_visualisation['is_weekend'] =␣
 ↪cab_rides_data_for_visualisation['weekday'].apply(lambda x: 1 if x >= 5 else␣
 ↪0)
weekday_counts = cab_rides_data_for_visualisation.groupby('is_weekend')['hour'].
 ↪count()

plt.figure(figsize=(8, 5))
weekday_counts.plot(kind='bar', title='Weekday vs Weekend Travel')
plt.xlabel('Is Weekend (0: Weekday, 1: Weekend)')
plt.ylabel('Number of Trips')
plt.xticks(rotation=0)
plt.show()
```



[28]:
```
# Creating a histogram of ride prices
plt.figure(figsize=(10, 6))
plt.hist(cab_rides_data_for_visualisation['price'], bins=30, color='blue',␣
 ↪alpha=0.7)
plt.title('Histogram of Ride Prices')
plt.xlabel('Price ($)')
plt.ylabel('Number of Rides')
plt.grid(True)
plt.show()
```

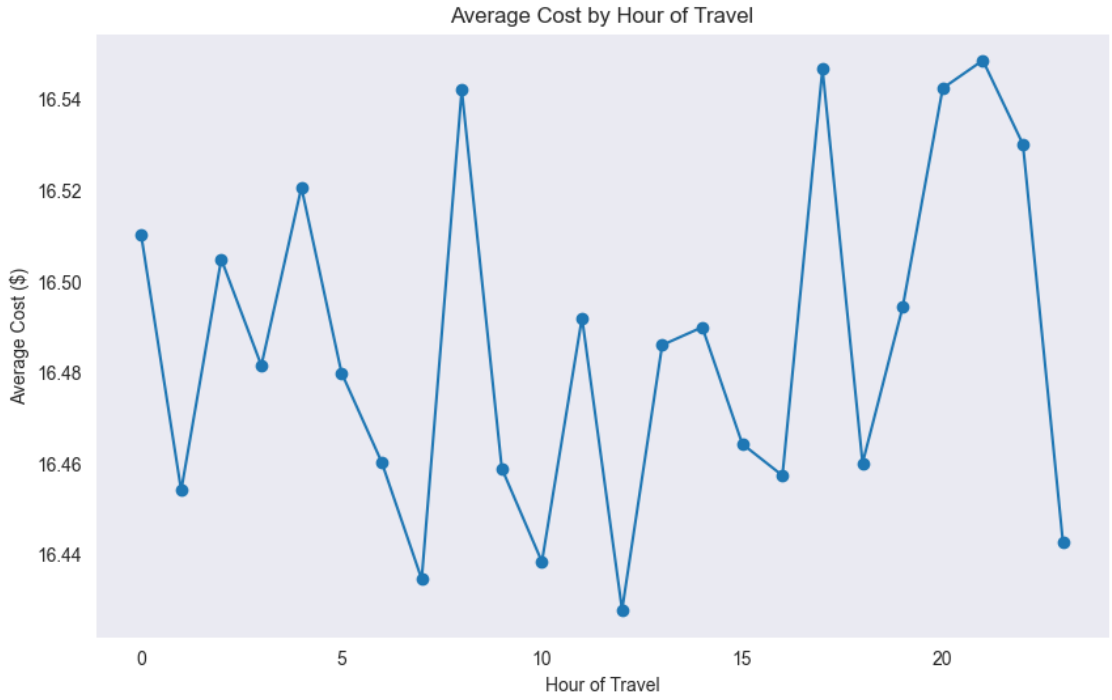


[29]:
```
# Avg cost of travel by the hour when the ride was taken
average_cost_by_hour = cab_rides_data_for_visualisation.
 ↪groupby('hour')['price'].mean()

# 2. Identify peak and low-cost hours
peak_cost_hour = average_cost_by_hour.idxmax()
peak_cost_value = average_cost_by_hour.max()

low_cost_hour = average_cost_by_hour.idxmin()
low_cost_value = average_cost_by_hour.min()

# 3. Visualize average cost across hours
plt.figure(figsize=(10, 6))
average_cost_by_hour.plot(kind='line', marker='o', title='Average Cost by Hour␣
 ↪of Travel')
plt.xlabel('Hour of Travel')
plt.ylabel('Average Cost ($)')
plt.grid()
plt.show()
```



[30]:
```
# Creating Heatmap of Average Prices by Distance and Cab Type

# Creating distance bins for better visualization
cab_rides_data_for_visualisation['distance_bins'] = pd.
 ↪cut(cab_rides_data_for_visualisation['distance'], bins=10)

# Creating a pivot table to analyze prices across distances and cab types
price_heatmap_data = cab_rides_data_for_visualisation.pivot_table(
    values='price',
    index='distance_bins',
    columns='cab_type',
    aggfunc="mean",
    observed=False
)

# Plotting the heatmap
plt.figure(figsize=(12, 8))
plt.title('Heatmap of Average Prices by Distance and Cab Type')
sns.heatmap(price_heatmap_data, annot=True, fmt=".1f", cmap='viridis')
plt.xlabel('Cab Type')
plt.ylabel('Distance Bins (miles)')
plt.show()
# Creating a scatter plot of distance vs price
plt.figure(figsize=(10, 6))
```

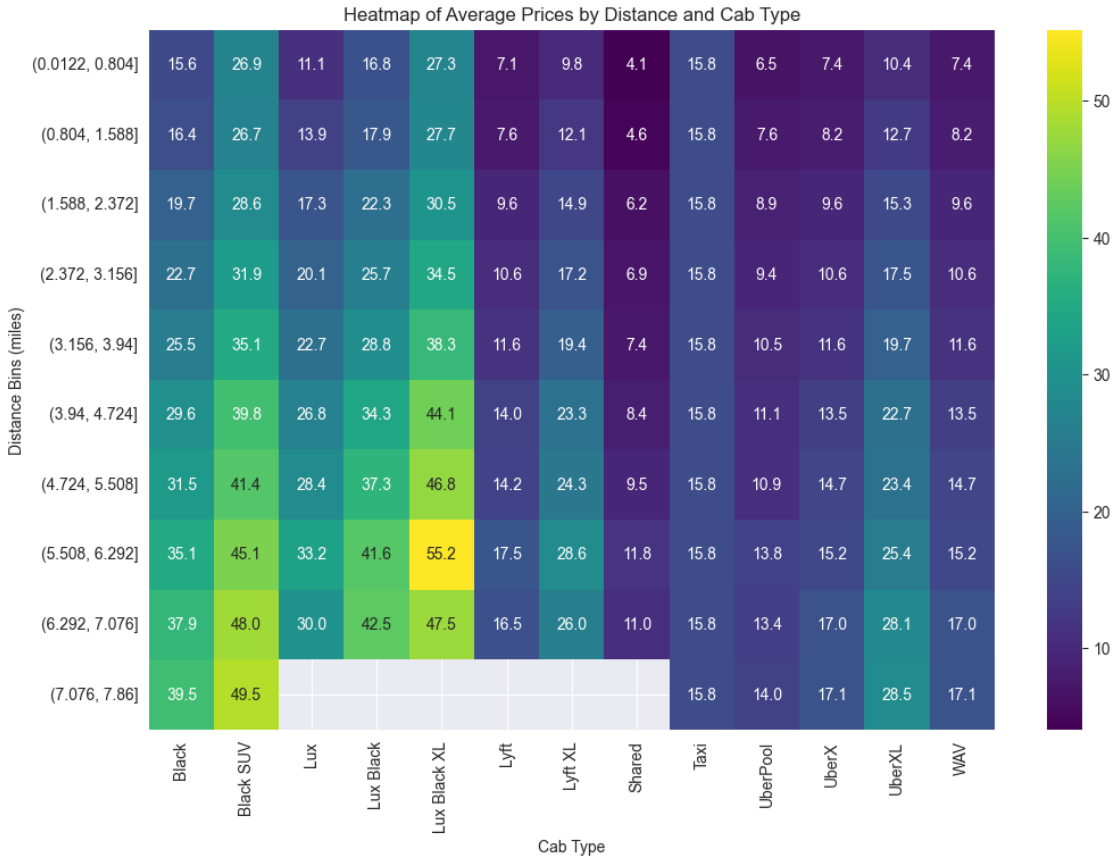
```
plt.scatter(cab_rides_data_for_visualisation['distance'],␣
 ↪cab_rides_data_for_visualisation['price'], alpha=0.5, color='red')
plt.title('Scatter Plot of Distance vs Price')
plt.xlabel('Distance (miles)')
plt.ylabel('Price ($)')
plt.grid(True)
plt.show()

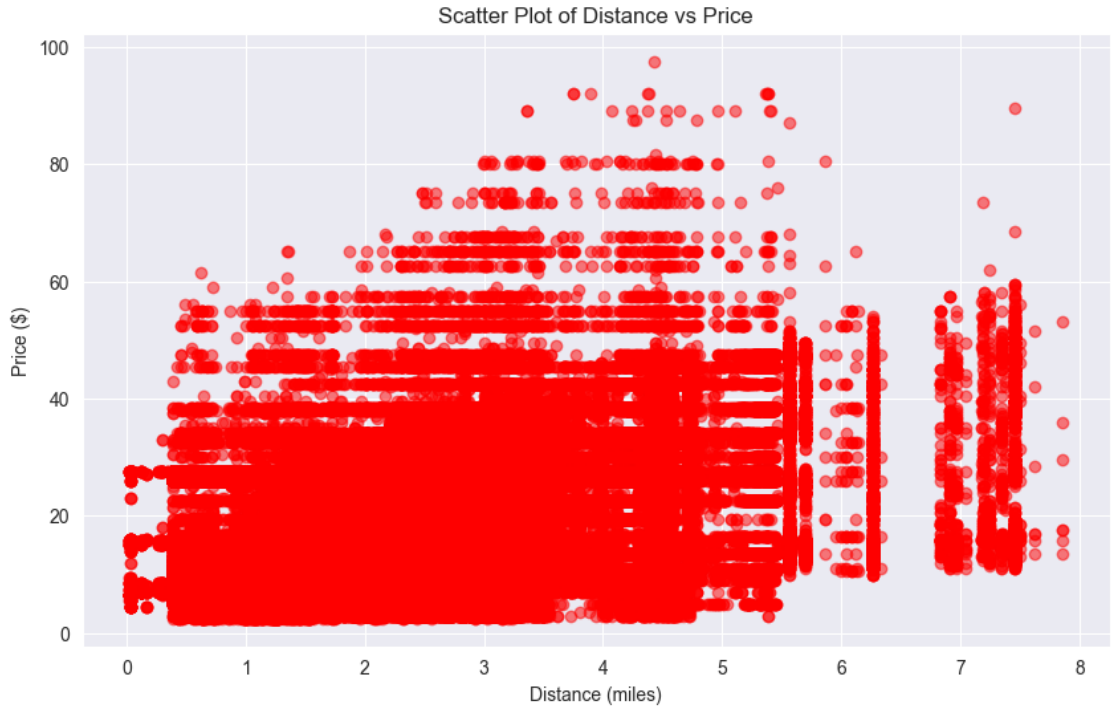
# Creating a pie chart of rides by source
source_counts = cab_rides_data_for_visualisation['source'].value_counts()

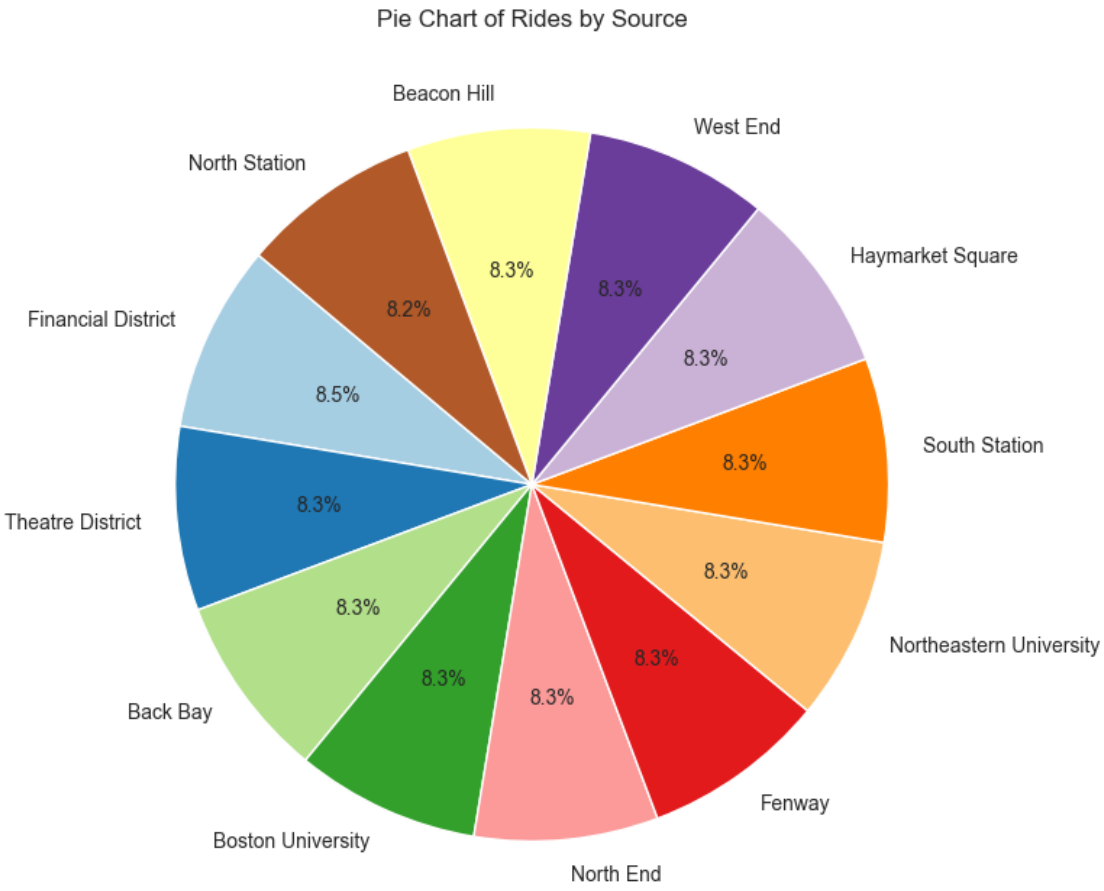
plt.figure(figsize=(10, 8))
source_counts.plot(kind='pie', autopct='%1.1f%%', startangle=140, colors=plt.cm.
 ↪Paired.colors)
plt.title('Pie Chart of Rides by Source')
plt.ylabel('')  # Removing the y-label as it's unnecessary for pie charts
plt.show()

# Grouping data by cab type to calculate the requested metrics
lyft_uber_analysis = cab_rides_data_for_visualisation.groupby('cab_type').agg(
    total_rides=('id', 'count'),
    average_price=('price', 'mean'),
    average_distance=('distance', 'mean'),
    average_surge=('surge_multiplier', 'mean')
)

lyft_uber_analysis
```


Heatmap of Average Prices by Distance and Cab Type
Distance Bins (miles)
(0.0122, 0.804] 15.6 26.9 11.1 16.8 27.3 7.1 9.8 4.1 15.8 6.5 7.4 10.4 7.4
(0.804, 1.588] 16.4 26.7 13.9 17.9 27.7 7.6 12.1 4.6 15.8 7.6 8.2 12.7 8.2
(1.588, 2.372] 19.7 28.6 17.3 22.3 30.5 9.6 14.9 6.2 15.8 8.9 9.6 15.3 9.6
(2.372, 3.156] 22.7 31.9 20.1 25.7 34.5 10.6 17.2 6.9 15.8 9.4 10.6 17.5 10.6
(3.156, 3.94] 25.5 35.1 22.7 28.8 38.3 11.6 19.4 7.4 15.8 10.5 11.6 19.7 11.6
(3.94, 4.724] 29.6 39.8 26.8 34.3 44.1 14.0 23.3 8.4 15.8 11.1 13.5 22.7 13.5
(4.724, 5.508] 31.5 41.4 28.4 37.3 46.8 14.2 24.3 9.5 15.8 10.9 14.7 23.4 14.7
(5.508, 6.292] 35.1 45.1 33.2 41.6 55.2 17.5 28.6 11.8 15.8 13.8 15.2 25.4 15.2
(6.292, 7.076] 37.9 48.0 30.0 42.5 47.5 16.5 26.0 11.0 15.8 13.4 17.0 28.1 17.0
(7.076, 7.86] 39.5 49.5 15.8 14.0 17.1 28.5 17.1
Black
Black SUV
Lux
Lux Black
Lux Black XL
Lyft
Lyft XL
Shared
Taxi
UberPool
UberX
UberXL
WAV
Cab Type
50
40
30
20
10


Scatter Plot of Distance vs Price
Price ($)
100
80
60
40
20
0
0
1
2
3
4
5
6
7
8
Distance (miles)



[30]:

cab_type	total_rides	average_price	average_distance	average_surge
Black	55095	20.523786	2.191399	1.000000
Black SUV	55096	30.286763	2.191378	1.000000
Lux	51235	17.771240	2.186968	1.037177
Lux Black	51235	23.062468	2.186968	1.037177
Lux Black XL	51235	32.324086	2.186968	1.037177
Lyft	51235	9.610885	2.186968	1.038045
Lyft XL	51235	15.309363	2.186968	1.038045
Shared	51233	6.029893	2.187012	1.000000
Taxi	55095	15.795334	2.191383	1.000000
UberPool	55091	8.752500	2.191396	1.000000
UberX	55094	9.765074	2.191390	1.000000
UberXL	55096	15.678144	2.191378	1.000000
WAV	55096	9.765019	2.191378	1.000000

1.1.10 Encode Labels for Model Training

[31]:
```
## Create a DF of selected features
columns_to_include = [
    'source', 'destination', 'cab_company', 'cab_type', 'price', 'distance',
    'surge_multiplier', 'apparentTemperature', 'precipIntensity',
    'visibility.1', 'precipIntensityMax', 'day', 'month', 'hour', 'minute',
]

selected_features = cab_rides_data[columns_to_include]
selected_features.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 693071 entries, 66422 to 166551
Data columns (total 15 columns):
 #   Column               Non-Null Count   Dtype
---  ------               --------------   -----
 0   source               693071 non-null  object
 1   destination          693071 non-null  object
 2   cab_company          693071 non-null  object
 3   cab_type             693071 non-null  object
 4   price                693071 non-null  float64
 5   distance             693071 non-null  float64
 6   surge_multiplier     693071 non-null  float64
 7   apparentTemperature  693071 non-null  float64
 8   precipIntensity      693071 non-null  float64
 9   visibility.1         693071 non-null  float64
 10  precipIntensityMax   693071 non-null  float64
 11  day                  693071 non-null  int32
 12  month                693071 non-null  int32
 13  hour                 693071 non-null  int32
 14  minute               693071 non-null  int32
dtypes: float64(7), int32(4), object(4)
memory usage: 74.0+ MB
```

[32]:
```
label_encoder = preprocessing.LabelEncoder()
# Create a list of columns to encode
golden_data = selected_features.copy()
cols_to_encode = [col for col in golden_data.columns if col not in ['price']]

# Apply label encoding to each column
for col in cols_to_encode:
    golden_data[col] = label_encoder.fit_transform(golden_data[col])

    # Get the mapping from encoded values to original names
    mapping = dict(zip(label_encoder.transform(label_encoder.classes_),␣
 ↪label_encoder.classes_))
```

```
    # Print the mapping for the column
    print(f"Mapping for {col} column:")
    print(mapping,"\n")
```

```
Mapping for source column:
{0: 'Back Bay', 1: 'Beacon Hill', 2: 'Boston University', 3: 'Fenway', 4:
'Financial District', 5: 'Haymarket Square', 6: 'North End', 7: 'North Station',
8: 'Northeastern University', 9: 'South Station', 10: 'Theatre District', 11:
'West End'}

Mapping for destination column:
{0: 'Back Bay', 1: 'Beacon Hill', 2: 'Boston University', 3: 'Fenway', 4:
'Financial District', 5: 'Haymarket Square', 6: 'North End', 7: 'North Station',
8: 'Northeastern University', 9: 'South Station', 10: 'Theatre District', 11:
'West End'}

Mapping for cab_company column:
{0: 'Lyft', 1: 'Uber'}

Mapping for cab_type column:
{0: 'Black', 1: 'Black SUV', 2: 'Lux', 3: 'Lux Black', 4: 'Lux Black XL', 5:
'Lyft', 6: 'Lyft XL', 7: 'Shared', 8: 'Taxi', 9: 'UberPool', 10: 'UberX', 11:
'UberXL', 12: 'WAV'}

Mapping for distance column:
{0: 0.02, 1: 0.03, 2: 0.04, 3: 0.12, 4: 0.17, 5: 0.27, 6: 0.29, 7: 0.3, 8: 0.35,
9: 0.38, 10: 0.39, 11: 0.4, 12: 0.41, 13: 0.42, 14: 0.43, 15: 0.44, 16: 0.45,
17: 0.46, 18: 0.47, 19: 0.48, 20: 0.49, 21: 0.5, 22: 0.51, 23: 0.52, 24: 0.53,
25: 0.54, 26: 0.55, 27: 0.56, 28: 0.57, 29: 0.58, 30: 0.59, 31: 0.6, 32: 0.61,
33: 0.62, 34: 0.63, 35: 0.64, 36: 0.65, 37: 0.66, 38: 0.67, 39: 0.68, 40: 0.69,
41: 0.7, 42: 0.71, 43: 0.72, 44: 0.73, 45: 0.74, 46: 0.75, 47: 0.76, 48: 0.77,
49: 0.78, 50: 0.79, 51: 0.8, 52: 0.81, 53: 0.82, 54: 0.83, 55: 0.84, 56: 0.85,
57: 0.86, 58: 0.87, 59: 0.88, 60: 0.89, 61: 0.9, 62: 0.91, 63: 0.92, 64: 0.93,
65: 0.94, 66: 0.95, 67: 0.96, 68: 0.97, 69: 0.98, 70: 0.99, 71: 1.0, 72: 1.01,
73: 1.02, 74: 1.03, 75: 1.04, 76: 1.05, 77: 1.06, 78: 1.07, 79: 1.08, 80: 1.09,
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Mapping for surge_multiplier column:
{0: 1.0, 1: 1.25, 2: 1.5, 3: 1.75, 4: 2.0, 5: 2.5, 6: 3.0}

Mapping for apparentTemperature column:
{0: 12.13, 1: 12.26, 2: 12.65, 3: 13.25, 4: 13.84, 5: 13.96, 6: 14.02, 7: 14.24, 8: 14.47, 9: 14.77, 10: 15.11, 11: 15.44, 12: 16.07, 13: 17.69, 14: 17.99, 15: 18.1, 16: 18.26, 17: 19.09, 18: 20.38, 19: 20.78, 20: 20.93, 21: 21.85, 22: 22.64, 23: 22.99, 24: 24.16, 25: 24.17, 26: 24.24, 27: 24.67, 28: 25.35, 29: 26.66, 30: 27.07, 31: 27.22, 32: 27.71, 33: 27.77, 34: 27.83, 35: 27.93, 36: 28.02, 37: 28.18, 38: 28.2, 39: 28.42, 40: 28.52, 41: 28.73, 42: 28.8, 43: 28.85, 44: 28.89, 45: 29.04, 46: 29.09, 47: 29.22, 48: 29.23, 49: 29.39, 50: 29.4, 51: 29.5, 52: 29.63, 53: 29.99, 54: 30.09, 55: 30.15, 56: 30.41, 57: 30.42, 58: 30.46, 59: 30.56, 60: 30.58, 61: 30.6, 62: 30.62, 63: 30.64, 64: 30.73, 65: 30.87, 66: 30.88, 67: 30.89, 68: 30.98, 69: 31.0, 70: 31.03, 71: 31.07, 72: 31.1, 73: 31.19, 74: 31.24, 75: 31.25, 76: 31.41, 77: 31.54, 78: 31.57, 79: 31.64, 80: 31.8, 81: 31.82, 82: 31.86, 83: 31.9, 84: 31.91, 85: 31.92, 86: 31.98, 87: 32.0, 88: 32.04, 89: 32.06, 90: 32.09, 91: 32.15, 92: 32.16, 93: 32.27, 94: 32.35, 95: 32.37, 96: 32.4, 97: 32.45, 98: 32.46, 99: 32.47, 100: 32.5, 101: 32.57, 102: 32.6, 103: 32.64, 104: 32.67, 105: 32.71, 106: 32.72, 107: 32.77, 108: 32.85, 109: 32.93, 110: 33.0, 111: 33.06, 112: 33.51, 113: 33.55, 114: 33.81, 115: 33.83, 116: 33.9, 117: 34.01, 118: 34.07, 119: 34.08, 120: 34.35, 121: 34.42, 122: 34.47, 123: 34.5, 124: 34.55, 125: 34.59, 126: 34.6, 127: 34.62, 128: 34.66, 129: 34.72, 130: 34.73, 131: 34.81, 132: 35.0, 133: 35.1, 134: 35.13, 135: 35.14, 136: 35.18, 137: 35.21, 138: 35.52, 139: 35.55, 140: 35.58, 141: 35.6, 142: 35.61, 143: 35.62, 144: 35.63, 145: 35.66, 146: 35.68, 147: 35.84, 148: 35.9, 149: 35.92, 150: 35.97, 151: 35.98, 152: 36.0, 153: 36.01, 154: 36.05, 155: 36.06, 156: 36.08, 157: 36.09, 158: 36.1, 159: 36.11, 160: 36.3, 161: 36.47, 162: 36.49, 163: 36.5, 164: 36.6, 165: 36.65, 166: 36.71, 167: 36.74, 168: 36.79, 169: 36.8, 170: 36.87, 171: 36.95, 172: 36.97, 173: 37.05, 174: 37.06, 175: 37.07, 176: 37.1, 177: 37.11, 178: 37.12, 179: 37.19, 180: 37.25, 181: 37.33, 182: 37.35, 183: 37.38, 184: 37.39, 185: 37.47, 186: 37.49, 187: 37.51, 188: 37.53, 189: 37.54, 190: 37.56, 191: 37.6, 192: 37.66, 193: 37.73, 194: 37.78, 195: 37.83, 196: 37.84, 197: 37.91, 198: 37.93, 199: 37.96, 200: 38.0, 201: 38.03, 202: 38.08, 203: 38.1, 204: 38.16, 205: 38.19, 206: 38.21, 207: 38.23, 208: 38.26, 209: 38.41, 210: 38.44, 211: 38.55, 212: 38.92, 213: 39.04, 214: 39.09, 215: 39.23, 216: 39.27, 217: 39.31, 218: 39.35, 219: 39.41, 220: 39.55, 221: 39.58, 222: 39.66, 223: 39.8, 224: 39.93, 225: 39.94, 226: 39.99, 227: 40.01, 228: 40.08, 229: 40.15, 230: 40.72, 231: 40.8, 232: 40.86, 233: 40.97, 234: 40.99, 235: 41.0, 236: 41.06, 237: 41.07, 238: 41.22, 239: 41.26, 240: 41.3, 241: 41.4, 242: 41.52, 243: 41.59, 244: 41.6, 245: 41.62, 246: 41.77, 247: 41.79, 248: 41.83, 249:

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315: 54.38, 316: 54.59, 317: 54.62, 318: 57.22}

Mapping for precipIntensity column:
{0: 0.0, 1: 0.0002, 2: 0.0003, 3: 0.0005, 4: 0.0006, 5: 0.0009, 6: 0.001, 7:
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21: 0.0053, 22: 0.0057, 23: 0.007, 24: 0.0071, 25: 0.0074, 26: 0.008, 27:
0.0089, 28: 0.0092, 29: 0.0094, 30: 0.0121, 31: 0.0187, 32: 0.0216, 33: 0.0246,
34: 0.0255, 35: 0.0274, 36: 0.0288, 37: 0.0308, 38: 0.0341, 39: 0.0342, 40:
0.0462, 41: 0.0488, 42: 0.0567, 43: 0.0591, 44: 0.0624, 45: 0.0674, 46: 0.0701,
47: 0.0737, 48: 0.0772, 49: 0.0786, 50: 0.0801, 51: 0.0813, 52: 0.0832, 53:
0.092, 54: 0.0923, 55: 0.1044, 56: 0.1058, 57: 0.1088, 58: 0.1264, 59: 0.1267,
60: 0.1289, 61: 0.1299, 62: 0.1447}

Mapping for visibility.1 column:
{0: 0.717, 1: 0.965, 2: 1.348, 3: 1.413, 4: 1.46, 5: 1.588, 6: 1.685, 7: 1.824,
8: 2.03, 9: 2.069, 10: 2.121, 11: 2.266, 12: 2.585, 13: 2.629, 14: 2.636, 15:
2.642, 16: 2.644, 17: 2.678, 18: 2.683, 19: 2.686, 20: 2.825, 21: 2.903, 22:
2.994, 23: 3.028, 24: 3.036, 25: 3.052, 26: 3.058, 27: 3.139, 28: 3.183, 29:
3.188, 30: 3.202, 31: 3.231, 32: 3.295, 33: 3.475, 34: 3.495, 35: 3.522, 36:
3.564, 37: 3.579, 38: 3.606, 39: 3.729, 40: 3.79, 41: 3.847, 42: 3.894, 43:
4.031, 44: 4.054, 45: 4.159, 46: 4.183, 47: 4.273, 48: 4.315, 49: 4.394, 50:
4.421, 51: 4.503, 52: 4.661, 53: 4.675, 54: 4.73, 55: 4.741, 56: 4.767, 57:
4.786, 58: 4.942, 59: 5.011, 60: 5.138, 61: 5.177, 62: 5.235, 63: 5.589, 64:
5.86, 65: 6.105, 66: 6.121, 67: 6.397, 68: 6.572, 69: 6.639, 70: 6.96, 71:
7.113, 72: 7.188, 73: 7.357, 74: 7.44, 75: 7.742, 76: 7.769, 77: 7.79, 78:
8.099, 79: 8.104, 80: 8.138, 81: 8.202, 82: 8.275, 83: 8.286, 84: 8.325, 85:
8.432, 86: 8.459, 87: 8.468, 88: 8.54, 89: 8.561, 90: 8.677, 91: 8.904, 92:
9.037, 93: 9.169, 94: 9.285, 95: 9.375, 96: 9.393, 97: 9.428, 98: 9.444, 99:
9.454, 100: 9.501, 101: 9.503, 102: 9.509, 103: 9.544, 104: 9.568, 105: 9.57,
106: 9.579, 107: 9.588, 108: 9.598, 109: 9.608, 110: 9.627, 111: 9.641, 112:
9.661, 113: 9.666, 114: 9.668, 115: 9.67, 116: 9.687, 117: 9.689, 118: 9.698,
119: 9.706, 120: 9.707, 121: 9.712, 122: 9.716, 123: 9.724, 124: 9.725, 125:
9.732, 126: 9.734, 127: 9.738, 128: 9.76, 129: 9.768, 130: 9.77, 131: 9.772,
132: 9.775, 133: 9.779, 134: 9.784, 135: 9.785, 136: 9.796, 137: 9.806, 138:
9.807, 139: 9.808, 140: 9.81, 141: 9.815, 142: 9.821, 143: 9.827, 144: 9.83,
145: 9.831, 146: 9.832, 147: 9.833, 148: 9.839, 149: 9.842, 150: 9.843, 151:
9.846, 152: 9.847, 153: 9.849, 154: 9.85, 155: 9.854, 156: 9.856, 157: 9.857,

```
158: 9.858, 159: 9.864, 160: 9.868, 161: 9.874, 162: 9.875, 163: 9.876, 164:
9.878, 165: 9.88, 166: 9.882, 167: 9.883, 168: 9.884, 169: 9.888, 170: 9.889,
171: 9.891, 172: 9.892, 173: 9.898, 174: 9.899, 175: 9.901, 176: 9.904, 177:
9.908, 178: 9.909, 179: 9.91, 180: 9.915, 181: 9.917, 182: 9.92, 183: 9.922,
184: 9.924, 185: 9.926, 186: 9.928, 187: 9.929, 188: 9.931, 189: 9.932, 190:
9.933, 191: 9.936, 192: 9.937, 193: 9.938, 194: 9.944, 195: 9.945, 196: 9.946,
197: 9.948, 198: 9.949, 199: 9.95, 200: 9.953, 201: 9.955, 202: 9.956, 203:
9.958, 204: 9.959, 205: 9.96, 206: 9.961, 207: 9.962, 208: 9.963, 209: 9.966,
210: 9.967, 211: 9.968, 212: 9.969, 213: 9.972, 214: 9.973, 215: 9.974, 216:
9.975, 217: 9.98, 218: 9.981, 219: 9.984, 220: 9.99, 221: 9.991, 222: 9.994,
223: 9.995, 224: 9.996, 225: 9.997, 226: 10.0}

Mapping for precipIntensityMax column:
{0: 0.0, 1: 0.0001, 2: 0.0003, 3: 0.0004, 4: 0.0005, 5: 0.0007, 6: 0.0028, 7:
0.0029, 8: 0.0056, 9: 0.0074, 10: 0.0075, 11: 0.0077, 12: 0.0079, 13: 0.008, 14:
0.0081, 15: 0.0082, 16: 0.0084, 17: 0.0087, 18: 0.0175, 19: 0.0177, 20: 0.0178,
21: 0.0181, 22: 0.0182, 23: 0.0183, 24: 0.0184, 25: 0.0185, 26: 0.0217, 27:
0.0221, 28: 0.0888, 29: 0.0894, 30: 0.0903, 31: 0.0904, 32: 0.0916, 33: 0.0954,
34: 0.0956, 35: 0.1055, 36: 0.1064, 37: 0.1215, 38: 0.1217, 39: 0.1225, 40:
0.1227, 41: 0.1228, 42: 0.1234, 43: 0.1245, 44: 0.1246, 45: 0.125, 46: 0.1252,
47: 0.1254, 48: 0.1257, 49: 0.1261, 50: 0.1266, 51: 0.1267, 52: 0.1276, 53:
0.13, 54: 0.1361, 55: 0.1396, 56: 0.1419, 57: 0.142, 58: 0.1422, 59: 0.1425, 60:
0.1429, 61: 0.143, 62: 0.1433, 63: 0.1438, 64: 0.1459}

Mapping for day column:
{0: 1, 1: 2, 2: 3, 3: 4, 4: 9, 5: 10, 6: 13, 7: 14, 8: 15, 9: 16, 10: 17, 11:
18, 12: 26, 13: 27, 14: 28, 15: 29, 16: 30}

Mapping for month column:
{0: 11, 1: 12}

Mapping for hour column:
{0: 0, 1: 1, 2: 2, 3: 3, 4: 4, 5: 5, 6: 6, 7: 7, 8: 8, 9: 9, 10: 10, 11: 11, 12:
12, 13: 13, 14: 14, 15: 15, 16: 16, 17: 17, 18: 18, 19: 19, 20: 20, 21: 21, 22:
22, 23: 23}

Mapping for minute column:
{0: 0, 1: 1, 2: 2, 3: 3, 4: 4, 5: 5, 6: 6, 7: 7, 8: 8, 9: 9, 10: 10, 11: 11, 12:
12, 13: 13, 14: 14, 15: 15, 16: 16, 17: 17, 18: 18, 19: 19, 20: 20, 21: 21, 22:
22, 23: 23, 24: 24, 25: 25, 26: 26, 27: 27, 28: 28, 29: 29, 30: 30, 31: 31, 32:
32, 33: 33, 34: 34, 35: 35, 36: 36, 37: 37, 38: 38, 39: 39, 40: 40, 41: 41, 42:
42, 43: 43, 44: 44, 45: 45, 46: 46, 47: 47, 48: 48, 49: 49, 50: 50, 51: 51, 52:
52, 53: 53, 54: 54, 55: 55, 56: 56, 57: 57, 58: 58, 59: 59}
```

[33]:
```
golden_data
```

[33]:

	source	destination	cab_company	cab_type	price	distance	\
66422	7	5	1	10	7.000000	27	
446073	10	6	1	8	15.830582	128	
184332	6	11	0	5	7.000000	94	
167114	2	1	0	2	19.500000	237	
184333	6	11	0	7	5.000000	94	
…	…	…	…	…	…	…	
34918	4	5	1	10	7.000000	96	
215397	3	10	1	1	33.500000	237	
166550	5	0	1	10	11.500000	201	
290785	8	1	0	4	34.000000	271	
166551	5	0	1	11	16.500000	201	

	surge_multiplier	apparentTemperature	precipIntensity	visibility.1	\
66422	0	248	0	6	
446073	0	248	0	6	
184332	0	248	0	6	
167114	0	248	0	6	
184333	0	248	0	6	
…	…	…	…	…	
34918	0	23	0	167	
215397	0	23	0	167	
166550	0	23	0	167	
290785	0	23	0	167	
166551	0	23	0	167	

	precipIntensityMax	day	month	hour	minute
66422	55	12	0	3	40
446073	55	12	0	3	40
184332	55	12	0	3	40
167114	55	12	0	3	40
184333	55	12	0	3	40
…	…	…	…	…	…
34918	7	11	1	19	15
215397	7	11	1	19	15
166550	7	11	1	19	15
290785	7	11	1	19	15
166551	7	11	1	19	15

[693071 rows x 15 columns]

1.1.11 Creating Train and Test Data

[34]:
```
target = 'price'

# Create feature matrix (X) and target vector (y)
X= golden_data.drop('price', axis=1)
```

```
y= golden_data['price']

# Split the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=42)

# Check the shapes of the training and testing sets
print("X_train shape:", X_train.shape)
print("X_test shape:", X_test.shape)
```

```
X_train shape: (554456, 14)
X_test shape: (138615, 14)
```

1.1.12 Linear Regression Model

[35]:
```
# Linear Regression
# Train the Linear Regression model
linear_model = LinearRegression()
linear_model.fit(X_train, y_train)

# Predict on the test set
y_pred_linear = linear_model.predict(X_test)

# Evaluate the model
print("Linear Regression Results:")
print("Mean Squared Error (MSE):", mean_squared_error(y_test, y_pred_linear))
print("Mean Absolute Error(MAE):", mean_absolute_error(y_test, y_pred_linear))
print("R-squared (R2):", r2_score(y_test, y_pred_linear))
mape = mean_absolute_percentage_error(y_test, y_pred_linear) * 100
print(f"Mean Absolute Percentage Error (MAPE): {mape:.2f}%")
accuracy = r2_score(y_test, y_pred_linear) * 100
print(f"Model Accuracy (based on R²): {accuracy:.2f}%")
```

```
Linear Regression Results:
Mean Squared Error (MSE): 39.642631412008164
Mean Absolute Error(MAE): 4.933013266600891
R-squared (R2): 0.5031924291020817
Mean Absolute Percentage Error (MAPE): 37.84%
Model Accuracy (based on R²): 50.32%
```

1.1.13 Random Forest Model

[36]:
```
# Train the Random Forest model
random_forest_model = RandomForestRegressor(random_state=42, max_depth=20)
random_forest_model.fit(X_train, y_train)

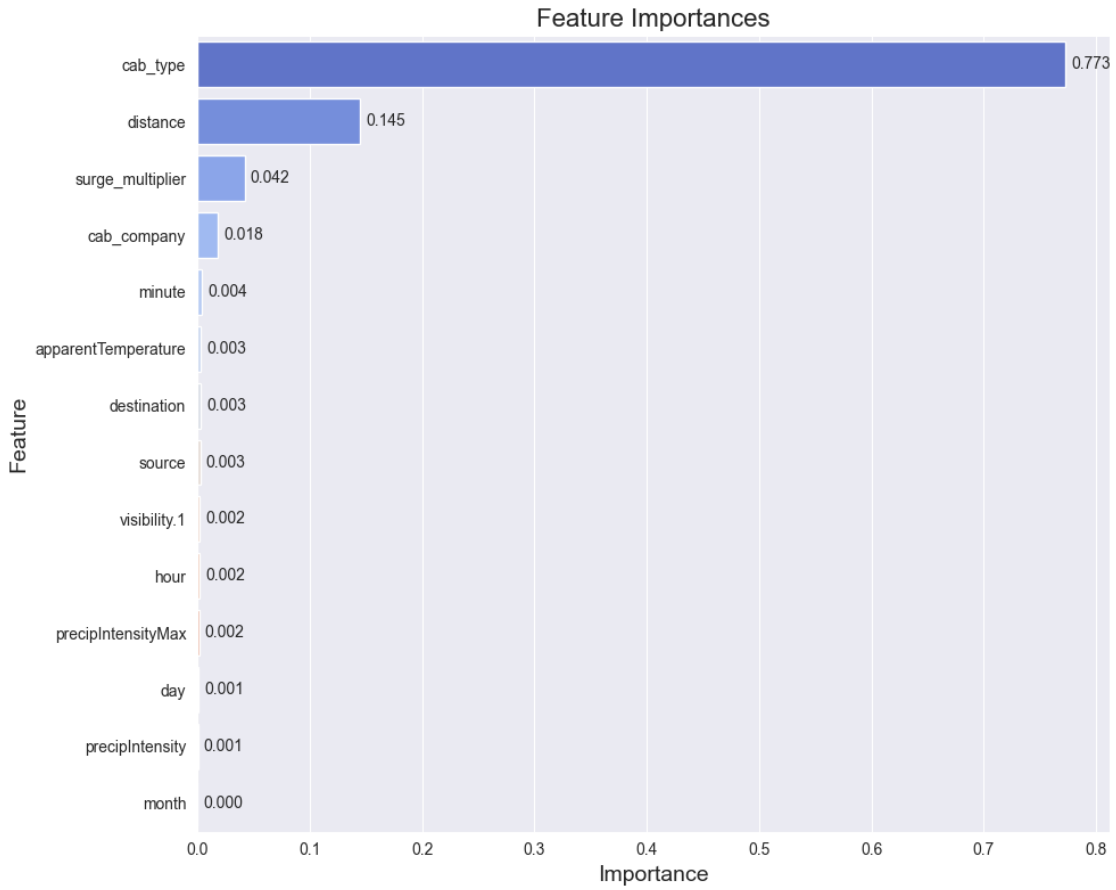
# Predict on the test set
y_pred_rf = random_forest_model.predict(X_test)
```

```
# Evaluate the model
print("Random Forest Regressor Results:")
print("Mean Squared Error (MSE):", mean_squared_error(y_test, y_pred_rf))
print("R-squared (R2):", r2_score(y_test, y_pred_rf))
mape = mean_absolute_percentage_error(y_test, y_pred_rf) * 100
print(f"Mean Absolute Percentage Error (MAPE): {mape:.2f}%")
accuracy = r2_score(y_test, y_pred_rf) * 100
print(f"Model Accuracy (based on R²): {accuracy:.2f}%")
```

```
Random Forest Regressor Results:
Mean Squared Error (MSE): 2.668005624619269
R-squared (R2): 0.9665641420284835
Mean Absolute Percentage Error (MAPE): 7.37%
Model Accuracy (based on R²): 96.66%
```

[37]:
```
# PLot the feature importances of the Random Forest model
importances = random_forest_model.feature_importances_
feature_names = X.columns
feature_importances = pd.DataFrame({'Feature': feature_names, 'Importance':␣
 ↪importances})
feature_importances = feature_importances.sort_values(by='Importance',␣
 ↪ascending=False)

plt.figure(figsize=(10, 8))
sns.barplot(
    x=feature_importances['Importance'],
    y=feature_importances['Feature'],
    palette='coolwarm'  ,
    hue=feature_importances['Feature'],
    dodge=False,
    legend=False
)
plt.title("Feature Importances", fontsize=16)
plt.xlabel("Importance", fontsize=14)
plt.ylabel("Feature", fontsize=14)
for i, v in enumerate(feature_importances['Importance']):
    plt.text(v + 0.005, i, f"{v:.3f}", va='center', fontsize=10)
plt.tight_layout()
plt.show()
```



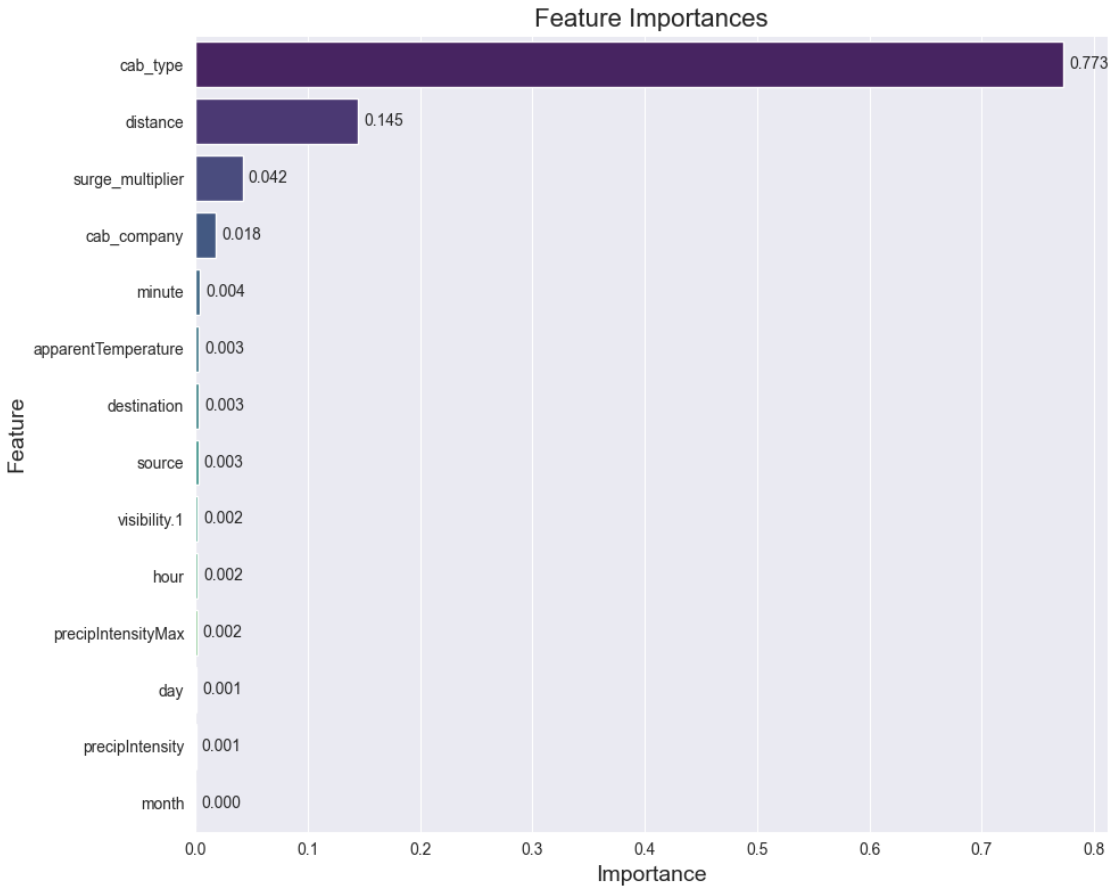
1.1.14 Decision Tree Regressor

[38]:
```
# Train the Decision Tree Regressor model
decision_tree_model = DecisionTreeRegressor(random_state=42)
decision_tree_model.fit(X_train, y_train)
y_pred_dt = decision_tree_model.predict(X_test)
mae = mean_absolute_error(y_test, y_pred_dt)
mse = mean_squared_error(y_test, y_pred_dt)
r2 = r2_score(y_test, y_pred_dt)
# Evaluate the model
print("Decision Tree Regressor Results:")
print("Mean Squared Error (MSE):", mean_squared_error(y_test, y_pred_dt))
print("R-squared (R2):", r2_score(y_test, y_pred_dt))
mape = mean_absolute_percentage_error(y_test, y_pred_dt) * 100
print(f"Mean Absolute Percentage Error (MAPE): {mape:.2f}%")
accuracy = r2_score(y_test, y_pred_dt) * 100
print(f"Model Accuracy (based on R²): {accuracy:.2f}%")
```

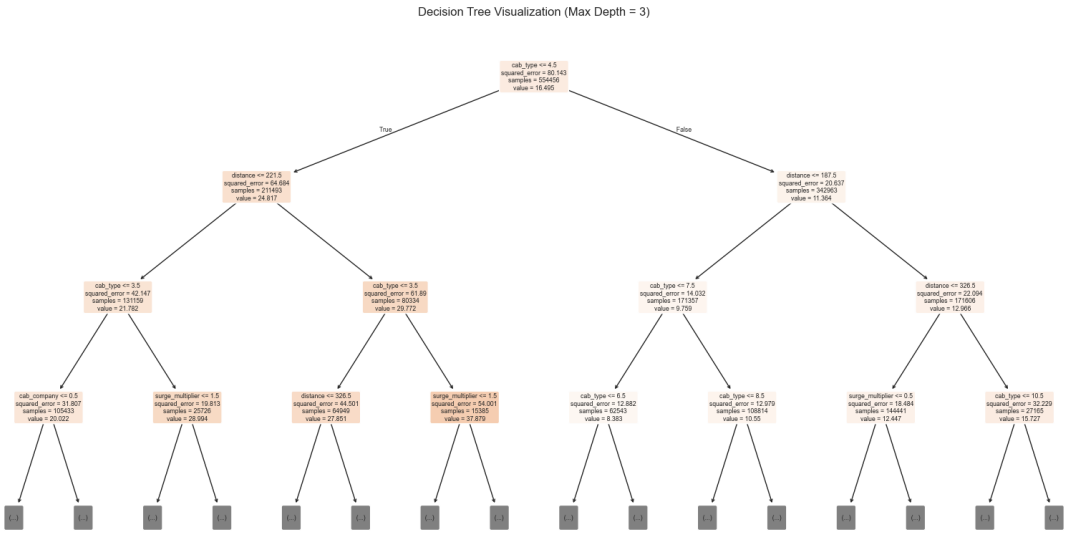
```
Decision Tree Regressor Results:
```

```
Mean Squared Error (MSE): 5.207165249251525
R-squared (R2): 0.9347430020005916
Mean Absolute Percentage Error (MAPE): 9.53%
Model Accuracy (based on R²): 93.47%
```

[39]:
```python
plt.figure(figsize=(10, 8))
sns.barplot(
    x=feature_importances['Importance'],
    y=feature_importances['Feature'],
    palette='viridis',
    hue=feature_importances['Feature'],
    dodge=False,
    legend=False
)
plt.title("Feature Importances", fontsize=16)
plt.xlabel("Importance", fontsize=14)
plt.ylabel("Feature", fontsize=14)
# Add annotations to each bar
for i, v in enumerate(feature_importances['Importance']):
    plt.text(v + 0.005, i, f"{v:.3f}", va='center', fontsize=10)

plt.tight_layout()
plt.show()
```



[40]:
```
plt.figure(figsize=(20, 10))
plot_tree(decision_tree_model, feature_names=X_train.columns, filled=True,␣
↪rounded=True, max_depth=3)
plt.title("Decision Tree Visualization (Max Depth = 3)")
plt.show()
```



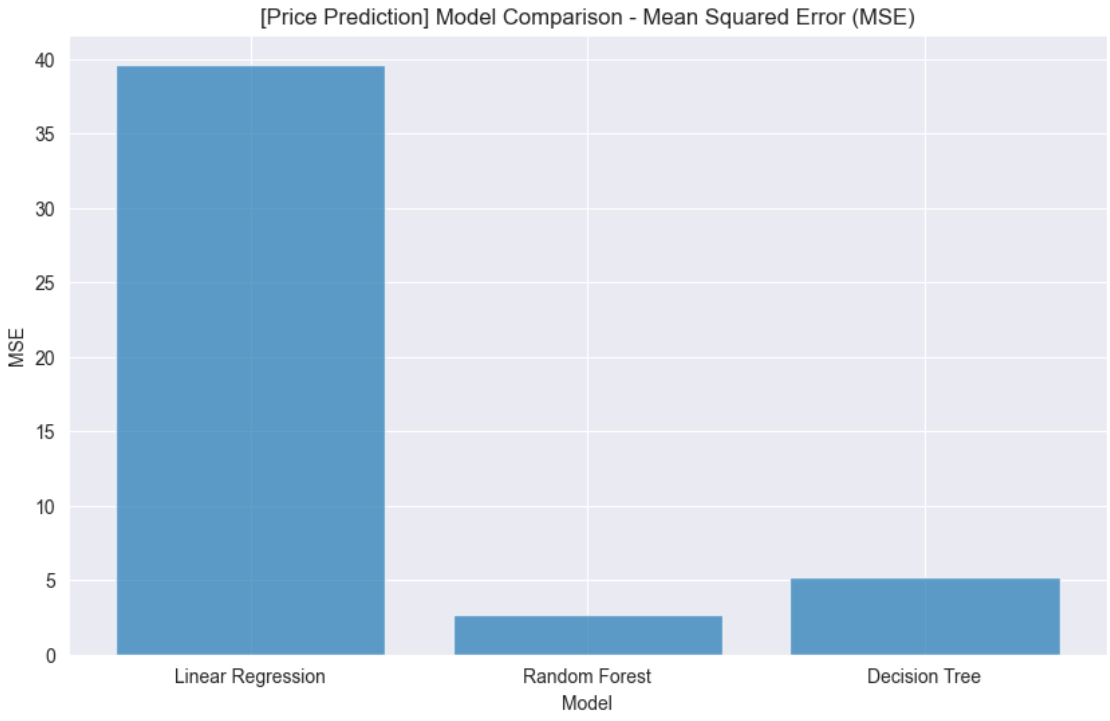
1.1.15 Model Comparisons

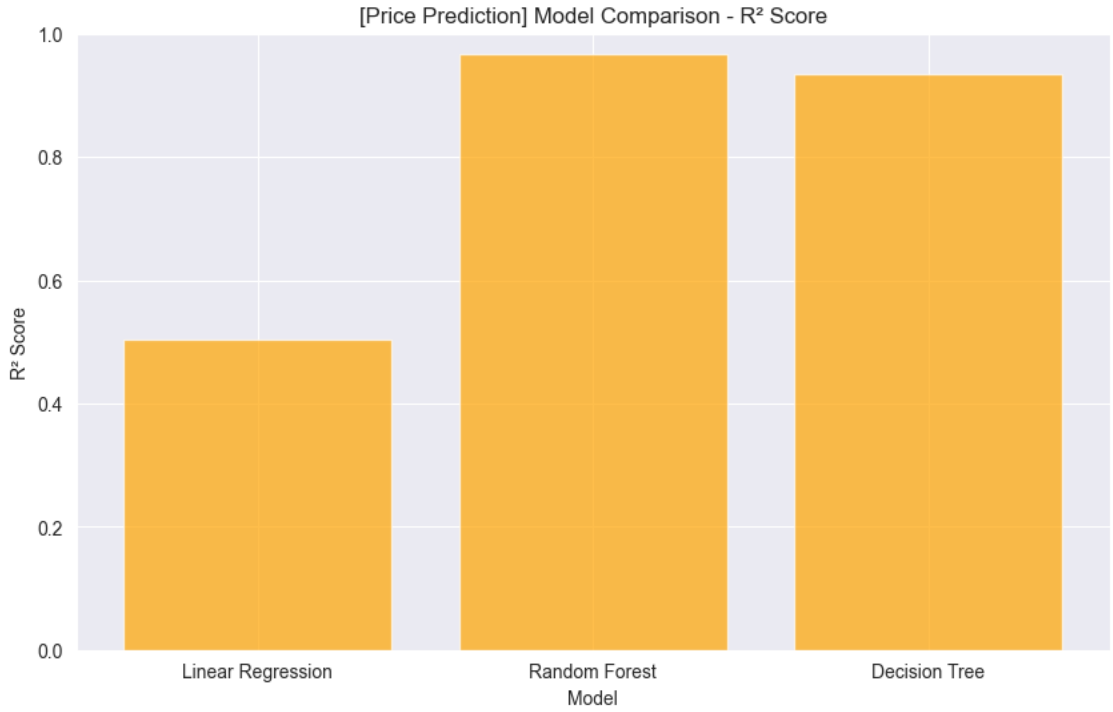
[41]:
```
# Compare the models
print("Model Comparison:")
print("Linear Regression - MSE:", mean_squared_error(y_test, y_pred_linear), "|␣
 ↪R2:", r2_score(y_test, y_pred_linear))
print("Random Forest Regressor - MSE:", mean_squared_error(y_test, y_pred_rf),␣
 ↪"| R2:", r2_score(y_test, y_pred_rf))
print("Decision Tree Regressor - MSE:", mean_squared_error(y_test, y_pred_dt),␣
 ↪"| R2:", r2_score(y_test, y_pred_dt))
```

```
Model Comparison:
Linear Regression - MSE: 39.642631412008164 | R2: 0.5031924291020817
Random Forest Regressor - MSE: 2.668005624619269 | R2: 0.9665641420284835
Decision Tree Regressor - MSE: 5.207165249251525 | R2: 0.9347430020005916
```

[42]:
```
# Define the models
models = ['Linear Regression', 'Random Forest', 'Decision Tree']

# Calculate MSE and R² values
mse_values = [
    mean_squared_error(y_test, y_pred_linear),
    mean_squared_error(y_test, y_pred_rf),
    mean_squared_error(y_test, y_pred_dt)
]
r2_values = [
    r2_score(y_test, y_pred_linear),
    r2_score(y_test, y_pred_rf),
```

```
    r2_score(y_test, y_pred_dt)
]

# Plot the MSE values
plt.figure(figsize=(10, 6))
plt.bar(models, mse_values, alpha=0.7, label='MSE')
plt.title('[Price Prediction] Model Comparison - Mean Squared Error (MSE)')
plt.ylabel('MSE')
plt.xlabel('Model')
plt.xticks(models)
plt.show()

# Plot the R² values
plt.figure(figsize=(10, 6))
plt.bar(models, r2_values, alpha=0.7, color='orange', label='R² Score')
plt.title('[Price Prediction] Model Comparison - R² Score')
plt.ylabel('R² Score')
plt.xlabel('Model')
plt.xticks(models)
plt.ylim(0, 1)  # R² ranges from 0 to 1
plt.show()
```





1.1.16 Splitting dataset into different cab company types

[43]:
```
# split selected features into different cab company types

uber_data_df = selected_features[selected_features['cab_company'] == 'Uber'].
 ↪copy(deep=True)
lyft_data_df = selected_features[selected_features['cab_company'] == 'Lyft'].
 ↪copy(deep=True)
uber_data_df.drop(['cab_company'], axis=1, inplace=True)
lyft_data_df.drop(['cab_company'], axis=1, inplace=True)
```

1.1.17 Uber Models

[44]:
```
# Create a list of columns to encode
cols_to_encode = [col for col in uber_data_df.columns if col not in ['price']]

# Apply label encoding to each column
for col in cols_to_encode:
    uber_data_df[col] = label_encoder.fit_transform(uber_data_df[col])

    # Get the mapping from encoded values to original names
    mapping = dict(zip(label_encoder.transform(label_encoder.classes_),␣
 ↪label_encoder.classes_))
```

```
uber_data_df
```

[44]:

	source	destination	cab_type	price	distance	surge_multiplier	\
66422	7	5	4	7.000000	19	0	
446073	10	6	2	15.830582	108	0	
32121	7	3	6	10.500000	255	0	
613927	10	3	4	19.500000	222	0	
613926	10	3	5	32.000000	222	0	
…	…	…	…	…	…	…	
204548	10	3	2	15.805276	217	0	
34918	4	5	4	7.000000	76	0	
215397	3	10	1	33.500000	217	0	
166550	5	0	4	11.500000	181	0	
166551	5	0	5	16.500000	181	0	

	apparentTemperature	precipIntensity	visibility.1	\
66422	248	0	6	
446073	248	0	6	
32121	248	0	6	
613927	248	0	6	
613926	248	0	6	
…	…	…	…	
204548	23	0	167	
34918	23	0	167	
215397	23	0	167	
166550	23	0	167	
166551	23	0	167	

	precipIntensityMax	day	month	hour	minute
66422	55	12	0	3	40
446073	55	12	0	3	40
32121	55	12	0	3	40
613927	55	12	0	3	40
613926	55	12	0	3	40
…	…	…	…	…	…
204548	7	11	1	19	15
34918	7	11	1	19	15
215397	7	11	1	19	15
166550	7	11	1	19	15
166551	7	11	1	19	15

[385663 rows x 14 columns]

[45]:
```
target = 'price'
# Create feature matrix (X) and target vector (y)
X_uber = uber_data_df.drop('price', axis=1)
```

```
y_uber = uber_data_df['price']

# Convert categorical columns (e.g., is_rain, day_of_week) to numerical values
# X = pd.get_dummies(X, columns=['day_of_week', 'is_weekend'], drop_first=True)

# Split the dataset into training and testing sets
X_train_uber, X_test_uber, y_train_uber, y_test_uber = train_test_split(X_uber,␣
 ↪y_uber, test_size=0.2, random_state=42)

# Check the shapes of the training and testing sets
print("X_train shape:", X_train_uber.shape)
print("X_test shape:", X_test_uber.shape)
```

```
X_train shape: (308530, 13)
X_test shape: (77133, 13)
```

1.1.18 Linear Regression Model for Uber

[46]:
```
# Linear Regression for Uber
# Train the Linear Regression model
linear_model = LinearRegression()
linear_model.fit(X_train_uber, y_train_uber)

# Predict on the test set
y_pred_linear_uber = linear_model.predict(X_test_uber)

# Evaluate the model
print("Linear Regression Results for Uber:")
print("Mean Squared Error (MSE):", mean_squared_error(y_test_uber,␣
 ↪y_pred_linear_uber))
print("R-squared (R2):", r2_score(y_test_uber, y_pred_linear_uber))
mape = mean_absolute_percentage_error(y_test_uber, y_pred_linear_uber) * 100
print(f"Mean Absolute Percentage Error (MAPE): {mape:.2f}%")
accuracy = r2_score(y_test_uber, y_pred_linear_uber) * 100
print(f"Model Accuracy (based on R²): {accuracy:.2f}%")
```

```
Linear Regression Results for Uber:
Mean Squared Error (MSE): 33.60441420310319
R-squared (R2): 0.4650209982259109
Mean Absolute Percentage Error (MAPE): 33.75%
Model Accuracy (based on R²): 46.50%
```

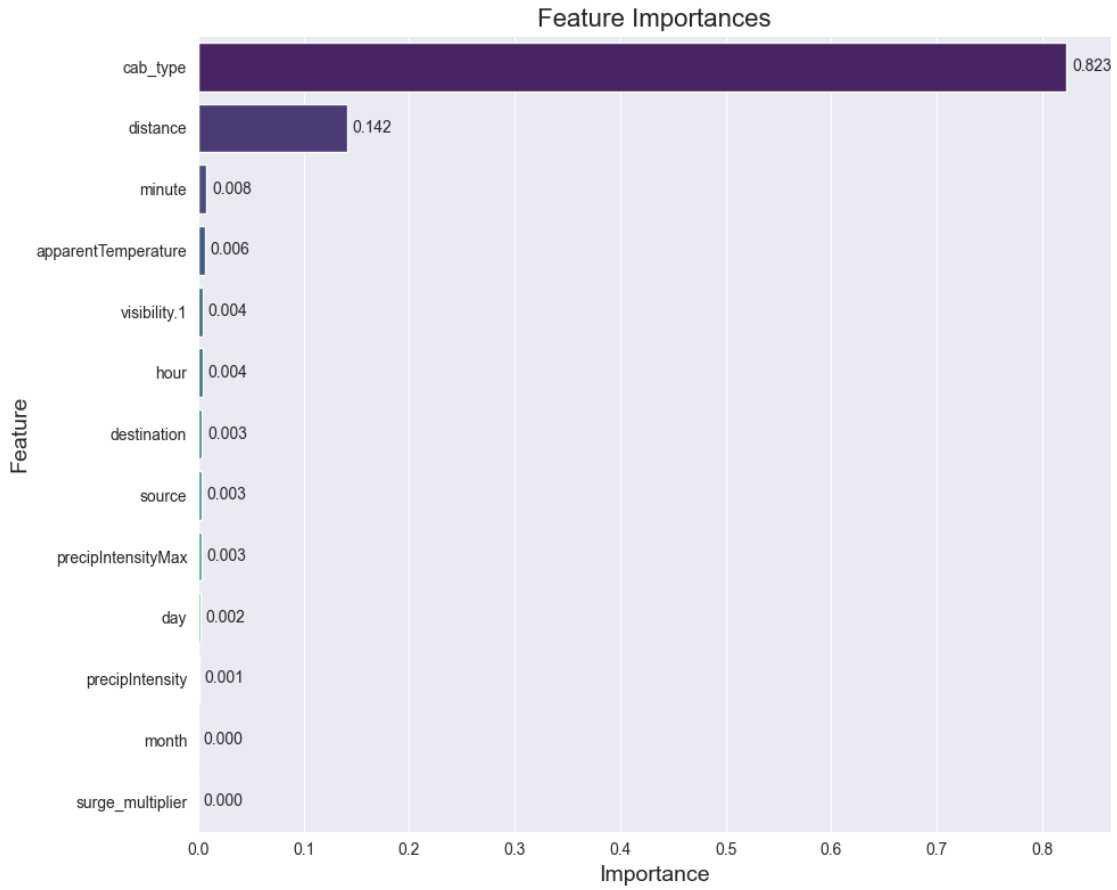
1.1.19 Random Forest Model for Uber

[47]:
```
# Train the Random Forest model
random_forest_model_uber = RandomForestRegressor(random_state=42, max_depth=20)
random_forest_model_uber.fit(X_train_uber, y_train_uber)
```

```
# Predict on the test set
y_pred_rf_uber = random_forest_model_uber.predict(X_test_uber)

# Evaluate the model
print("Random Forest Regressor Results for Uber:")
print("Mean Squared Error (MSE):", mean_squared_error(y_test_uber,␣
 ↪y_pred_rf_uber))
print("R-squared (R2):", r2_score(y_test_uber, y_pred_rf_uber))
mape = mean_absolute_percentage_error(y_test_uber, y_pred_rf_uber) * 100
print(f"Mean Absolute Percentage Error (MAPE): {mape:.2f}%")
accuracy = r2_score(y_test_uber, y_pred_rf_uber) * 100
print(f"Model Accuracy (based on R²): {accuracy:.2f}%")
```

```
Random Forest Regressor Results for Uber:
Mean Squared Error (MSE): 3.3024890916269998
R-squared (R2): 0.9474246952519327
Mean Absolute Percentage Error (MAPE): 7.16%
Model Accuracy (based on R²): 94.74%
```

[48]:
```
# Get feature importances and sort them in descending order
importances_uber = random_forest_model_uber.feature_importances_
feature_names_uber = X_uber.columns
feature_importances_uber = pd.DataFrame({'Feature': feature_names_uber,␣
 ↪'Importance': importances_uber})
feature_importances_uber = feature_importances_uber.
 ↪sort_values(by='Importance', ascending=False)

# Plot the feature importances
plt.figure(figsize=(10, 8))
sns.barplot(
    x=feature_importances_uber['Importance'],
    y=feature_importances_uber['Feature'],
    palette='viridis' ,
    hue=feature_importances_uber['Feature'],
    dodge=False,
    legend=False
)
plt.title("Feature Importances", fontsize=16)
plt.xlabel("Importance", fontsize=14)
plt.ylabel("Feature", fontsize=14)
# Add annotations to each bar
for i, v in enumerate(feature_importances_uber['Importance']):
    plt.text(v + 0.005, i, f"{v:.3f}", va='center', fontsize=10)

plt.tight_layout()
plt.show()
```



1.1.20 Decision Tree Regressor for Uber

[49]:
```
# Decision Tree Regressor for Uber
dt_model_uber = DecisionTreeRegressor(random_state=42)
dt_model_uber.fit(X_train_uber, y_train_uber)
y_pred_dt_uber = dt_model_uber.predict(X_test_uber)

# Evaluate the model
print("Decision Tree Regressor Results for Uber:")
print("Mean Squared Error (MSE):", mean_squared_error(y_test_uber,␣
 ↪y_pred_dt_uber))
print("R-squared (R2):", r2_score(y_test_uber, y_pred_dt_uber))
mape = mean_absolute_percentage_error(y_test_uber, y_pred_dt_uber) * 100
print(f"Mean Absolute Percentage Error (MAPE): {mape:.2f}%")
accuracy = r2_score(y_test_uber, y_pred_dt_uber) * 100
print(f"Model Accuracy (based on R²): {accuracy:.2f}%")

# Optional: Feature Importance
feature_importances = pd.DataFrame({
```

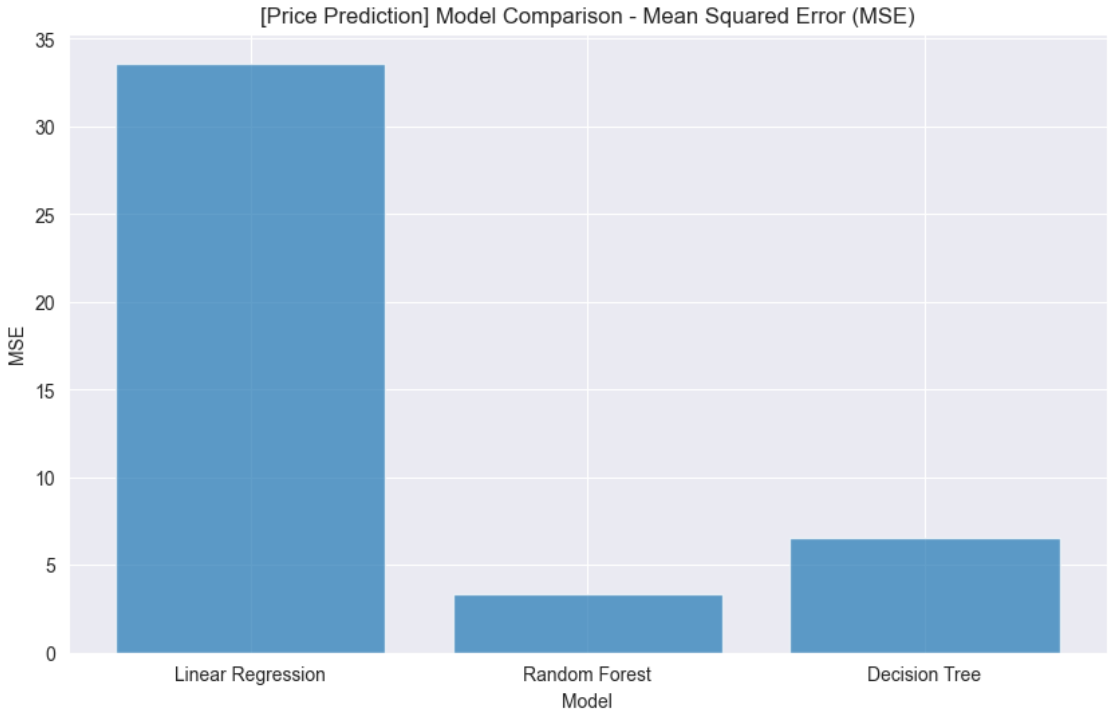
```
    'Feature': X_train_uber.columns,
    'Importance': dt_model_uber.feature_importances_
}).sort_values(by='Importance', ascending=False)

print("\nFeature Importances:")
print(feature_importances)
```

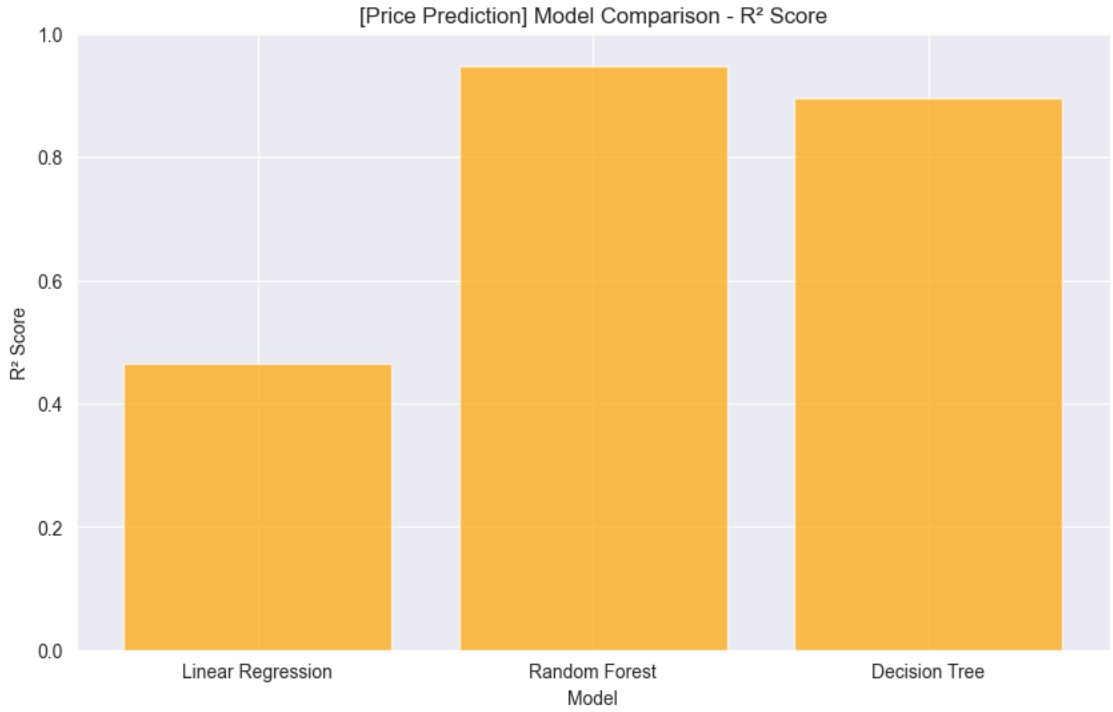
```
Decision Tree Regressor Results for Uber:
Mean Squared Error (MSE): 6.546888864940355
R-squared (R2): 0.8957741667947821
Mean Absolute Percentage Error (MAPE): 9.77%
Model Accuracy (based on R²): 89.58%

Feature Importances:
                 Feature  Importance
2              cab_type    0.812525
3              distance    0.140141
12               minute    0.012678
5   apparentTemperature    0.007844
11                 hour    0.005848
7          visibility.1    0.005215
1           destination    0.003701
0                source    0.003612
8    precipIntensityMax    0.003505
9                   day    0.002986
6       precipIntensity    0.001551
10                month    0.000393
4       surge_multiplier    0.000000
```

1.1.21 Uber Model Evaluations

[50]:
```
# Define the models
models = ['Linear Regression', 'Random Forest', 'Decision Tree']

# Calculate MSE and R² values
mse_values = [
    mean_squared_error(y_test_uber, y_pred_linear_uber),
    mean_squared_error(y_test_uber, y_pred_rf_uber),
    mean_squared_error(y_test_uber, y_pred_dt_uber)
]
r2_values = [
    r2_score(y_test_uber, y_pred_linear_uber),
    r2_score(y_test_uber, y_pred_rf_uber),
    r2_score(y_test_uber, y_pred_dt_uber)
]

# Plot the MSE values
plt.figure(figsize=(10, 6))
```

```
plt.bar(models, mse_values, alpha=0.7, label='MSE')
plt.title('[Price Prediction] Model Comparison - Mean Squared Error (MSE)')
plt.ylabel('MSE')
plt.xlabel('Model')
plt.xticks(models)
plt.show()

# Plot the R² values
plt.figure(figsize=(10, 6))
plt.bar(models, r2_values, alpha=0.7, color='orange', label='R² Score')
plt.title('[Price Prediction] Model Comparison - R² Score')
plt.ylabel('R² Score')
plt.xlabel('Model')
plt.xticks(models)
plt.ylim(0, 1)  # R² ranges from 0 to 1
plt.show()
```





1.1.22 Lyft Models

[51]:
```
# Create a list of columns to encode
cols_to_encode = [col for col in lyft_data_df.columns if col not in ['price']]

# Apply label encoding to each column
for col in cols_to_encode:
    lyft_data_df[col] = label_encoder.fit_transform(lyft_data_df[col])

    # Get the mapping from encoded values to original names
    mapping = dict(zip(label_encoder.transform(label_encoder.classes_),␣
 ↪label_encoder.classes_))

    # Print the mapping for the column
    # print(f"Mapping for {col} column:")
    # print(mapping,"\n")
lyft_data_df
```

[51]:

	source	destination	cab_type	price	distance	surge_multiplier	\
184332	6	11	3	7.0	84	0	
167114	2	1	0	19.5	227	0	
184333	6	11	5	5.0	84	0	
184334	6	11	0	13.5	84	0	

```
184335       6           11          1   19.5        84                  0
…          …           …         …     …         …                 …
205379       8            1          0   16.5       201                 0
290784       8            1          5    9.0       261                 0
290783       8            1          4   16.5       261                 0
290782       8            1          3   11.0       261                 0
290785       8            1          2   34.0       261                 0

        apparentTemperature  precipIntensity  visibility.1  \
184332                  248                0             6
167114                  248                0             6
184333                  248                0             6
184334                  248                0             6
184335                  248                0             6
…                     …                  …           …
205379                   23                0           167
290784                   23                0           167
290783                   23                0           167
290782                   23                0           167
290785                   23                0           167

        precipIntensityMax  day  month  hour  minute
184332                  55   12      0     3      40
167114                  55   12      0     3      40
184333                  55   12      0     3      40
184334                  55   12      0     3      40
184335                  55   12      0     3      40
…                     …  …    …      …     …
205379                   7   11      1    19      15
290784                   7   11      1    19      15
290783                   7   11      1    19      15
290782                   7   11      1    19      15
290785                   7   11      1    19      15

[307408 rows x 14 columns]
```

[52]:
```
target = 'price'
# Create feature matrix (X) and target vector (y)
X_lyft = lyft_data_df.drop('price', axis=1)
y_lyft = lyft_data_df['price']

# Convert categorical columns (e.g., is_rain, day_of_week) to numerical values
# X = pd.get_dummies(X, columns=['day_of_week', 'is_weekend'], drop_first=True)

# Split the dataset into training and testing sets
X_train_lyft, X_test_lyft, y_train_lyft, y_test_lyft = train_test_split(X_lyft,␣
 ↪y_lyft, test_size=0.2, random_state=42)
```

```
# Check the shapes of the training and testing sets
print("X_train shape:", X_train_lyft.shape)
print("X_test shape:", X_test_lyft.shape)
```

```
X_train shape: (245926, 13)
X_test shape: (61482, 13)
```

1.1.23 Linear Regression for Lyft

[53]:
```
# Linear Regression for Uber
# Train the Linear Regression model
linear_model_lyft = LinearRegression()
linear_model_lyft.fit(X_train_lyft, y_train_lyft)

# Predict on the test set
y_pred_linear_lyft = linear_model_lyft.predict(X_test_lyft)

# Evaluate the model
print("Linear Regression Results for Lyft:")
print("Mean Squared Error (MSE):", mean_squared_error(y_test_lyft,␣
 ↪y_pred_linear_lyft))
print("R-squared (R2):", r2_score(y_test_lyft, y_pred_linear_lyft))
mape = mean_absolute_percentage_error(y_test_lyft, y_pred_linear_lyft) * 100
print(f"Mean Absolute Percentage Error (MAPE): {mape:.2f}%")
accuracy = r2_score(y_test_lyft, y_pred_linear_lyft) * 100
print(f"Model Accuracy (based on R²): {accuracy:.2f}%")
```

```
Linear Regression Results for Lyft:
Mean Squared Error (MSE): 54.106045904704565
R-squared (R2): 0.4606320361760139
Mean Absolute Percentage Error (MAPE): 40.76%
Model Accuracy (based on R²): 46.06%
```

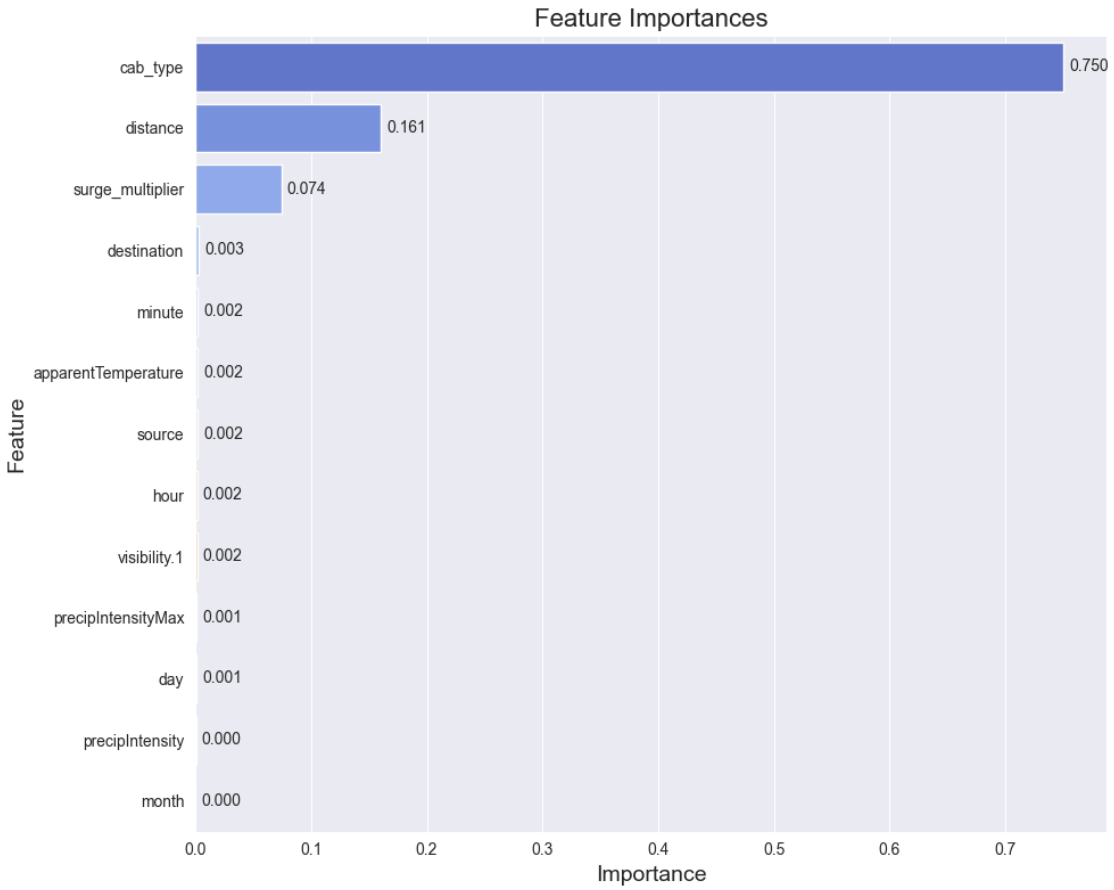
1.1.24 Random forest for Lyft

[54]:
```
# Train the Random Forest model
random_forest_model_lyft = RandomForestRegressor(random_state=42, max_depth=20)
random_forest_model_lyft.fit(X_train_lyft, y_train_lyft)

# Predict on the test set
y_pred_rf_lyft = random_forest_model_lyft.predict(X_test_lyft)

# Evaluate the model
print("Random Forest Regressor Results for Lyft:")
print("Mean Squared Error (MSE):", mean_squared_error(y_test_lyft,␣
 ↪y_pred_rf_lyft))
print("R-squared (R2):", r2_score(y_test_lyft, y_pred_rf_lyft))
```

```
mape = mean_absolute_percentage_error(y_test_lyft, y_pred_rf_lyft) * 100
print(f"Mean Absolute Percentage Error (MAPE): {mape:.2f}%")
accuracy = r2_score(y_test_lyft, y_pred_rf_lyft) * 100
print(f"Model Accuracy (based on R²): {accuracy:.2f}%")
```

```
Random Forest Regressor Results for Lyft:
Mean Squared Error (MSE): 1.921273379316906
R-squared (R2): 0.9808473657014866
Mean Absolute Percentage Error (MAPE): 7.84%
Model Accuracy (based on R²): 98.08%
```

[55]:
```
# Get feature importances and sort them in descending order
importances_lyft = random_forest_model_lyft.feature_importances_
feature_names_lyft = X_lyft.columns
feature_importances_lyft = pd.DataFrame({'Feature': feature_names_lyft,␣
 ↪'Importance': importances_lyft})
feature_importances_lyft = feature_importances_lyft.
 ↪sort_values(by='Importance', ascending=False)

# Plot the feature importances
plt.figure(figsize=(10, 8))
sns.barplot(
    x=feature_importances_lyft['Importance'],
    y=feature_importances_lyft['Feature'],
    palette='coolwarm' ,
    hue=feature_importances_lyft['Feature'],
    dodge=False,
    legend=False
)
plt.title("Feature Importances", fontsize=16)
plt.xlabel("Importance", fontsize=14)
plt.ylabel("Feature", fontsize=14)

# Add annotations to each bar
for i, v in enumerate(feature_importances_lyft['Importance']):
    plt.text(v + 0.005, i, f"{v:.3f}", va='center', fontsize=10)

plt.tight_layout()
plt.show()
```



1.1.25 Decision Regressor for Lyft

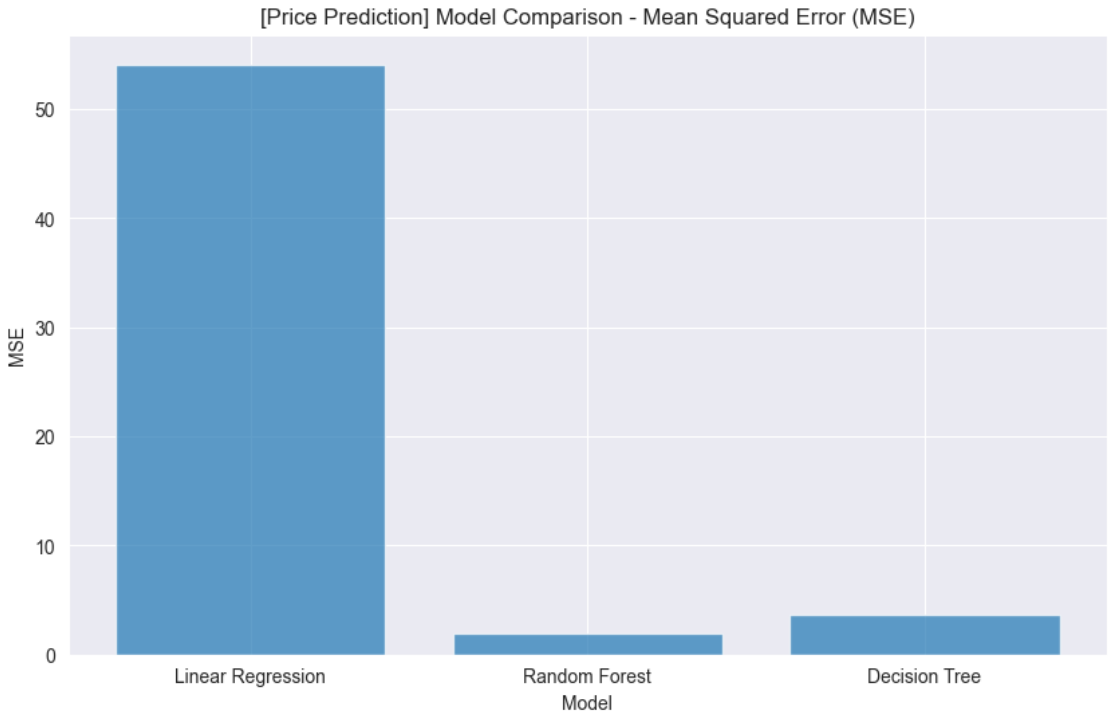
[56]:
```
# Decision Regressor Model for Lyft
dt_model_lyft = DecisionTreeRegressor(random_state=42)
dt_model_lyft.fit(X_train_lyft, y_train_lyft)
y_pred_dt_lyft = dt_model_lyft.predict(X_test_lyft)

mae = mean_absolute_error(y_test_lyft, y_pred_dt_lyft)
mse = mean_squared_error(y_test_lyft, y_pred_dt_lyft)
r2 = r2_score(y_test_lyft, y_pred_dt_lyft)

print("Decision Regressor Results for Lyft:")
print(f"Mean Absolute Error (MAE): {mae}")
print(f"Mean Squared Error (MSE): {mse}")
print(f"R² Score: {r2}")
mae = mean_absolute_percentage_error(y_test_lyft, y_pred_dt_lyft) * 100
print(f"Mean Absolute Percentage Error (MAPE): {mape:.2f}%")
accuracy = r2_score(y_test_lyft, y_pred_dt_lyft) * 100
print(f"Model Accuracy (based on R²): {accuracy:.2f}%")
```

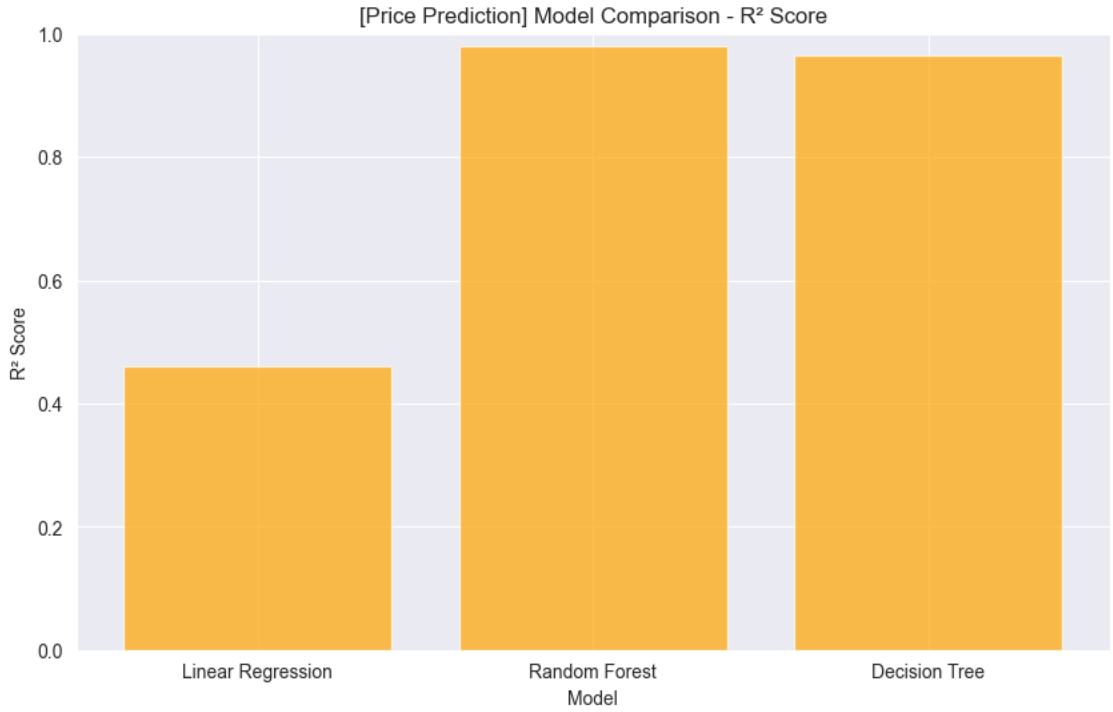
```
# Optional: Feature Importance
feature_importances = pd.DataFrame({
    'Feature': X_train_lyft.columns,
    'Importance': dt_model_lyft.feature_importances_
}).sort_values(by='Importance', ascending=False)

print("\nFeature Importances:")
print(feature_importances)
```

```
Decision Regressor Results for Lyft:
Mean Absolute Error (MAE): 1.0933652125825444
Mean Squared Error (MSE): 3.6335568018101054
R² Score: 0.963778093540916
Mean Absolute Percentage Error (MAPE): 7.84%
Model Accuracy (based on R²): 96.38%

Feature Importances:
                Feature  Importance
2              cab_type    0.746423
3              distance    0.160794
4      surge_multiplier    0.073585
12               minute    0.003466
5   apparentTemperature    0.002969
1           destination    0.002909
0                source    0.002287
11                 hour    0.002174
7          visibility.1    0.002118
8    precipIntensityMax    0.001402
9                    day    0.001229
6       precipIntensity    0.000530
10                 month    0.000115
```

[57]:
```
# Model Comparison for Lyft
# Define the models
models = ['Linear Regression', 'Random Forest', 'Decision Tree']

# Calculate MSE and R² values
mse_values = [
    mean_squared_error(y_test_lyft, y_pred_linear_lyft),
    mean_squared_error(y_test_lyft, y_pred_rf_lyft),
    mean_squared_error(y_test_lyft, y_pred_dt_lyft)
]
r2_values = [
    r2_score(y_test_lyft, y_pred_linear_lyft),
    r2_score(y_test_lyft, y_pred_rf_lyft),
```

```
    r2_score(y_test_lyft, y_pred_dt_lyft)
]

# Plot the MSE values
plt.figure(figsize=(10, 6))
plt.bar(models, mse_values, alpha=0.7, label='MSE')
plt.title('[Price Prediction] Model Comparison - Mean Squared Error (MSE)')
plt.ylabel('MSE')
plt.xlabel('Model')
plt.xticks(models)
plt.show()

# Plot the R² values
plt.figure(figsize=(10, 6))
plt.bar(models, r2_values, alpha=0.7, color='orange', label='R² Score')
plt.title('[Price Prediction] Model Comparison - R² Score')
plt.ylabel('R² Score')
plt.xlabel('Model')
plt.xticks(models)
plt.ylim(0, 1)  # R² ranges from 0 to 1
plt.show()
```





1.2 Model Usage Helper Functions

[58]:
```
# Features and target
X_func = golden_data[['cab_company', 'cab_type', 'surge_multiplier',␣
 ↪'distance']]
y_func = golden_data['price']

# Split the data into training and testing sets
X_train_func, X_test_func, y_train_func, y_test_func = train_test_split(X_func,␣
 ↪y_func, test_size=0.2, random_state=42)

# Initialize the RandomForestRegressor model
random_forest_model = RandomForestRegressor(n_estimators=100, random_state=42)

# Train the model
random_forest_model.fit(X_train_func, y_train_func)

# Make predictions on the test set
y_pred_func = random_forest_model.predict(X_test_func)

# Evaluate the model
mse = mean_squared_error(y_test_func, y_pred_func)
r2 = r2_score(y_test_func, y_pred_func)
```

```
print("Mean Squared Error (MSE):", mse)
print("R-squared (R2):", r2)

# Function to predict price based on 4 input features
def predict_cab_price(cab_company, cab_type, surge_multiplier, distance):
    # Map inputs to an array based on feature order
    x_input = [cab_company, cab_type, surge_multiplier, distance]
    return random_forest_model.predict([x_input])[0]

# Example usage to predict the price
cab_company = 0  # 0 for 'Uber'
cab_type = 1     # 1 for 'UberX'
surge_multiplier = 1.3
distance = 10.5

predicted_price = predict_cab_price(cab_company, cab_type, surge_multiplier,␣
 ↪distance)
print(f"Predicted Cab Price: ${predicted_price:.2f}")
```

```
Mean Squared Error (MSE): 2.7531933507446182
R-squared (R2): 0.9654965563062645
Predicted Cab Price: $20.18
```

```
/Users/amolbohora/NEU/CS6620/CS66220-Project/.venv/lib/python3.9/site-
packages/sklearn/base.py:493: UserWarning: X does not have valid feature names,
but RandomForestRegressor was fitted with feature names
  warnings.warn(
```

[ ]: