Food Delivery Time Prediction

```
# Get the list of installed packages
!pip freeze > requirements.txt
```

Import Libraries

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from geopy.distance import geodesic

%matplotlib inline

df = pd.read_csv('data.csv')
df.replace("NaN",np.nan,regex=True,inplace=True)
df.head()
```

```
        ID Delivery_person_ID Delivery_person_Age
Delivery_person_Ratings  \
0  0x4607     INDORES13DEL02                   37
4.9
1  0xb379     BANGRES18DEL02                   34
4.5
2  0x5d6d     BANGRES19DEL01                   23
4.4
3  0x7a6a    COIMBRES13DEL02                   38
4.7
4  0x70a2     CHENRES12DEL01                   32
4.6

   Restaurant_latitude  Restaurant_longitude
Delivery_location_latitude  \
0            22.745049             75.892471
22.765049
1            12.913041             77.683237
13.043041
2            12.914264             77.678400
12.924264
3            11.003669             76.976494
11.053669
4            12.972793             80.249982
13.012793

   Delivery_location_longitude  Order_Date Time_Orderd
Time_Order_picked  \
0                    75.912471  19-03-2022    11:30:00
```

```
11:45:00
1                    77.813237  25-03-2022    19:45:00
19:50:00
2                    77.688400  19-03-2022    08:30:00
08:45:00
3                    77.026494  05-04-2022    18:00:00
18:10:00
4                    80.289982  26-03-2022    13:30:00
13:45:00

       Weatherconditions Road_traffic_density  Vehicle_condition  \
0       conditions Sunny                High                  2
1      conditions Stormy                 Jam                  2
2  conditions Sandstorms                 Low                  0
3       conditions Sunny              Medium                  0
4      conditions Cloudy                High                  1

  Type_of_order Type_of_vehicle multiple_deliveries Festival
City  \
0        Snack      motorcycle                   0       No
Urban
1        Snack         scooter                   1       No
Metropolitian
2       Drinks      motorcycle                   1       No
Urban
3       Buffet      motorcycle                   1       No
Metropolitian
4        Snack         scooter                   1       No
Metropolitian

  Time_taken(min)
0        (min) 24
1        (min) 33
2        (min) 26
3        (min) 21
4        (min) 30
```

```
df.shape
```

```
(45593, 20)
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 45593 entries, 0 to 45592
Data columns (total 20 columns):
 #   Column                       Non-Null Count  Dtype
---  ------                       --------------  -----
 0   ID                           45593 non-null  object
 1   Delivery_person_ID           45593 non-null  object
```

```
 2   Delivery_person_Age          43739 non-null  object
 3   Delivery_person_Ratings      43685 non-null  object
 4   Restaurant_latitude          45593 non-null  float64
 5   Restaurant_longitude         45593 non-null  float64
 6   Delivery_location_latitude   45593 non-null  float64
 7   Delivery_location_longitude  45593 non-null  float64
 8   Order_Date                   45593 non-null  object
 9   Time_Orderd                  43862 non-null  object
 10  Time_Order_picked            45593 non-null  object
 11  Weatherconditions            44977 non-null  object
 12  Road_traffic_density         44992 non-null  object
 13  Vehicle_condition            45593 non-null  int64
 14  Type_of_order                45593 non-null  object
 15  Type_of_vehicle              45593 non-null  object
 16  multiple_deliveries          44600 non-null  object
 17  Festival                     45365 non-null  object
 18  City                         44393 non-null  object
 19  Time_taken(min)              45593 non-null  object
dtypes: float64(4), int64(1), object(15)
memory usage: 7.0+ MB
```

```
df['Delivery_person_Age'] = df['Delivery_person_Age'].astype(float)
df['Delivery_person_Ratings'] =
df['Delivery_person_Ratings'].astype(float)
```

```
df.describe()
```

```
       Delivery_person_Age  Delivery_person_Ratings
Restaurant_latitude  \
count         43739.000000             43685.000000
45593.000000
mean             29.567137                 4.633780
17.017729
std               5.815155                 0.334716
8.185109
min              15.000000                 1.000000            -
30.905562
25%              25.000000                 4.500000
12.933284
50%              30.000000                 4.700000
18.546947
75%              35.000000                 4.900000
22.728163
max              50.000000                 6.000000
30.914057

       Restaurant_longitude  Delivery_location_latitude  \
count          45593.000000                45593.000000
mean              70.231332                   17.465186
std               22.883647                    7.335122
```

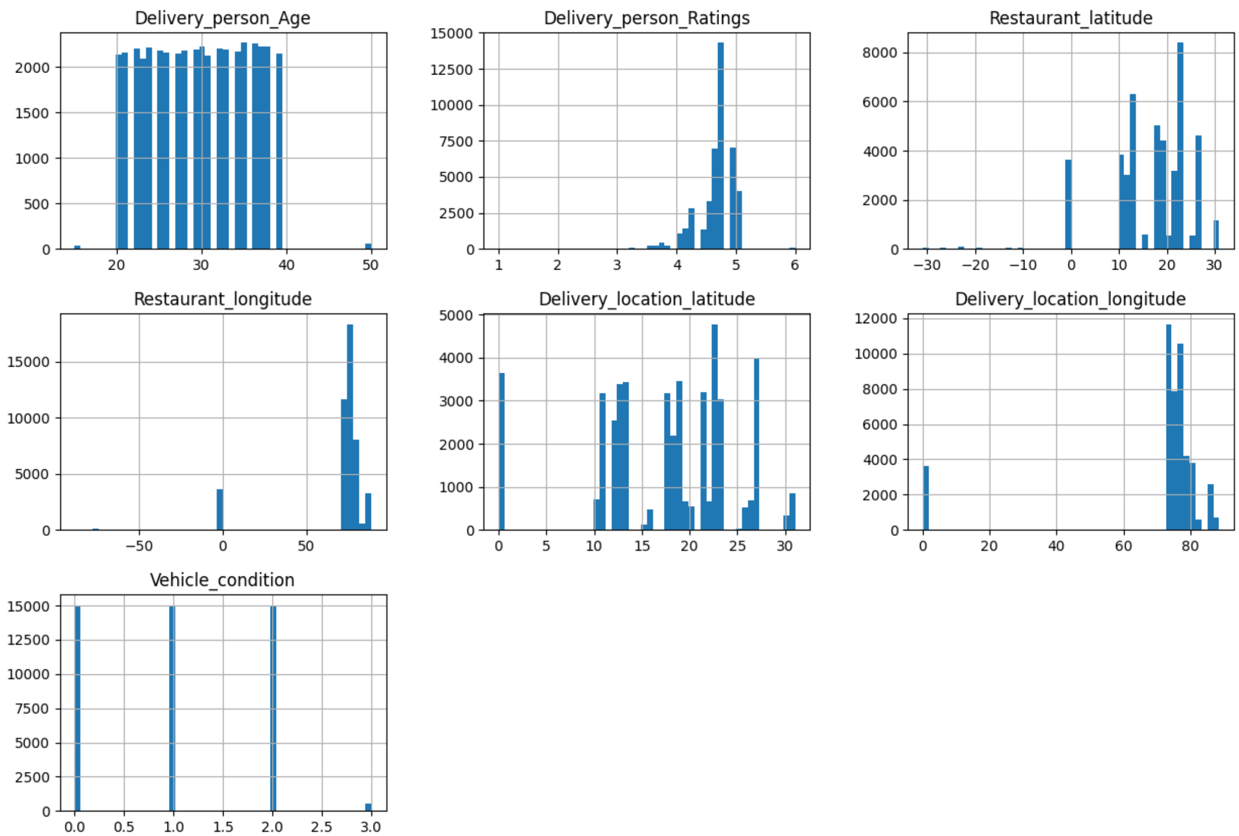
```
min               -88.366217                         0.010000
25%                73.170000                        12.988453
50%                75.898497                        18.633934
75%                78.044095                        22.785049
max                88.433452                        31.054057

       Delivery_location_longitude  Vehicle_condition
count                 45593.000000       45593.000000
mean                     70.845702           1.023359
std                      21.118812           0.839065
min                       0.010000           0.000000
25%                      73.280000           0.000000
50%                      76.002574           1.000000
75%                      78.107044           2.000000
max                      88.563452           3.000000
```

```
df.isnull().sum()
```

```
ID                                0
Delivery_person_ID                0
Delivery_person_Age            1854
Delivery_person_Ratings        1908
Restaurant_latitude               0
Restaurant_longitude              0
Delivery_location_latitude        0
Delivery_location_longitude       0
Order_Date                        0
Time_Orderd                    1731
Time_Order_picked                 0
Weatherconditions               616
Road_traffic_density            601
Vehicle_condition                 0
Type_of_order                     0
Type_of_vehicle                   0
multiple_deliveries             993
Festival                        228
City                           1200
Time_taken(min)                   0
dtype: int64
```

EDA

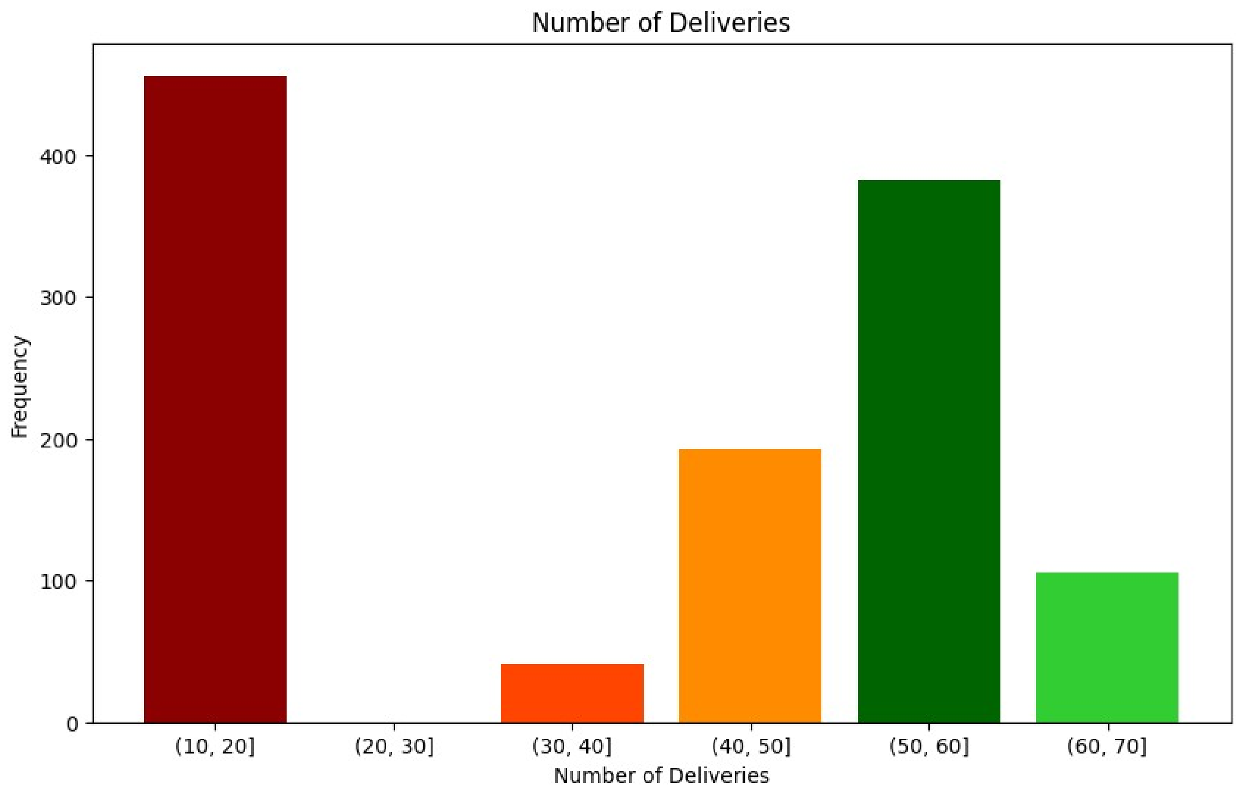
```
df.hist(bins=50, figsize=(15, 10))
plt.show()
```



Delivery_Person_ID

```
df['Delivery_person_ID'].value_counts()

PUNERES01DEL01     67
JAPRES11DEL02      67
HYDRES04DEL02      66
JAPRES03DEL01      66
VADRES11DEL02      66
                   ..
DEHRES18DEL03       7
AURGRES11DEL03      7
KOLRES09DEL03       6
KOCRES16DEL03       6
BHPRES010DEL03      5
Name: Delivery_person_ID, Length: 1320, dtype: int64

delivery_person_counts = df['Delivery_person_ID'].value_counts()

delivery_categories = pd.cut(delivery_person_counts, bins=range(10,
71, 10))
category_counts = delivery_categories.value_counts().sort_index()

plt.figure(figsize=(10, 6))
colors = ['darkred', 'salmon', 'orangered', 'darkorange', 'darkgreen',
```

```
'limegreen']
plt.bar(category_counts.index.astype(str), category_counts.values,
color=colors)
plt.title('Number of Deliveries')
plt.xlabel('Number of Deliveries')
plt.ylabel('Frequency')
plt.show()
```

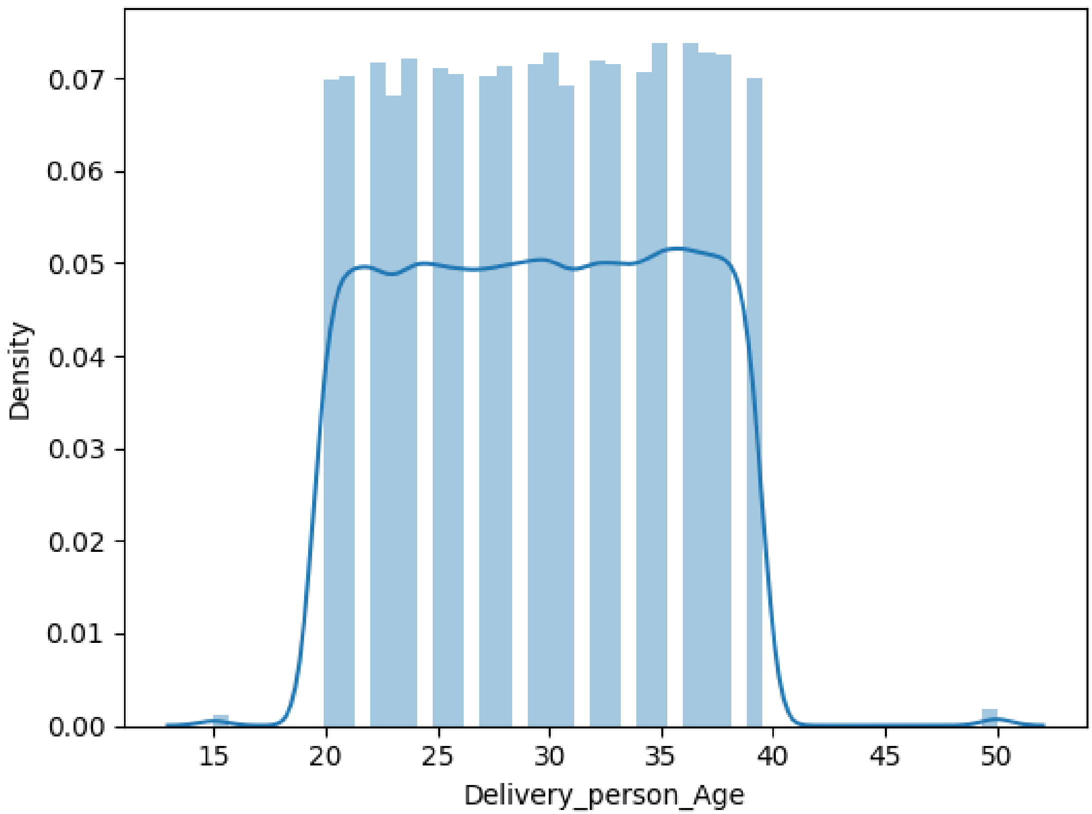


- More than 400 person delivered 10 to 20 numbers of deliveries.

Delivery Person Age

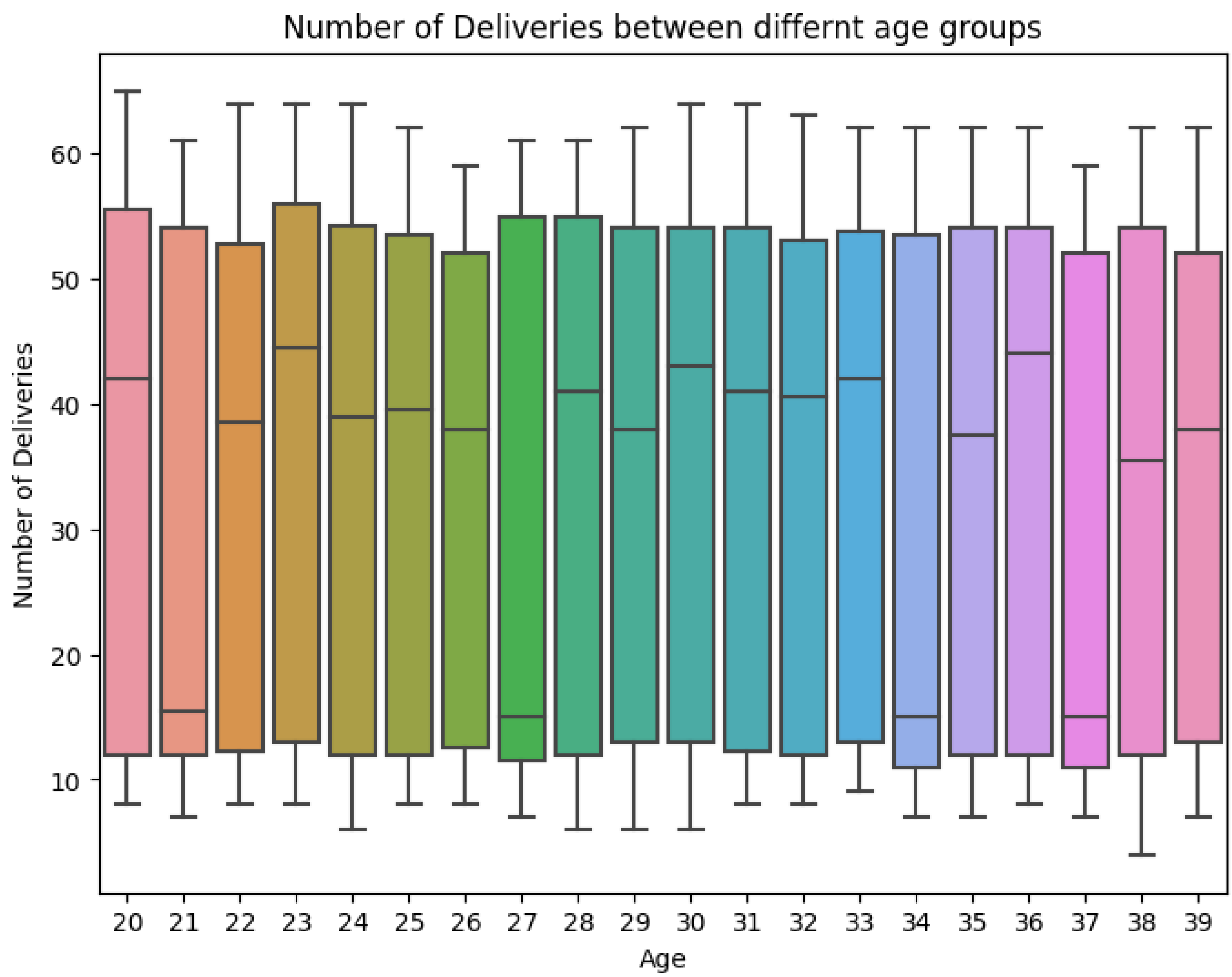
```
sns.distplot(df['Delivery_person_Age'])
plt.show()

<ipython-input-13-18ba03e5e2e6>:1: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn
v0.14.0.

Please adapt your code to use either `displot` (a figure-level
function with
similar flexibility) or `histplot` (an axes-level function for
histograms).
```

```
For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(df['Delivery_person_Age'])
```



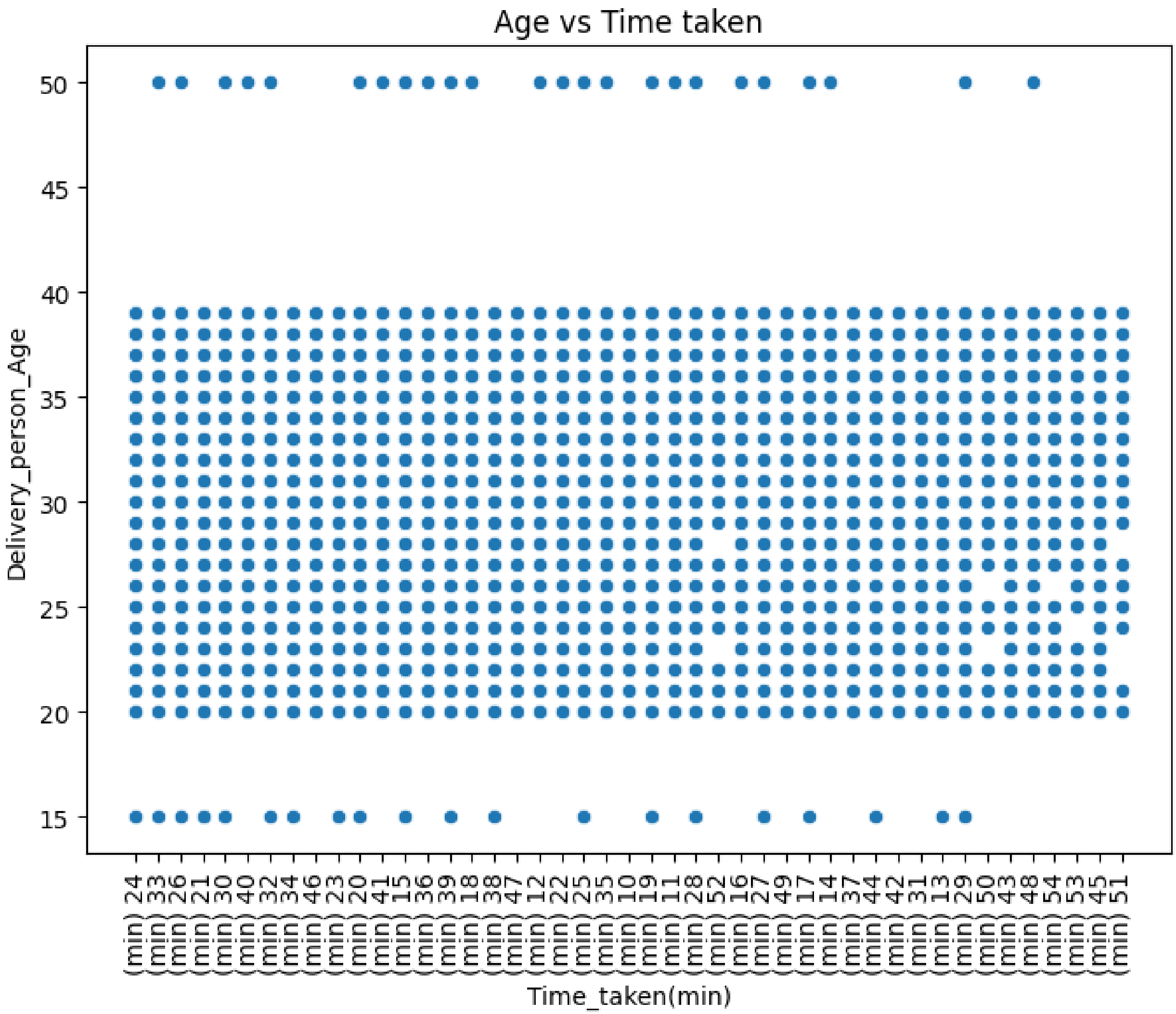
- Almost uniform distribution from range 20-40.

```
deliveries_by_person_df =
pd.DataFrame(df.groupby('Delivery_person_ID')
['Delivery_person_Age'].count())
deliveries_by_person_df = deliveries_by_person_df.rename(columns =
{'Delivery_person_Age': 'Number_of_Deliveries'})
deliveries_by_person_df['Delivery_person_Age'] =
df.groupby('Delivery_person_ID')
['Delivery_person_Age'].first().astype(int)
# deliveries_by_person_df

plt.figure(figsize=(8, 6))
sns.boxplot(data=deliveries_by_person_df, x='Delivery_person_Age',
y='Number_of_Deliveries')
plt.title("Number of Deliveries between differnt age groups")
plt.xlabel("Age")
plt.ylabel("Number of Deliveries")
plt.show()
```



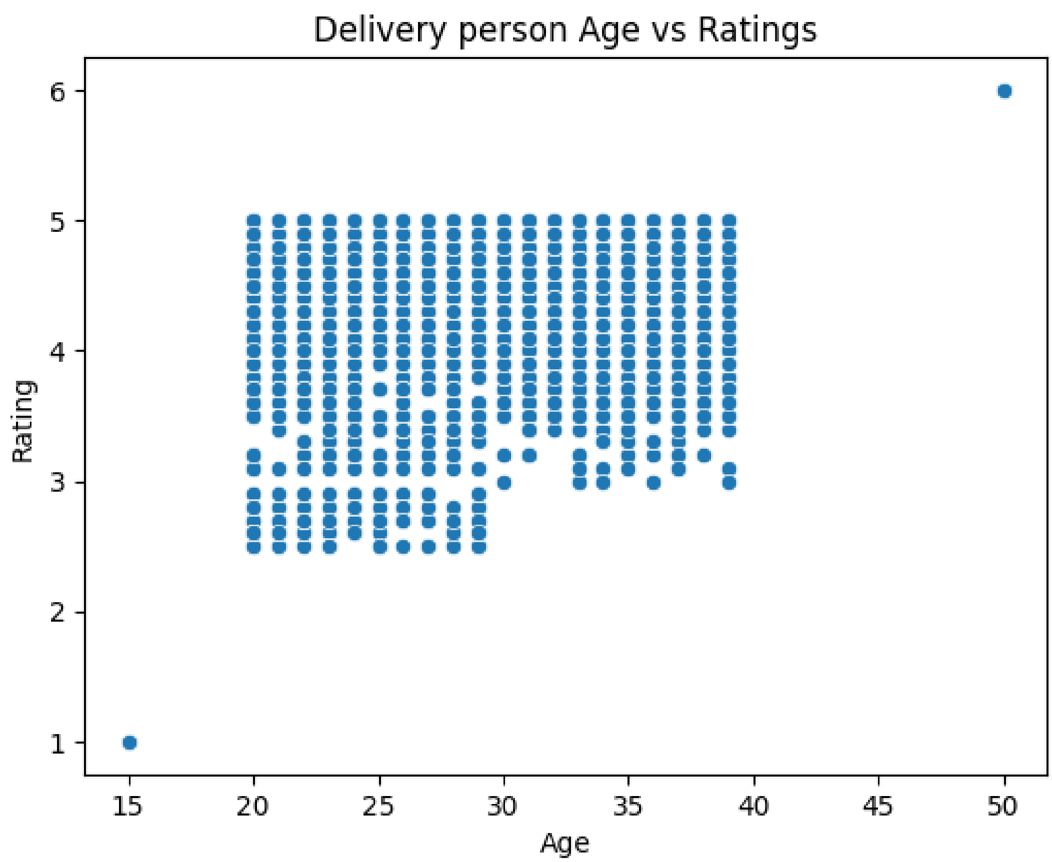
- Age group of 21, 27, 34, 37 has the lower average number of deliveries compared to other age groups.

```
plt.figure(figsize=(8, 6))
sns.scatterplot(y=df['Delivery_person_Age'], x=df['Time_taken(min)'])
plt.xticks(rotation=90)
plt.title('Age vs Time taken')
plt.show()
```



- There is not correlation between Delivery Person's Age and Time taken to deliver the food.

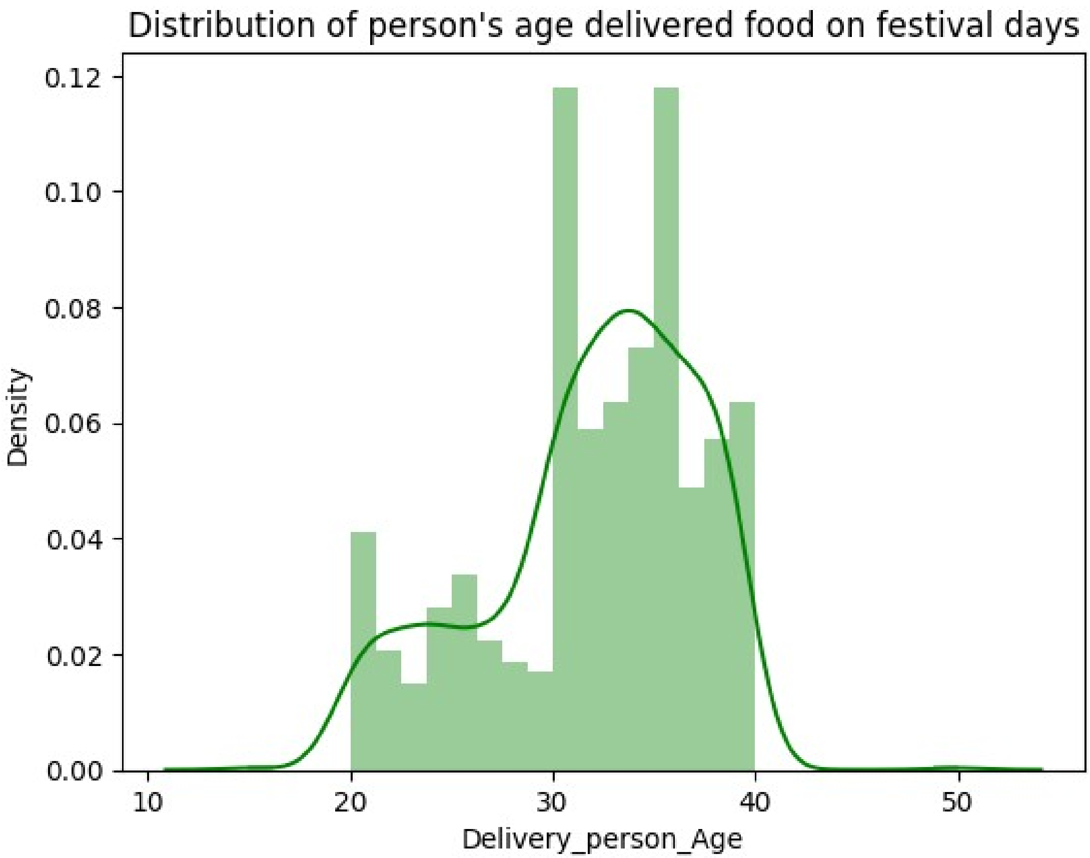
```
sns.scatterplot(x=df['Delivery_person_Age'],
y=df['Delivery_person_Ratings'])
plt.title("Delivery person Age vs Ratings")
plt.xlabel("Age")
plt.ylabel("Rating")
plt.show()
```



- There is a person with the age of 15 delivering the food, which is an outlier.

```
festival_age = df[df['Festival'].str.strip().str.lower() == 'yes']
['Delivery_person_Age']
sns.distplot(festival_age, color='green')
plt.title("Distribution of person's age delivered food on festival
days")
plt.show()
```

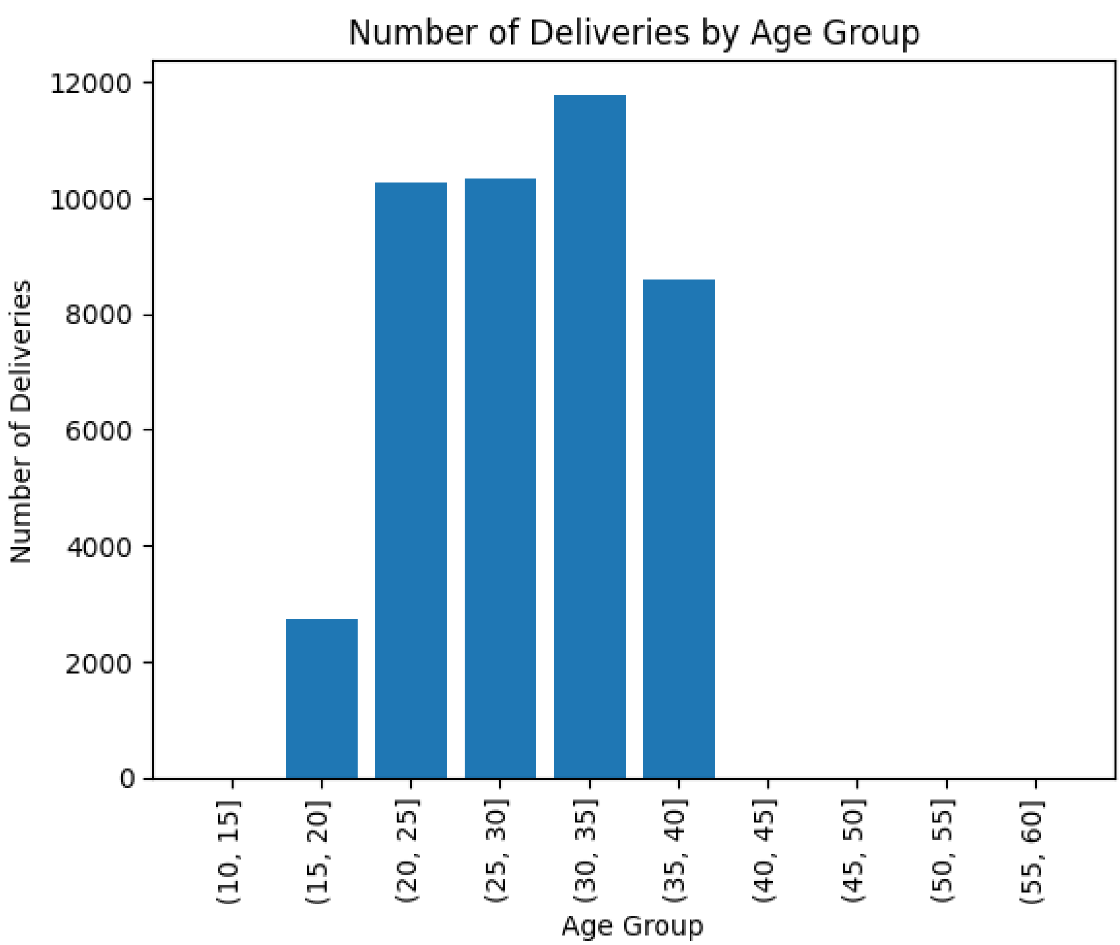
```
<ipython-input-17-a6ae4eb94752>:2: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn
v0.14.0.

Please adapt your code to use either `displot` (a figure-level
function with
similar flexibility) or `histplot` (an axes-level function for
histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(festival_age, color='green')
```



- Most of the people in age range of 30-40 do deliveries during festival, where range 20-30 decreases during that time.

```
deliveries_by_person_df

                    Number_of_Deliveries  Delivery_person_Age
Delivery_person_ID
AGRRES010DEL01                        13                   34
AGRRES010DEL02                        14                   37
AGRRES010DEL03                        13                   33
AGRRES01DEL01                          9                   34
AGRRES01DEL02                         14                   24
...                                  ...                  ...
VADRES19DEL02                         58                   38
VADRES19DEL03                         38                   29
VADRES20DEL01                         56                   34
VADRES20DEL02                         49                   36
VADRES20DEL03                         34                   35

[1320 rows x 2 columns]

deliveries_by_person_df =
pd.DataFrame(df.groupby('Delivery_person_ID')
['Delivery_person_Age'].count())
```

```
deliveries_by_person_df = deliveries_by_person_df.rename(columns =
{'Delivery_person_Age': 'Number_of_Deliveries'})
deliveries_by_person_df['Delivery_person_Age'] =
df.groupby('Delivery_person_ID')
['Delivery_person_Age'].first().astype(int)

age_bins = [10, 15, 20, 25, 30, 35, 40, 45, 50, 55, 60]
deliveries_by_person_df['Delivery_Person_Age_group'] =
pd.cut(deliveries_by_person_df['Delivery_person_Age'], bins=age_bins)
deliveries_by_age_group =
deliveries_by_person_df.groupby('Delivery_Person_Age_group')
['Number_of_Deliveries'].sum()
plt.bar(deliveries_by_age_group.index.astype(str),
deliveries_by_age_group)

plt.xlabel('Age Group')
plt.ylabel('Number of Deliveries')
plt.title('Number of Deliveries by Age Group')
plt.xticks(rotation=90)
plt.show()
```



- Most of the deliveries are made by age range of (30, 35) followed by age range of (25, 30) and (20, 25).

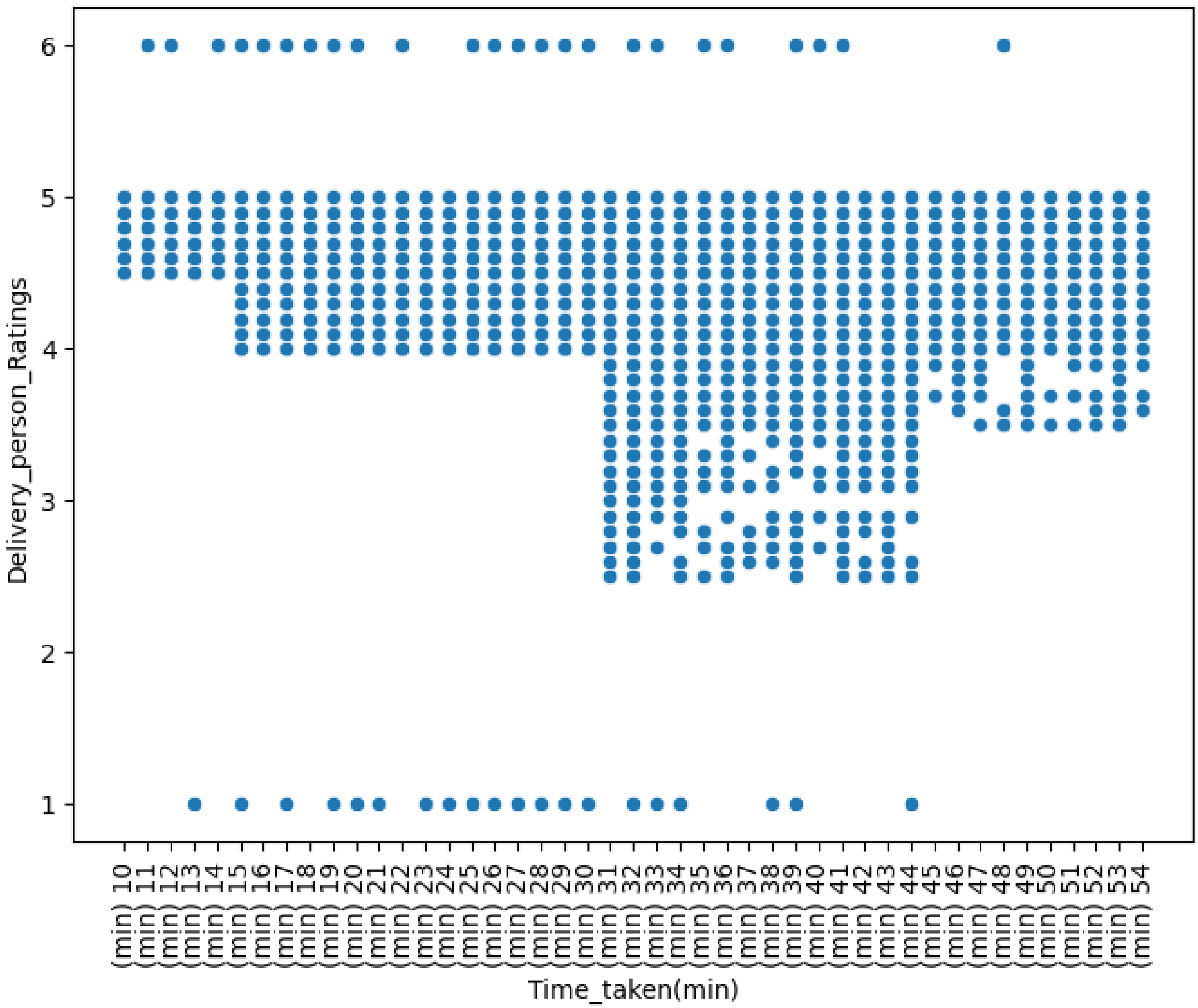
Delivery Person Ratings

```
plt.figure(figsize=(8, 6))
sns.distplot(df['Delivery_person_Ratings'], bins=10)
plt.title('Distribution of Delivery person rating')
plt.show()
```

```
<ipython-input-20-17e346c115bd>:2: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn
v0.14.0.

Please adapt your code to use either `displot` (a figure-level
function with
similar flexibility) or `histplot` (an axes-level function for
histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(df['Delivery_person_Ratings'], bins=10)
```

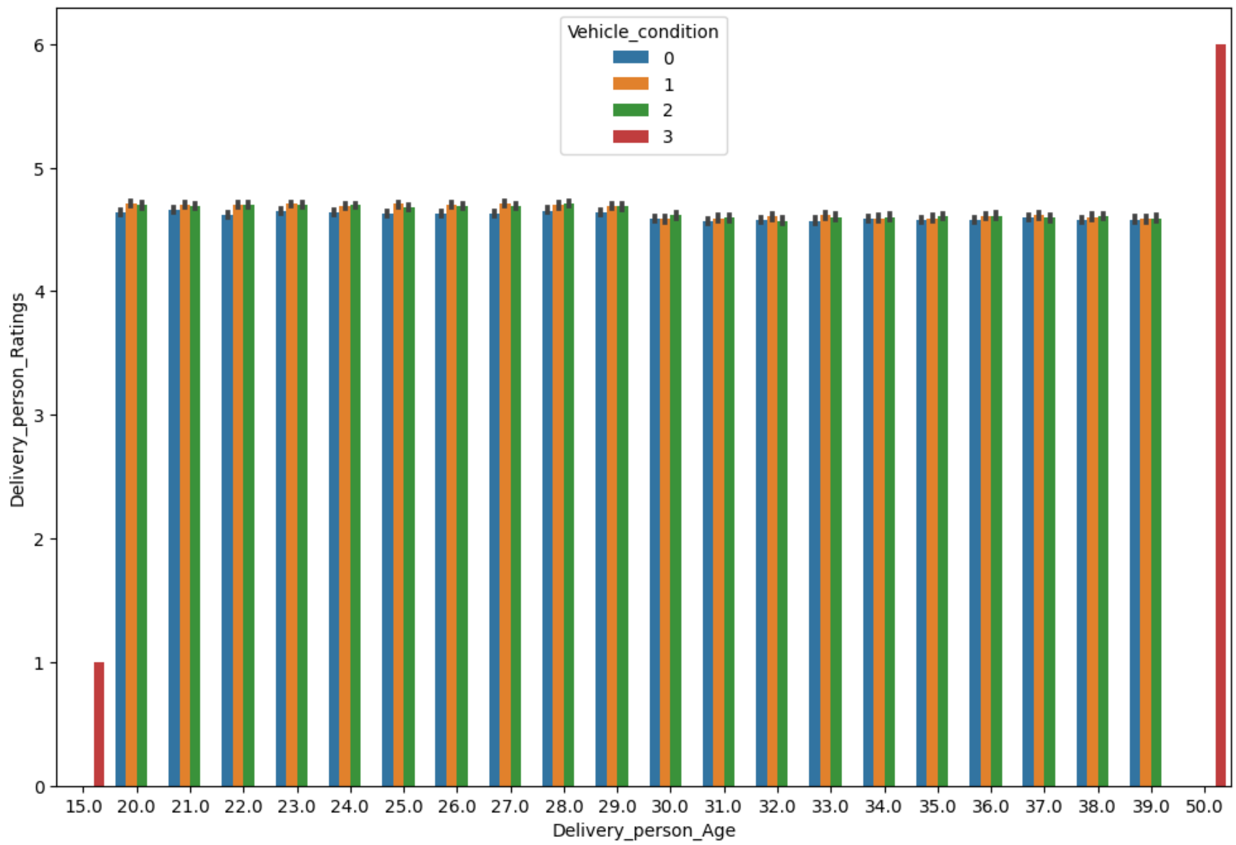
- Most of the delivery person has rating between 4 and 5.
- There is a person with rating of 6. We can consider it as an outlier.

```
plt.figure(figsize=(8, 6))
sorted_df = df.sort_values('Time_taken(min)')
sns.scatterplot(y=sorted_df['Delivery_person_Ratings'],
x=sorted_df['Time_taken(min)'])
plt.xticks(rotation=90)
plt.show()
```



- There is no correlation between person's rating and time taken to deliver the food.

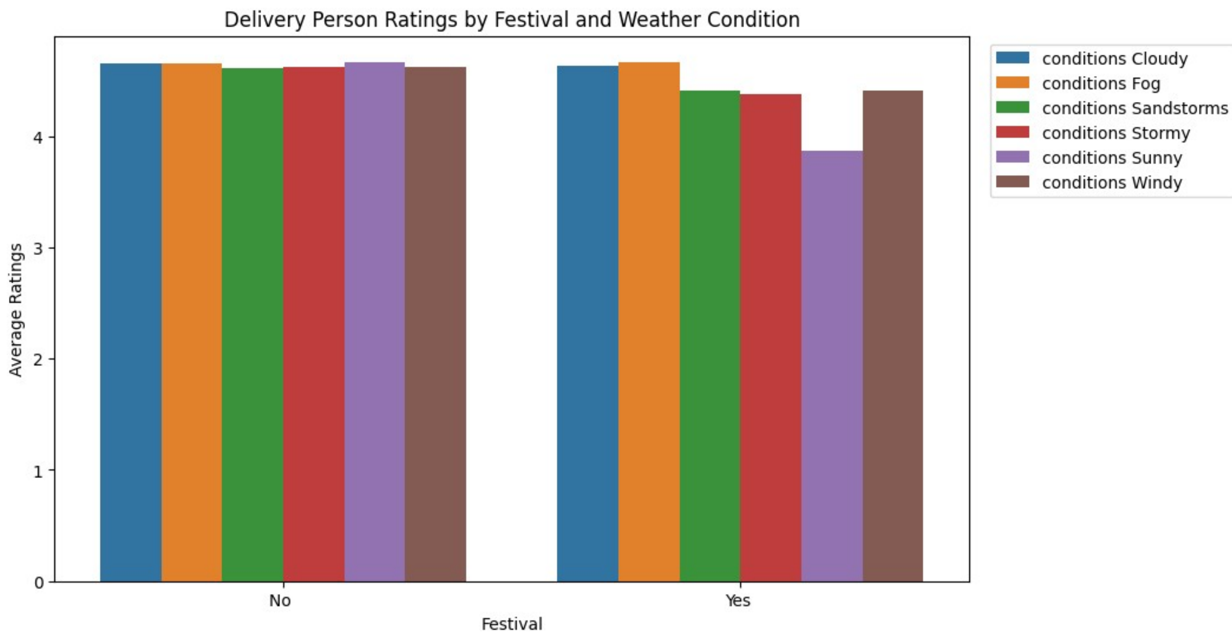
```
plt.figure(figsize=(12, 8))
sns.barplot(x=df['Delivery_person_Age'],
y=df['Delivery_person_Ratings'], hue=df['Vehicle_condition'])
plt.show()
```



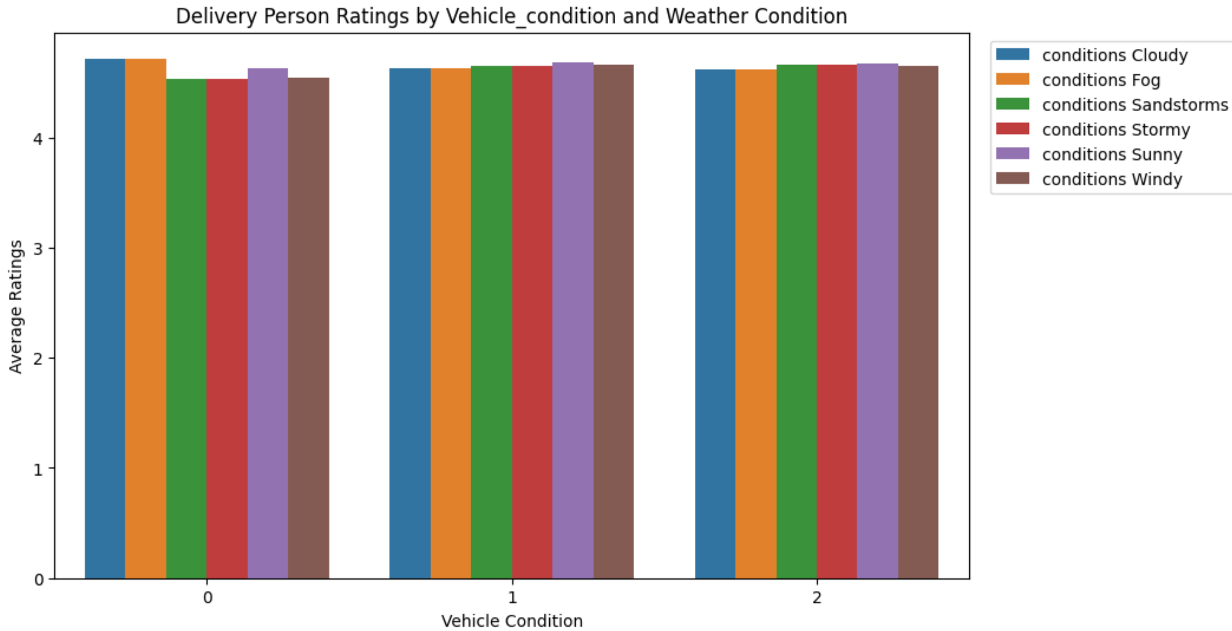
- Vehicle condition does not influence the delivery person ratings.

```
# df['Delivery_person_Age'].value_counts()
# grouped_ratings = df.groupby(['Festival', 'City'])
['Delivery_person_Ratings'].mean().reset_index()

# plt.figure(figsize=(10, 6))
# sns.barplot(data=grouped_ratings, x='Festival',
y='Delivery_person_Ratings', hue='City')
# plt.title('Delivery Person Ratings by Festival and City')
# plt.xlabel('Festival')
# plt.ylabel('Average Ratings')
# plt.legend(title='City')
# plt.show()

grouped_ratings = df.groupby(['Festival', 'Weatherconditions'])
['Delivery_person_Ratings'].mean().reset_index()

plt.figure(figsize=(10, 6))
sns.barplot(data=grouped_ratings, x='Festival',
y='Delivery_person_Ratings', hue='Weatherconditions')
plt.title('Delivery Person Ratings by Festival and Weather Condition')
plt.xlabel('Festival')
plt.ylabel('Average Ratings')
```

```
plt.legend(loc='upper right', bbox_to_anchor=(1.3, 1))
plt.show()
```

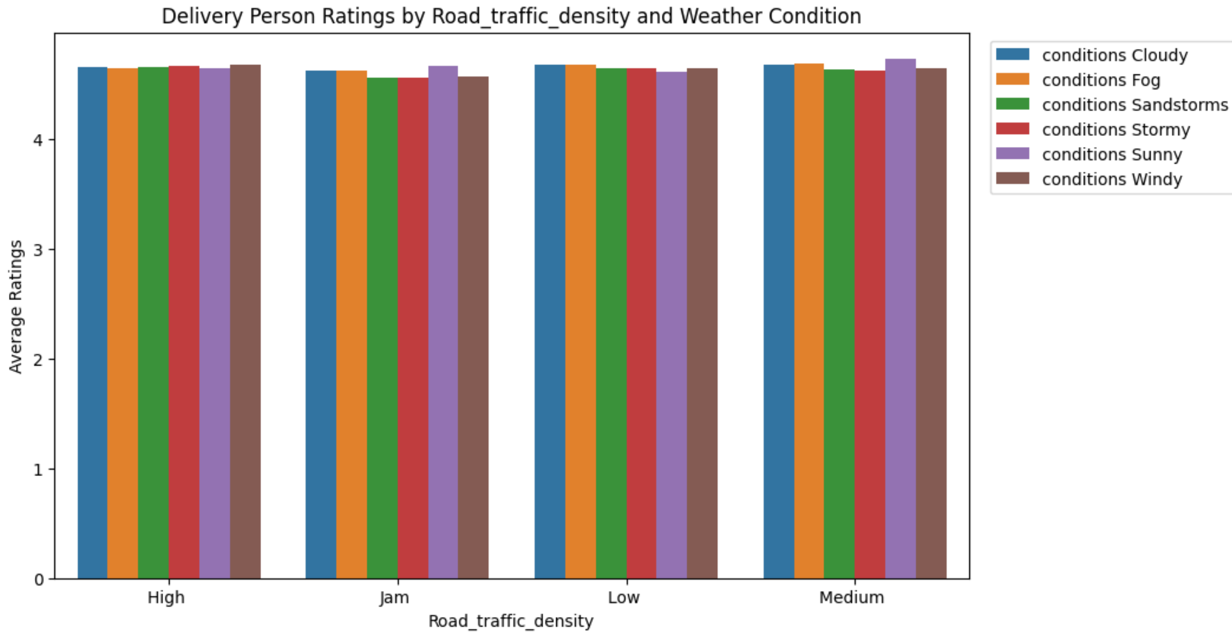



```
grouped_ratings = df.groupby(['Vehicle_condition',
'Weatherconditions'])['Delivery_person_Ratings'].mean().reset_index()

plt.figure(figsize=(10, 6))
sns.barplot(data=grouped_ratings, x='Vehicle_condition',
y='Delivery_person_Ratings', hue='Weatherconditions')
plt.title('Delivery Person Ratings by Vehicle_condition and Weather
Condition')
plt.xlabel('Vehicle Condition')
plt.ylabel('Average Ratings')
plt.legend(loc='upper right', bbox_to_anchor=(1.3, 1))
plt.show()
```



- Vehicle condition and Weather Condition does not effect the Delivery person rating.

```
grouped_ratings = df.groupby(['Road_traffic_density',
'Weatherconditions'])['Delivery_person_Ratings'].mean().reset_index()

plt.figure(figsize=(10, 6))
sns.barplot(data=grouped_ratings, x='Road_traffic_density',
y='Delivery_person_Ratings', hue='Weatherconditions')
plt.title('Delivery Person Ratings by Road_traffic_density and Weather
Condition')
plt.xlabel('Road_traffic_density')
plt.ylabel('Average Ratings')
plt.legend(loc='upper right', bbox_to_anchor=(1.3, 1))
plt.show()
```



- Road traffic density and Weather Condition does not influence the delivery person rating.

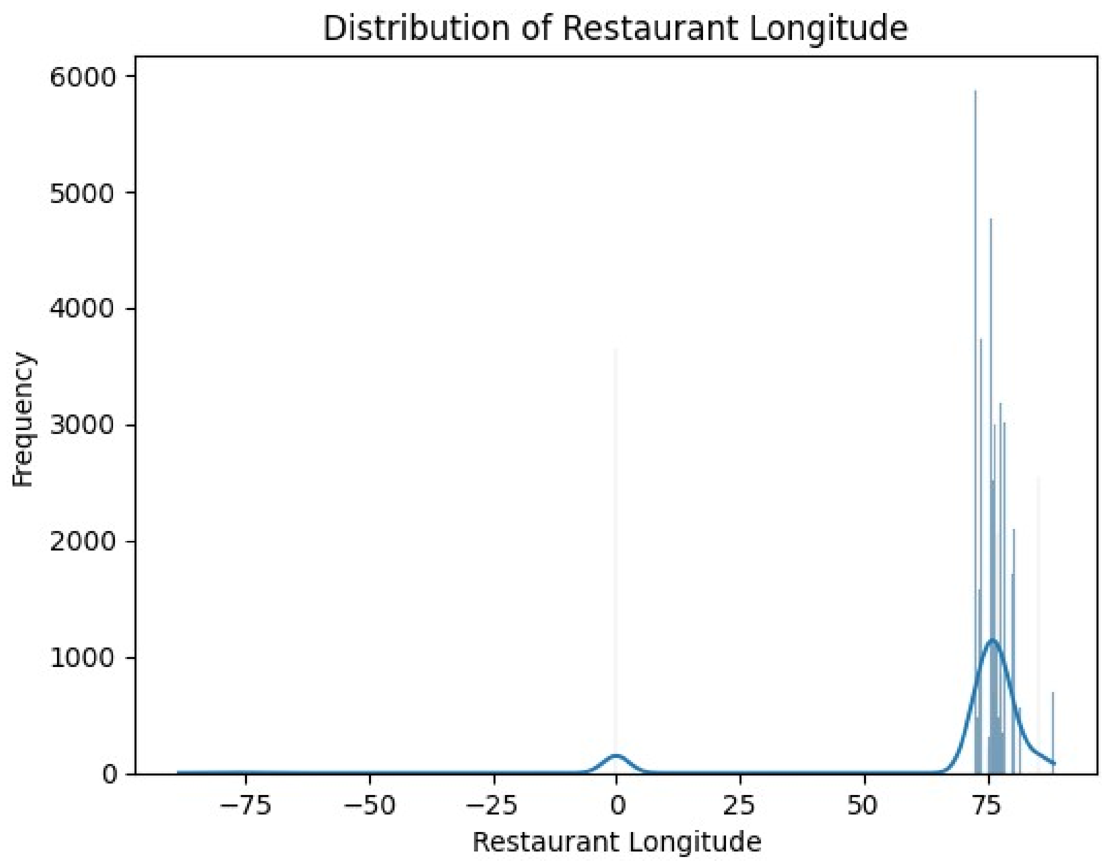
```
plt.figure(figsize=(15, 7))
temp = df.groupby(['Delivery_person_Ratings'])
['Time_taken(min)'].value_counts().sort_index().reset_index(name='Coun
t')
temp['Time_taken(min)_grouped'] = temp['Time_taken(min)'].str.split("
", expand=True)[1]

time_bins = [10, 20, 30, 40, 50, 60]
temp['Time_taken(min)_grouped'] =
pd.to_numeric(temp['Time_taken(min)_grouped'], errors='coerce')
temp['Time_taken(min)_grouped'] =
pd.cut(temp['Time_taken(min)_grouped'], bins=time_bins)
sns.barplot(x=temp['Delivery_person_Ratings'], y=temp['Count'],
hue=temp['Time_taken(min)_grouped'])
plt.legend(loc='upper right', bbox_to_anchor=(1.1, 1))
plt.xticks(rotation=90)
plt.title('Delivery person rating based on time taken for delivery')
plt.show()
```

- Delivery person with the low delivery time has higher delivery person rating.

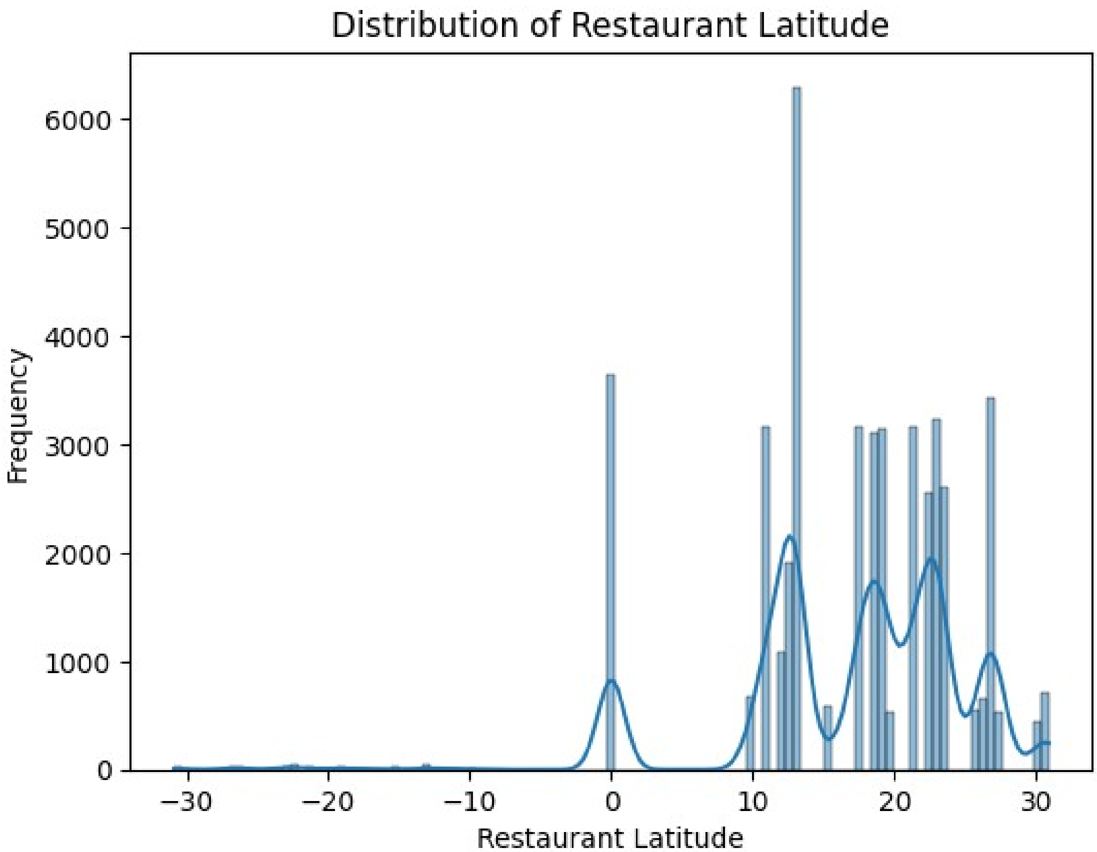
Restaurant Location Longitude and Latitude

```
# Check for missing, zero, and NaN values in Restaurant longitude and
latitude
missing_longitude = df['Restaurant_longitude'].isnull().sum()
missing_latitude = df['Restaurant_latitude'].isnull().sum()
zero_longitude = (df['Restaurant_longitude'] == 0).sum()
zero_latitude = (df['Restaurant_latitude'] == 0).sum()
nan_longitude = np.isnan(df['Restaurant_longitude']).sum()
nan_latitude = np.isnan(df['Restaurant_latitude']).sum()

print(f"Missing Restaurant longitude values: {missing_longitude}")
print(f"Missing Restaurant latitude values: {missing_latitude}")
print(f"Zero Restaurant longitude values: {zero_longitude}")
print(f"Zero Restaurant latitude values: {zero_latitude}")
print(f"NaN Restaurant longitude values: {nan_longitude}")
print(f"NaN Restaurant latitude values: {nan_latitude}")

Missing Restaurant longitude values: 0
Missing Restaurant latitude values: 0
Zero Restaurant longitude values: 3640
Zero Restaurant latitude values: 3640
NaN Restaurant longitude values: 0
NaN Restaurant latitude values: 0

# Visualize the distribution of Restaurant longitude
sns.histplot(df['Restaurant_longitude'], kde=True)
plt.xlabel('Restaurant Longitude')
plt.ylabel('Frequency')
```

```
plt.title('Distribution of Restaurant Longitude')
plt.show()
```




```
# Visualize the distribution of Restaurant latitude
sns.histplot(df['Restaurant_latitude'], kde=True)
plt.xlabel('Restaurant Latitude')
plt.ylabel('Frequency')
plt.title('Distribution of Restaurant Latitude')
plt.show()
```




```
# Scatter plot of Restaurant locations
plt.scatter(df['Restaurant_longitude'], df['Restaurant_latitude'])
plt.xlabel('Restaurant Longitude')
plt.ylabel('Restaurant Latitude')
plt.title('Scatter Plot of Restaurant Locations')
plt.show()
```

- Latitude and Longitude with negative values are considered as outliers.

```
!pip install folium

Requirement already satisfied: folium in
/usr/local/lib/python3.10/dist-packages (0.14.0)
Requirement already satisfied: branca>=0.6.0 in
/usr/local/lib/python3.10/dist-packages (from folium) (0.6.0)
Requirement already satisfied: jinja2>=2.9 in
/usr/local/lib/python3.10/dist-packages (from folium) (3.1.2)
Requirement already satisfied: numpy in
/usr/local/lib/python3.10/dist-packages (from folium) (1.23.5)
Requirement already satisfied: requests in
/usr/local/lib/python3.10/dist-packages (from folium) (2.31.0)
Requirement already satisfied: MarkupSafe>=2.0 in
/usr/local/lib/python3.10/dist-packages (from jinja2>=2.9->folium)
(2.1.3)
Requirement already satisfied: charset-normalizer<4,>=2 in
/usr/local/lib/python3.10/dist-packages (from requests->folium)
(3.2.0)
Requirement already satisfied: idna<4,>=2.5 in
/usr/local/lib/python3.10/dist-packages (from requests->folium) (3.4)
Requirement already satisfied: urllib3<3,>=1.21.1 in
/usr/local/lib/python3.10/dist-packages (from requests->folium)
```

```
(1.26.16)
Requirement already satisfied: certifi>=2017.4.17 in
/usr/local/lib/python3.10/dist-packages (from requests->folium)
(2023.7.22)
```

```
import folium
from folium.plugins import HeatMap

map = df[['Restaurant_longitude',
'Restaurant_latitude','Delivery_location_longitude',
'Delivery_location_latitude']]
map = map[(map['Restaurant_latitude'] > 0) &
(map['Restaurant_longitude'] > 0)]

restaurant_map = map[['Restaurant_latitude',
'Restaurant_longitude']].value_counts().sort_index().reset_index(name=
'Count')
# # restaurant_map
# bounds = [[22.699358, 88.563452], [108.22, 122.1290]]
m = folium.Map(location=[20.5937, 78.9629], zoom_start=5)
HeatMap(data=restaurant_map[['Restaurant_latitude',
'Restaurant_longitude', 'Count']]).add_to(m)
m
```

```
<folium.folium.Map at 0x7cbb7e64b100>
```

Restaurant location plays an important role in deciding the time needed for delivery. Restaurant in busy locations are more affected by traffic conditions.

Delivery Location Longitude and Latitude

```
# Delivery location Map
Delivery_map = map[['Delivery_location_latitude',
'Delivery_location_longitude']].value_counts().sort_index().reset_inde
x(name='Count')
m = folium.Map(location=[20.5937, 78.9629], zoom_start=5)
# m.fit_bounds(bounds)
HeatMap(data=Delivery_map[['Delivery_location_latitude',
'Delivery_location_longitude', 'Count']]).add_to(m)
m
```

```
<folium.folium.Map at 0x7cbb7b0a6890>
```

- Delivery location plays an important role in deciding the time needed for delivery. Delivery in busy locations are more affected by traffic conditions.

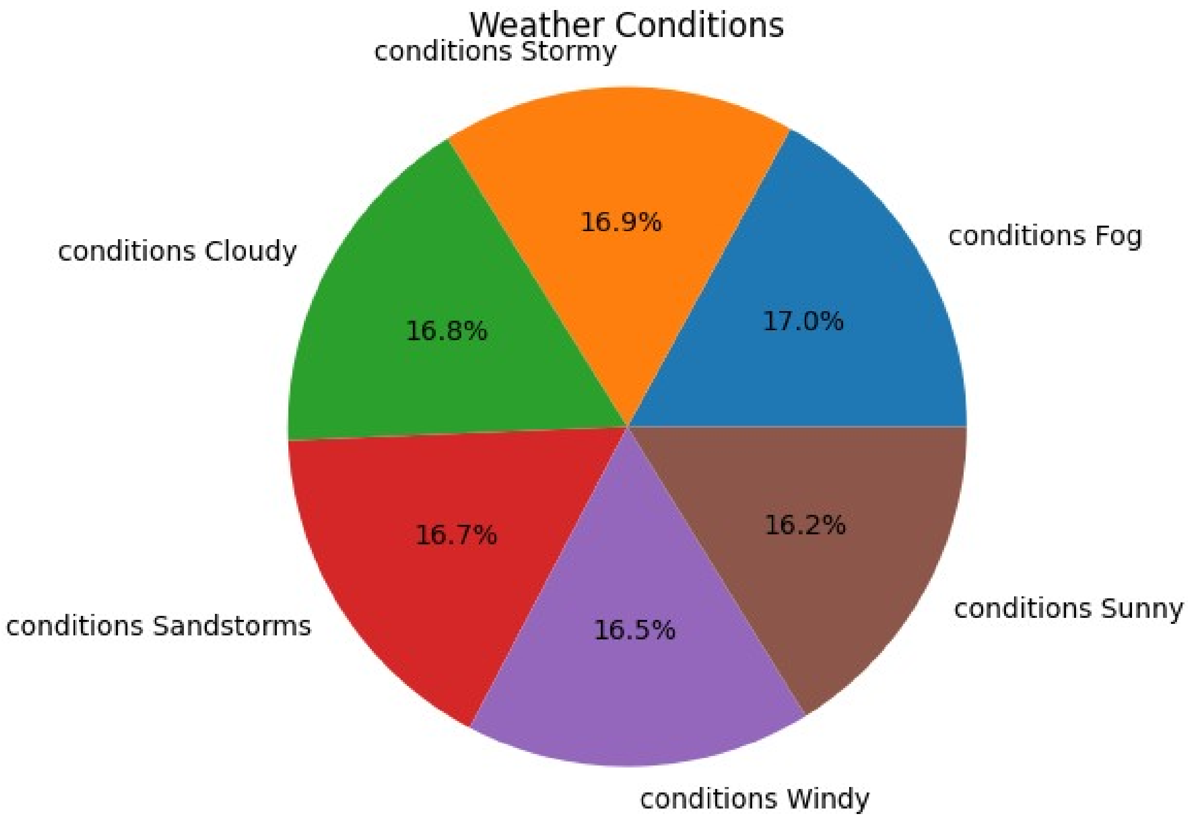
```
restaurant_map
```

	Restaurant_latitude	Restaurant_longitude	Count
0	9.957144	76.296783	41

```
1              9.959778           76.296106     39
2              9.960846           76.293936     27
3              9.966783           76.242981     31
4              9.970717           76.285447     30
..                  ...                 ...    ...
383           30.899584           75.809346     41
384           30.899992           75.831338     38
385           30.902872           75.826808     32
386           30.905562           75.832841     37
387           30.914057           75.839820     42

[388 rows x 3 columns]

Delivery_map

      Delivery_location_latitude  Delivery_location_longitude  Count
0                       9.967144                    76.306783      4
1                       9.969778                    76.306106      3
2                       9.970846                    76.303936      2
3                       9.976783                    76.252981      2
4                       9.977144                    76.316783      4
...                          ...                          ...    ...
4355                   31.039992                    75.971338      3
4356                   31.042872                    75.966808      2
4357                   31.044057                    75.969820      4
4358                   31.045562                    75.972841      3
4359                   31.054057                    75.979820      3

[4360 rows x 3 columns]
```

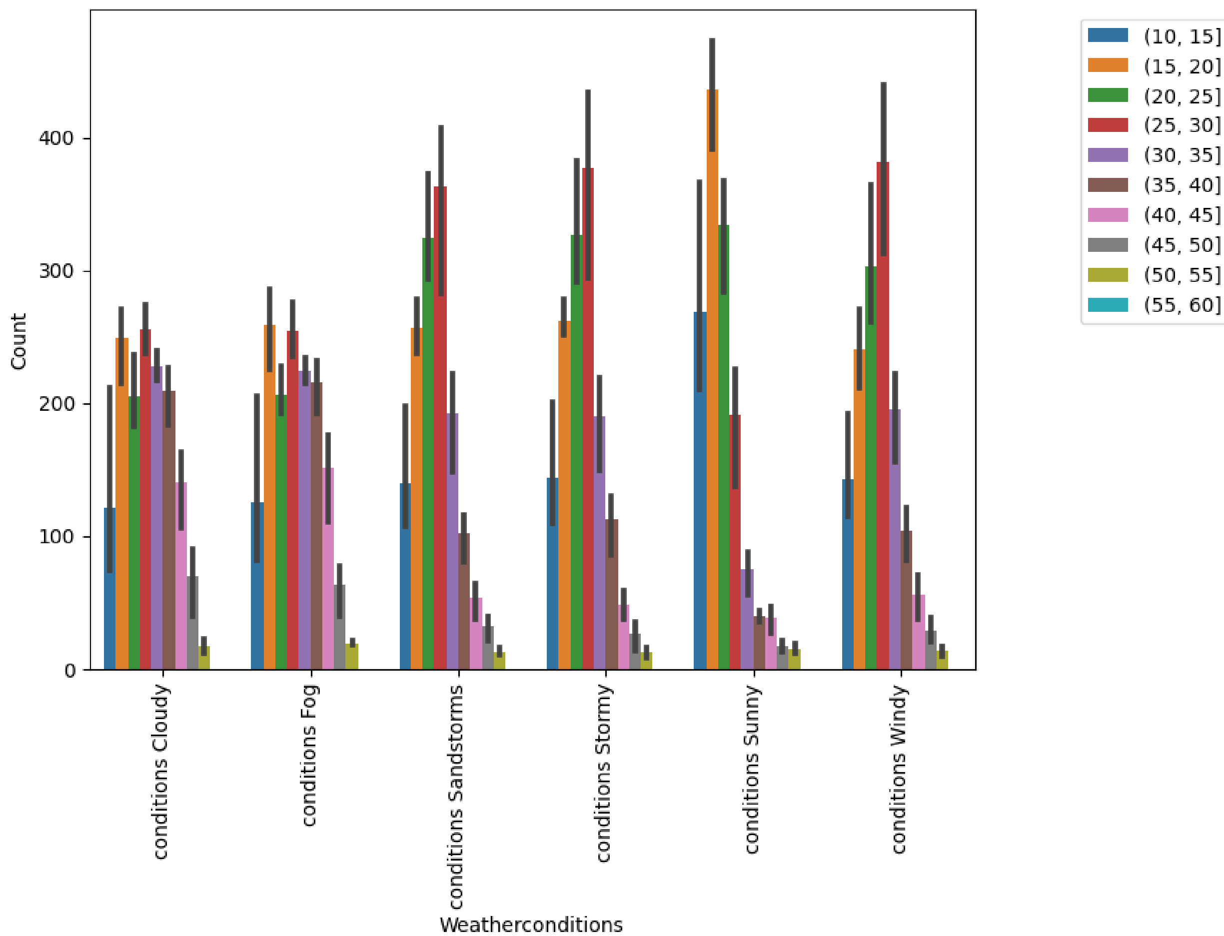
Weather Condition

```python
plt.figure(figsize=(6, 5))
value_counts = df['Weatherconditions'].value_counts()
plt.pie(value_counts, labels=value_counts.index, autopct='%1.1f%%')
plt.axis('equal')
plt.title('Weather Conditions')
plt.show()
```



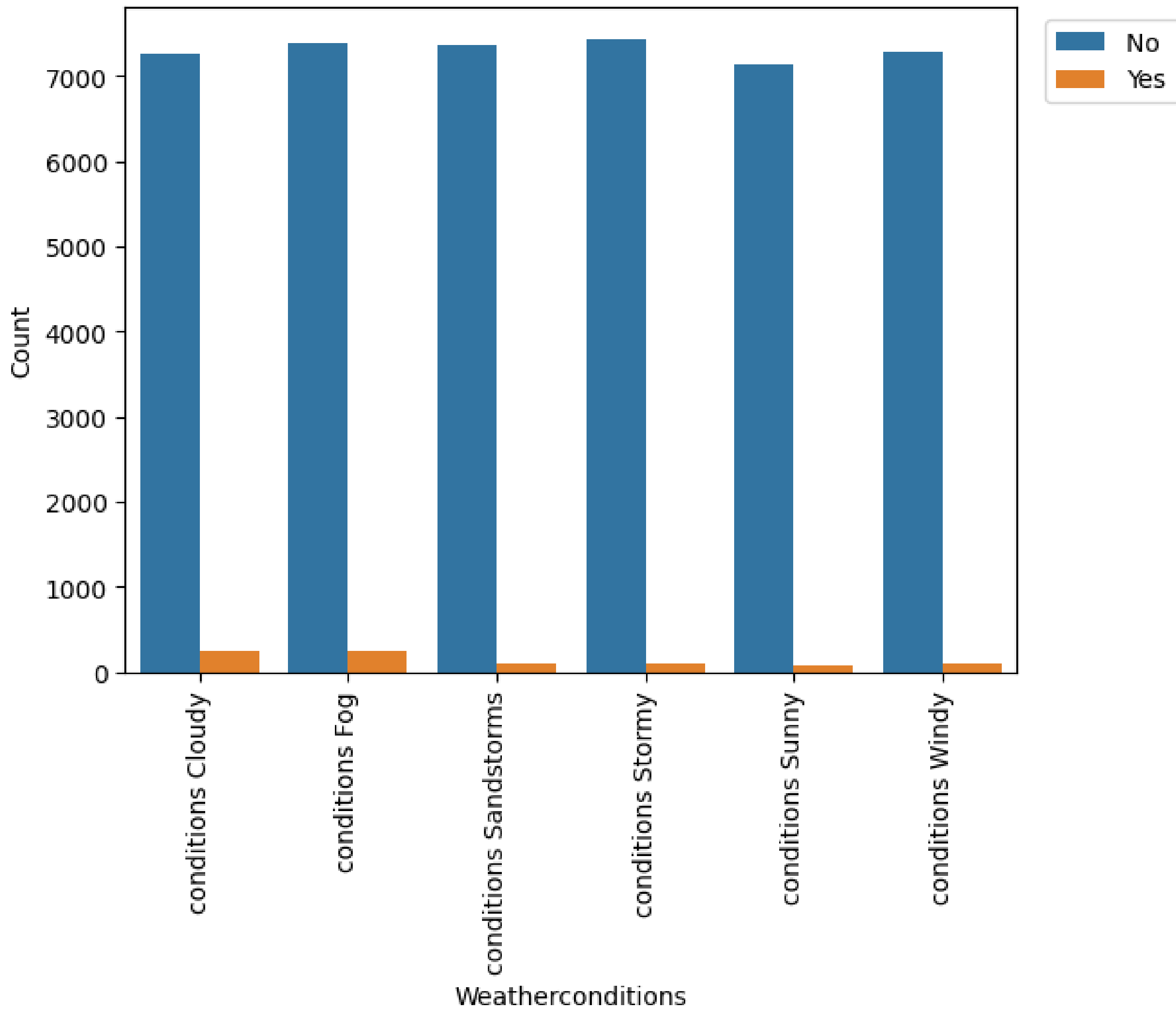
- Equal distribution of Weather Condition. Less important to model.

```
plt.figure(figsize=(8, 6))
temp = df.groupby(['Weatherconditions'])
['Time_taken(min)'].value_counts().sort_index().reset_index(name='Coun
t')
temp['Time_taken(min)_grouped'] = temp['Time_taken(min)'].str.split("
", expand=True)[1]

time_bins = [10, 15, 20, 25, 30, 35, 40, 45, 50, 55, 60]
temp['Time_taken(min)_grouped'] =
pd.to_numeric(temp['Time_taken(min)_grouped'], errors='coerce')
temp['Time_taken(min)_grouped'] =
pd.cut(temp['Time_taken(min)_grouped'], bins=time_bins)
sns.barplot(x=temp['Weatherconditions'], y=temp['Count'],
hue=temp['Time_taken(min)_grouped'])
plt.legend(loc='upper right', bbox_to_anchor=(1.3, 1))
plt.xticks(rotation=90)
plt.show()
```



- In every weather condition most of the deliveries took 25-30 mins. However, on sunny day most of the deliveries took 10-15 mins.

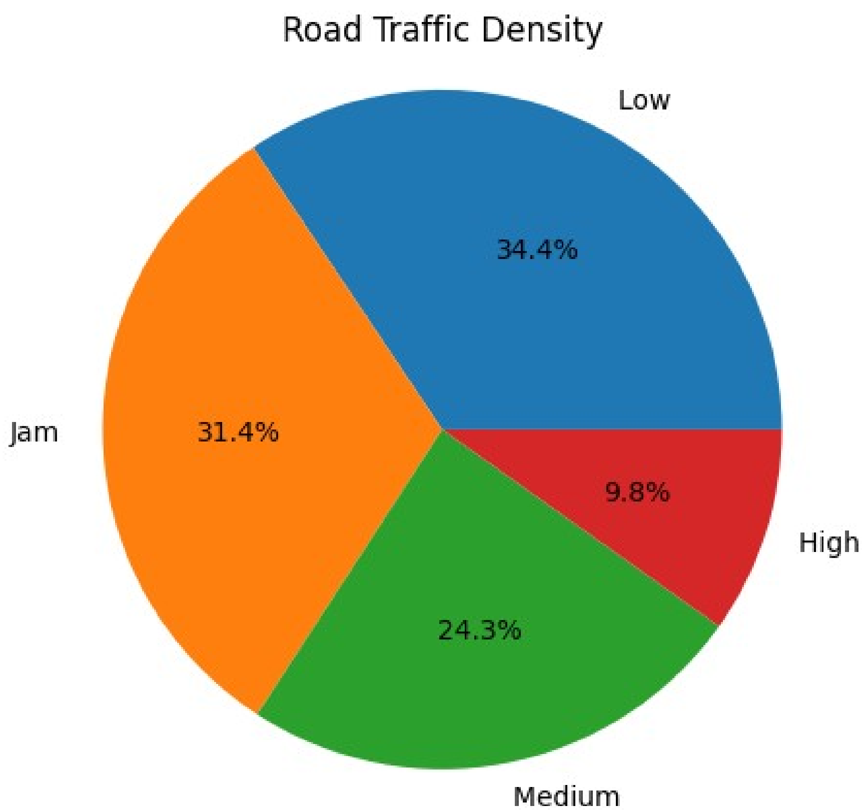
```
temp = df.groupby(['Weatherconditions'])
['Festival'].value_counts().sort_index().reset_index(name='Count')
sns.barplot(x=temp['Weatherconditions'], y=temp['Count'],
hue=temp['Festival'])
plt.legend(loc='upper right', bbox_to_anchor=(1.2, 1))
plt.xticks(rotation=90)
plt.show()
```



- On festival days more deliveries are being made during cloudy weather as people try to avoid going out in the rain.

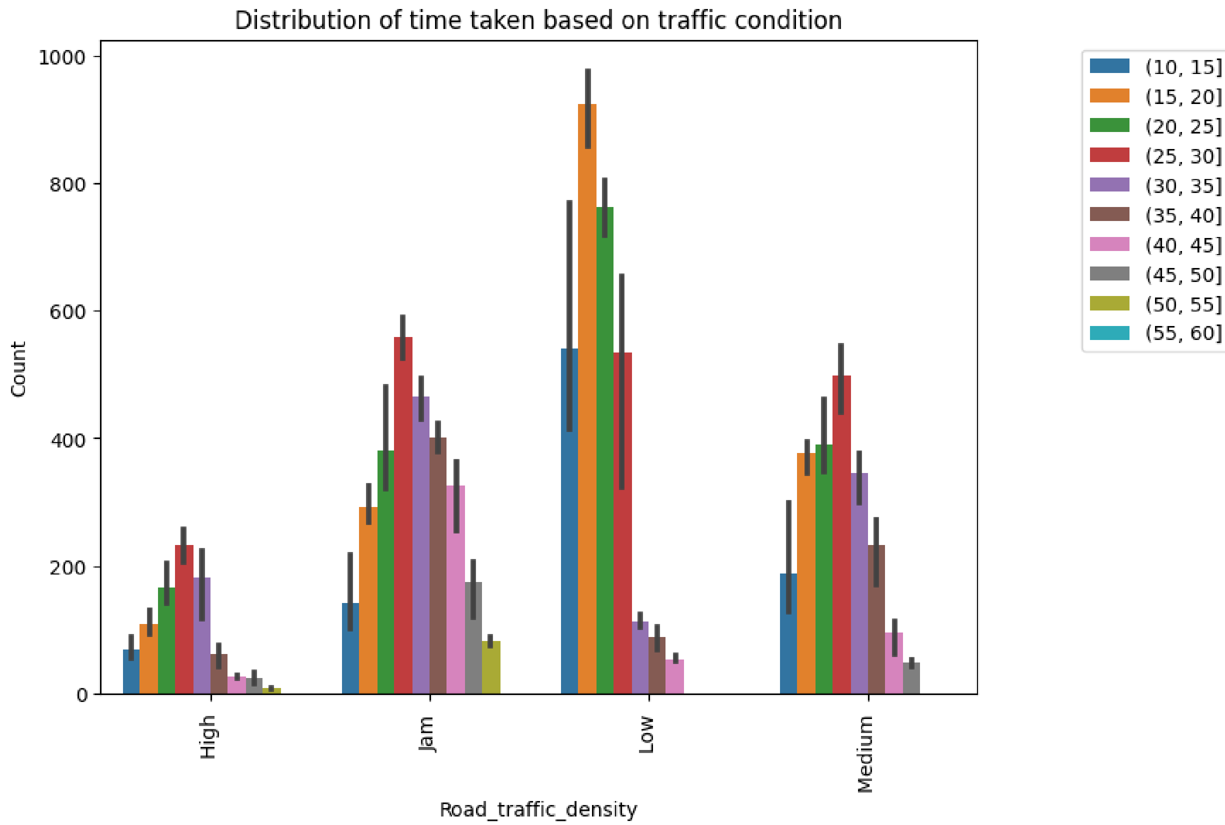
Road Traffic

```
plt.figure(figsize=(6, 5))
value_counts = df['Road_traffic_density'].value_counts()
plt.pie(value_counts, labels=value_counts.index, autopct='%1.1f%%')
plt.axis('equal')
plt.title('Road Traffic Density')
plt.show()
```



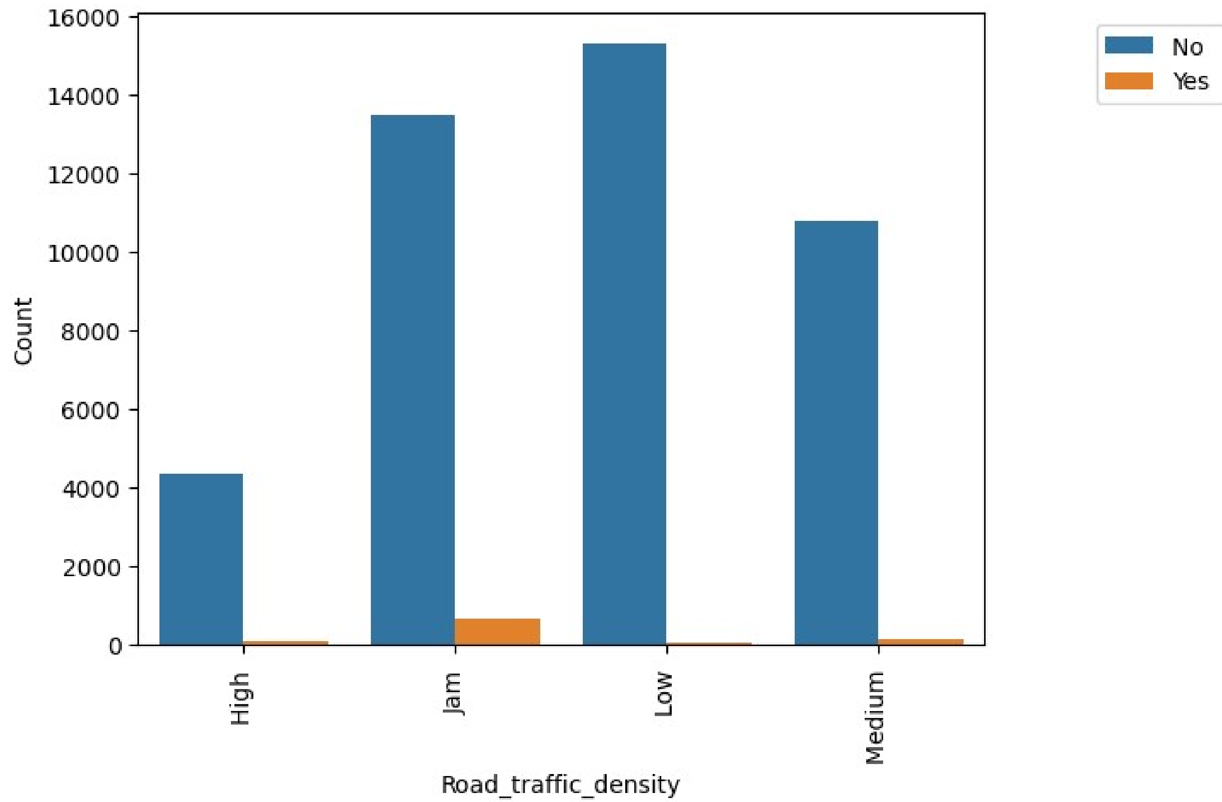
- Most of the deliveries are made during Low and Jam traffic condition.

```
plt.figure(figsize=(8, 6))
# Group the data by 'Road_traffic_density' and 'Time_taken(min)',
count occurrences, and sort by index
temp = df.groupby(['Road_traffic_density'])
['Time_taken(min)'].value_counts().sort_index().reset_index(name='Coun
t')
temp['Time_taken(min)_grouped'] = temp['Time_taken(min)'].str.split("
", expand=True)[1]

time_bins = [10, 15, 20, 25, 30, 35, 40, 45, 50, 55, 60]
temp['Time_taken(min)_grouped'] =
pd.to_numeric(temp['Time_taken(min)_grouped'], errors='coerce')
temp['Time_taken(min)_grouped'] =
pd.cut(temp['Time_taken(min)_grouped'], bins=time_bins)
sns.barplot(x=temp['Road_traffic_density'], y=temp['Count'],
hue=temp['Time_taken(min)_grouped'])
plt.legend(loc='upper right', bbox_to_anchor=(1.3, 1))
plt.title('Distribution of time taken based on traffic condition')
plt.xticks(rotation=90)
plt.show()
```



- Road Traffic Density affects the Time taken for deliveries.
- Deliveries during low traffic does not take more than 45 mins while during Jam condition it took more than 45 mins to deliver some of the deliveries.

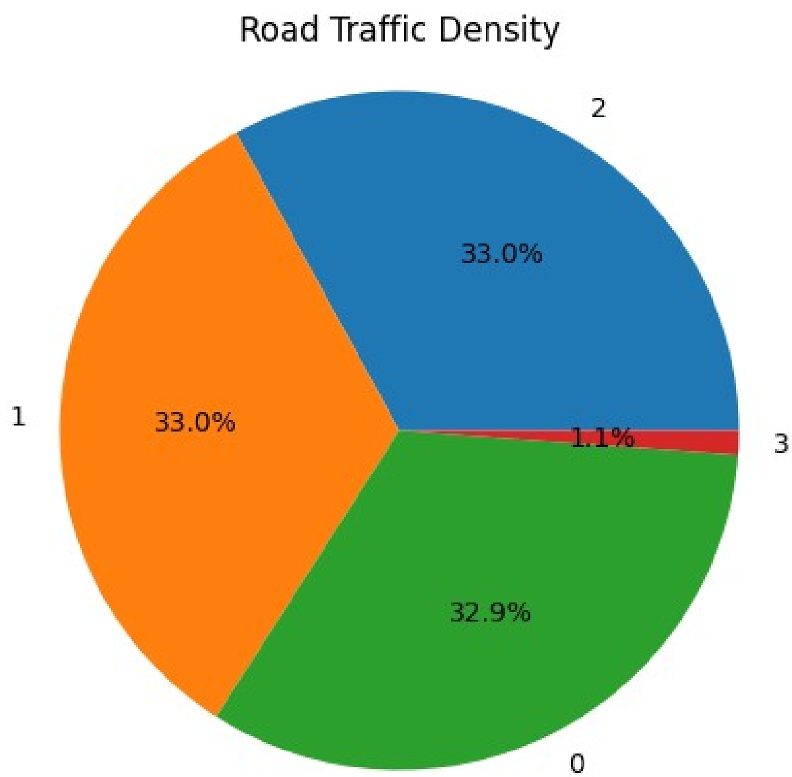
```
# Group the data by 'Vehicle_condition' and 'Festival', count
occurrences, and sort by index
temp = df.groupby(['Road_traffic_density'])
['Festival'].value_counts().sort_index().reset_index(name='Count')
sns.barplot(x=temp['Road_traffic_density'], y=temp['Count'],
hue=temp['Festival'])
plt.legend(loc='upper right', bbox_to_anchor=(1.3, 1))
plt.xticks(rotation=90)
plt.show()
```



- During the festival days, roads are Jam.

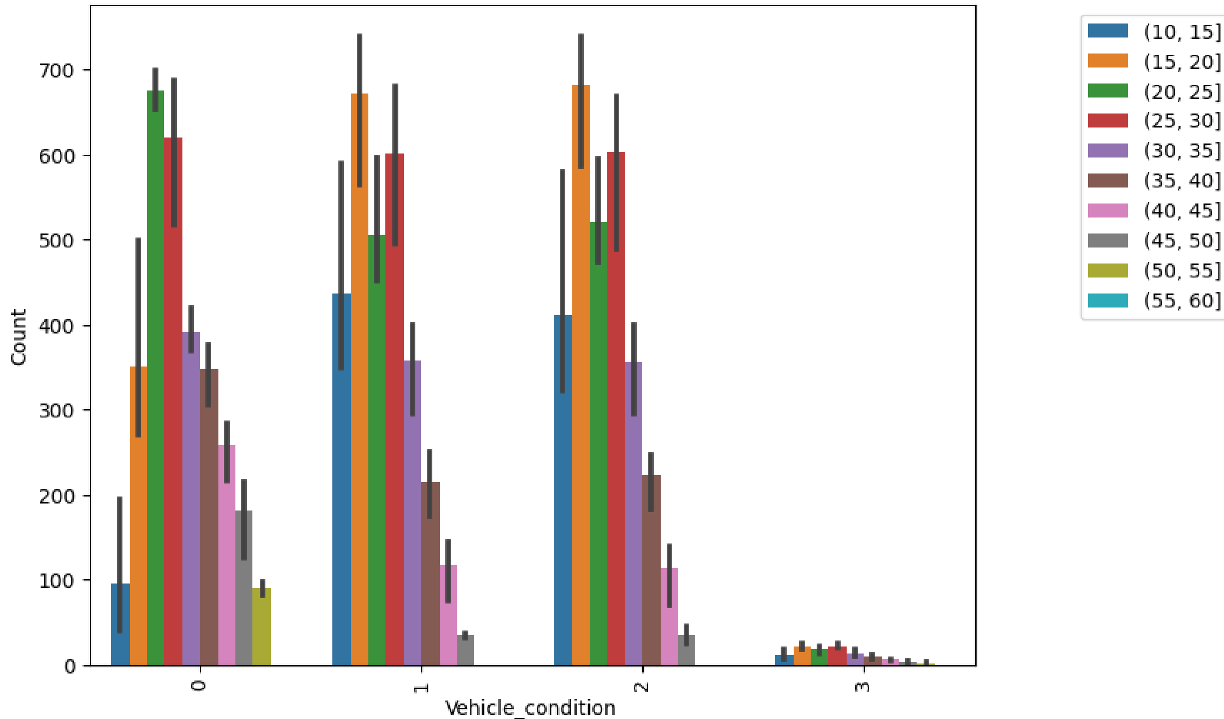
Vehicle Condition

```
df['Vehicle_condition'].value_counts()

2    15034
1    15030
0    15009
3      520
Name: Vehicle_condition, dtype: int64

plt.figure(figsize=(6, 5))
value_counts = df['Vehicle_condition'].value_counts()
plt.pie(value_counts, labels=value_counts.index, autopct='%1.1f%%')
plt.axis('equal')
plt.title('Road Traffic Density')
plt.show()
```



- There are only few delivery person that uses vehicles with bad condition.

```
plt.figure(figsize=(8, 6))

# Group the data by 'Vehicle_condition' and 'Time_taken(min)', count
occurrences, and sort by index
temp = df.groupby(['Vehicle_condition'])
['Time_taken(min)'].value_counts().sort_index().reset_index(name='Coun
t')
temp['Time_taken(min)_grouped'] = temp['Time_taken(min)'].str.split("
", expand=True)[1]

time_bins = [10, 15, 20, 25, 30, 35, 40, 45, 50, 55, 60]
temp['Time_taken(min)_grouped'] =
pd.to_numeric(temp['Time_taken(min)_grouped'], errors='coerce')
temp['Time_taken(min)_grouped'] =
pd.cut(temp['Time_taken(min)_grouped'], bins=time_bins)
sns.barplot(x=temp['Vehicle_condition'], y=temp['Count'],
hue=temp['Time_taken(min)_grouped'])
plt.legend(loc='upper right', bbox_to_anchor=(1.3, 1))
plt.xticks(rotation=90)
plt.show()
```

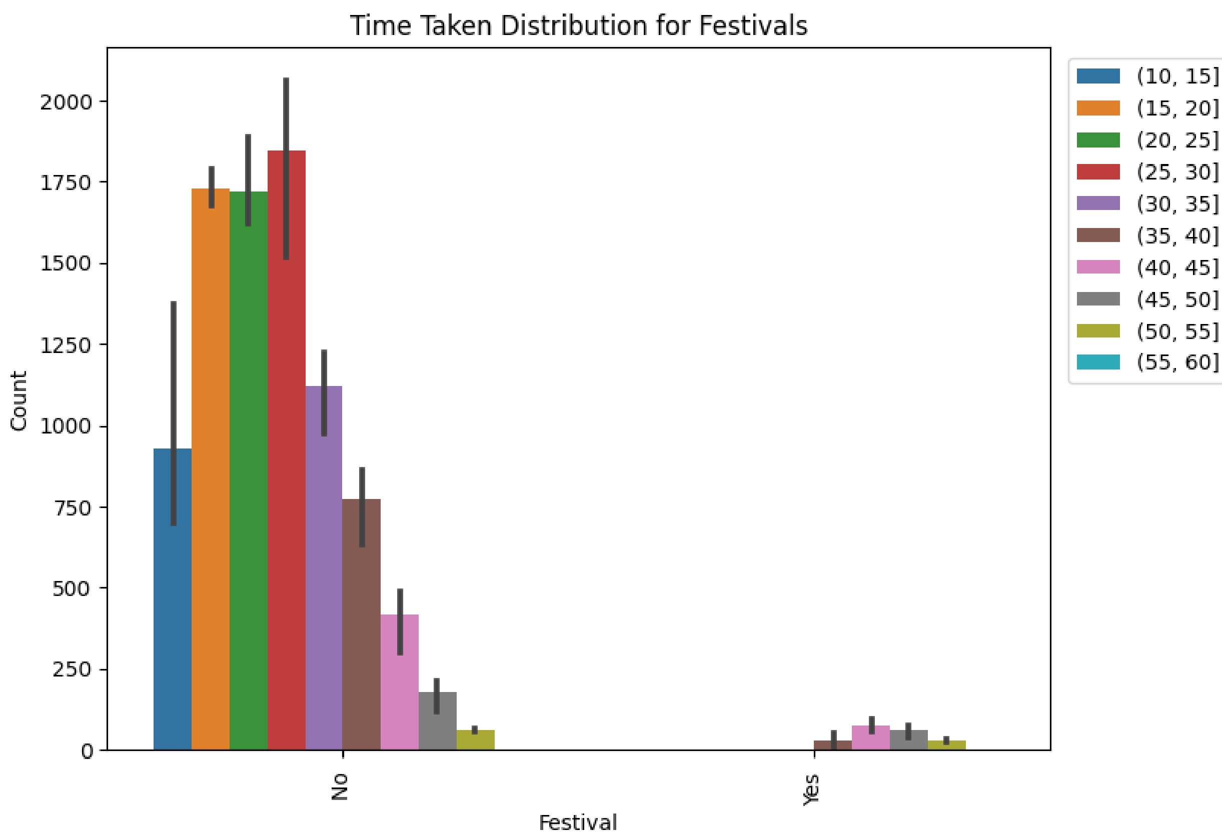


- The best vehicle condition typically requires 20 to 25 minutes for food delivery, whereas vehicles in good and average conditions take 15 to 20 minutes for the same task.

Festival

```
plt.figure(figsize=(8, 6))

# Group the data by 'Festival' and 'Time_taken(min)', then calculate
the counts and sort by index
temp = df.groupby(['Festival'])
['Time_taken(min)'].value_counts().sort_index().reset_index(name='Coun
t')

# Extract the minute values from 'Time_taken(min)' and create a new
column 'Time_taken(min)_grouped'
temp['Time_taken(min)_grouped'] = temp['Time_taken(min)'].str.split("
", expand=True)[1]

time_bins = [10, 15, 20, 25, 30, 35, 40, 45, 50, 55, 60]
temp['Time_taken(min)_grouped'] =
pd.to_numeric(temp['Time_taken(min)_grouped'], errors='coerce')
temp['Time_taken(min)_grouped'] =
pd.cut(temp['Time_taken(min)_grouped'], bins=time_bins)
sns.barplot(x=temp['Festival'], y=temp['Count'],
hue=temp['Time_taken(min)_grouped'])
plt.legend(loc='upper right', bbox_to_anchor=(1.2, 1))
plt.title("Time Taken Distribution for Festivals")
```

```
plt.xticks(rotation=90)
plt.show()
```

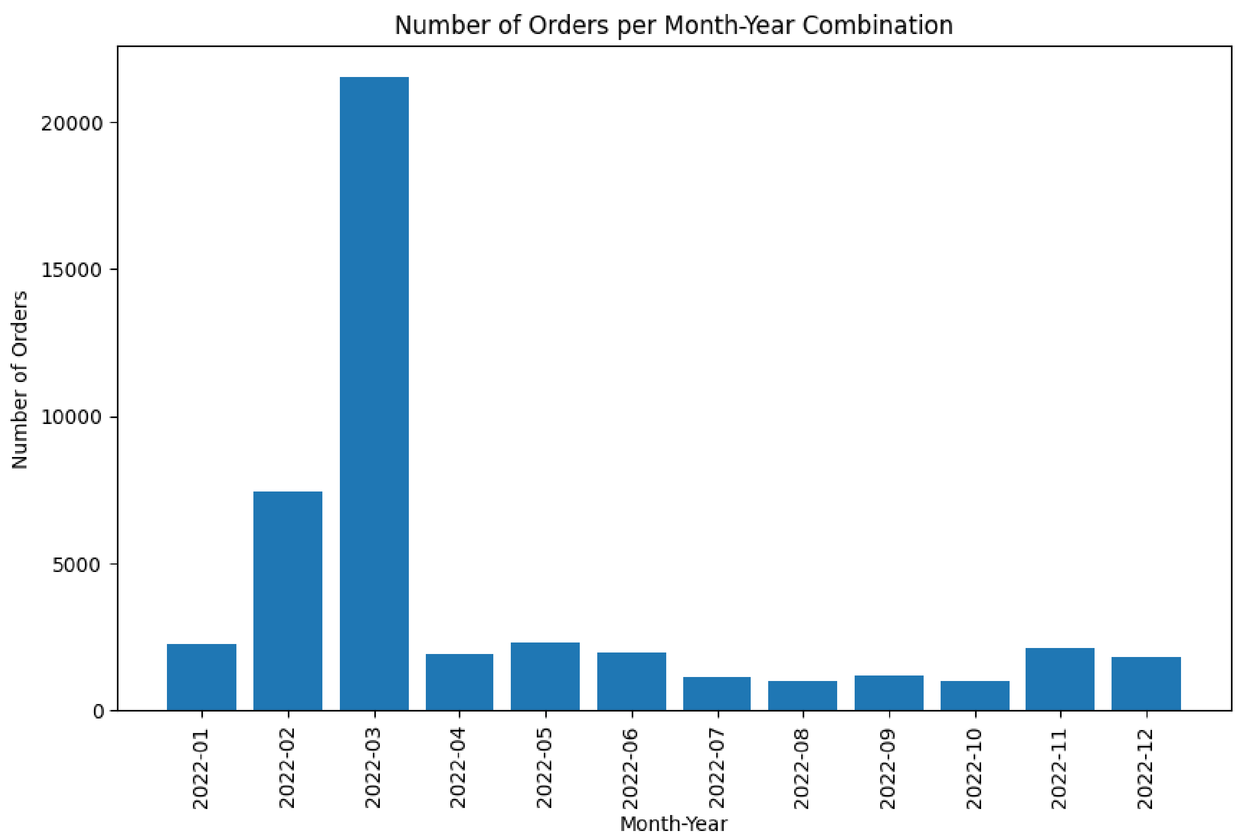


- Delivery times were longer during festival days as opposed to regular days.

Order date

```
# Count the number of missing or null values in the "Order date"
column
missing_values = df['Order_Date'].isnull().sum()
print("Number of missing or null values in Order date:",
missing_values)

Number of missing or null values in Order date: 0

# Histogram for number of orders per month/year

# Extract month and year from "Order_Date" column
df['Month_Year'] = pd.to_datetime(df['Order_Date']).dt.to_period('M')

# Count the number of orders per month-year combination
orders_per_month_year = df['Month_Year'].value_counts()

# Sort the values by month-year
```

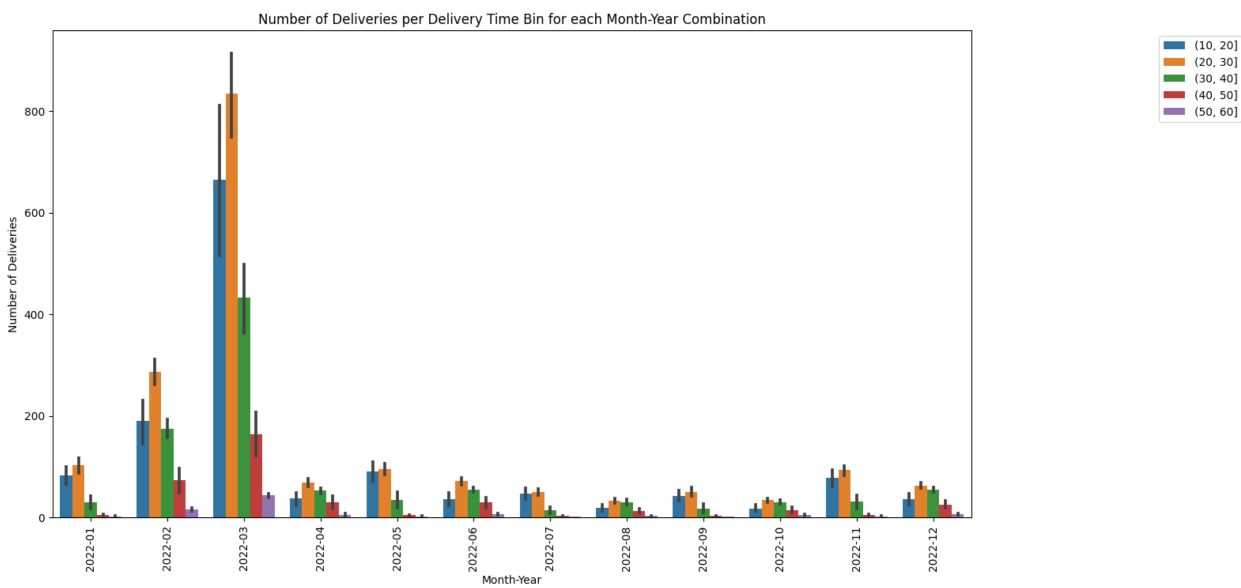
```
orders_per_month_year = orders_per_month_year.sort_index()

plt.figure(figsize=(10, 6))
plt.bar(orders_per_month_year.index.astype(str),
orders_per_month_year.values)
plt.xlabel('Month-Year')
plt.ylabel('Number of Orders')
plt.title('Number of Orders per Month-Year Combination')
plt.xticks(rotation=90)
plt.show()

<ipython-input-48-2bb26b6f72c9>:4: UserWarning: Parsing dates in
DD/MM/YYYY format when dayfirst=False (the default) was specified.
This may lead to inconsistently parsed dates! Specify a format to
ensure consistent parsing.
  df['Month_Year'] =
pd.to_datetime(df['Order_Date']).dt.to_period('M')
```



- March has the more than 20000 number of deliveries, which is higher than any other months in year 2022.

```
# Define time bins
time_bins = [10, 20, 30, 40, 50, 60]
```

```python
# Group by Month_Year and Time_taken(min), and count the number of deliveries per bin
temp = df.groupby(['Month_Year',
'Time_taken(min)']).size().reset_index(name='Count')
temp['Time_taken(min)_grouped'] = temp['Time_taken(min)'].str.split("
", expand=True)[1]

# Convert the time component to numeric and categorize into time bins
temp['Time_taken(min)_grouped'] =
pd.to_numeric(temp['Time_taken(min)_grouped'], errors='coerce')
temp['Time_taken(min)_grouped'] =
pd.cut(temp['Time_taken(min)_grouped'], bins=time_bins)

# Plot the bar plot
plt.figure(figsize=(15, 8))
sns.barplot(x='Month_Year', y='Count', hue='Time_taken(min)_grouped',
data=temp)
plt.xlabel('Month-Year')
plt.ylabel('Number of Deliveries')
plt.title('Number of Deliveries per Delivery Time Bin for each Month-
Year Combination')
plt.legend(loc='upper right', bbox_to_anchor=(1.3, 1))
plt.xticks(rotation=90)
plt.show()
```



- March 2022 had the most number of orders placed. Most of the orders in that month took average deliverey time of 15-20 mins.

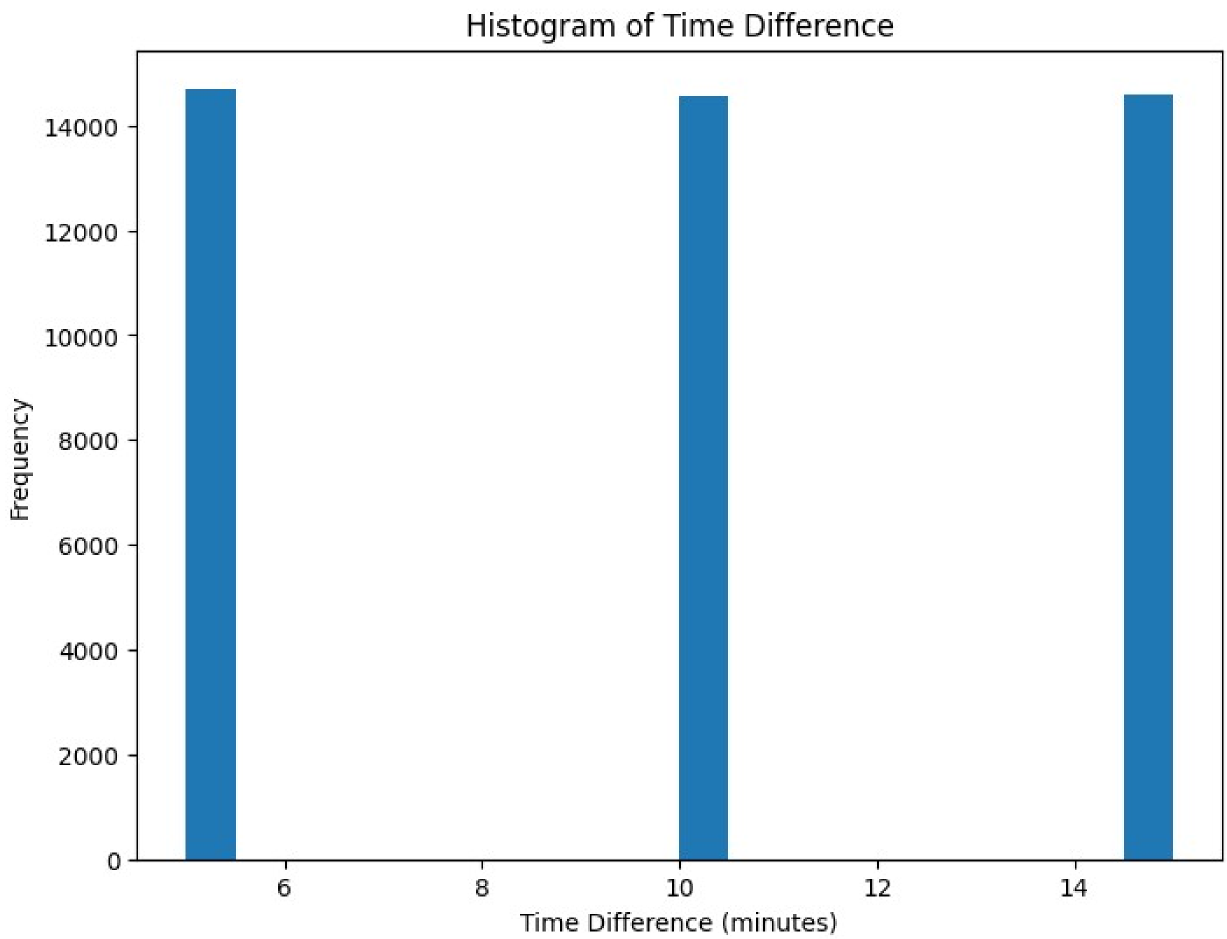
Time ordered and Time order picked

```
missing_values_ordered = df['Time_Orderd'].isnull().sum()
nan_count_ordered = (df['Time_Orderd'] == 'NaN ').sum()

missing_values_picked = df['Time_Order_picked'].isnull().sum()
nan_count_picked = (df['Time_Order_picked'] == 'NaN ').sum()

print("Number of missing values in Time_Orderd:",
missing_values_ordered)
print("Number of 'NaN' values in Time_Ordered:", nan_count_ordered)
print()
print("Number of missing values in Time_Order_picked:",
missing_values_picked)
print("Number of 'NaN' values in Time_Order_Picked:",
nan_count_picked)
```

```
Number of missing values in Time_Orderd: 1731
Number of 'NaN' values in Time_Ordered: 0

Number of missing values in Time_Order_picked: 0
Number of 'NaN' values in Time_Order_Picked: 0
```

```
# Calculate the time difference between Time_Order_picked and
Time_Ordered
data_filtered = df[df['Time_Orderd'] != 'NaN '].copy()
data_filtered.reset_index(drop=True, inplace=True)

data_filtered['Time_Orderd'] =
pd.to_datetime(data_filtered['Time_Orderd'], format='%H:%M:
%S').dt.time
data_filtered['Time_Order_picked'] =
pd.to_datetime(data_filtered['Time_Order_picked'], format='%H:%M:
%S').dt.time

# Calculate the time difference between 'Time_Order_picked' and
'Time_Orderd' columns in minutes
data_filtered['Time_Difference'] = np.where(
    data_filtered['Time_Order_picked'] >=
data_filtered['Time_Orderd'],
    (pd.to_timedelta(data_filtered['Time_Order_picked'].astype(str)) -
pd.to_timedelta(data_filtered['Time_Orderd'].astype(str))).dt.total_se
conds() / 60,
    (pd.to_timedelta(data_filtered['Time_Order_picked'].astype(str)) +
pd.to_timedelta('1 day') -
pd.to_timedelta(data_filtered['Time_Orderd'].astype(str))).dt.total_se
conds() / 60
)

plt.figure(figsize=(8, 6))
plt.hist(data_filtered['Time_Difference'].dropna(), bins=20)
```

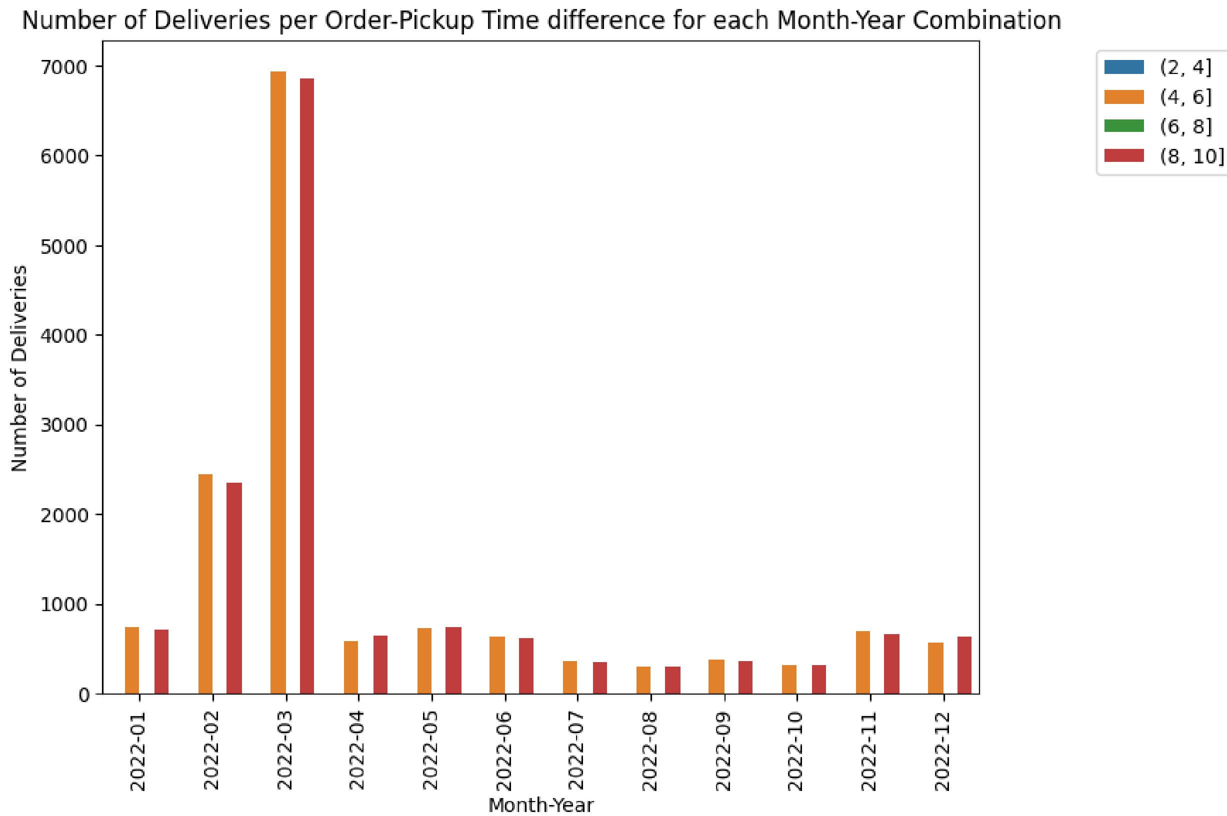
```
plt.xlabel('Time Difference (minutes)')
plt.ylabel('Frequency')
plt.title('Histogram of Time Difference')
plt.show()

# Print the statistics of the time difference
time_diff_stats = data_filtered['Time_Difference'].describe()
print("Statistics of Time Difference:")
print(time_diff_stats)
```




```
Statistics of Time Difference:
count    43862.000000
mean         9.989399
std          4.087516
min          5.000000
25%          5.000000
50%         10.000000
75%         15.000000
max         15.000000
Name: Time_Difference, dtype: float64
```

```
# Define time bins
time_bins = [2, 4, 6, 8, 10]

data_filtered['Month_Year'] =
pd.to_datetime(data_filtered['Order_Date']).dt.to_period('M')

temp = data_filtered.groupby(['Month_Year',
'Time_Difference']).size().reset_index(name='Count')
temp['Time_Difference_grouped'] = pd.cut(temp['Time_Difference'],
bins=time_bins)

plt.figure(figsize=(8, 6))
sns.barplot(x='Month_Year', y='Count', hue='Time_Difference_grouped',
data=temp)
plt.xlabel('Month-Year')
plt.ylabel('Number of Deliveries')
plt.title('Number of Deliveries per Order-Pickup Time difference for
each Month-Year Combination')
plt.legend(loc='upper right', bbox_to_anchor=(1.3, 1))
plt.xticks(rotation=90)
plt.show()
```

```
<ipython-input-52-d3de744feb20>:4: UserWarning: Parsing dates in
DD/MM/YYYY format when dayfirst=False (the default) was specified.
This may lead to inconsistently parsed dates! Specify a format to
ensure consistent parsing.
  data_filtered['Month_Year'] =
pd.to_datetime(data_filtered['Order_Date']).dt.to_period('M')
```



Most of the orders take 4-6 minutes or 8-10 minutes to be prepared.

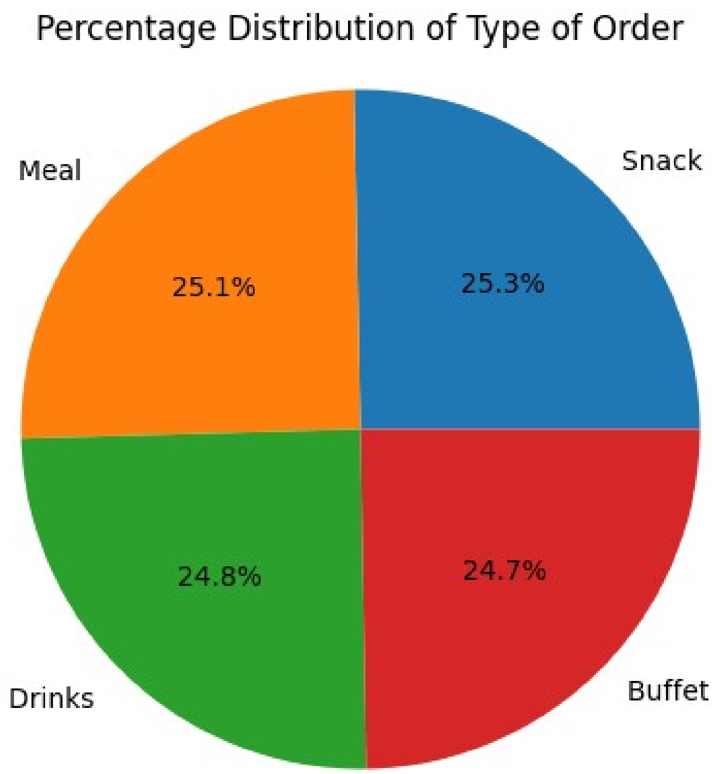
Type of order and Type of vehicle

```
# Examine unique values in 'Type of order' column
unique_orders = df['Type_of_order'].unique()
print("Unique Orders:")
print(unique_orders)

# Examine unique values in 'Type of vehicle' column
unique_vehicles = df['Type_of_vehicle'].unique()
print("\nUnique Vehicles:")
print(unique_vehicles)
```

```
Unique Orders:
['Snack ' 'Drinks ' 'Buffet ' 'Meal ']

Unique Vehicles:
['motorcycle ' 'scooter ' 'electric_scooter ' 'bicycle ']
```

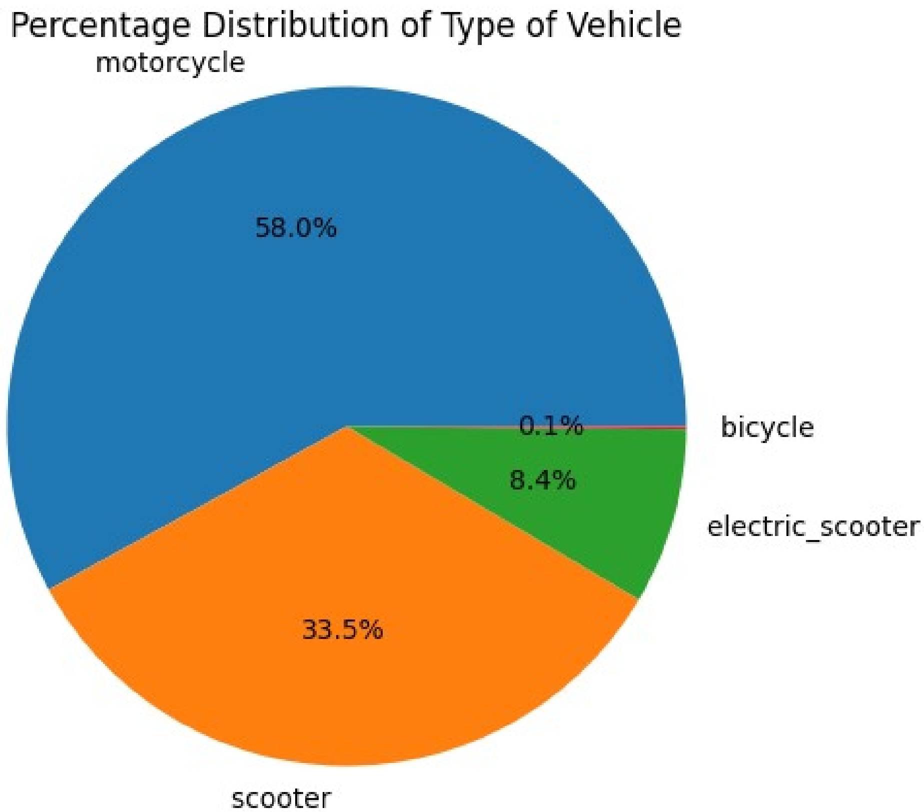
```
plt.figure(figsize=(6, 5))
order_counts = df['Type_of_order'].value_counts()
plt.pie(order_counts, labels=order_counts.index, autopct='%1.1f%%')
plt.axis('equal')
```

```
plt.title('Percentage Distribution of Type of Order')
plt.show()
```



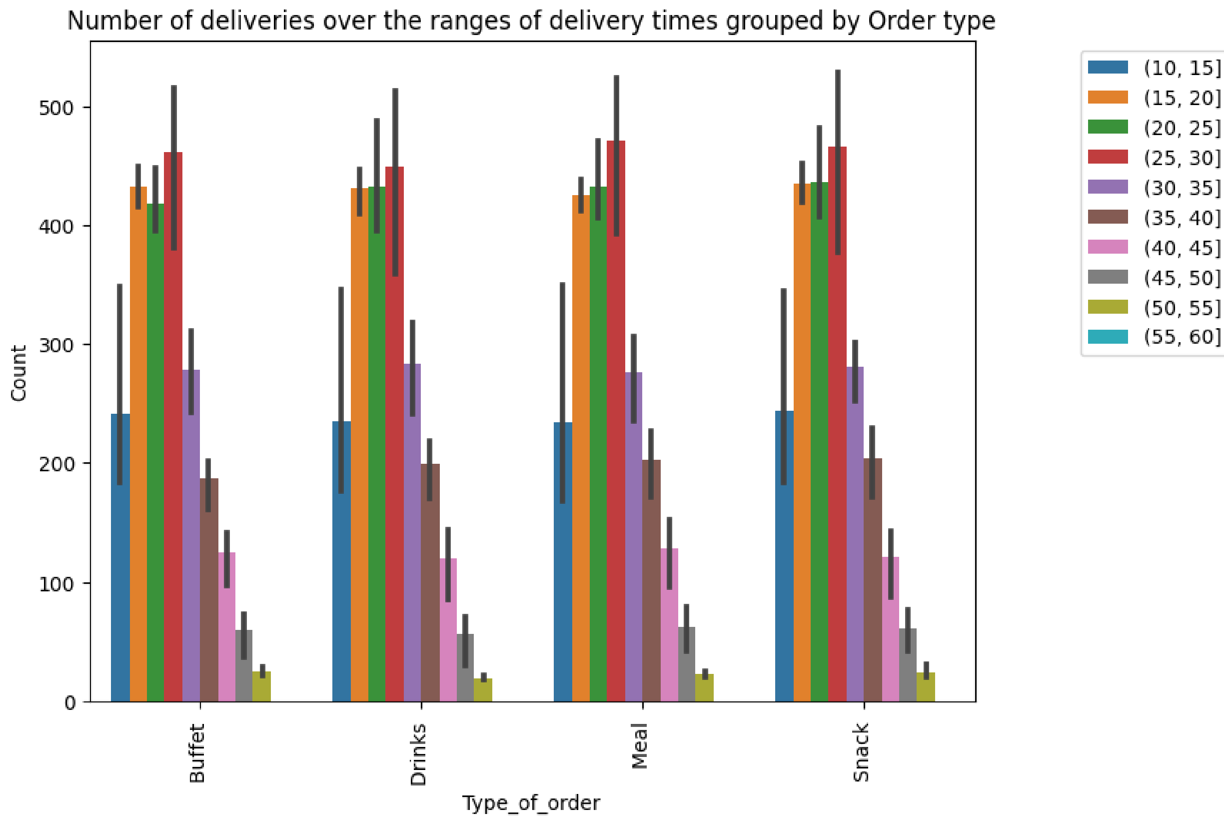
- Type of food has same distribution

```
plt.figure(figsize=(6, 5))
vehicle_counts = df['Type_of_vehicle'].value_counts()
plt.pie(vehicle_counts, labels=vehicle_counts.index, autopct='%1.1f%
%')
plt.axis('equal')
plt.title('Percentage Distribution of Type of Vehicle')
plt.show()
```

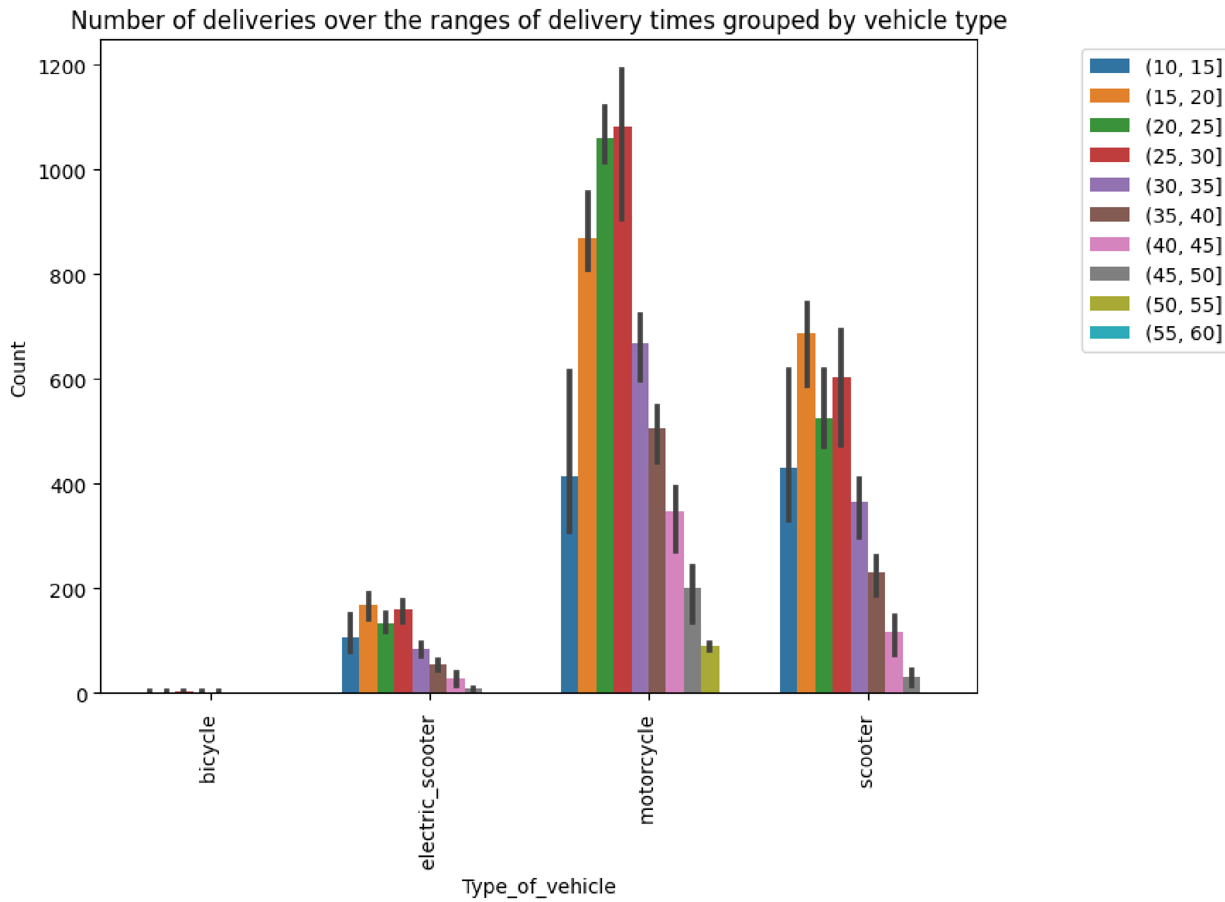


- Most of the deliveries are made by using motorcycle and scooter.

```
plt.figure(figsize=(8, 6))
temp = df.groupby(['Type_of_order'])
['Time_taken(min)'].value_counts().sort_index().reset_index(name='Coun
t')
temp['Time_taken(min)_grouped'] = temp['Time_taken(min)'].str.split("
", expand=True)[1]

time_bins = [10, 15, 20, 25, 30, 35, 40, 45, 50, 55, 60]
temp['Time_taken(min)_grouped'] =
pd.to_numeric(temp['Time_taken(min)_grouped'], errors='coerce')
temp['Time_taken(min)_grouped'] =
pd.cut(temp['Time_taken(min)_grouped'], bins=time_bins)
sns.barplot(x=temp['Type_of_order'], y=temp['Count'],
hue=temp['Time_taken(min)_grouped'])
plt.legend(loc='upper right', bbox_to_anchor=(1.3, 1))
plt.xticks(rotation=90)
plt.title('Number of deliveries over the ranges of delivery times
grouped by Order type')
plt.show()
```



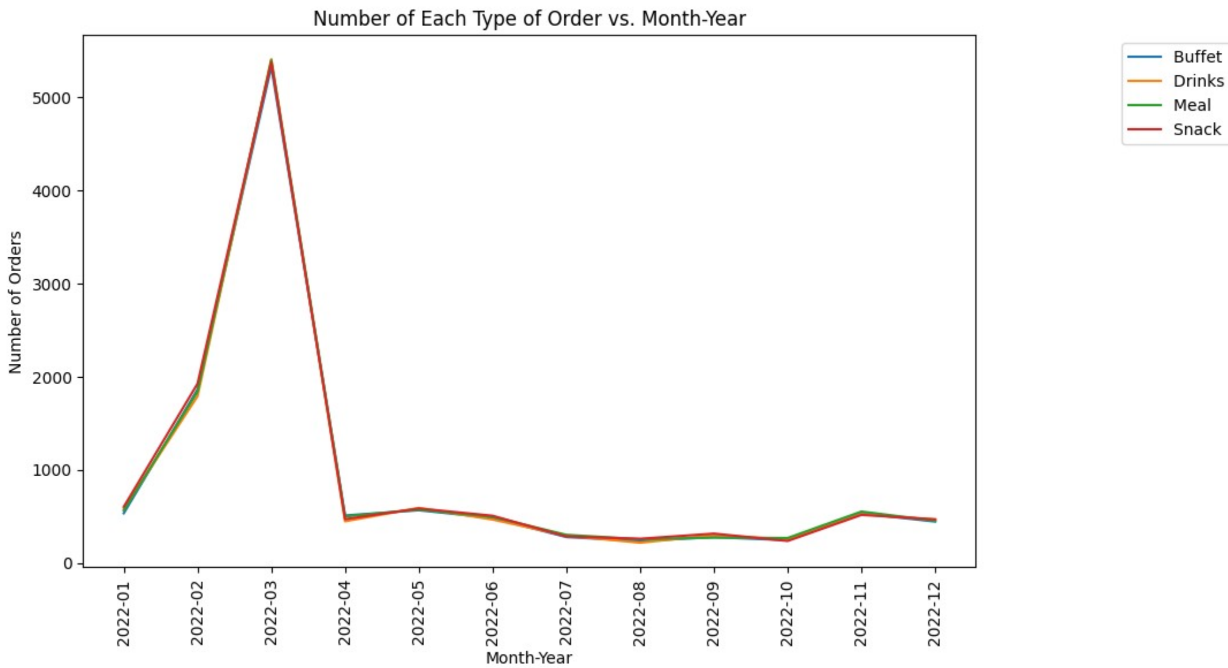

```
plt.figure(figsize=(8, 6))
temp = df.groupby(['Type_of_vehicle'])
['Time_taken(min)'].value_counts().sort_index().reset_index(name='Coun
t')
temp['Time_taken(min)_grouped'] = temp['Time_taken(min)'].str.split("
", expand=True)[1]

time_bins = [10, 15, 20, 25, 30, 35, 40, 45, 50, 55, 60]
temp['Time_taken(min)_grouped'] =
pd.to_numeric(temp['Time_taken(min)_grouped'], errors='coerce')
temp['Time_taken(min)_grouped'] =
pd.cut(temp['Time_taken(min)_grouped'], bins=time_bins)
sns.barplot(x=temp['Type_of_vehicle'], y=temp['Count'],
hue=temp['Time_taken(min)_grouped'])
plt.legend(loc='upper right', bbox_to_anchor=(1.3, 1))
plt.xticks(rotation=90)
plt.title('Number of deliveries over the ranges of delivery times
grouped by vehicle type')
plt.show()
```



- Significant deliveries are typically delivered via motorcycles, with delivery times ranging from 25 to 30 minutes. On the other hand, scooters tend to complete major deliveries within a time frame of 15 to 20 minutes.

```
# Group by Month_Year and Type_of_order, and count the number of each
type of order per month-year combination
order_counts_per_month = data_filtered.groupby(['Month_Year',
'Type_of_order']).size().reset_index(name='Count')

# Convert "Month_Year" to string for plotting
order_counts_per_month['Month_Year'] =
order_counts_per_month['Month_Year'].astype(str)

# Create a line graph
plt.figure(figsize=(10, 6))

# Loop through each type of order and plot a line for each
for order_type in order_counts_per_month['Type_of_order'].unique():
    order_type_data =
order_counts_per_month[order_counts_per_month['Type_of_order'] ==
order_type]
    plt.plot(order_type_data['Month_Year'], order_type_data['Count'],
label=order_type)
```

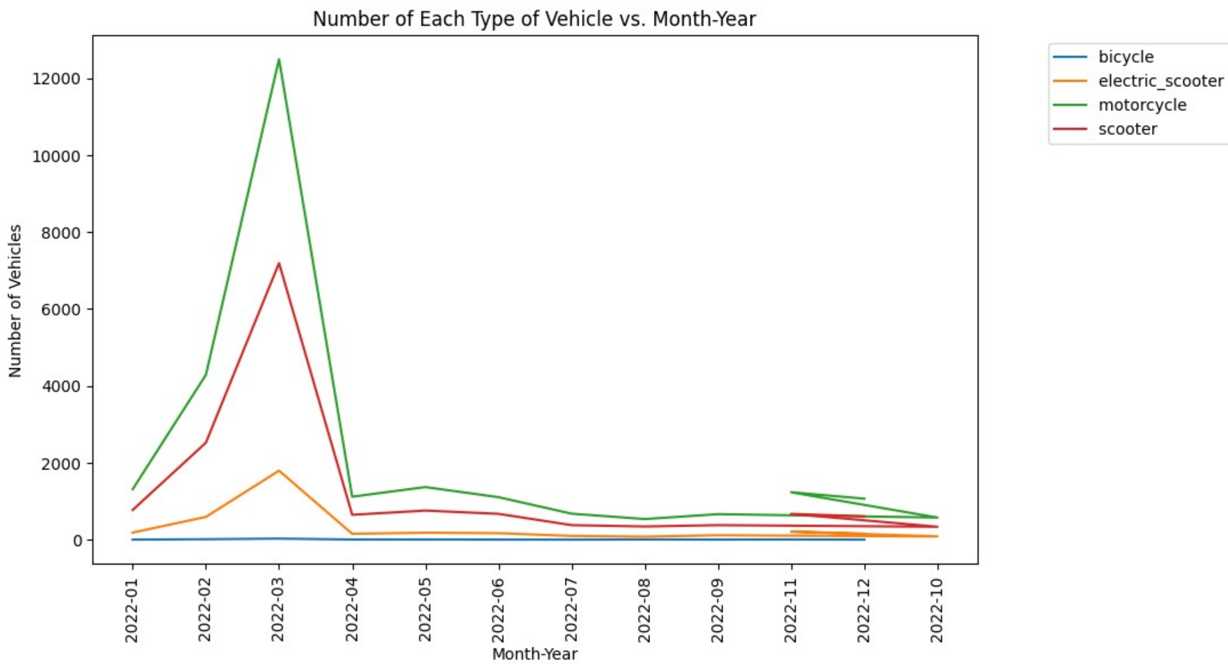
```
plt.xlabel('Month-Year')
plt.ylabel('Number of Orders')
plt.title('Number of Each Type of Order vs. Month-Year')
plt.legend(loc='upper right', bbox_to_anchor=(1.3, 1))
plt.xticks(rotation=90)
plt.show()
```



- No significant difference between order type over the given period of time.

```
vehicle_counts_per_month = data_filtered.groupby(['Month_Year',
'Type_of_vehicle']).size().reset_index(name='Count')

# Convert "Month_Year" to string for plotting
vehicle_counts_per_month['Month_Year'] =
vehicle_counts_per_month['Month_Year'].astype(str)

# Create a line graph
plt.figure(figsize=(10, 6))

# Loop through each type of vehicle and plot a line for each
for vehicle_type in
vehicle_counts_per_month['Type_of_vehicle'].unique():
    vehicle_type_data =
vehicle_counts_per_month[vehicle_counts_per_month['Type_of_vehicle']
== vehicle_type]
    plt.plot(vehicle_type_data['Month_Year'],
vehicle_type_data['Count'], label=vehicle_type)
```

```
plt.xlabel('Month-Year')
plt.ylabel('Number of Vehicles')
plt.title('Number of Each Type of Vehicle vs. Month-Year')
plt.legend(loc='upper right', bbox_to_anchor=(1.3, 1))
plt.xticks(rotation=90)
plt.show()
```



The number of deliveries across order types and vehicle types have been consistent throughout the months. Most of the orders were delivered on the motorcycles while the bicycle is the least used vehicle for delivery.

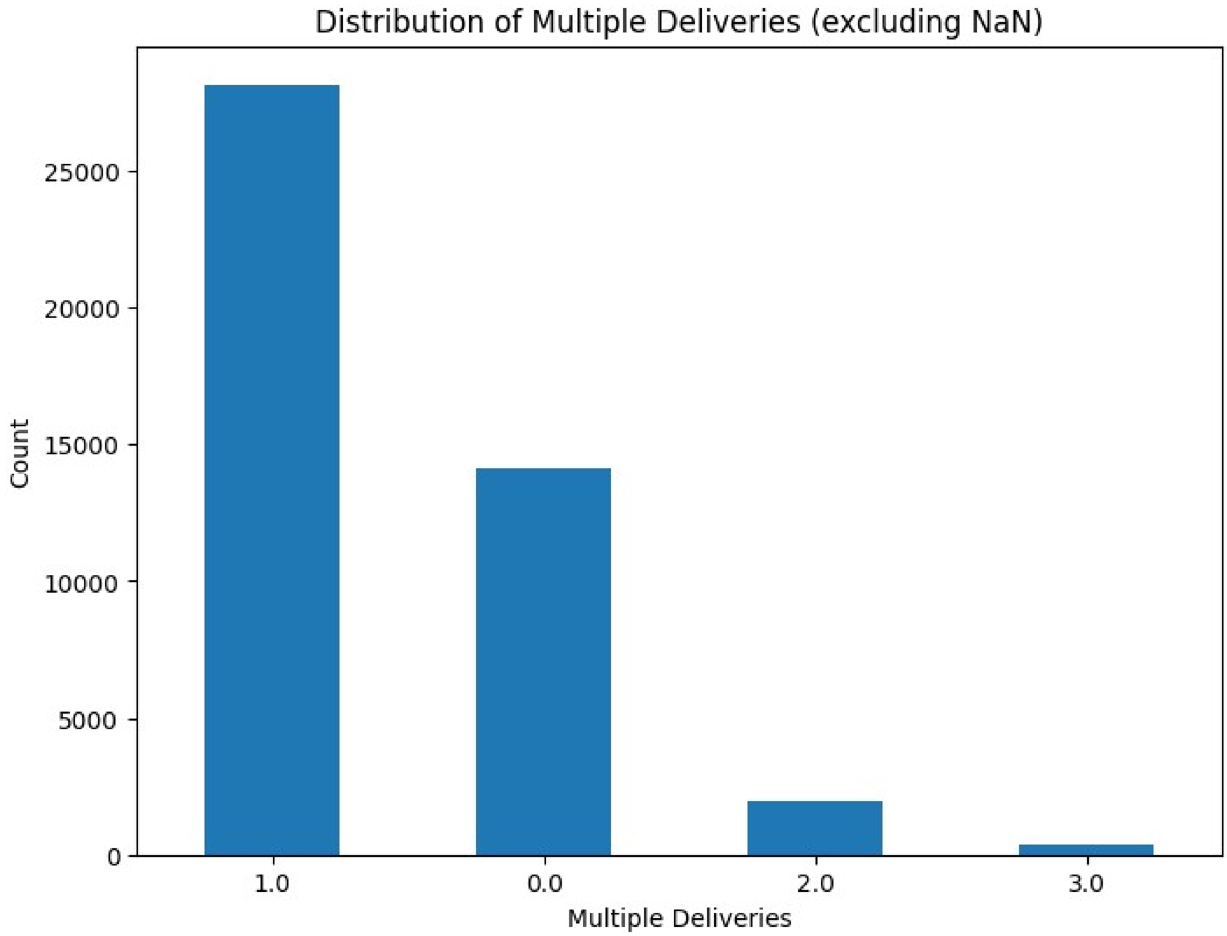
Multiple deliveries

```
# Count the number of rows with NaN string values in "Multiple
Deliveries" column
nan_rows_count = df[df['multiple_deliveries'] == 'NaN '].shape[0]
print("Number of rows with NaN values in 'Multiple Deliveries'
column:", nan_rows_count)

Number of rows with NaN values in 'Multiple Deliveries' column: 0

# Filter the rows with non-NaN string values in "Multiple Deliveries"
column
filtered_data = df[df['multiple_deliveries'] != 'NaN '].copy()

# Convert the values in "multiple_deliveries" column to numeric
filtered_data.loc[:, 'multiple_deliveries'] =
pd.to_numeric(filtered_data['multiple_deliveries'])
```

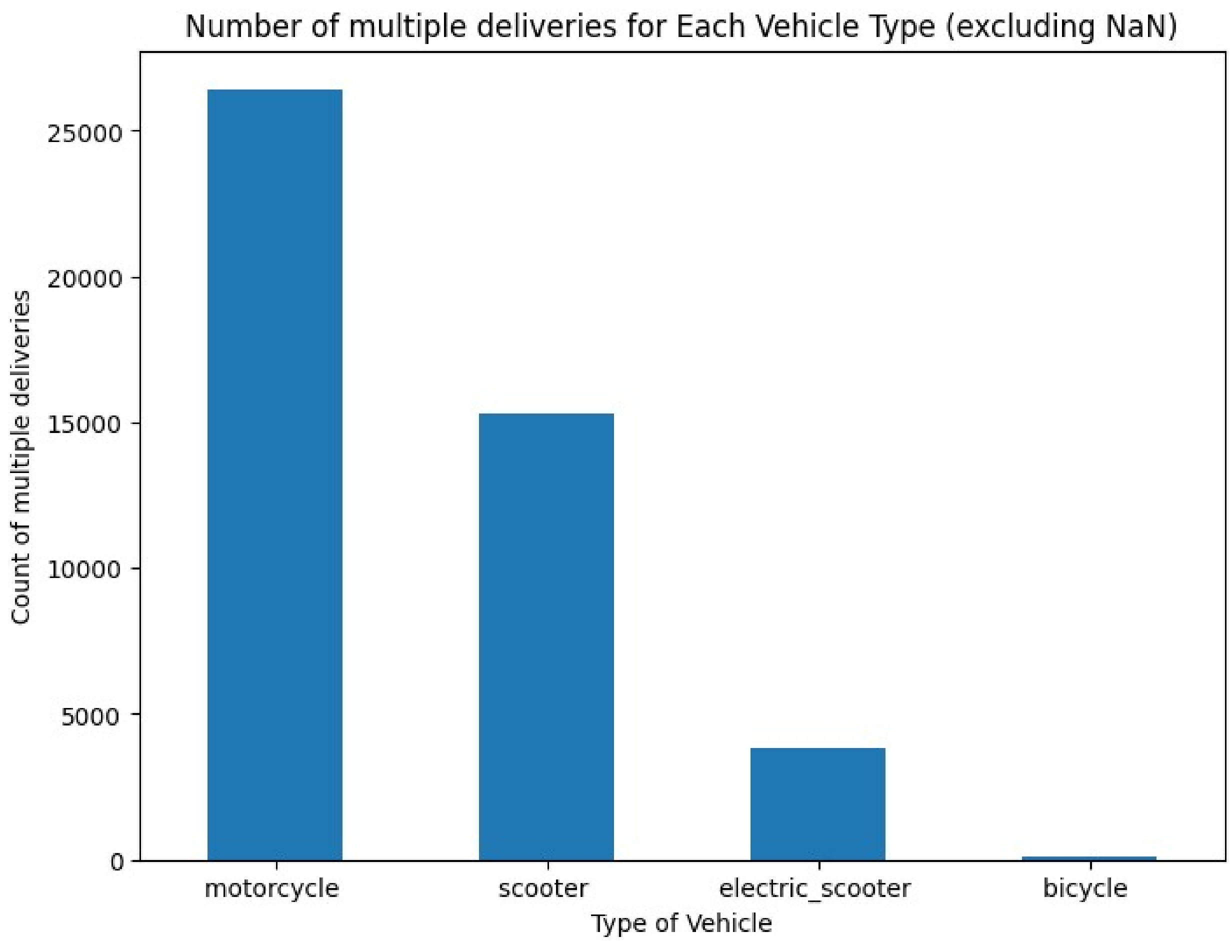
```python
# Count the number of deliveries with multiple deliveries
multiple_deliveries_count = filtered_data['multiple_deliveries'].sum()

# Calculate the percentage of deliveries with multiple deliveries
total_deliveries = len(filtered_data)
percentage_multiple_deliveries = (multiple_deliveries_count /
total_deliveries) * 100

# Print the results
print("Number of Deliveries with Multiple Deliveries (excluding
NaN):", multiple_deliveries_count)
print("Percentage of Deliveries with Multiple Deliveries (excluding
NaN): {:.2f}%".format(percentage_multiple_deliveries))

# Plot the distribution of multiple deliveries
plt.figure(figsize=(8, 6))
filtered_data['multiple_deliveries'].value_counts().plot(kind='bar')
plt.xlabel('Multiple Deliveries')
plt.ylabel('Count')
plt.title('Distribution of Multiple Deliveries (excluding NaN)')
plt.xticks(rotation=0)
plt.show()
```

```
Number of Deliveries with Multiple Deliveries (excluding NaN): 33212.0
Percentage of Deliveries with Multiple Deliveries (excluding NaN):
72.84%
```

```
<ipython-input-61-c576e7e90889>:5: DeprecationWarning: In a future
version, `df.iloc[:, i] = newvals` will attempt to set the values
inplace instead of always setting a new array. To retain the old
behavior, use either `df[df.columns[i]] = newvals` or, if columns are
non-unique, `df.isetitem(i, newvals)`
  filtered_data.loc[:, 'multiple_deliveries'] =
pd.to_numeric(filtered_data['multiple_deliveries'])
```



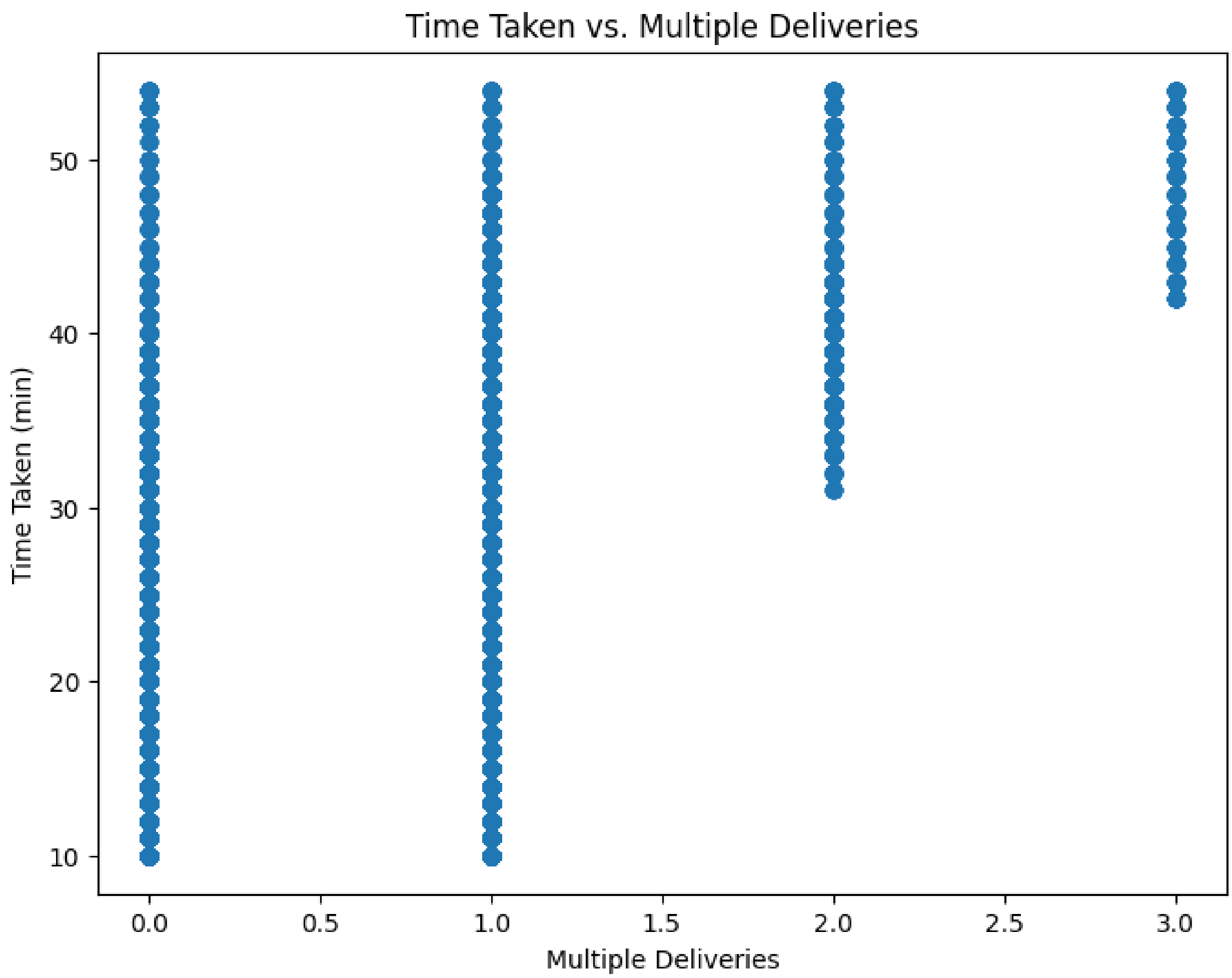

```
# Plot the distribution of multiple deliveries
plt.figure(figsize=(8, 6))
vehicle_counts = filtered_data['Type_of_vehicle'].value_counts()
vehicle_counts.plot(kind='bar')
plt.xlabel('Type of Vehicle')
plt.ylabel('Count of multiple deliveries')
plt.title('Number of multiple deliveries for Each Vehicle Type
(excluding NaN)')
plt.xticks(rotation=0)
plt.show()
```



- Motorcycles are primarily utilized for significant deliveries.

```
# Convert the values in "multiple_deliveries" column to numeric
filtered_data['multiple_deliveries'] =
pd.to_numeric(filtered_data['multiple_deliveries'])
filtered_data['Time_taken(min)_grouped'] =
filtered_data['Time_taken(min)'].str.split(" ", expand=True)[1]

# Convert the values in "multiple_deliveries" column to numeric
filtered_data['multiple_deliveries'] =
pd.to_numeric(filtered_data['multiple_deliveries'])

# Convert the 'Time_taken(min)_grouped' column to numeric
filtered_data['Time_taken(min)_grouped'] =
pd.to_numeric(filtered_data['Time_taken(min)_grouped'],
errors='coerce')

# Create a scatter plot
plt.figure(figsize=(8, 6))
plt.scatter(filtered_data['multiple_deliveries'],
filtered_data['Time_taken(min)_grouped'])
plt.xlabel('Multiple Deliveries')
```

```
plt.ylabel('Time Taken (min)')
plt.title('Time Taken vs. Multiple Deliveries')
plt.show()
```



Multiple deliveries cause an increase in the time taken for the delivery. 2-3 combined deliveries need a large amount of time to reach the customer as opposed to 0-1 multiple deliveries.

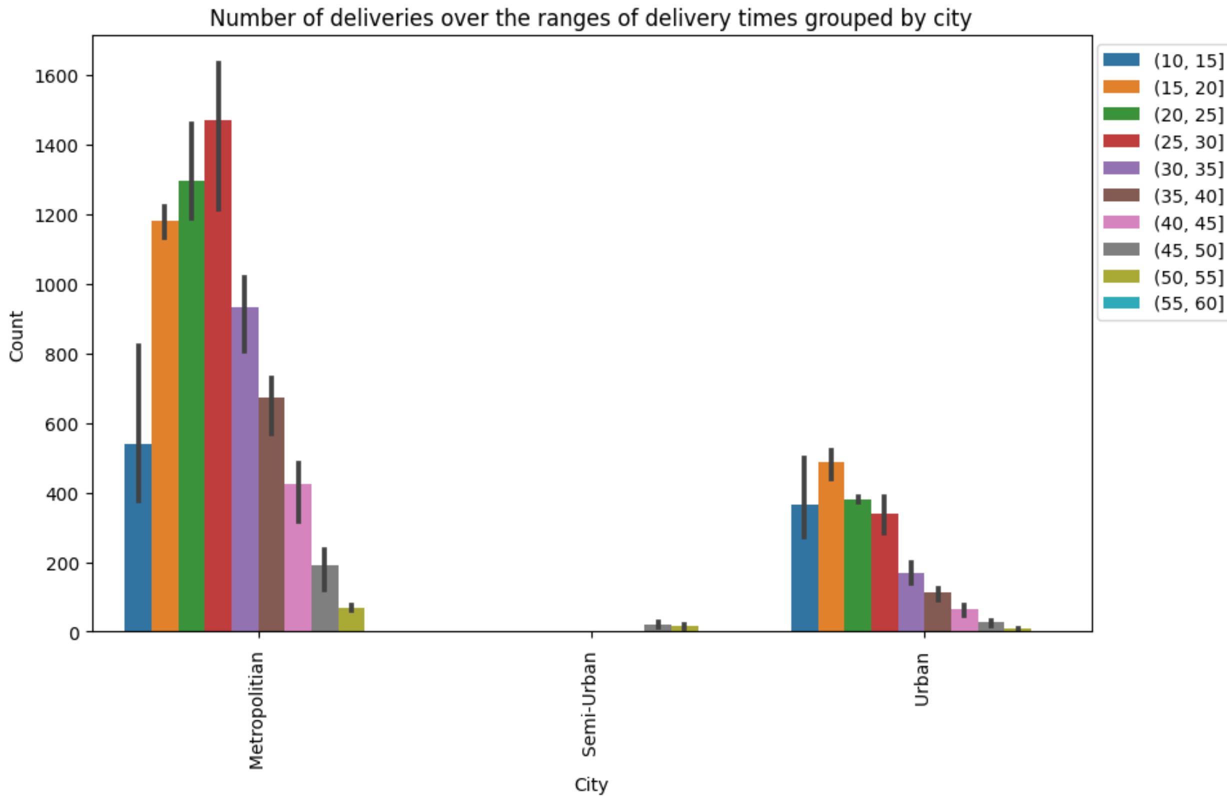
City

```
# Count of each unique value in the 'City' column
city_counts = df['City'].value_counts()

# Count of entries equal to string 'NaN' in the 'City' column
nan_count = (df['City'] == 'NaN ').sum()

# Percentage of entries equal to string 'NaN'
nan_percentage = (nan_count / len(df)) * 100

print("Count of each unique value in the 'City' column:")
print(city_counts)
```

```
print("\nNumber of entries equal to 'NaN' in the 'City' column:",
nan_count)
print("Percentage of entries equal to 'NaN': {:.2f}
%".format(nan_percentage))
```

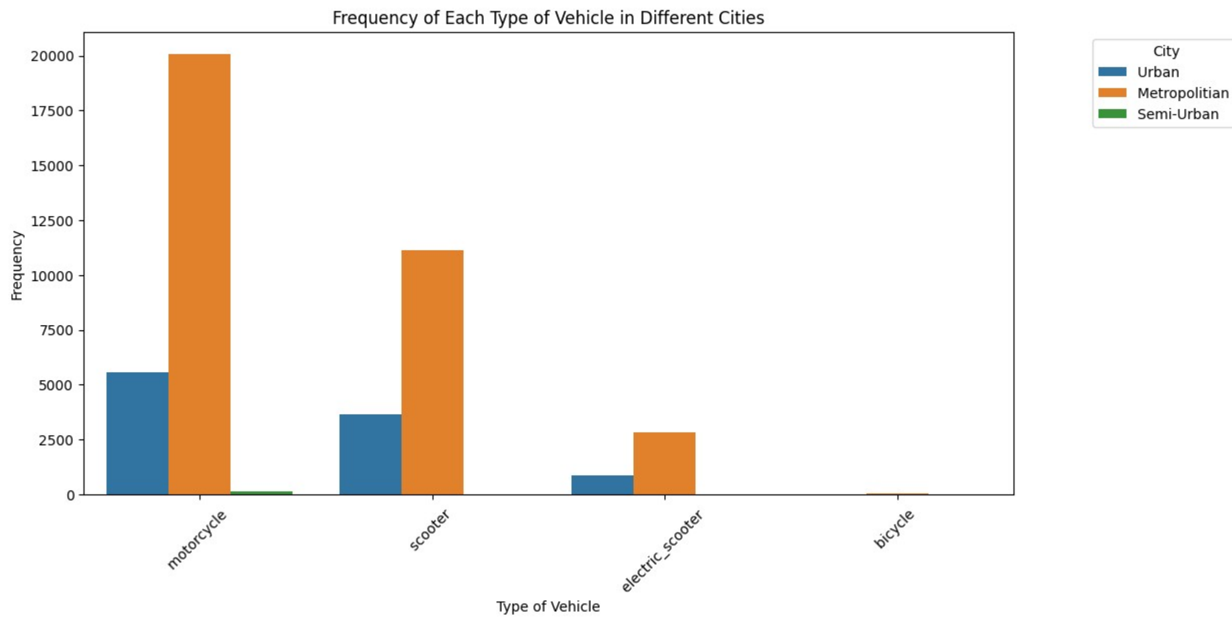
```
Count of each unique value in the 'City' column:
Metropolitian     34093
Urban             10136
Semi-Urban          164
Name: City, dtype: int64

Number of entries equal to 'NaN' in the 'City' column: 0
Percentage of entries equal to 'NaN': 0.00%
```

```
plt.figure(figsize=(10, 6))
temp = df.groupby(['City'])
['Time_taken(min)'].value_counts().sort_index().reset_index(name='Coun
t')
temp['Time_taken(min)_grouped'] = temp['Time_taken(min)'].str.split("
", expand=True)[1]

time_bins = [10, 15, 20, 25, 30, 35, 40, 45, 50, 55, 60]
temp['Time_taken(min)_grouped'] =
pd.to_numeric(temp['Time_taken(min)_grouped'], errors='coerce')
temp['Time_taken(min)_grouped'] =
pd.cut(temp['Time_taken(min)_grouped'], bins=time_bins)
sns.barplot(x=temp['City'], y=temp['Count'],
hue=temp['Time_taken(min)_grouped'])
plt.legend(loc='upper right', bbox_to_anchor=(1.15, 1))
plt.xticks(rotation=90)
plt.title('Number of deliveries over the ranges of delivery times
grouped by city')
plt.show()
```



In metropolitian cities, most of the deliveries take 25-30 mins, while in urban cities, most of the deliveries take 15-20 mins. Thus, the average time required for order deliveries is more in the metropolitian cities.

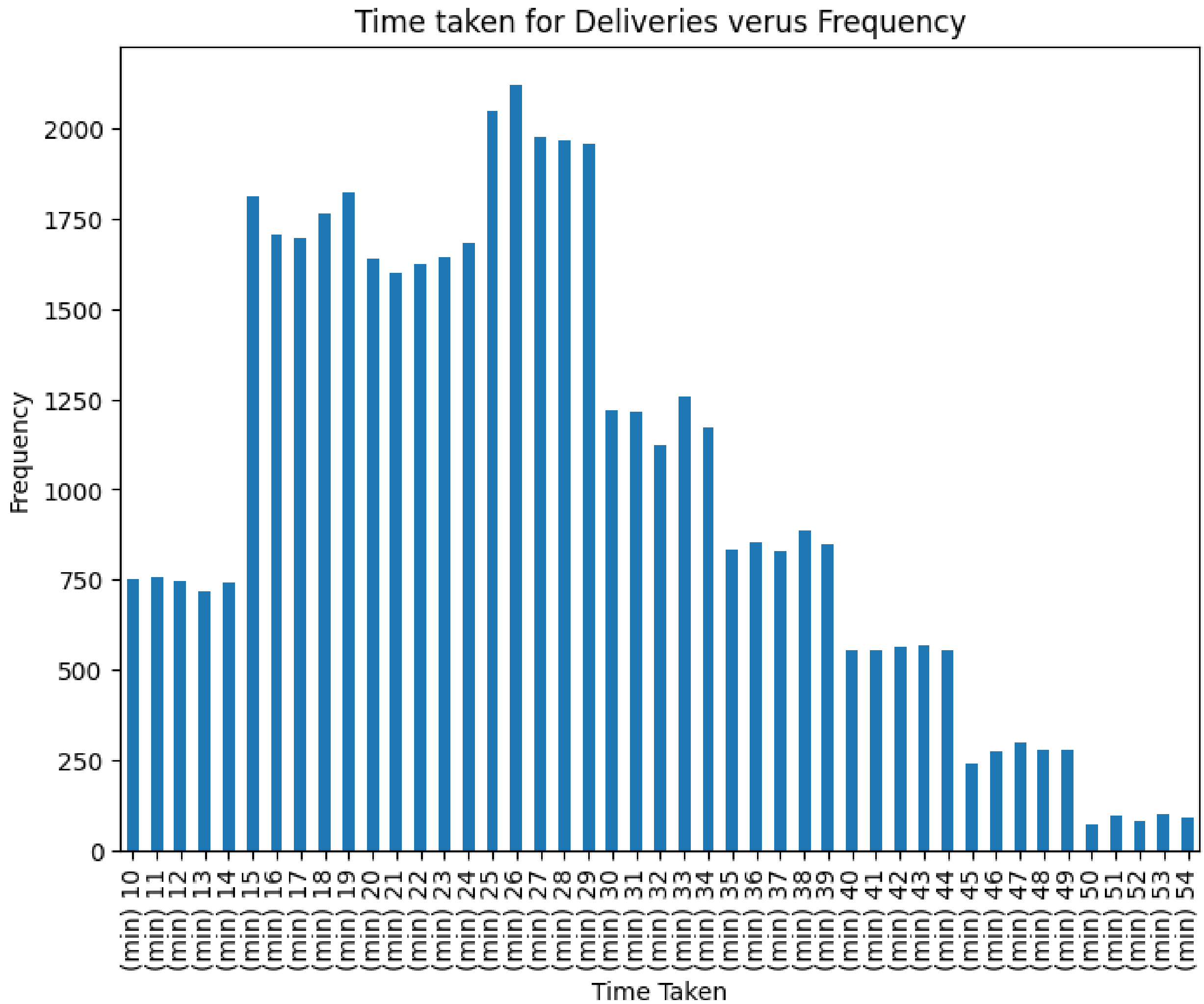
```
plt.figure(figsize=(12, 6))
sns.countplot(x='Type_of_vehicle', hue='City', data=df)
plt.xlabel('Type of Vehicle')
plt.ylabel('Frequency')
plt.title('Frequency of Each Type of Vehicle in Different Cities')
plt.legend(title='City', loc='upper right', bbox_to_anchor=(1.25, 1))
plt.xticks(rotation=45)
plt.show()
```



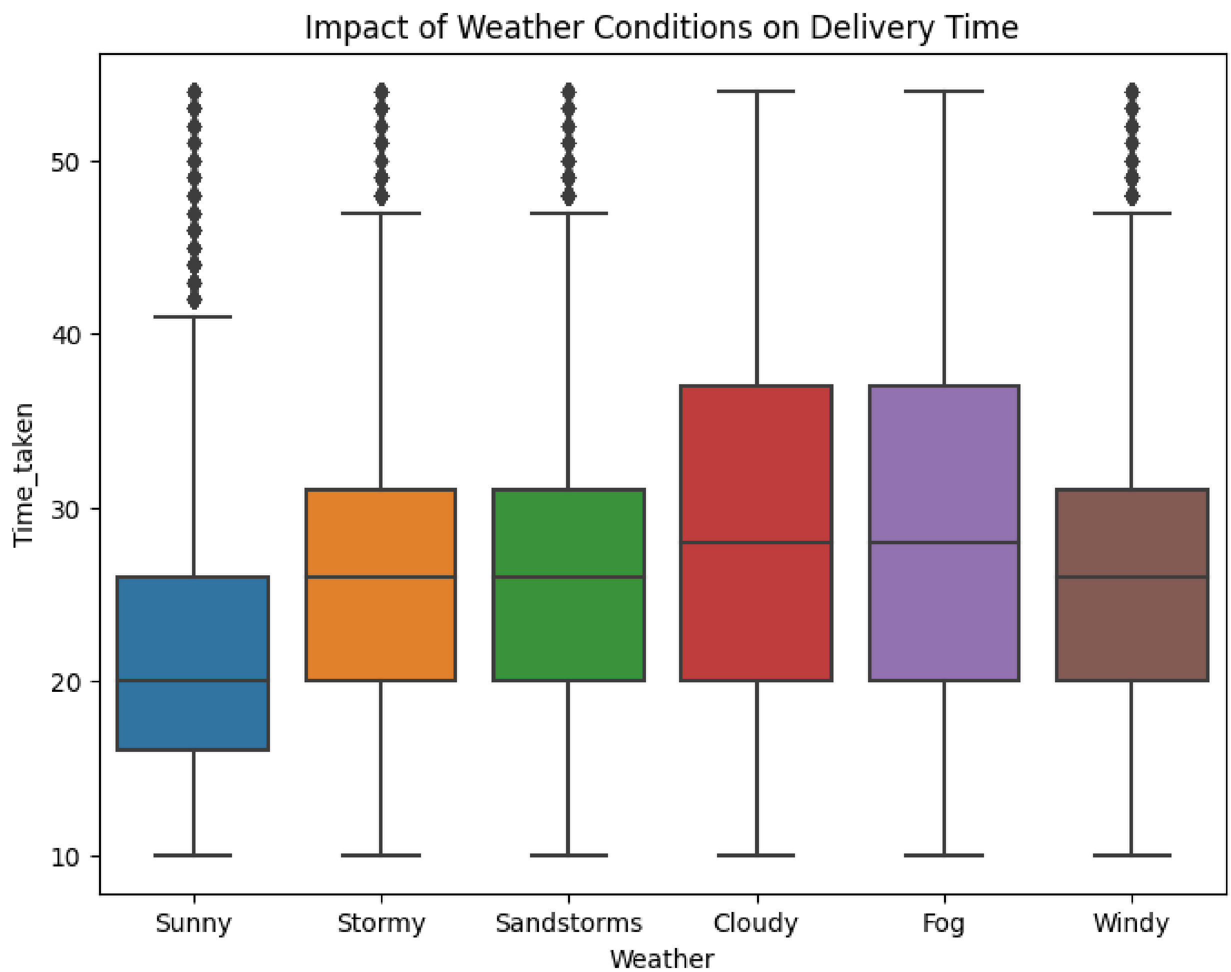
Motorcycle is the most widely used vehicle in all of the types of cities, while bicycle is the least popular vehicle.

Time Taken

```
plt.figure(figsize=(8, 6))
df['Time_taken(min)'].value_counts().sort_index().plot(kind='bar')
plt.xlabel('Time Taken')
plt.ylabel('Frequency')
plt.title('Time taken for Deliveries verus Frequency')
plt.show()
```

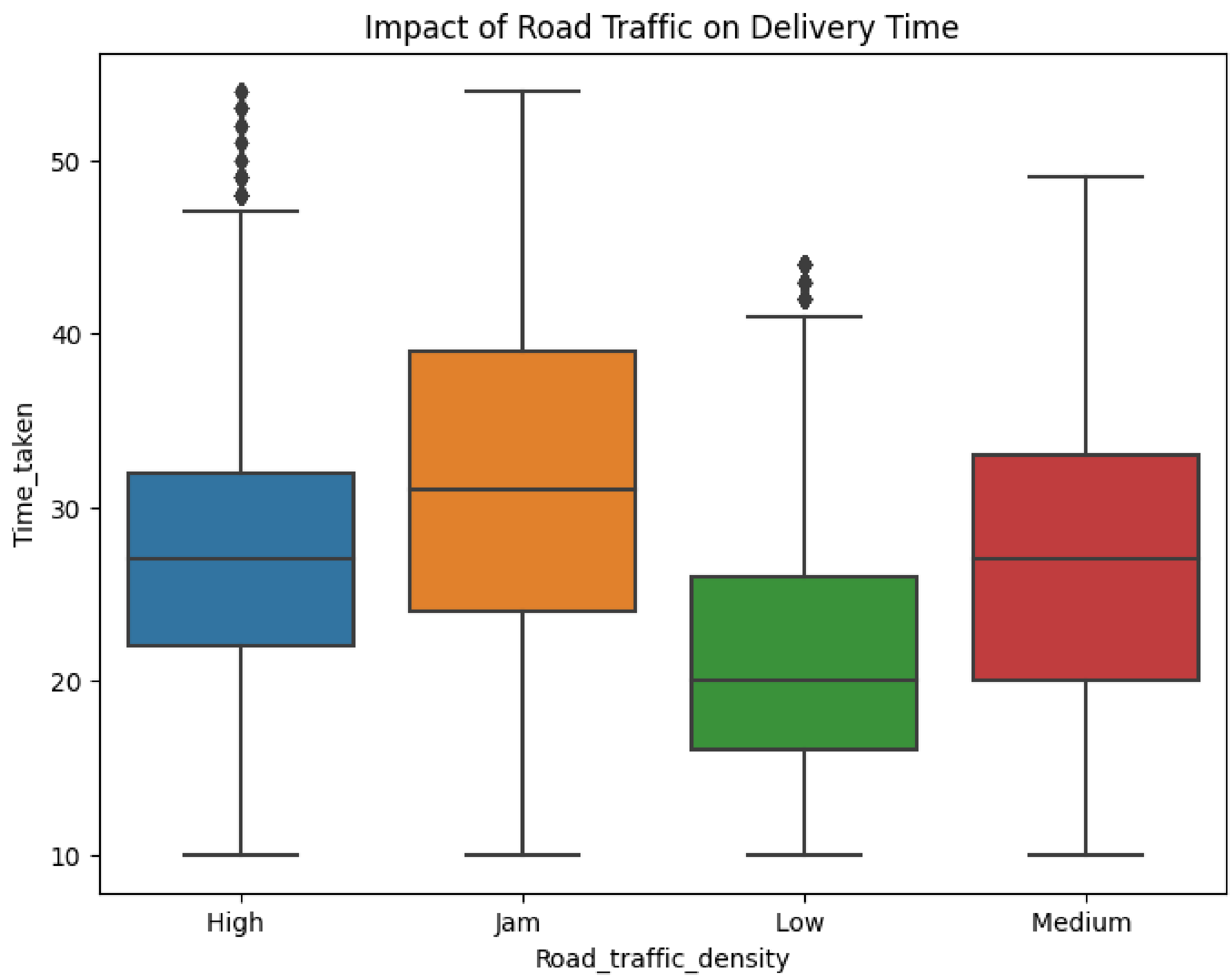



```
# Boxplot Analysis with respect to Time taken: Weather Condition
plt.figure(figsize=(8, 6))
temp = pd.DataFrame()
temp['Time_taken'] = df['Time_taken(min)'].str.split(" ", expand=True)
[1]
temp['Weather'] = df['Weatherconditions'].str.split(" ", expand=True)
[1]
temp['Time_taken'] = temp['Time_taken'].astype(int)
sns.boxplot(y=temp['Time_taken'], x=temp['Weather'])
plt.title("Impact of Weather Conditions on Delivery Time")
plt.show()
```



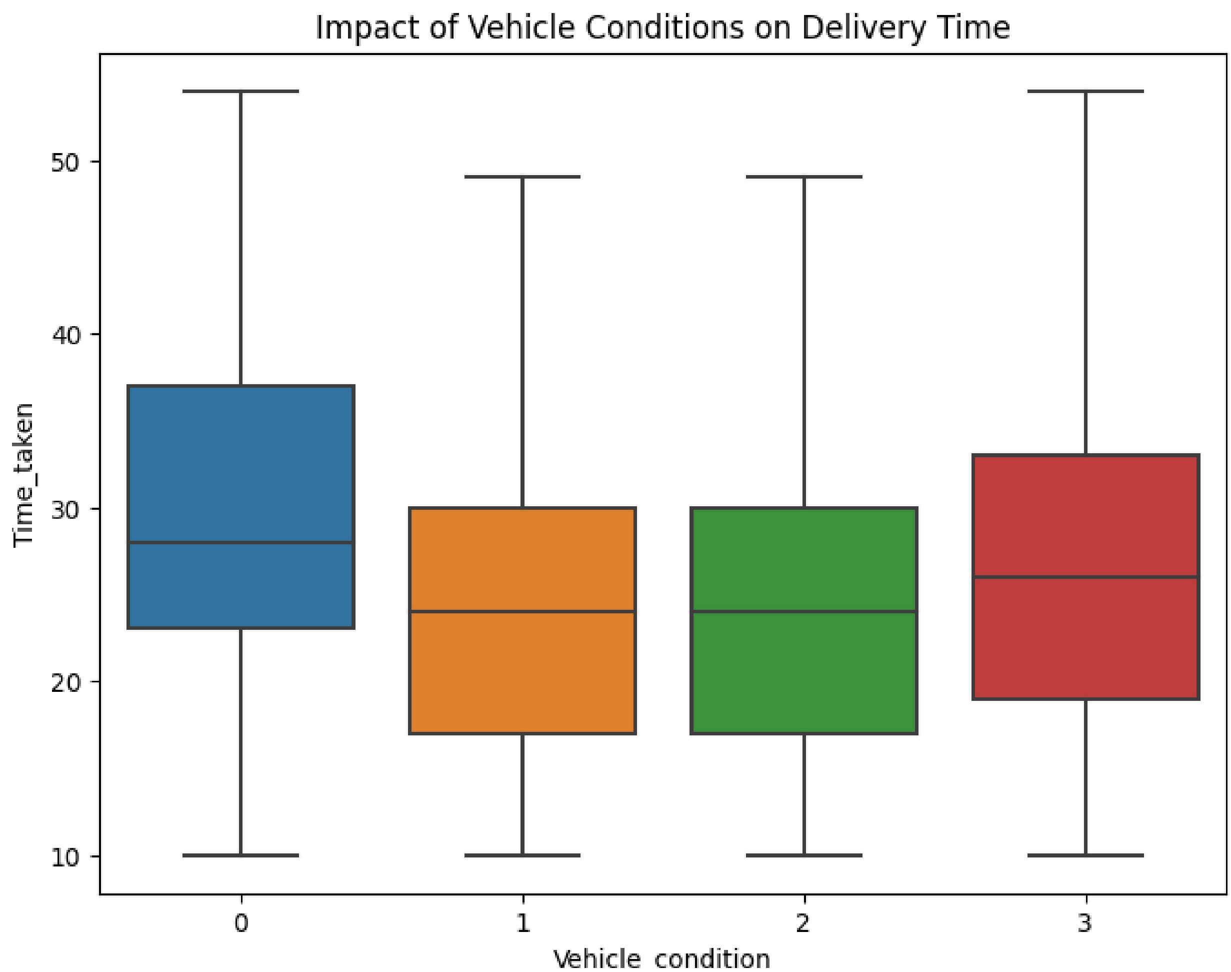
- Cloudy and fog weather condition took more time to deliver food compare to other weather conditions.

```
# Boxplot Analysis with respect to Time taken: Road Traffic Density
plt.figure(figsize=(8, 6))
temp = pd.DataFrame()
temp['Time_taken'] = df['Time_taken(min)'].str.split(" ", expand=True)
[1]
temp['Time_taken'] = temp['Time_taken'].astype(int)
sns.boxplot(y=temp['Time_taken'], x=df['Road_traffic_density'])
plt.title("Impact of Road Traffic on Delivery Time")
plt.show()
```



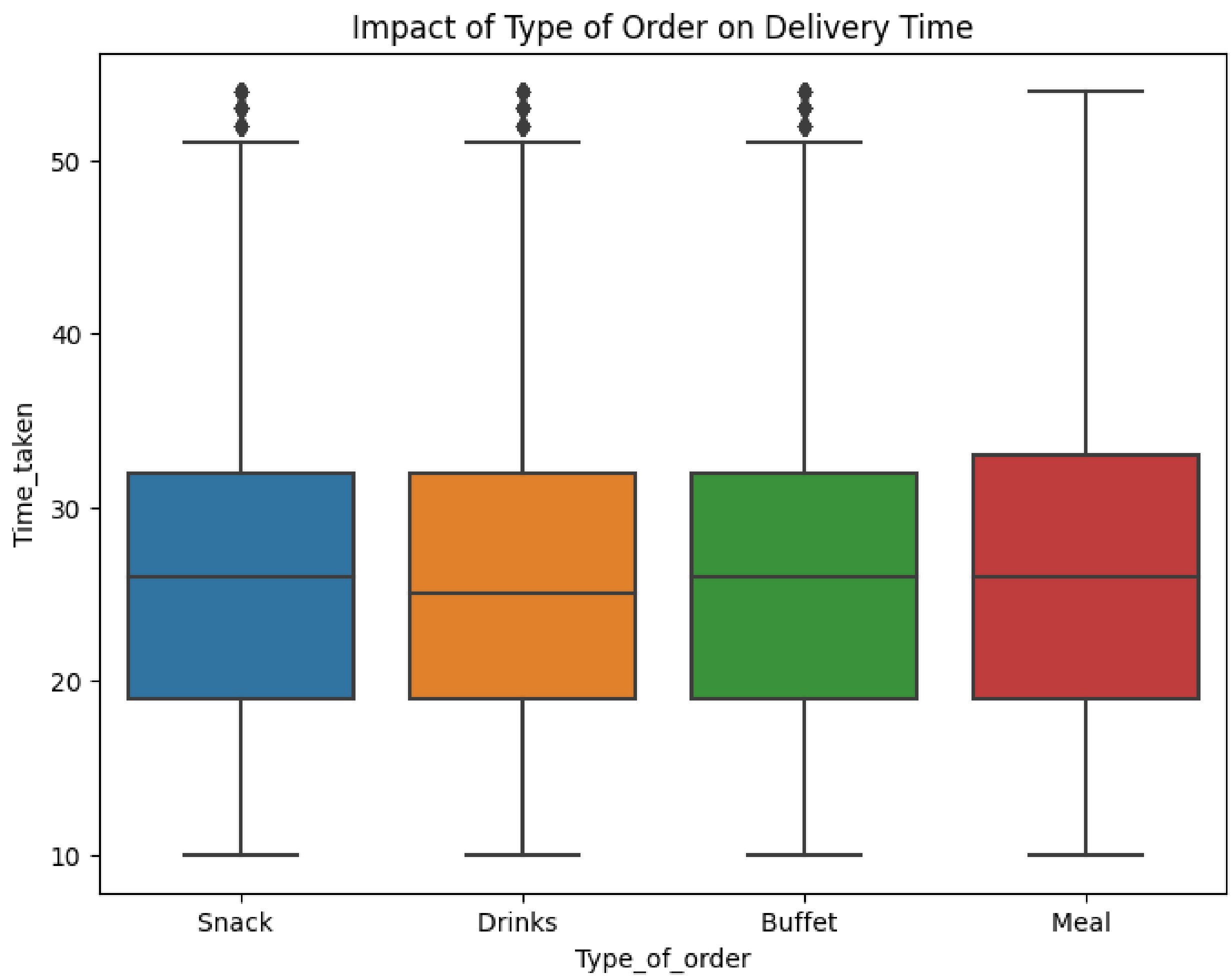
- Appears to be a promising correlation between road traffic density and the duration it takes to deliver food.

```
# Boxplot Analysis with respect to Time taken: Vehicle Condition
plt.figure(figsize=(8, 6))
temp = pd.DataFrame()
temp['Time_taken'] = df['Time_taken(min)'].str.split(" ", expand=True)
[1]
temp['Time_taken'] = temp['Time_taken'].astype(int)
sns.boxplot(y=temp['Time_taken'], x=df['Vehicle_condition'])
plt.title("Impact of Vehicle Conditions on Delivery Time")
plt.show()
```



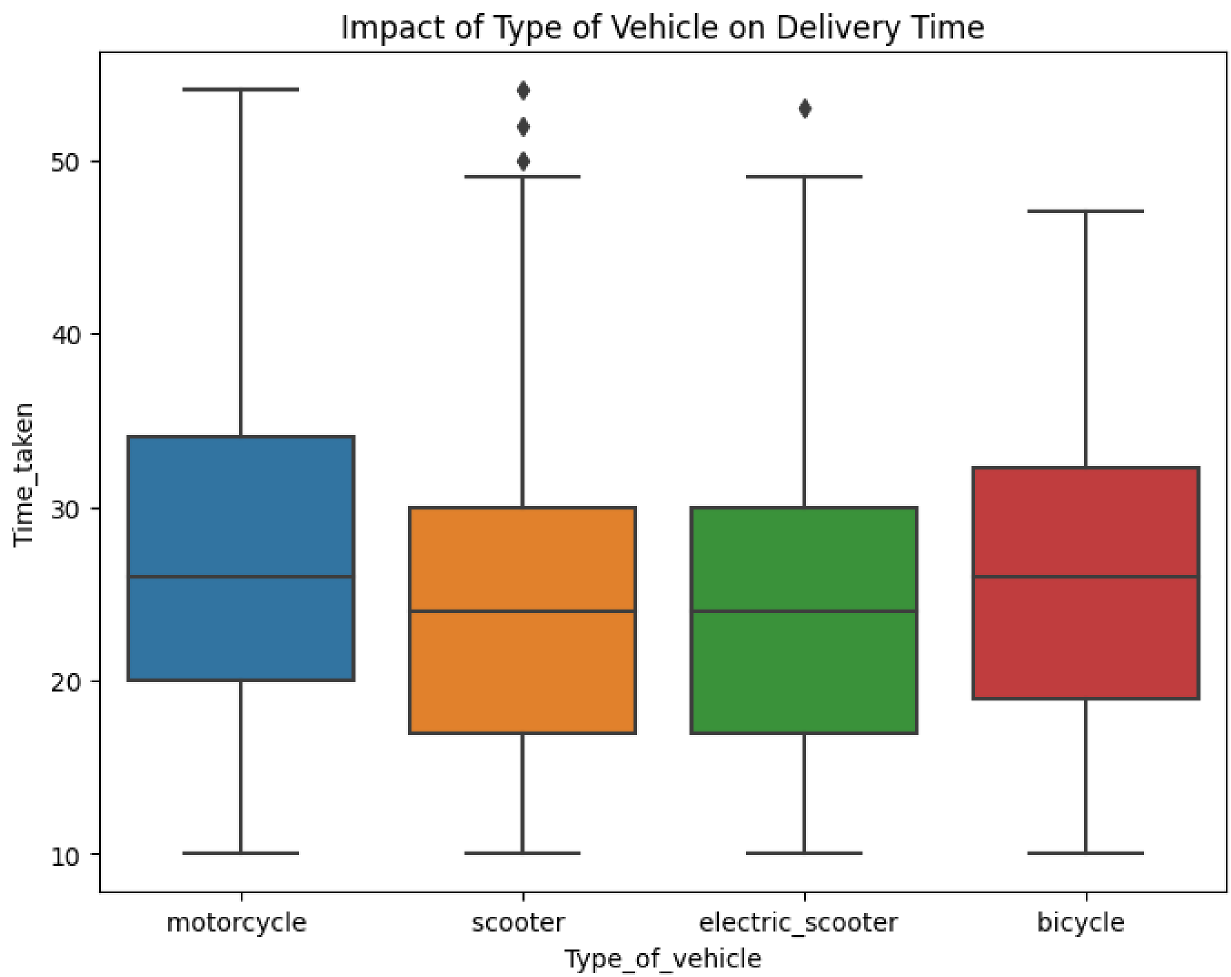
- There is a slight correlation between vehicle condition and time taken to deliver the food.
- Even there is a low number of deliveries made by person whose vehicle condition is poor, has taken max time.

```
# Boxplot Analysis with respect to Time taken: Type of Order
plt.figure(figsize=(8, 6))
temp = pd.DataFrame()
temp['Time_taken'] = df['Time_taken(min)'].str.split(" ", expand=True)
[1]
temp['Time_taken'] = temp['Time_taken'].astype(int)
sns.boxplot(y=temp['Time_taken'], x=df['Type_of_order'])
plt.title("Impact of Type of Order on Delivery Time")
plt.show()
```



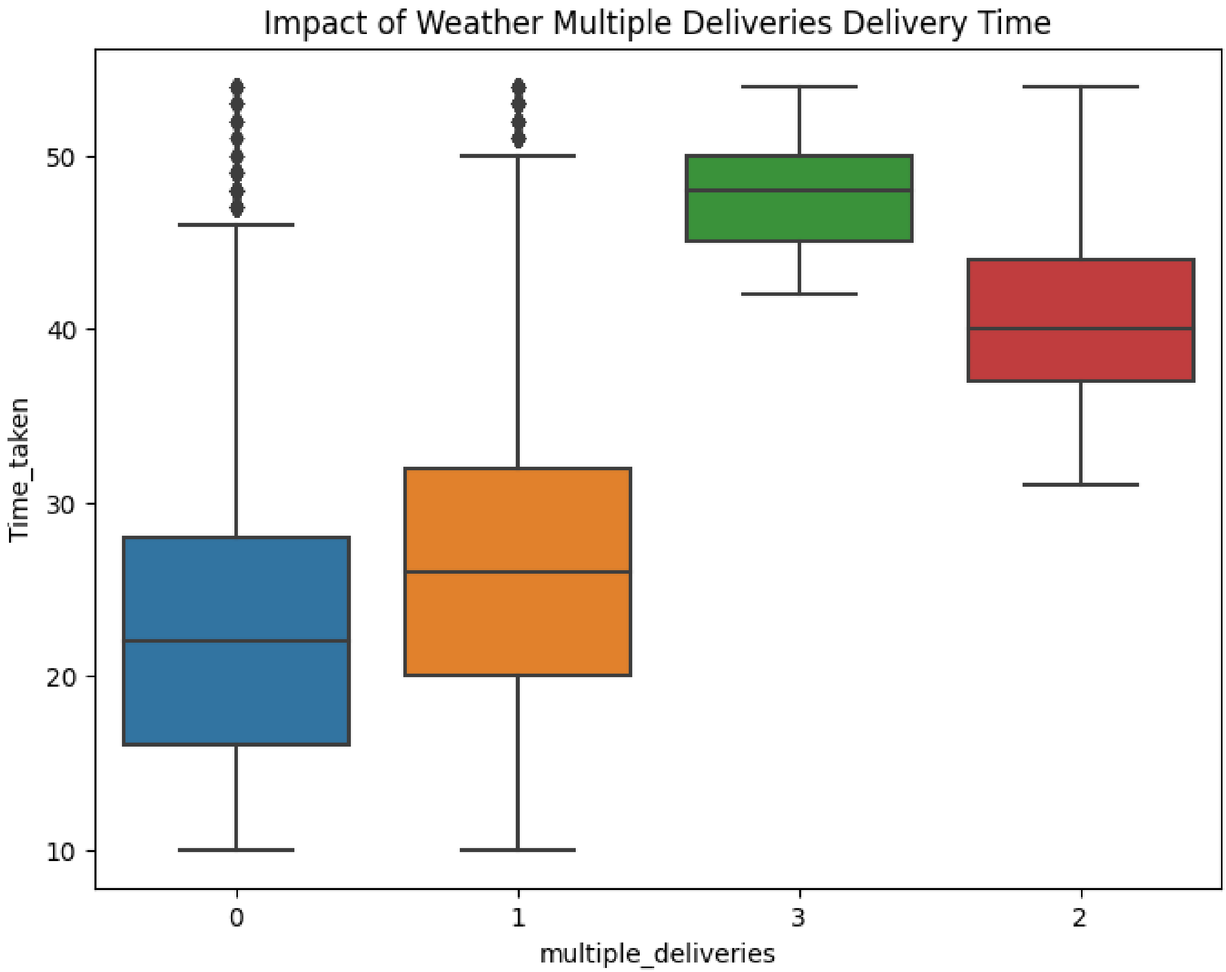
- There is no significant correlation between type of order and time taken to deliver the order.

```
# Boxplot Analysis with respect to Time taken: Type of Vehicle
plt.figure(figsize=(8, 6))
temp = pd.DataFrame()
temp['Time_taken'] = df['Time_taken(min)'].str.split(" ", expand=True)
[1]
temp['Time_taken'] = temp['Time_taken'].astype(int)
sns.boxplot(y=temp['Time_taken'], x=df['Type_of_vehicle'])
plt.title("Impact of Type of Vehicle on Delivery Time")
plt.show()
```



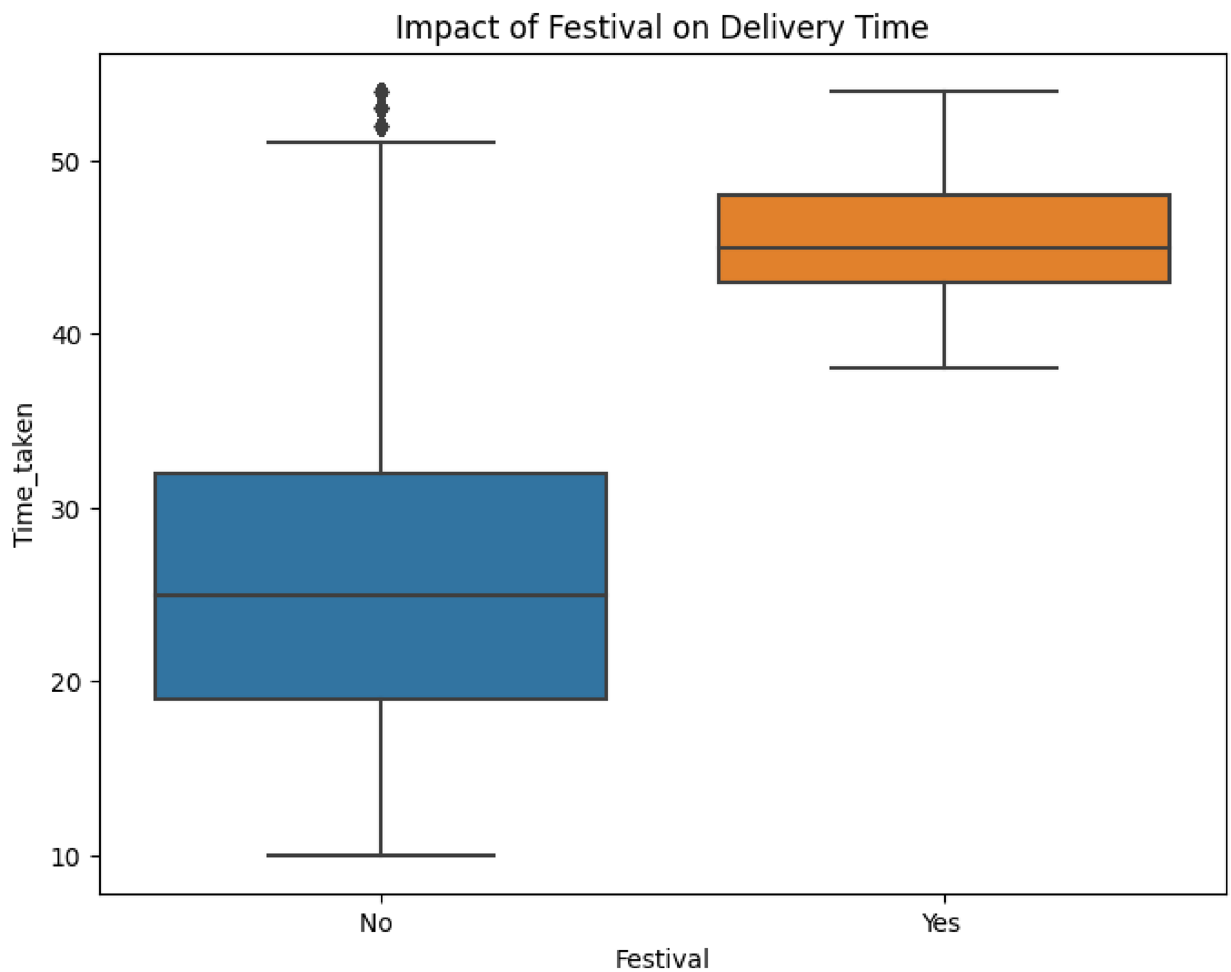
- No significant correlation between type of vehicle and time taken to deliver the food.
- Even with major number of deliveries made by motorcycle and scooter there is not much mean difference in vehicle types.

```
# Boxplot Analysis with respect to Time taken: Multiple Deliveries
plt.figure(figsize=(8, 6))
temp = pd.DataFrame()
temp['Time_taken'] = df['Time_taken(min)'].str.split(" ", expand=True)
[1]
temp['Time_taken'] = temp['Time_taken'].astype(int)
sns.boxplot(y=temp['Time_taken'], x=df['multiple_deliveries'])
plt.title("Impact of Weather Multiple Deliveries Delivery Time")
plt.show()
```



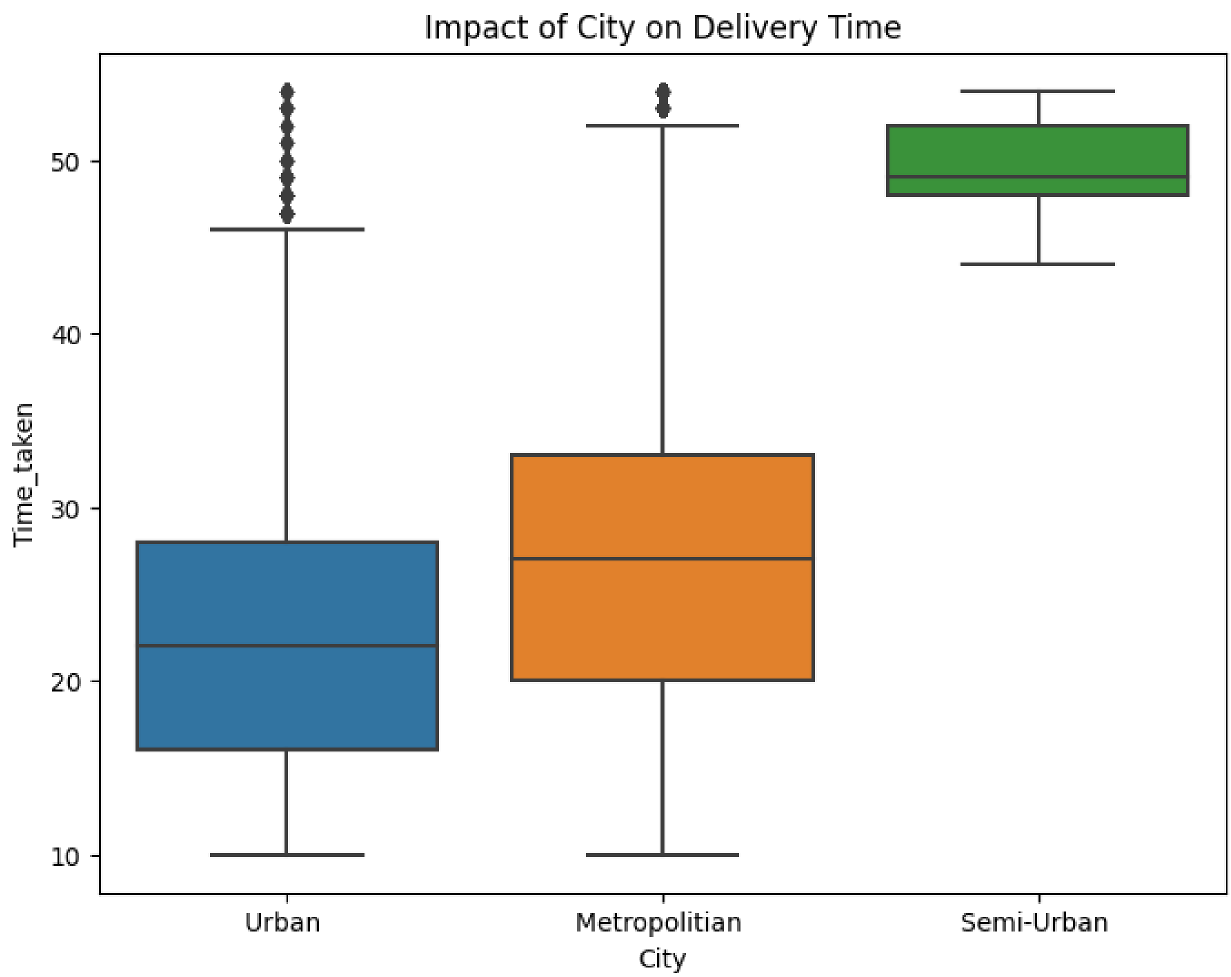
- Number of Deliveries affects the time taken to finish the delivery. Hence, Multiple Deliveries is an important feature.

```
# Boxplot Analysis with respect to Time taken: Festival
plt.figure(figsize=(8, 6))
temp = pd.DataFrame()
temp['Time_taken'] = df['Time_taken(min)'].str.split(" ", expand=True)
[1]
temp['Time_taken'] = temp['Time_taken'].astype(int)
sns.boxplot(y=temp['Time_taken'], x=df['Festival'])
plt.title("Impact of Festival on Delivery Time")
plt.show()
```



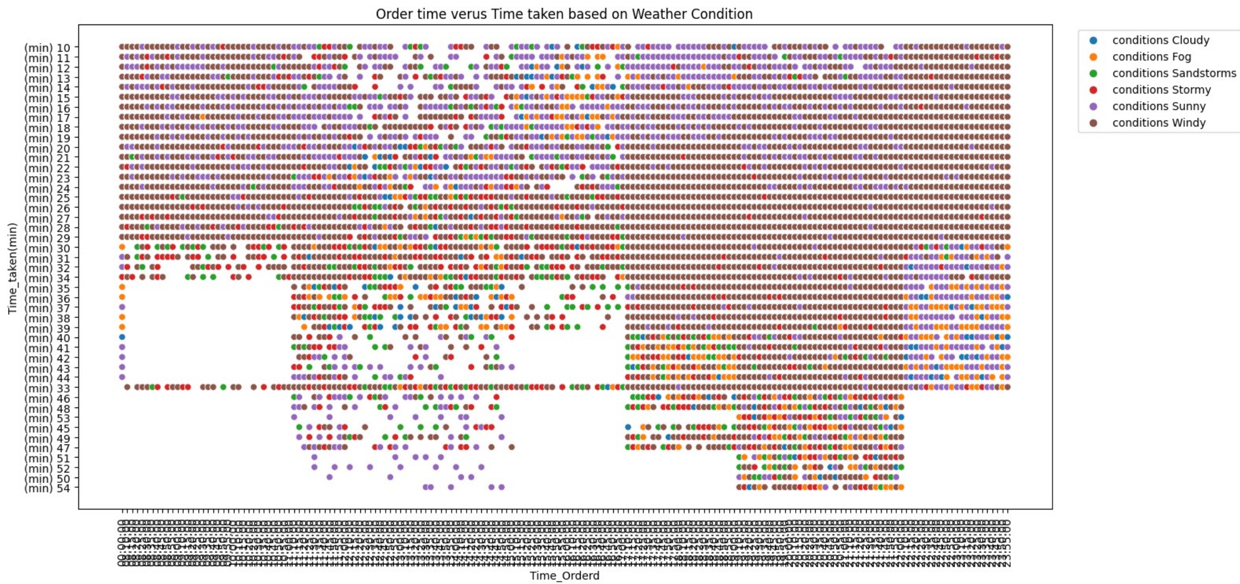
- The delivery time for food is longer during festivals as compared to regular non-festival days.

```
# Boxplot Analysis with respect to Time taken: City
plt.figure(figsize=(8, 6))
temp = pd.DataFrame()
temp['Time_taken'] = df['Time_taken(min)'].str.split(" ", expand=True)
[1]
temp['Time_taken'] = temp['Time_taken'].astype(int)
sns.boxplot(y=temp['Time_taken'], x=df['City'])
plt.title("Impact of City on Delivery Time")
plt.show()
```



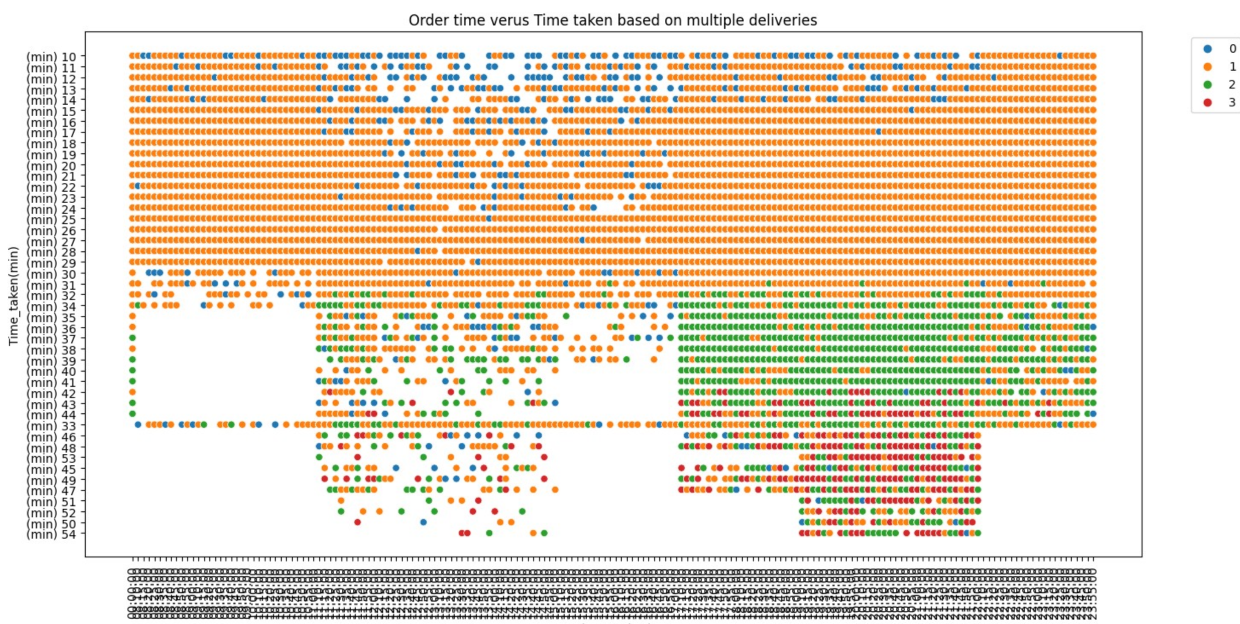
- The type of city has an impact on the delivery time taken.

```
# Order time verus Time taken based on Weather Condition
plt.figure(figsize=(16, 8))
sorted_df = df.sort_values(['Time_Orderd', 'Time_taken(min)',
'Weatherconditions'], ascending=[True, True, True])
sns.scatterplot(x=sorted_df['Time_Orderd'],
y=sorted_df['Time_taken(min)'], hue=sorted_df['Weatherconditions'])
plt.legend(loc='upper right', bbox_to_anchor=(1.2, 1))
plt.xticks(rotation=90)
plt.title('Order time verus Time taken based on Weather Condition')
plt.show()
```



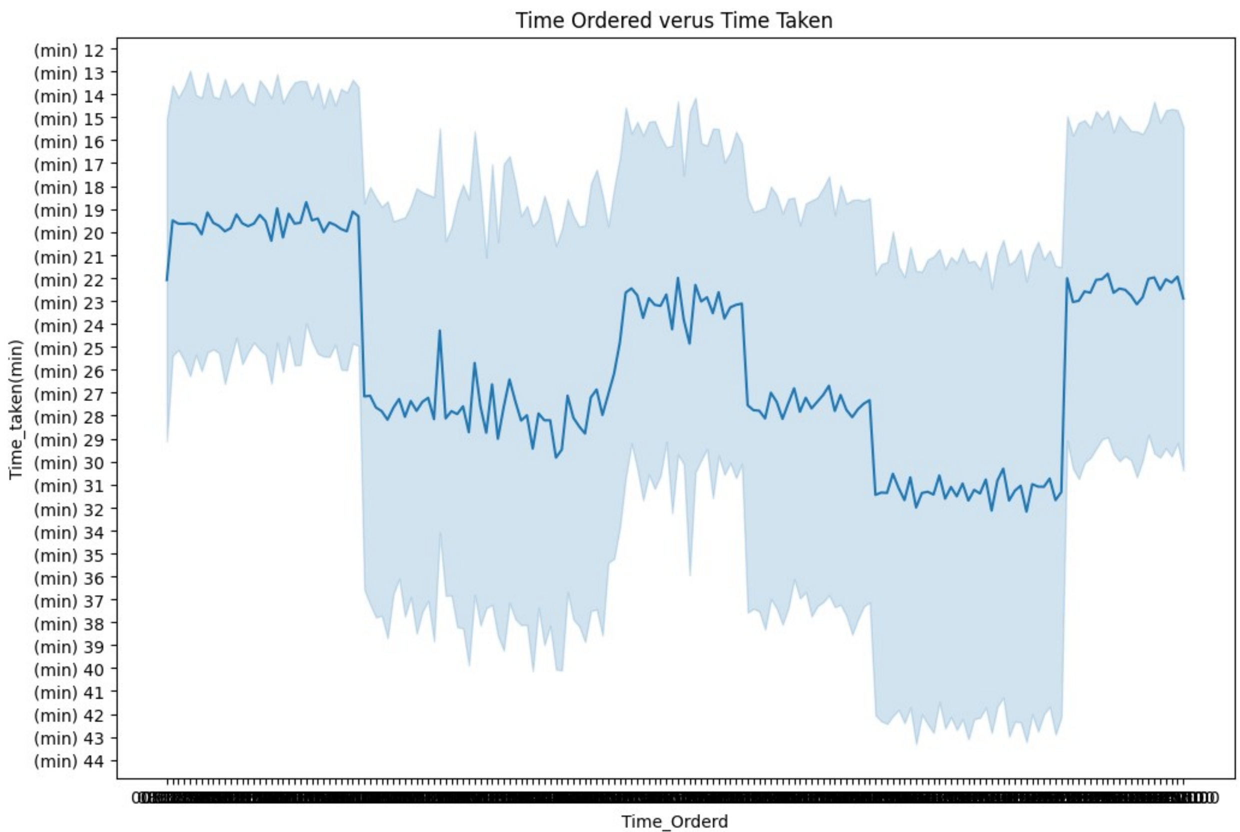
- One important thing to notice is that most of the deliveries that took more time are during sunny day around afternoon.

```
# Order time verus Time taken based on multiple deliveries
plt.figure(figsize=(16, 8))
sorted_df = df.sort_values(['Time_Orderd', 'Time_taken(min)',
'multiple_deliveries'], ascending=[True, True, True])
sns.scatterplot(x=sorted_df['Time_Orderd'],
y=sorted_df['Time_taken(min)'], hue=sorted_df['multiple_deliveries'])
plt.legend(loc='upper right', bbox_to_anchor=(1.1, 1))
plt.xticks(rotation=90)
plt.title('Order time verus Time taken based on multiple deliveries')
plt.show()
```



- More than 2 deliveries took more than 30 mins for every deliveries.

```
# Time ordered verus time taken
plt.figure(figsize=(12, 8))
sorted_df = df.sort_values(['Time_Orderd', 'Time_taken(min)'],
ascending=[True, True])
sns.lineplot(x='Time_Orderd', y='Time_taken(min)', data=sorted_df,
errorbar='sd')
plt.title('Time Ordered verus Time Taken')
plt.show()
```



- The standard deviation of delivery times for both early and late deliveries falls within the range of 19 to 23. However, deliveries made at other times tend to have longer durations.

Data Cleaning

Time_taken(min) column contains the text '(min)' in it, which should be removed so that it is converted to a numeric data type. Similarly, the text 'conditions' must be removed from the Weatherconditions column.

Some restaurant latitudes and longitudes have incorrect values, these rows have been removed from the data frame.

```
def clean_delivery_data(df):
    # Extract the numeric part from 'Time_taken(min)' column and
convert to integers
    df['Time_taken(min)'] = df['Time_taken(min)'].apply(lambda x:
int(x.split(" ")[1].strip()))

    # Remove ratings with 6 value
    df.drop(df[df['Delivery_person_Ratings'] == 6].index,
inplace=True)

    # Remove record with age of 15
    df.drop(df[df['Delivery_person_Age'] == 15].index, inplace=True)

    # Extract the second part from 'Weatherconditions' column and
handle missing values
    df['Weatherconditions'] = df['Weatherconditions'].apply(lambda x:
x.split(" ")[1].strip() if not pd.isna(x) else np.nan)

    # Remove incorrect locations based on latitude and longitude
    df.drop(df[(df['Restaurant_latitude'] <= 0) |
(df['Restaurant_longitude'] <= 0)].index, inplace=True)

    return df

df.head()
```

```
        ID Delivery_person_ID  Delivery_person_Age
Delivery_person_Ratings  \
0  0x4607     INDORES13DEL02                 37.0
4.9
1  0xb379     BANGRES18DEL02                 34.0
4.5
2  0x5d6d     BANGRES19DEL01                 23.0
4.4
3  0x7a6a    COIMBRES13DEL02                 38.0
4.7
4  0x70a2     CHENRES12DEL01                 32.0
4.6

   Restaurant_latitude  Restaurant_longitude
Delivery_location_latitude  \
0            22.745049             75.892471
22.765049
1            12.913041             77.683237
13.043041
2            12.914264             77.678400
12.924264
3            11.003669             76.976494
11.053669
4            12.972793             80.249982
```

```
13.012793

   Delivery_location_longitude  Order_Date Time_Orderd  ...  \
0                    75.912471  19-03-2022    11:30:00  ...
1                    77.813237  25-03-2022    19:45:00  ...
2                    77.688400  19-03-2022    08:30:00  ...
3                    77.026494  05-04-2022    18:00:00  ...
4                    80.289982  26-03-2022    13:30:00  ...

       Weatherconditions Road_traffic_density Vehicle_condition  \
0       conditions Sunny                High                 2
1      conditions Stormy                 Jam                 2
2  conditions Sandstorms                 Low                 0
3       conditions Sunny              Medium                 0
4      conditions Cloudy                High                 1

   Type_of_order Type_of_vehicle multiple_deliveries Festival
City  \
0         Snack      motorcycle                   0      No
Urban
1         Snack         scooter                   1      No
Metropolitian
2        Drinks      motorcycle                   1      No
Urban
3        Buffet      motorcycle                   1      No
Metropolitian
4         Snack         scooter                   1      No
Metropolitian

  Time_taken(min) Month_Year
0        (min) 24    2022-03
1        (min) 33    2022-03
2        (min) 26    2022-03
3        (min) 21    2022-05
4        (min) 30    2022-03

[5 rows x 21 columns]

df = clean_delivery_data(df)
df.head()

        ID Delivery_person_ID  Delivery_person_Age
Delivery_person_Ratings  \
0  0x4607     INDORES13DEL02                 37.0
4.9
1  0xb379     BANGRES18DEL02                 34.0
4.5
2  0x5d6d     BANGRES19DEL01                 23.0
4.4
3  0x7a6a    COIMBRES13DEL02                 38.0
```

```
4.7
4  0x70a2     CHENRES12DEL01                  32.0
4.6

   Restaurant_latitude  Restaurant_longitude
Delivery_location_latitude  \
0            22.745049             75.892471
22.765049
1            12.913041             77.683237
13.043041
2            12.914264             77.678400
12.924264
3            11.003669             76.976494
11.053669
4            12.972793             80.249982
13.012793

   Delivery_location_longitude  Order_Date Time_Orderd  ...
Weatherconditions  \
0                    75.912471  19-03-2022    11:30:00  ...
Sunny
1                    77.813237  25-03-2022    19:45:00  ...
Stormy
2                    77.688400  19-03-2022    08:30:00  ...
Sandstorms
3                    77.026494  05-04-2022    18:00:00  ...
Sunny
4                    80.289982  26-03-2022    13:30:00  ...
Cloudy

  Road_traffic_density Vehicle_condition  Type_of_order
Type_of_vehicle  \
0                 High                 2         Snack      motorcycle

1                  Jam                 2         Snack         scooter

2                  Low                 0        Drinks      motorcycle

3               Medium                 0        Buffet      motorcycle

4                 High                 1         Snack         scooter


  multiple_deliveries Festival           City Time_taken(min)
Month_Year
0                   0      No          Urban              24
2022-03
1                   1      No   Metropolitian             33
2022-03
2                   1      No          Urban              26
```

```
2022-03
3                    1       No    Metropolitian                 21
2022-05
4                    1       No    Metropolitian                 30
2022-03

[5 rows x 21 columns]
```

```
df[['Time_taken(min)','Weatherconditions']].head()
```

```
   Time_taken(min) Weatherconditions
0               24             Sunny
1               33            Stormy
2               26        Sandstorms
3               21             Sunny
4               30            Cloudy
```

The numeric data columns have been converted to float type. The values in Order_Date column are not in the same format. They have been converted so that all the dates follow a common format.

```
def convert_data_types(df):
    # Convert 'Delivery_person_Age', 'Delivery_person_Ratings', and
'multiple_deliveries' to float64
    df['Delivery_person_Age'] =
df['Delivery_person_Age'].astype('float64')
    df['Delivery_person_Ratings'] =
df['Delivery_person_Ratings'].astype('float64')
    df['multiple_deliveries'] =
df['multiple_deliveries'].astype('float64')

    # Convert 'Order_Date' column to datetime format, handling mixed
date formats
    df['Order_Date'] = pd.to_datetime(df['Order_Date'],
errors='coerce')

    # Separate dates with NaT (Not-a-Time) values based on the '/' or
'-' separator
    dates_with_slash = df['Order_Date']
[df['Order_Date'].dt.strftime('%m/%d/%Y').notnull()]
    dates_with_hyphen = df['Order_Date']
[df['Order_Date'].dt.strftime('%m-%d-%Y').notnull()]

    # Reformat dates with the '/' separator to the desired format '%d-
%m-%Y'
    df.loc[dates_with_slash.index, 'Order_Date'] =
dates_with_slash.dt.strftime('%d-%m-%Y')

    return df
```

```
df = convert_data_types(df)
df[['Delivery_person_Age','Delivery_person_Ratings','multiple_deliveri
es','Order_Date']].head()
```

```
<ipython-input-83-a77abfd75c39>:8: UserWarning: Parsing dates in
DD/MM/YYYY format when dayfirst=False (the default) was specified.
This may lead to inconsistently parsed dates! Specify a format to
ensure consistent parsing.
  df['Order_Date'] = pd.to_datetime(df['Order_Date'], errors='coerce')
<ipython-input-83-a77abfd75c39>:15: UserWarning: Parsing dates in
DD/MM/YYYY format when dayfirst=False (the default) was specified.
This may lead to inconsistently parsed dates! Specify a format to
ensure consistent parsing.
  df.loc[dates_with_slash.index, 'Order_Date'] =
dates_with_slash.dt.strftime('%d-%m-%Y')
<ipython-input-83-a77abfd75c39>:15: DeprecationWarning: In a future
version, `df.iloc[:, i] = newvals` will attempt to set the values
inplace instead of always setting a new array. To retain the old
behavior, use either `df[df.columns[i]] = newvals` or, if columns are
non-unique, `df.isetitem(i, newvals)`
  df.loc[dates_with_slash.index, 'Order_Date'] =
dates_with_slash.dt.strftime('%d-%m-%Y')

   Delivery_person_Age  Delivery_person_Ratings
multiple_deliveries  \
0                 37.0                      4.9                  0.0

1                 34.0                      4.5                  1.0

2                 23.0                      4.4                  1.0

3                 38.0                      4.7                  1.0

4                 32.0                      4.6                  1.0


   Order_Date
0  19-03-2022
1  25-03-2022
2  19-03-2022
3  04-05-2022
4  26-03-2022
```

Handling NULL/NaN values

Most of the features have NaN values in form of the string 'NaN '. They have to be converted to NaN which can be recognized by numpy and pandas.

```
def convert_nan_to_nan(df):
    # Replace the string 'NaN' with numpy.nan in the DataFrame
```

```
    df.replace('NaN ', np.nan, regex=True, inplace=True)

convert_nan_to_nan(df)
# df.head()

df.isnull().sum()
```

```
ID                                0
Delivery_person_ID                0
Delivery_person_Age            1476
Delivery_person_Ratings        1515
Restaurant_latitude               0
Restaurant_longitude              0
Delivery_location_latitude        0
Delivery_location_longitude       0
Order_Date                        0
Time_Orderd                    1276
Time_Order_picked                 0
Weatherconditions               371
Road_traffic_density            359
Vehicle_condition                 0
Type_of_order                     0
Type_of_vehicle                   0
multiple_deliveries             897
Festival                        215
City                           1097
Time_taken(min)                   0
Month_Year                        0
dtype: int64
```

Delivery Person Id

```
df['Delivery_person_ID'].isnull().sum()
```

```
0
```

```
df['Delivery_person_ID'].value_counts().sort_values()
```

```
BHPRES010DEL03      5
KOLRES010DEL03      6
KOLRES09DEL03       6
KOCRES16DEL03       6
BHPRES08DEL03       6
                   ..
INDORES15DEL01     65
JAPRES03DEL01      66
VADRES11DEL02      66
PUNERES01DEL01     67
JAPRES11DEL02      67
Name: Delivery_person_ID, Length: 1170, dtype: int64
```

- No NaN values found in Delivery Id.
- There are few number of delivery person who delivered items more than 50 compared to less number of delivery persons.
- More than 400 Delivery people delivered food in range of (10, 20) , followed by the range of (50, 60) number of deliveries. These data are confirmed by the histplot above.

Delivery Person Age

```
# Printing number of NaN values
print('Number of NaN values: ',
df['Delivery_person_Age'].isna().sum())
```

```
Number of NaN values:  1476
```

```
df['Delivery_person_Age'].value_counts().sort_index()
```

```
20.0    1955
21.0    1961
22.0    2021
23.0    1933
24.0    2035
25.0    1984
26.0    1980
27.0    1966
28.0    1997
29.0    2007
30.0    2036
31.0    1936
32.0    1999
33.0    2010
34.0    1986
35.0    2093
36.0    2070
37.0    2042
38.0    2018
39.0    1968
Name: Delivery_person_Age, dtype: int64
```

- Most of the values ranges from age 20-39. Hence, it is a good choice to take the range from that range to fill the values.

```
def handle_delv_person_age(df):
  df['Delivery_person_Age'] =
df['Delivery_person_Age'].astype('float32')

  lower_bound = 20
  upper_bound = 40

  missing_count = df['Delivery_person_Age'].isnull().sum()
  random_ages = np.random.randint(lower_bound, upper_bound + 1,
```

```
size=missing_count)
  print(random_ages)
  df.loc[df['Delivery_person_Age'].isnull(), 'Delivery_person_Age'] =
random_ages

handle_delv_person_age(df)
```

```
[28 25 40 ... 37 33 38]
```

```
df['Delivery_person_Age'].value_counts().sort_index()
```

```
20.0    2022
21.0    2041
22.0    2096
23.0    2009
24.0    2111
25.0    2044
26.0    2039
27.0    2038
28.0    2089
29.0    2061
30.0    2108
31.0    2020
32.0    2066
33.0    2074
34.0    2059
35.0    2160
36.0    2131
37.0    2113
38.0    2084
39.0    2040
40.0      68
Name: Delivery_person_Age, dtype: int64
```

Delivery Person Rating

```
df['Delivery_person_Ratings'].unique()
```

```
array([4.9, 4.5, 4.4, 4.7, 4.6, 4.8, 4.2, 4.3, 4. , 4.1, 5. , nan,
3.8,
       3.9, 3.7, 2.6, 3.5, 2.5, 3.6, 3.1, 2.7, 3.3, 3.4, 3.2, 2.8,
2.9,
       3. ])
```

```
df['Delivery_person_Ratings'].isnull().sum()
```

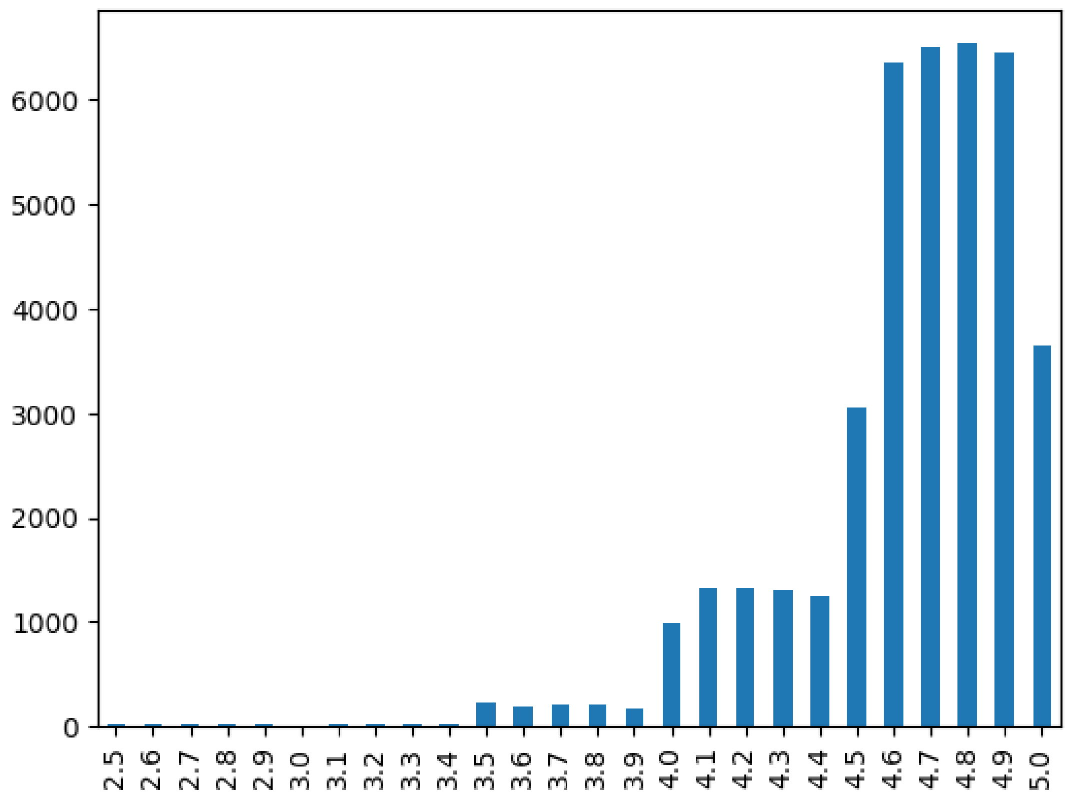
```
1515
```

```
df['Delivery_person_Ratings'].value_counts().sort_index()
```

```
2.5      18
2.6      20
2.7      21
2.8      17
2.9      18
3.0       6
3.1      28
3.2      26
3.3      23
3.4      31
3.5     236
3.6     193
3.7     202
3.8     215
3.9     174
4.0     994
4.1    1320
4.2    1329
4.3    1299
4.4    1243
4.5    3053
4.6    6359
4.7    6494
4.8    6535
4.9    6455
5.0    3649
Name: Delivery_person_Ratings, dtype: int64
```

```
df['Delivery_person_Ratings'].value_counts().sort_index().plot(kind='bar')
```

```
<Axes: >
```




```
# df['Delivery_person_Ratings'] =
df['Delivery_person_Ratings'].fillna(df['Delivery_person_Ratings'].mea
n())
def handle_delv_person_ratings(df):
  df['Delivery_person_Ratings'] =
df['Delivery_person_Ratings'].astype(float).round(2)

  lower_bound = 3.0
  upper_bound = 4.0

  missing_count = df['Delivery_person_Ratings'].isnull().sum()
  random_ratings = np.random.uniform(lower_bound, upper_bound + 1,
size=missing_count)
  random_ratings = np.round(random_ratings, decimals=1)
  print(random_ratings)
  df.loc[df['Delivery_person_Ratings'].isnull(),
'Delivery_person_Ratings'] = random_ratings

handle_delv_person_ratings(df)

[4.8 4.1 3.2 ... 3.7 3.5 3.2]
```

- NaN values on the Delivery Person ratings column have been filled with random selection from the available choices of values. This will prevent unbiased predictions.

```
df['Delivery_person_Ratings'].isnull().sum()
```

```
0
```

Delivery Longitude, Delivery Latitude

```
df[['Delivery_location_longitude',
'Delivery_location_latitude']].isnull().sum()
```

```
Delivery_location_longitude    0
Delivery_location_latitude     0
dtype: int64
```

Weather Condition

```
df['Weatherconditions'].isnull().sum()
```

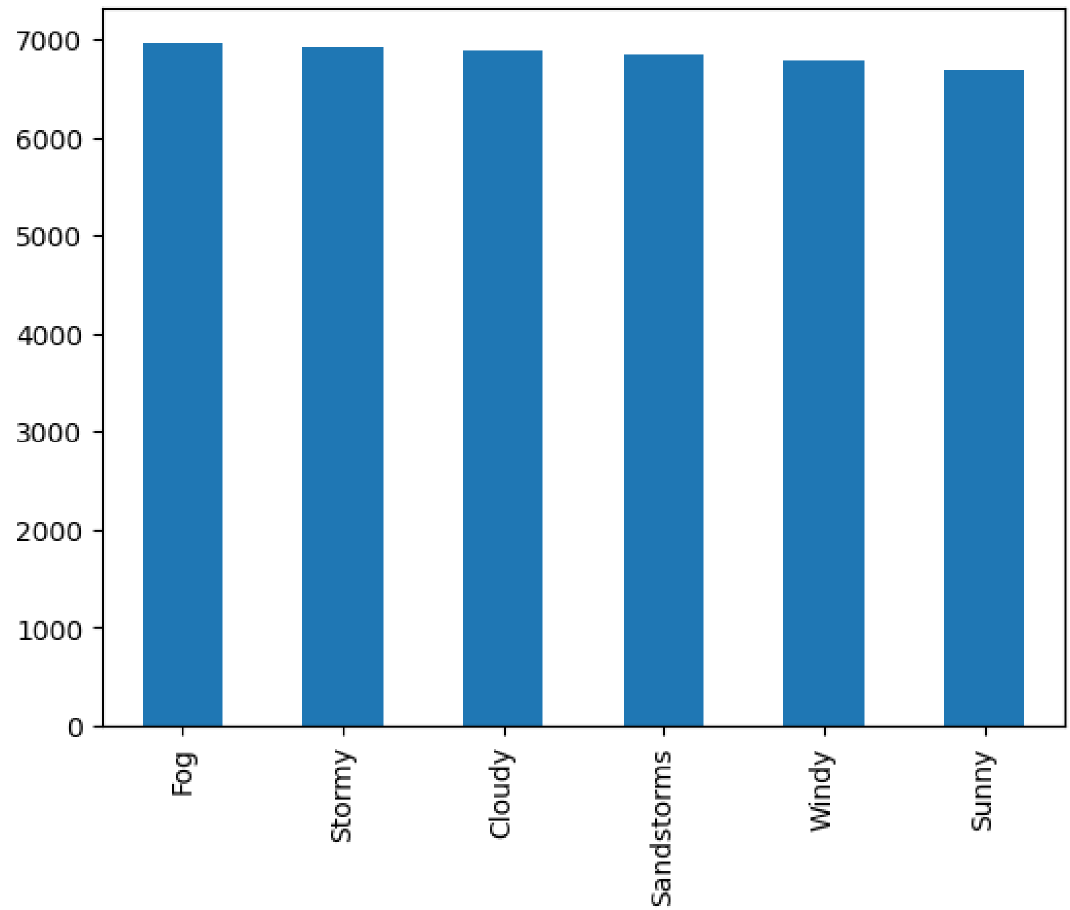
```
371
```

```
df['Weatherconditions'].value_counts()
```

```
Fog           6962
Stormy        6932
Cloudy        6881
Sandstorms    6853
Windy         6792
Sunny         6682
Name: Weatherconditions, dtype: int64
```

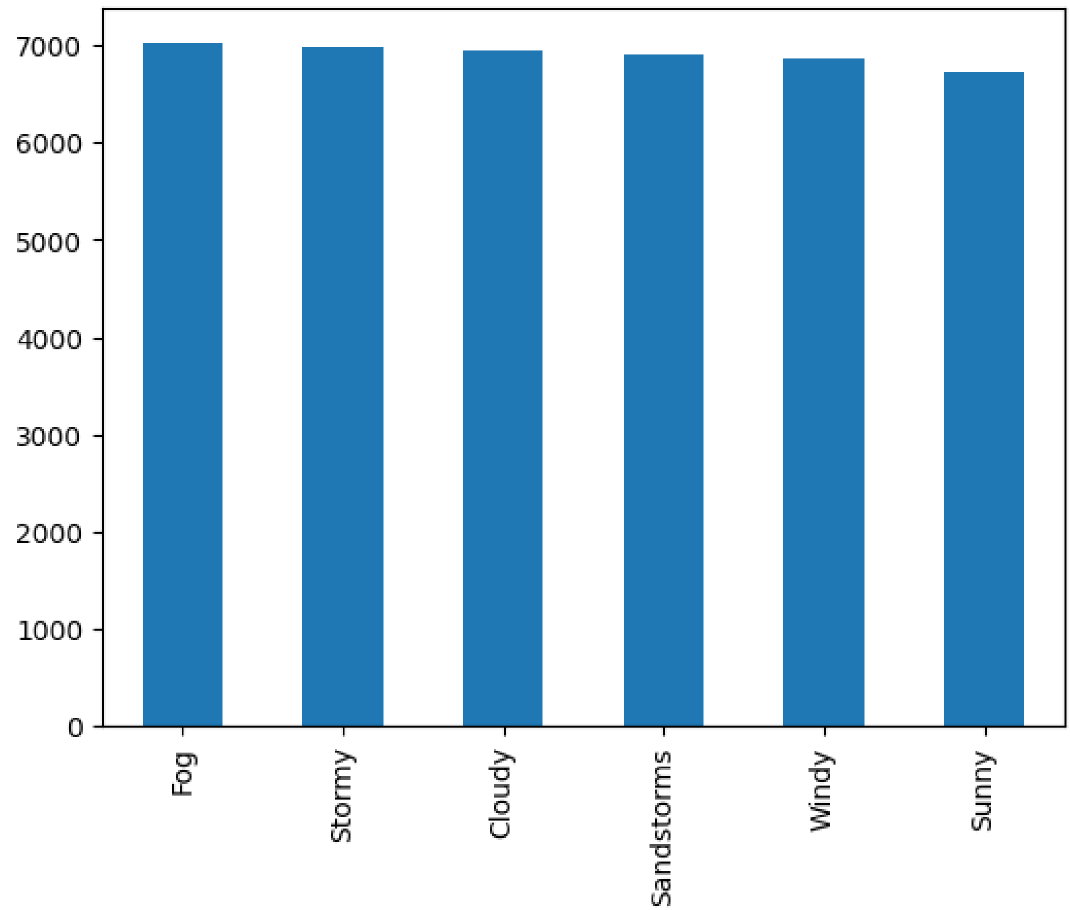
```
df['Weatherconditions'].value_counts().plot(kind='bar')
```

```
<Axes: >
```



- For better understanding its better to lose the conditions words as a prefix
- Since the weather conditions are almost equally distributed, we can fill the missing values with random choices.

```
def handle_weather_conditions(df):
  weather_options = df['Weatherconditions'].unique()[:-1]
  missing_count = df['Weatherconditions'].isnull().sum()
  random_weather = np.random.choice(weather_options,
size=missing_count)
  df.loc[df['Weatherconditions'].isnull(), 'Weatherconditions'] =
random_weather

handle_weather_conditions(df)

df['Weatherconditions'].isnull().sum()

0

df['Weatherconditions'].value_counts().plot(kind='bar')

<Axes: >
```




```
df.head()

        ID Delivery_person_ID  Delivery_person_Age
Delivery_person_Ratings  \
0  0x4607     INDORES13DEL02                 37.0
4.9
1  0xb379     BANGRES18DEL02                 34.0
4.5
2  0x5d6d     BANGRES19DEL01                 23.0
4.4
3  0x7a6a    COIMBRES13DEL02                 38.0
4.7
4  0x70a2     CHENRES12DEL01                 32.0
4.6

   Restaurant_latitude  Restaurant_longitude
Delivery_location_latitude  \
0             22.745049             75.892471
22.765049
1             12.913041             77.683237
13.043041
2             12.914264             77.678400
```

```
12.924264
3            11.003669            76.976494
11.053669
4            12.972793            80.249982
13.012793

   Delivery_location_longitude  Order_Date Time_Orderd  ...
Weatherconditions  \
0                    75.912471  19-03-2022    11:30:00  ...
Sunny
1                    77.813237  25-03-2022    19:45:00  ...
Stormy
2                    77.688400  19-03-2022    08:30:00  ...
Sandstorms
3                    77.026494  04-05-2022    18:00:00  ...
Sunny
4                    80.289982  26-03-2022    13:30:00  ...
Cloudy

  Road_traffic_density Vehicle_condition  Type_of_order
Type_of_vehicle  \
0                 High                 2         Snack      motorcycle

1                  Jam                 2         Snack         scooter

2                  Low                 0        Drinks      motorcycle

3               Medium                 0        Buffet      motorcycle

4                 High                 1         Snack         scooter


  multiple_deliveries  Festival            City Time_taken(min)
Month_Year
0                 0.0        No           Urban              24
2022-03
1                 1.0        No   Metropolitian              33
2022-03
2                 1.0        No           Urban              26
2022-03
3                 1.0        No   Metropolitian              21
2022-05
4                 1.0        No   Metropolitian              30
2022-03

[5 rows x 21 columns]
```

Road Traffic Density

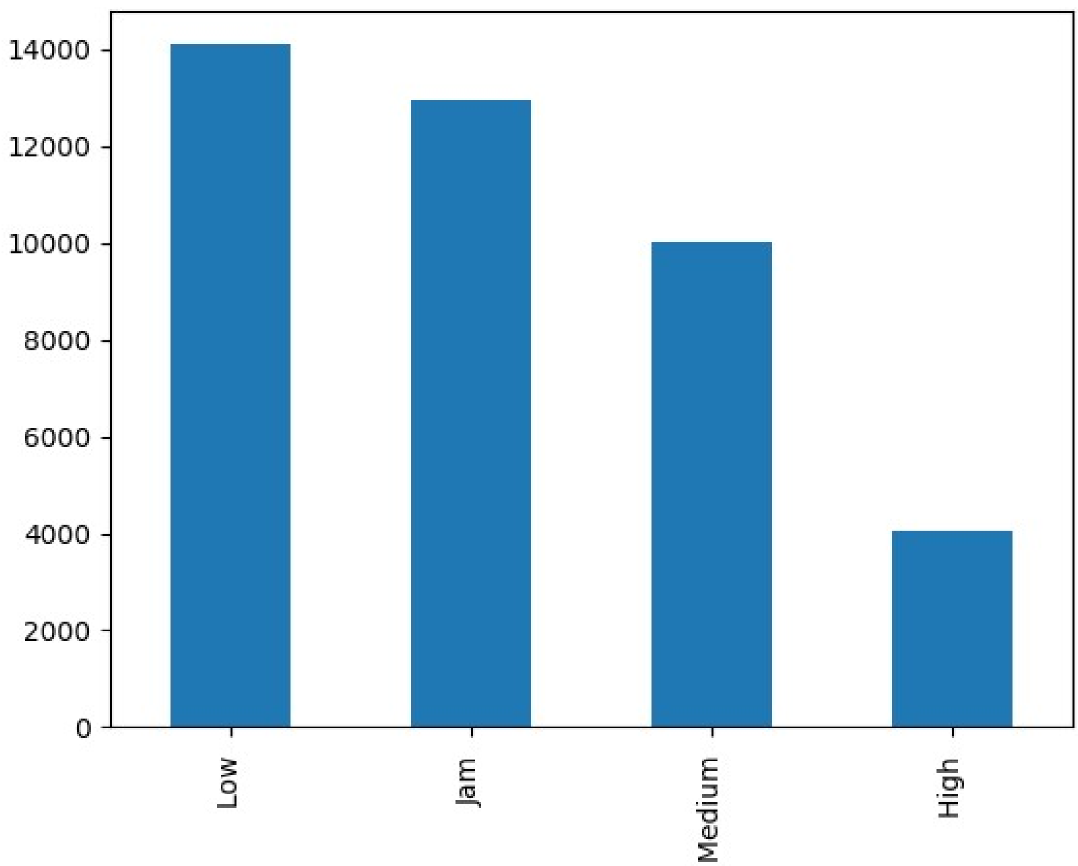
```
df['Road_traffic_density'].isnull().sum()
```

```
359
```

```python
df['Road_traffic_density'].value_counts()
```

```
Low         14095
Jam         12950
Medium      10023
High         4046
Name: Road_traffic_density, dtype: int64
```

```python
df['Road_traffic_density'].value_counts().plot(kind='bar')
plt.show()
```




```python
def handle_traffic_density(df):
  road_traffic_options = df['Road_traffic_density'].unique()[:-1]
  missing_count = df['Road_traffic_density'].isnull().sum()
  road_traffic_options = np.random.choice(road_traffic_options,
size=missing_count)
  df.loc[df['Road_traffic_density'].isnull(), 'Road_traffic_density']
= road_traffic_options

handle_traffic_density(df)
```

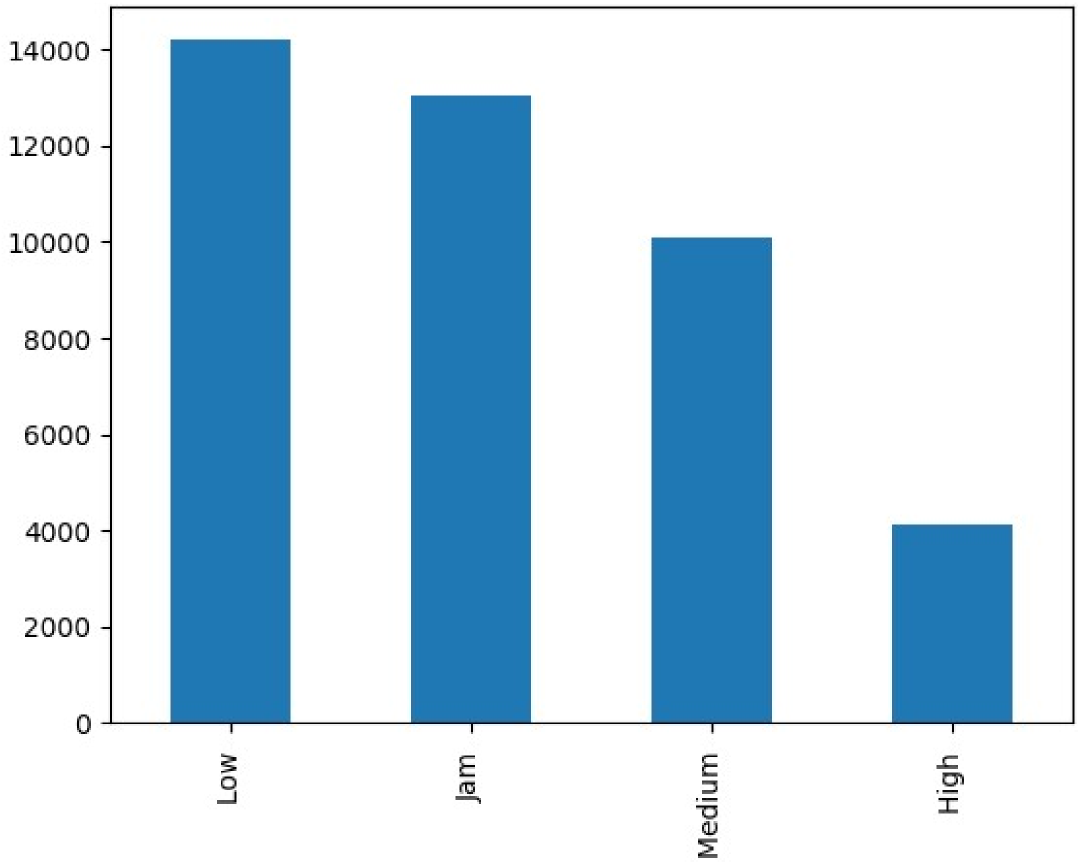
- Missing values in Road_traffic_density have been filled in using the random selections from available choices.

```
df['Road_traffic_density'].isnull().sum()
```

```
0
```

```
df['Road_traffic_density'].value_counts().plot(kind='bar')
```

```
<Axes: >
```



Vehicle Condition

```
df['Vehicle_condition'].isnull().sum()
```

```
0
```

Festival

```
df['Festival'].isnull().sum()
```

```
215
```

```
df['Festival'].unique()
```

```
array(['No ', 'Yes ', nan], dtype=object)

df['Festival'].value_counts()

No      40446
Yes       812
Name: Festival, dtype: int64
```

- There is a major bias with festival feature. We can simple just take the mode for this as small number of missing values won't affect the results.

```
def handle_festival(df):
  df['Festival'] = df['Festival'].fillna(df['Festival'].mode()[0])

handle_festival(df)

df['Festival'].isnull().sum()

0

df['Festival'].value_counts()

No      40661
Yes       812
Name: Festival, dtype: int64
```

Time Taken

```
df['Time_taken(min)'].isnull().sum()

0
```

Restaurant Longitude, Restaurant Latitude

```
df[['Restaurant_longitude', 'Restaurant_latitude']].isnull().sum()

Restaurant_longitude    0
Restaurant_latitude     0
dtype: int64
```

Multiple deliveries

```
def handle_multiple_deliveries(df):
  # Printing all unique values in the "multiple_deliveries" column
  unique_values = df['multiple_deliveries'].unique()
  print('Unique values in multiple deliveries:')
  print(unique_values)

  # Replace the NaN values with mode
  df['multiple_deliveries'].fillna(df['multiple_deliveries'].mode()
[0], inplace=True)
```

```
  # Printing all unique values in the "multiple_deliveries" column
  unique_values = df['multiple_deliveries'].unique()
  print('Unique values in multiple deliveries after handling NaN
values:')
  print(unique_values)

handle_multiple_deliveries(df)

Unique values in multiple deliveries:
[ 0.  1.  3. nan  2.]
Unique values in multiple deliveries after handling NaN values:
[0. 1. 3. 2.]
```

- As seen in EDA, most of the deliveries have just one order delivery. However, many deliveries also have two or three orders. Thus, it is appropriate to fill in the missing values with the mode.

City

```
# Get the number of counts of each unique value in the "City" column,
including NaN
city_counts = df['City'].value_counts(dropna=False)

print(city_counts)

Metropolitian     31068
Urban              9161
NaN                1097
Semi-Urban          147
Name: City, dtype: int64
```

- Due to high bias in the City column, it is suitable to fill in the missing values with the mode.

```
def handle_city(df):
  # Calculate the mode of the "City" column
  city_mode = df['City'].mode()[0]

  # Impute NaN values in "City" column with the mode
  df['City'].fillna(city_mode, inplace=True)

  # Get the number of counts of each unique value in the "City"
column, including NaN
  city_counts = df['City'].value_counts(dropna=False)

  print(city_counts)

handle_city(df)
```

```
Metropolitian     32165
Urban              9161
Semi-Urban          147
Name: City, dtype: int64
```

```
# Check null values in the dataframe
df.isnull().sum()
```

```
ID                                0
Delivery_person_ID                0
Delivery_person_Age               0
Delivery_person_Ratings           0
Restaurant_latitude               0
Restaurant_longitude              0
Delivery_location_latitude        0
Delivery_location_longitude       0
Order_Date                        0
Time_Orderd                    1276
Time_Order_picked                 0
Weatherconditions                 0
Road_traffic_density              0
Vehicle_condition                 0
Type_of_order                     0
Type_of_vehicle                   0
multiple_deliveries               0
Festival                          0
City                              0
Time_taken(min)                   0
Month_Year                        0
dtype: int64
```

Feature Engineering

Delivery Person Id

```
df.columns
```

```
Index(['ID', 'Delivery_person_ID', 'Delivery_person_Age',
       'Delivery_person_Ratings', 'Restaurant_latitude',
       'Restaurant_longitude', 'Delivery_location_latitude',
       'Delivery_location_longitude', 'Order_Date', 'Time_Orderd',
       'Time_Order_picked', 'Weatherconditions',
'Road_traffic_density',
       'Vehicle_condition', 'Type_of_order', 'Type_of_vehicle',
       'multiple_deliveries', 'Festival', 'City', 'Time_taken(min)',
       'Month_Year'],
      dtype='object')
```

```
def feature_extract(df):
  df['City_code'] = df['Delivery_person_ID'].str.split("RES",
expand=True)[0]

feature_extract(df)
df.head()
```

```
        ID Delivery_person_ID  Delivery_person_Age
Delivery_person_Ratings  \
0  0x4607     INDORES13DEL02                  37.0
4.9
1  0xb379     BANGRES18DEL02                  34.0
4.5
2  0x5d6d     BANGRES19DEL01                  23.0
4.4
3  0x7a6a    COIMBRES13DEL02                  38.0
4.7
4  0x70a2     CHENRES12DEL01                  32.0
4.6

   Restaurant_latitude  Restaurant_longitude
Delivery_location_latitude  \
0            22.745049             75.892471
22.765049
1            12.913041             77.683237
13.043041
2            12.914264             77.678400
12.924264
3            11.003669             76.976494
11.053669
4            12.972793             80.249982
13.012793

   Delivery_location_longitude  Order_Date Time_Orderd  ...  \
0                    75.912471  19-03-2022    11:30:00  ...
1                    77.813237  25-03-2022    19:45:00  ...
2                    77.688400  19-03-2022    08:30:00  ...
3                    77.026494  04-05-2022    18:00:00  ...
4                    80.289982  26-03-2022    13:30:00  ...

  Road_traffic_density Vehicle_condition Type_of_order
Type_of_vehicle  \
0                High                 2        Snack      motorcycle

1                 Jam                 2        Snack         scooter

2                 Low                 0       Drinks      motorcycle

3              Medium                 0       Buffet      motorcycle
```

```
4                  High                      1         Snack          scooter


  multiple_deliveries Festival            City Time_taken(min)
Month_Year  \
0                 0.0       No           Urban                24
2022-03
1                 1.0       No    Metropolitian                33
2022-03
2                 1.0       No           Urban                26
2022-03
3                 1.0       No    Metropolitian                21
2022-05
4                 1.0       No    Metropolitian                30
2022-03

   City_code
0       INDO
1       BANG
2       BANG
3      COIMB
4       CHEN

[5 rows x 22 columns]
```

Distance between Restaurant Location and Delivery Location

```
def calculate_distance(df):
  df['Distance'] = np.zeros(len(df))
  restaurant_location = df[['Restaurant_latitude',
'Restaurant_longitude']].to_numpy()
  delivery_location = df[['Delivery_location_latitude',
'Delivery_location_longitude']].to_numpy()

  df['Distance'] = np.array([geodesic(restaurant, delivery) for
restaurant, delivery in zip(restaurant_location, delivery_location)])
  df['Distance'] = df['Distance'].astype('str').str.extract('(\
d+)').astype('int64')

  df.drop(['Restaurant_latitude', 'Restaurant_longitude',
'Delivery_location_latitude', 'Delivery_location_longitude'], axis=1,
inplace=True)

calculate_distance(df)
df.head()

        ID Delivery_person_ID  Delivery_person_Age
Delivery_person_Ratings  \
```

```
0  0x4607     INDORES13DEL02                  37.0
4.9
1  0xb379     BANGRES18DEL02                  34.0
4.5
2  0x5d6d     BANGRES19DEL01                  23.0
4.4
3  0x7a6a    COIMBRES13DEL02                  38.0
4.7
4  0x70a2     CHENRES12DEL01                  32.0
4.6

   Order_Date Time_Orderd Time_Order_picked Weatherconditions  \
0  19-03-2022    11:30:00          11:45:00             Sunny
1  25-03-2022    19:45:00          19:50:00            Stormy
2  19-03-2022    08:30:00          08:45:00        Sandstorms
3  04-05-2022    18:00:00          18:10:00             Sunny
4  26-03-2022    13:30:00          13:45:00            Cloudy

  Road_traffic_density  Vehicle_condition Type_of_order
Type_of_vehicle  \
0                High                  2        Snack      motorcycle

1                 Jam                  2        Snack         scooter

2                 Low                  0       Drinks      motorcycle

3              Medium                  0       Buffet      motorcycle

4                High                  1        Snack         scooter


   multiple_deliveries Festival            City  Time_taken(min)
Month_Year  \
0                  0.0       No           Urban                24
2022-03
1                  1.0       No   Metropolitian                33
2022-03
2                  1.0       No           Urban                26
2022-03
3                  1.0       No   Metropolitian                21
2022-05
4                  1.0       No   Metropolitian                30
2022-03

  City_code  Distance
0      INDO         3
1      BANG        20
2      BANG         1
3     COIMB         7
4      CHEN         6
```

```python
df.columns
```

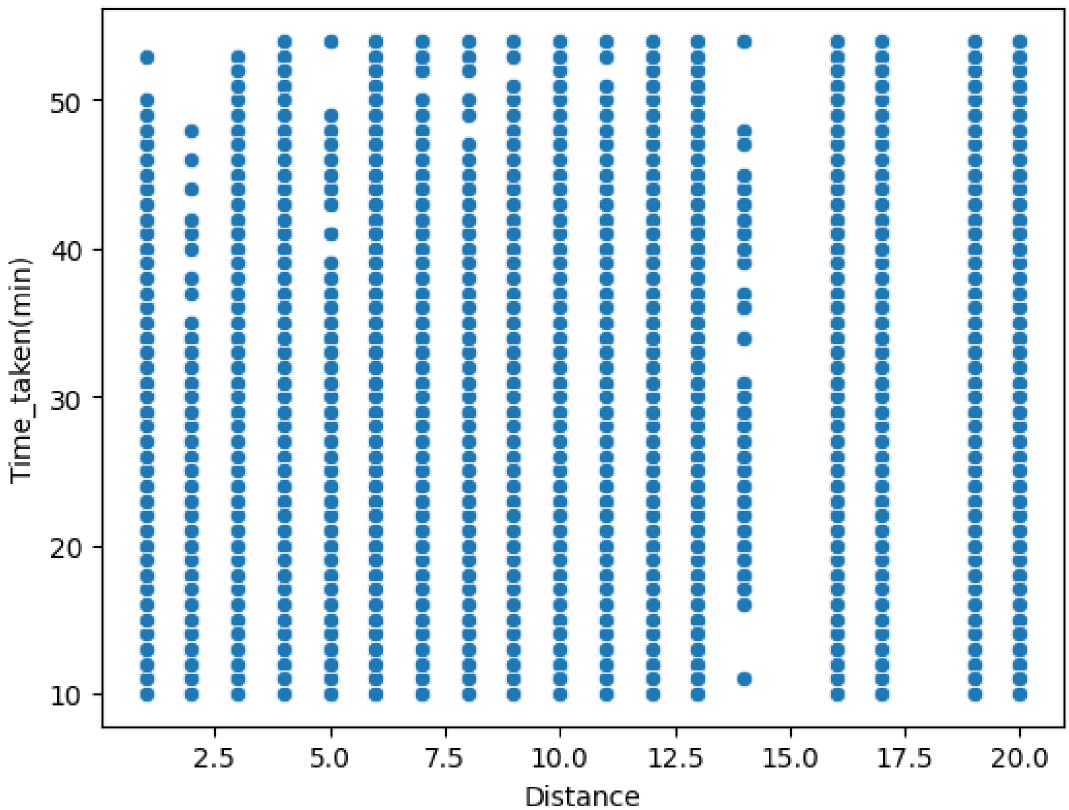
```
Index(['ID', 'Delivery_person_ID', 'Delivery_person_Age',
       'Delivery_person_Ratings', 'Order_Date', 'Time_Orderd',
       'Time_Order_picked', 'Weatherconditions',
'Road_traffic_density',
       'Vehicle_condition', 'Type_of_order', 'Type_of_vehicle',
       'multiple_deliveries', 'Festival', 'City', 'Time_taken(min)',
       'Month_Year', 'City_code', 'Distance'],
      dtype='object')
```

```python
df['Distance'].value_counts().sort_index()
```

```
1     3744
2      526
3     3202
4     3703
5      515
6     3208
7     3753
8      511
9     3187
10    3729
11     534
12    3197
13    3648
14      62
16    2543
17    1174
19    2462
20    1775
Name: Distance, dtype: int64
```

```python
sns.scatterplot(x=df['Distance'], y=df['Time_taken(min)'])
```

```
<Axes: xlabel='Distance', ylabel='Time_taken(min)'>
```



Time ordered and Time picked

```
# Get the number of missing, null, and NaN values in "Time_Orderd"
column
missing_values_ordered = df['Time_Orderd'].isnull().sum()
# Count the number of values equal to "NaN" in "Time_Ordered" column
nan_count_ordered = (df['Time_Orderd'] == 'NaN ').sum()

# Print the counts of missing, null, and NaN values
print("Number of missing values in Time_Orderd:",
missing_values_ordered)
print("Number of 'NaN' values in Time_Ordered:", nan_count_ordered)

# Get the number of missing, null, and NaN values in
"Time_Order_picked" column
missing_values_picked = df['Time_Order_picked'].isnull().sum()
# Count the number of values equal to "NaN" in "Time_Order_Picked"
column
nan_count_picked = (df['Time_Order_picked'] == 'NaN ').sum()

print("Number of missing values in Time_Order_picked:",
missing_values_picked)
print("Number of 'NaN' values in Time_Order_Picked:",
nan_count_picked)
```

```
Number of missing values in Time_Orderd: 1276
Number of 'NaN' values in Time_Ordered: 0
Number of missing values in Time_Order_picked: 0
Number of 'NaN' values in Time_Order_Picked: 0
```

```
def calculate_time_difference_in_minutes(df):
    # Convert 'Time_Orderd' and 'Time_Order_picked' columns to
datetime format
    df['Time_Orderd'] = pd.to_datetime(df['Time_Orderd'])
    df['Time_Order_picked'] = pd.to_datetime(df['Time_Order_picked'])

    # Add a day to 'Time_Order_picked' when it is earlier than
'Time_Orderd'
    df['Time_Order_picked'] += np.where(df['Time_Order_picked'] <
df['Time_Orderd'], pd.Timedelta(days=1), pd.Timedelta(days=0))

    # Calculate the time difference in minutes and store it in the
'Time_Difference' column
    df['Time_Difference'] = (df['Time_Order_picked'] -
df['Time_Orderd']).dt.total_seconds() / 60.0

    # Replace missing time differences (NaN) with the median of the
non-missing values
    median_difference = df['Time_Difference'].dropna().median()
    df['Time_Difference'].fillna(median_difference, inplace=True)

    df.drop(['Time_Orderd', 'Time_Order_picked'], axis=1,
inplace=True)

calculate_time_difference_in_minutes(df)
```

```
<ipython-input-133-3f086cbdc6cf>:7: PerformanceWarning:
Adding/subtracting object-dtype array to DatetimeArray not vectorized.
  df['Time_Order_picked'] += np.where(df['Time_Order_picked'] <
df['Time_Orderd'], pd.Timedelta(days=1), pd.Timedelta(days=0))
```

```
difference_counts = df['Time_Difference'].value_counts(dropna=False)

print(difference_counts)
```

```
10.0    14608
5.0     13515
15.0    13350
Name: Time_Difference, dtype: int64
```

```
df.columns
```

```
Index(['ID', 'Delivery_person_ID', 'Delivery_person_Age',
       'Delivery_person_Ratings', 'Order_Date', 'Weatherconditions',
       'Road_traffic_density', 'Vehicle_condition', 'Type_of_order',
       'Type_of_vehicle', 'multiple_deliveries', 'Festival', 'City',
```

```
       'Time_taken(min)', 'Month_Year', 'City_code', 'Distance',
       'Time_Difference'],
      dtype='object')
```

Order date

```
def add_date_features(data_frame):
  # Convert 'Order_Date' to datetime format
  data_frame['Order_Date'] = pd.to_datetime(data_frame['Order_Date'])

  # Extract day, month, quarter, and year from 'Order_Date'
  data_frame["order_day"] = data_frame.Order_Date.dt.day
  data_frame["order_month"] = data_frame.Order_Date.dt.month
  data_frame["order_quarter"] = data_frame.Order_Date.dt.quarter

  # Extract additional date-related features
  data_frame['order_day_of_week'] =
data_frame.Order_Date.dt.day_of_week.astype(int)  # 0 for Monday, 1
for Tuesday, ..., 6 for Sunday
  data_frame["is_month_start"] =
data_frame.Order_Date.dt.is_month_start.astype(int)  # 1 if the date
is the start of the month, else 0
  data_frame["is_month_end"] =
data_frame.Order_Date.dt.is_month_end.astype(int)  # 1 if the date is
the end of the month, else 0
  data_frame["is_quarter_start"] =
data_frame.Order_Date.dt.is_quarter_start.astype(int)  # 1 if the date
is the start of the quarter, else 0
  data_frame["is_quarter_end"] =
data_frame.Order_Date.dt.is_quarter_end.astype(int)  # 1 if the date
is the end of the quarter, else 0

  # Mark weekends (Saturday and Sunday) with 1, and weekdays with 0
  data_frame['is_weekend'] =
np.where(data_frame['order_day_of_week'].isin([5, 6]), 1, 0)

  data_frame.drop(['Order_Date'], axis=1, inplace=True)

add_date_features(df)
df.head()
```

```
<ipython-input-137-04545b21215a>:3: UserWarning: Parsing dates in
DD/MM/YYYY format when dayfirst=False (the default) was specified.
This may lead to inconsistently parsed dates! Specify a format to
ensure consistent parsing.
  data_frame['Order_Date'] = pd.to_datetime(data_frame['Order_Date'])
```

```
        ID Delivery_person_ID  Delivery_person_Age
Delivery_person_Ratings  \
0  0x4607     INDORES13DEL02                 37.0
```

```
4.9
1  0xb379     BANGRES18DEL02                  34.0
4.5
2  0x5d6d     BANGRES19DEL01                  23.0
4.4
3  0x7a6a    COIMBRES13DEL02                  38.0
4.7
4  0x70a2     CHENRES12DEL01                  32.0
4.6

  Weatherconditions Road_traffic_density  Vehicle_condition
Type_of_order  \
0             Sunny                High                  2
Snack
1            Stormy                 Jam                  2
Snack
2        Sandstorms                 Low                  0
Drinks
3             Sunny              Medium                  0
Buffet
4            Cloudy                High                  1
Snack

  Type_of_vehicle  multiple_deliveries  ... Time_Difference order_day
\
0      motorcycle                  0.0  ...            15.0        19

1         scooter                  1.0  ...             5.0        25

2      motorcycle                  1.0  ...            15.0        19

3      motorcycle                  1.0  ...            10.0         5

4         scooter                  1.0  ...            15.0        26


   order_month order_quarter order_day_of_week  is_month_start
is_month_end  \
0            3             1                 5               0
0
1            3             1                 4               0
0
2            3             1                 5               0
0
3            4             2                 1               0
0
4            3             1                 5               0
0

   is_quarter_start  is_quarter_end  is_weekend
```

```
0                  0               0           1
1                  0               0           0
2                  0               0           1
3                  0               0           0
4                  0               0           1

[5 rows x 26 columns]
```

Label Encoding

```
from sklearn.preprocessing import LabelEncoder

def label_encode_column(data_frame, column_name):
  label_encoder = LabelEncoder()
  data_frame[column_name] =
label_encoder.fit_transform(data_frame[column_name])
```

Weathercondition

```
# Encoding Weather Condition feature
Weatherconditions_counts =
df['Weatherconditions'].value_counts(dropna=False)
print('Values before label encoding:')
print(Weatherconditions_counts)

label_encode_column(df, 'Weatherconditions')

Weatherconditions_counts =
df['Weatherconditions'].value_counts(dropna=False)
print('\nValues after label encoding:')
print(Weatherconditions_counts)

Values before label encoding:
Fog           7025
Stormy        6987
Cloudy        6949
Sandstorms    6915
Windy         6861
Sunny         6736
Name: Weatherconditions, dtype: int64

Values after label encoding:
1    7025
3    6987
0    6949
2    6915
5    6861
```

```
4    6736
Name: Weatherconditions, dtype: int64
```

Road Traffic

```
# Label Encoding Road Traffic Density feature
road_traffic_counts =
df['Road_traffic_density'].value_counts(dropna=False)
print('Values before label encoding:')
print(road_traffic_counts)

label_encode_column(df, 'Road_traffic_density')

road_traffic_counts =
df['Road_traffic_density'].value_counts(dropna=False)
print('\nValues after label encoding:')
print(road_traffic_counts)
```

```
Values before label encoding:
Low        14190
Jam        13044
Medium     10104
High        4135
Name: Road_traffic_density, dtype: int64

Values after label encoding:
2    14190
1    13044
3    10104
0     4135
Name: Road_traffic_density, dtype: int64
```

Festival

```
# Label Encoding Festival feature
Festival_counts = df['Festival'].value_counts(dropna=False)
print('Values before label encoding:')
print(Festival_counts)

label_encode_column(df, 'Festival')

Festival_counts = df['Festival'].value_counts(dropna=False)
print('\nValues after label encoding:')
print(Festival_counts)
```

```
Values before label encoding:
No      40661
Yes       812
Name: Festival, dtype: int64
```

```
Values after label encoding:
0    40661
1      812
Name: Festival, dtype: int64
```

City

```python
# Label Encoding City feature
City_counts = df['City'].value_counts(dropna=False)
print('Values before label encoding:')
print(City_counts)

label_encode_column(df, 'City')

City_counts = df['City'].value_counts(dropna=False)
print('\nValues after label encoding:')
print(City_counts)
```

```
Values before label encoding:
Metropolitian     32165
Urban              9161
Semi-Urban          147
Name: City, dtype: int64

Values after label encoding:
0    32165
2     9161
1      147
Name: City, dtype: int64
```

City Code

```python
# Label Encoding City Code feature
City_code_counts = df['City_code'].value_counts(dropna=False)
print('Values before label encoding:')
print(City_code_counts)

label_encode_column(df, 'City_code')

City_code_counts = df['City_code'].value_counts(dropna=False)
print('\nValues after label encoding:')
print(City_code_counts)
```

```
Values before label encoding:
JAP       3419
BANG      3166
SUR       3162
HYD       3161
COIMB     3146
MUM       3146
```

```
INDO      3138
CHEN      3113
PUNE      3113
MYS       2989
RANCHI    2543
VAD       1564
KOC        682
LUDH       670
KOL        667
KNP        650
GOA        586
ALH        553
AGR        536
AURG       534
DEH        474
BHP        461
Name: City_code, dtype: int64

Values after label encoding:
11    3419
3     3166
20    3162
9     3161
6     3146
16    3146
10    3138
5     3113
18    3113
17    2989
19    2543
21    1564
13     682
15     670
14     667
12     650
8      586
1      553
0      536
2      534
7      474
4      461
Name: City_code, dtype: int64
```

Type of order

```
# Label Encoding Type of order feature
order_counts = df['Type_of_order'].value_counts(dropna=False)
print('Values before label encoding:')
print(order_counts)
```

```
label_encode_column(df, 'Type_of_order')

order_counts = df['Type_of_order'].value_counts(dropna=False)
print('\nValues after label encoding:')
print(order_counts)
```

```
Values before label encoding:
Snack      10498
Meal       10384
Drinks     10337
Buffet     10254
Name: Type_of_order, dtype: int64

Values after label encoding:
3    10498
2    10384
1    10337
0    10254
Name: Type_of_order, dtype: int64
```

Type of vehicle

```
# Label Encoding Type of vehicle feature
vehicle_counts = df['Type_of_vehicle'].value_counts(dropna=False)
print('Values before label encoding:')
print(vehicle_counts)

label_encode_column(df, 'Type_of_vehicle')

vehicle_counts = df['Type_of_vehicle'].value_counts(dropna=False)
print('\nValues after label encoding:')
print(vehicle_counts)
```

```
Values before label encoding:
motorcycle           24192
scooter              13862
electric_scooter      3384
bicycle                 35
Name: Type_of_vehicle, dtype: int64

Values after label encoding:
2    24192
3    13862
1     3384
0       35
Name: Type_of_vehicle, dtype: int64
```

```
df.head()
```

```
        ID Delivery_person_ID  Delivery_person_Age
Delivery_person_Ratings  \
0  0x4607     INDORES13DEL02                 37.0
4.9
1  0xb379     BANGRES18DEL02                 34.0
4.5
2  0x5d6d     BANGRES19DEL01                 23.0
4.4
3  0x7a6a    COIMBRES13DEL02                 38.0
4.7
4  0x70a2     CHENRES12DEL01                 32.0
4.6

   Weatherconditions  Road_traffic_density  Vehicle_condition
Type_of_order  \
0                  4                     0                  2
3
1                  3                     1                  2
3
2                  2                     2                  0
1
3                  4                     3                  0
0
4                  0                     0                  1
3

   Type_of_vehicle  multiple_deliveries  ...  Time_Difference
order_day  \
0                2                  0.0  ...             15.0
19
1                3                  1.0  ...              5.0
25
2                2                  1.0  ...             15.0
19
3                2                  1.0  ...             10.0
5
4                3                  1.0  ...             15.0
26

   order_month order_quarter  order_day_of_week  is_month_start
is_month_end  \
0            3              1                  5               0
0
1            3              1                  4               0
0
2            3              1                  5               0
0
3            4              2                  1               0
0
4            3              1                  5               0
```

```
0

   is_quarter_start  is_quarter_end  is_weekend
0                 0               0           1
1                 0               0           0
2                 0               0           1
3                 0               0           0
4                 0               0           1

[5 rows x 26 columns]
```

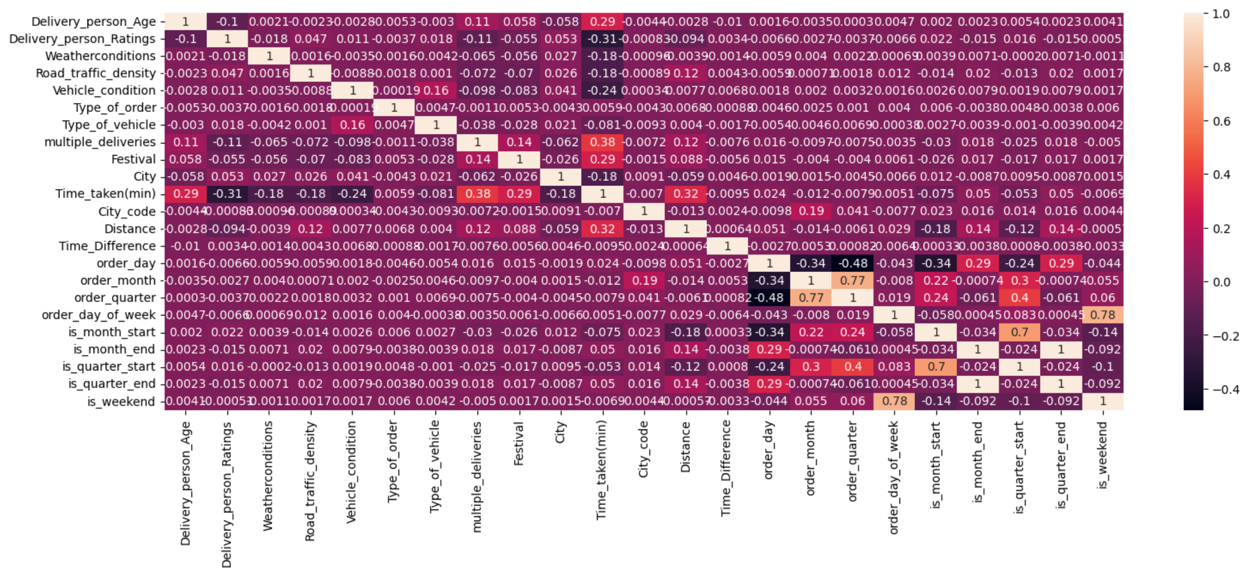
```python
df['order_day'].value_counts().sort_index()
```

```
1     2113
2     1862
3     2163
4     1798
5     2152
6     1799
7     1065
8      895
9     1082
10     926
11    1837
12    1596
13    1845
14    1594
15    1861
16    1628
17    1806
18    1597
19    1068
20     925
21    1066
23     895
24    1083
25     910
26    1090
27     895
28    1058
29     907
30    1060
31     897
Name: order_day, dtype: int64
```

Feature Selection

```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 41473 entries, 0 to 45592
Data columns (total 26 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   ID                        41473 non-null  object
 1   Delivery_person_ID        41473 non-null  object
 2   Delivery_person_Age       41473 non-null  float32
 3   Delivery_person_Ratings   41473 non-null  float64
 4   Weatherconditions         41473 non-null  int64
 5   Road_traffic_density      41473 non-null  int64
 6   Vehicle_condition         41473 non-null  int64
 7   Type_of_order             41473 non-null  int64
 8   Type_of_vehicle           41473 non-null  int64
 9   multiple_deliveries       41473 non-null  float64
 10  Festival                  41473 non-null  int64
 11  City                      41473 non-null  int64
 12  Time_taken(min)           41473 non-null  int64
 13  Month_Year                41473 non-null  period[M]
 14  City_code                 41473 non-null  int64
 15  Distance                  41473 non-null  int64
 16  Time_Difference           41473 non-null  float64
 17  order_day                 41473 non-null  int64
 18  order_month               41473 non-null  int64
 19  order_quarter             41473 non-null  int64
 20  order_day_of_week         41473 non-null  int64
 21  is_month_start            41473 non-null  int64
 22  is_month_end              41473 non-null  int64
 23  is_quarter_start          41473 non-null  int64
 24  is_quarter_end            41473 non-null  int64
 25  is_weekend                41473 non-null  int64
dtypes: float32(1), float64(3), int64(19), object(2), period[M](1)
memory usage: 9.4+ MB

plt.figure(figsize=(18, 6))
sns.heatmap(df.corr(numeric_only=True), annot=True)
plt.show()
```



- Several pairs shows strong correlation which suggests redundancy in data hence only one of the feature needs to be taken from that pair.
- order_day_of_week and is_weekend
- is_quarter_start and is_month_start
- order_day is correlated with many of the featured engineered features hence we can drop order_day

```
df.drop(['ID', 'Delivery_person_ID', 'is_weekend', 'is_quarter_start',
'order_day', 'Month_Year'], axis=1, inplace=True)
```

Data Preprocessing

```
# Pipeline for processing of data
from sklearn.pipeline import Pipeline
from sklearn.base import BaseEstimator, TransformerMixin
from IPython.utils import io

class data_cleaning(BaseEstimator, TransformerMixin):
  def fit(self, X, y=None):
    return self

  def transform(self, df):
    clean_delivery_data(df)
    convert_data_types(df)
    return df

class handle_null_values(BaseEstimator, TransformerMixin):
  def fit(self, X, y=None):
```

```
    return self

  def transform(self, df):
    convert_nan_to_nan(df)
    handle_delv_person_age(df)
    handle_delv_person_ratings(df)
    handle_weather_conditions(df)
    handle_traffic_density(df)
    handle_festival(df)
    handle_multiple_deliveries(df)
    handle_city(df)
    return df

class feature_engineering(BaseEstimator, TransformerMixin):
  def fit(self, X, y=None):
    return self

  def transform(self, df):
    feature_extract(df)
    calculate_distance(df)
    calculate_time_difference_in_minutes(df)
    add_date_features(df)
    return df

class data_preprocessing(BaseEstimator, TransformerMixin):
  def fit(self, X, y=None):
    return self

  def transform(self, df):
    label_encode_column(df, 'Weatherconditions')
    label_encode_column(df, 'Road_traffic_density')
    label_encode_column(df, 'Festival')
    label_encode_column(df, 'City')
    label_encode_column(df, 'City_code')
    label_encode_column(df, 'Type_of_order')
    label_encode_column(df, 'Type_of_vehicle')
    return df

class feature_selection(BaseEstimator, TransformerMixin):
  def fit(self, X, y=None):
    return self

  def transform(self, df):
    df.drop(['ID', 'Delivery_person_ID', 'is_weekend',
'is_quarter_start', 'order_day'], axis=1, inplace=True)
    return df

pipeline = Pipeline([
    ('data_cleaning', data_cleaning()),
    ('handle_null_values', handle_null_values()),
```

```
    ('feature_engineering', feature_engineering()),
    ('data_preprocessing', data_preprocessing()),
    ('feature_selection', feature_selection())
])

df = pd.read_csv('data.csv')

with io.capture_output() as captured:
  df = pipeline.fit_transform(df)


df.to_csv('final_data.csv', index=False)

df.head()
```

```
   Delivery_person_Age  Delivery_person_Ratings  Weatherconditions  \
0                 37.0                      4.9                  5
1                 34.0                      4.5                  4
2                 23.0                      4.4                  3
3                 38.0                      4.7                  5
4                 32.0                      4.6                  0

   Road_traffic_density  Vehicle_condition  Type_of_order
Type_of_vehicle  \
0                     0                  2              3
2
1                     1                  2              3
3
2                     2                  0              1
2
3                     3                  0              0
2
4                     0                  1              3
3

   multiple_deliveries  Festival  City  Time_taken(min)  City_code
Distance  \
0                  0.0         0     2               24         10
3
1                  1.0         0     0               33          3
20
2                  1.0         0     2               26          3
1
3                  1.0         0     0               21          6
7
4                  1.0         0     0               30          5
6

   Time_Difference  order_month  order_quarter  order_day_of_week  \
0             15.0            3              1                  5
```

```
1            5.0          3            1                  4
2           15.0          3            1                  5
3           10.0          4            2                  1
4           15.0          3            1                  5

   is_month_start  is_month_end  is_quarter_end
0               0             0               0
1               0             0               0
2               0             0               0
3               0             0               0
4               0             0               0
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 41522 entries, 0 to 45592
Data columns (total 20 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   Delivery_person_Age      41522 non-null  float32
 1   Delivery_person_Ratings  41522 non-null  float64
 2   Weatherconditions        41522 non-null  int64
 3   Road_traffic_density     41522 non-null  int64
 4   Vehicle_condition        41522 non-null  int64
 5   Type_of_order            41522 non-null  int64
 6   Type_of_vehicle          41522 non-null  int64
 7   multiple_deliveries      41522 non-null  float64
 8   Festival                 41522 non-null  int64
 9   City                     41522 non-null  int64
 10  Time_taken(min)          41522 non-null  int64
 11  City_code                41522 non-null  int64
 12  Distance                 41522 non-null  int64
 13  Time_Difference          41522 non-null  float64
 14  order_month              41522 non-null  int64
 15  order_quarter            41522 non-null  int64
 16  order_day_of_week        41522 non-null  int64
 17  is_month_start           41522 non-null  int64
 18  is_month_end             41522 non-null  int64
 19  is_quarter_end           41522 non-null  int64
dtypes: float32(1), float64(3), int64(16)
memory usage: 7.5 MB
```

Train_Test_Split

```
from sklearn.model_selection import train_test_split

X = df.drop('Time_taken(min)', axis=1).values
y = df['Time_taken(min)'].values

# Split the data into training 80% and testing 20% sets
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)

# Split the training data into training 80% and validation 20% sets
X_train, X_val, y_train, y_val = train_test_split(X_train, y_train,
test_size=0.2, random_state=42)

X_train.shape, y_train.shape, X_val.shape, y_val.shape
```

```
((26573, 19), (26573,), (6644, 19), (6644,))
```

Standardization

```
from sklearn.preprocessing import StandardScaler

# StandardScaler Train set
sc = StandardScaler()
X_train = sc.fit_transform(X_train)

# StandardScaler Test set and StandardScaler val set
X_val = sc.transform(X_val)
X_test = sc.transform(X_test)
```

Model Training

Implementation from scratch

Linear Regression

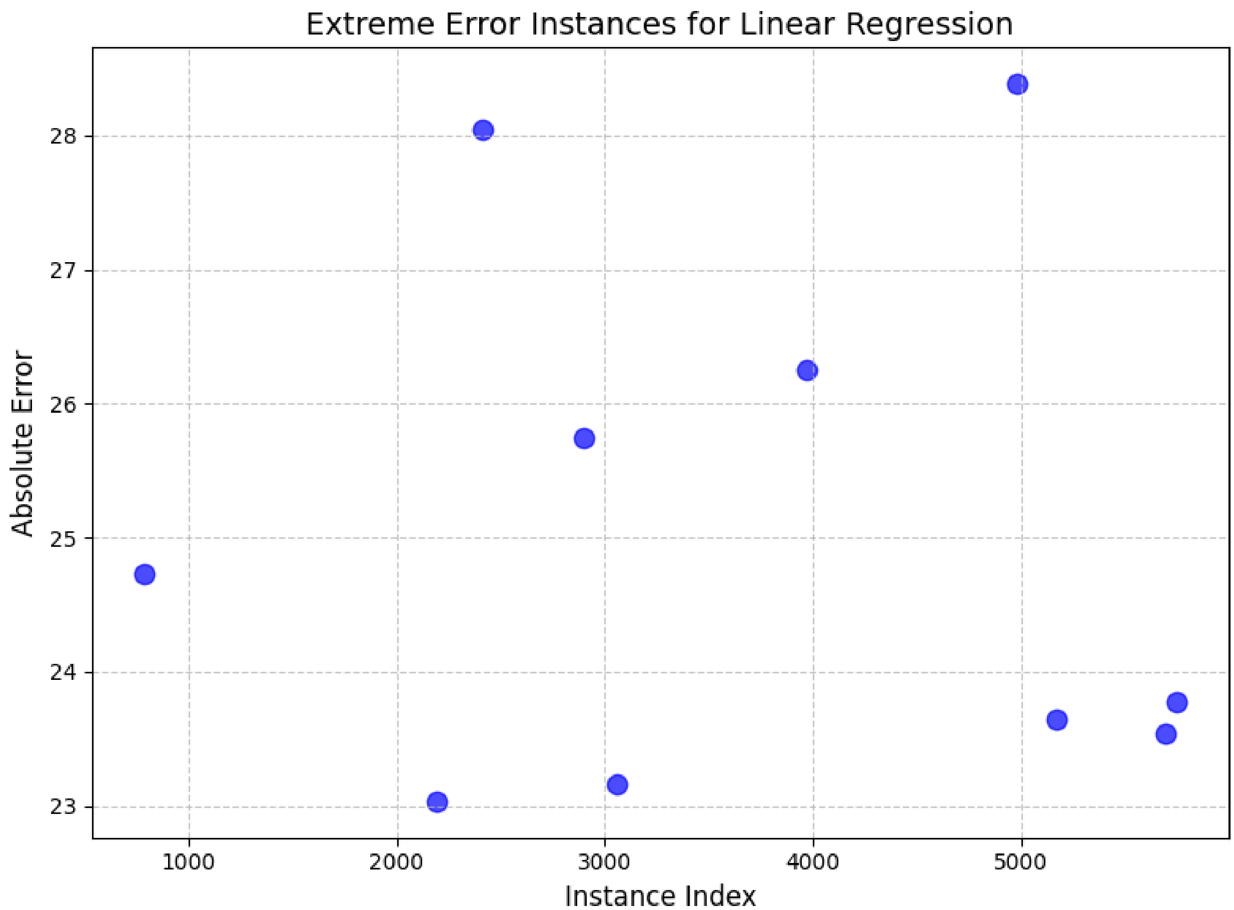
```
import numpy as np
from sklearn.metrics import mean_squared_error, mean_absolute_error,
r2_score

class Linear_Regression:

    def __init__(self):
      self.w = None
      self.b = None

    def fit(self, X, y):
      X = np.c_[np.ones(X.shape[0]), X]  # Add a column of ones for
the bias term
      self.w = np.linalg.pinv(X.T @ X) @ X.T @ y
      # print(self.w)
      self.b = self.w[0]  # Intercept
      self.w = self.w[1:]  # Coefficients for the features

    def predict(self, X):
```

```
        return X @ self.w + self.b

    def get_coefficients(self):
        return self.w, self.b

linear_model = Linear_Regression()
linear_model.fit(X_train, y_train)

y_pred = linear_model.predict(X_val)

mse = mean_squared_error(y_val, y_pred)
rmse = np.sqrt(mse)
mae = mean_absolute_error(y_val, y_pred)
r2 = r2_score(y_val, y_pred)
print("Mean Squared Error:", mse)
print("Root Mean Squared Error:", rmse)
print("Mean Absolute Error:", mae)
print("R-squared:", r2)
print("Coefficients (w):", linear_model.get_coefficients())  # Exclude
the bias term
```

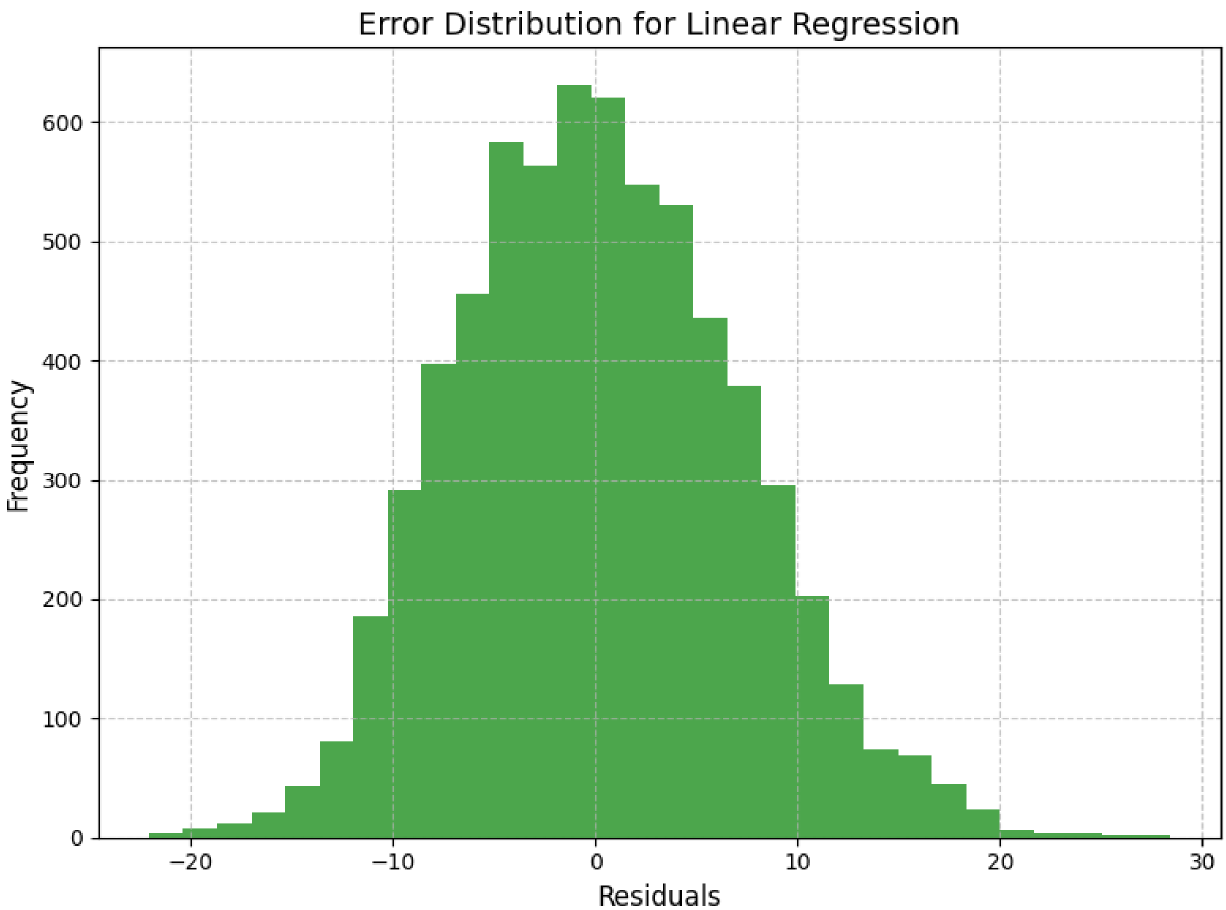
```
Mean Squared Error: 47.96832150691804
Root Mean Squared Error: 6.925916654632658
Mean Absolute Error: 5.574468125726359
R-squared: 0.46868752353666077
Coefficients (w): (array([ 2.20991609, -1.98470218, -1.53348488, -
1.6251673 , -1.89558726,
        0.03799888, -0.27844071,  2.07655741,  1.56835155, -
0.9546427 ,
       -0.02701357,  2.47583044, -0.03654881,  0.02505729, -
0.00288066,
       -0.09735544, -0.14203539,  0.03814412,  0.03814412]),
26.22022353516736)
```

```
# Find indices of instances with highest absolute errors (extreme
errors)
extreme_error_indices = np.argsort(-np.abs(y_pred - y_val))[:10]

extreme_error_data = []
for idx in extreme_error_indices:
    extreme_error_data.append({
        'Instance Index': idx,
        'True Value': y_val[idx],
        'Predicted Value': y_pred[idx],
        'Absolute Error': np.abs(y_pred[idx] - y_val[idx])
    })

# Plot extreme error instances for Linear Regression
plt.figure(figsize=(8, 6))
error_values = [data['Absolute Error'] for data in extreme_error_data]
```

```
instance_indices = [data['Instance Index'] for data in
extreme_error_data]
plt.scatter(instance_indices, error_values, color='b', alpha=0.7,
s=80)
plt.xlabel('Instance Index', fontsize=12)
plt.ylabel('Absolute Error', fontsize=12)
plt.title('Extreme Error Instances for Linear Regression',
fontsize=14)
plt.grid(True, linestyle='--', alpha=0.7)
plt.tight_layout()
plt.show()

# Plot error distribution for Linear Regression
errors = y_val - y_pred

plt.figure(figsize=(8, 6))
plt.hist(errors, bins=30, alpha=0.7, color='g')
plt.xlabel('Residuals', fontsize=12)
plt.ylabel('Frequency', fontsize=12)
plt.title('Error Distribution for Linear Regression', fontsize=14)
plt.grid(True, linestyle='--', alpha=0.7)
plt.tight_layout()
plt.show()
```



Extreme Error Instances for Linear Regression
Absolute Error
Instance Index
23
24
25
26
27
28
1000
2000
3000
4000
5000



Ridge Regression

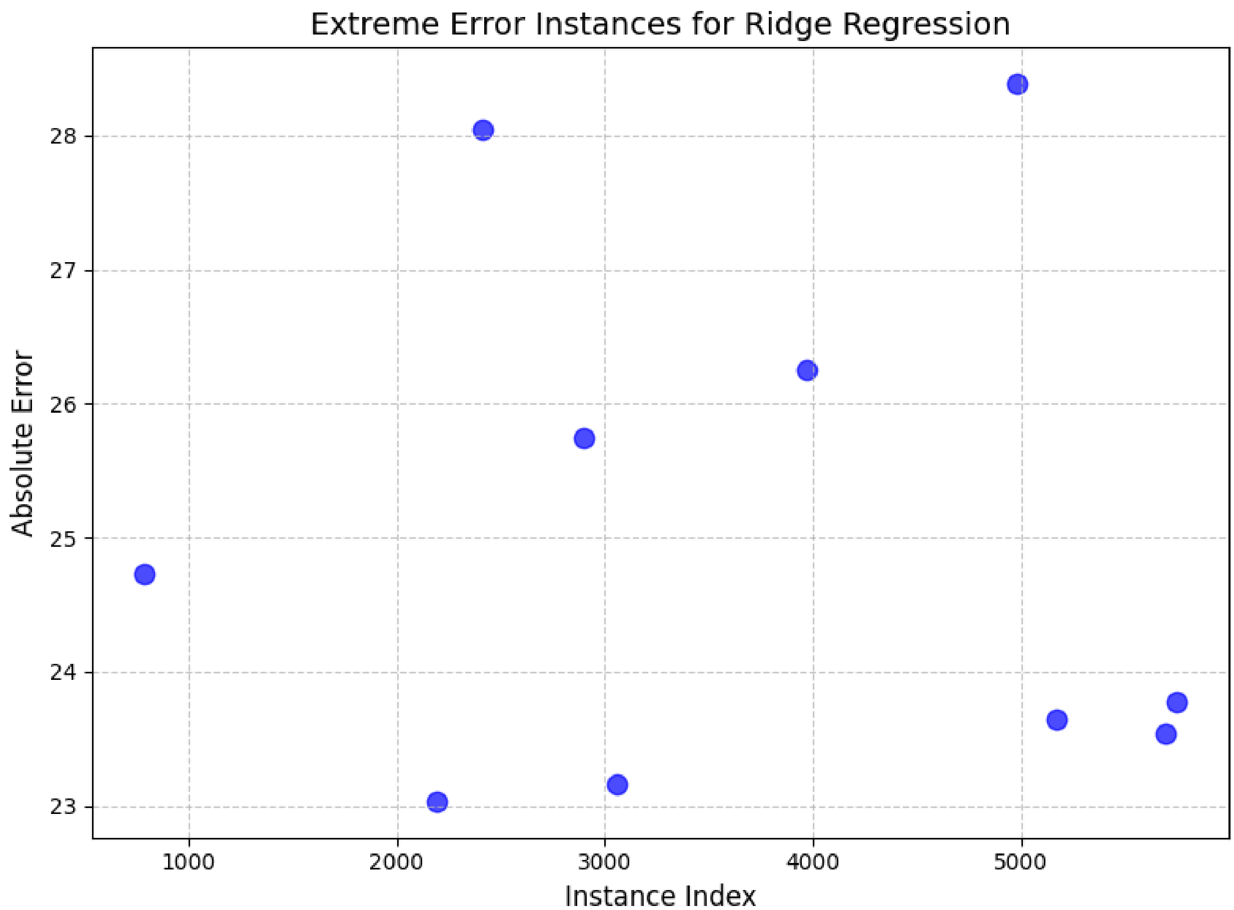
```
class Ridge_Regression:
    def __init__(self, alpha=1.0):
      self.alpha = alpha
      self.coef_ = None

    def fit(self, X, y):
      # Add a column of ones to the feature matrix for the intercept
term
      X = np.c_[np.ones(X.shape[0]), X]

      # Compute the coefficient matrix using the closed-form solution
      identity = np.identity(X.shape[1])
      self.coef_ = np.linalg.inv(X.T @ X + self.alpha * identity) @
X.T @ y

    def predict(self, X):
      # Add a column of ones to the feature matrix for the intercept
term
      X = np.c_[np.ones(X.shape[0]), X]
```

```
        # Predict using the coefficient matrix
        return X @ self.coef_

    def get_coefficient(self):
        return self.coef_


ridge_model = Ridge_Regression(alpha=0.01)
ridge_model.fit(X_train, y_train)

# Make predictions on test data
y_pred = ridge_model.predict(X_val)

# Evaluate the model's performance
mse = mean_squared_error(y_val, y_pred)
rmse = np.sqrt(mse)
mae = mean_absolute_error(y_val, y_pred)
r2 = r2_score(y_val, y_pred)
print("Mean Squared Error:", mse)
print("Root Mean Squared Error:", rmse)
print("Mean Absolute Error:", mae)
print("R-squared:", r2)
print("Coefficient = ", ridge_model.get_coefficient())
```

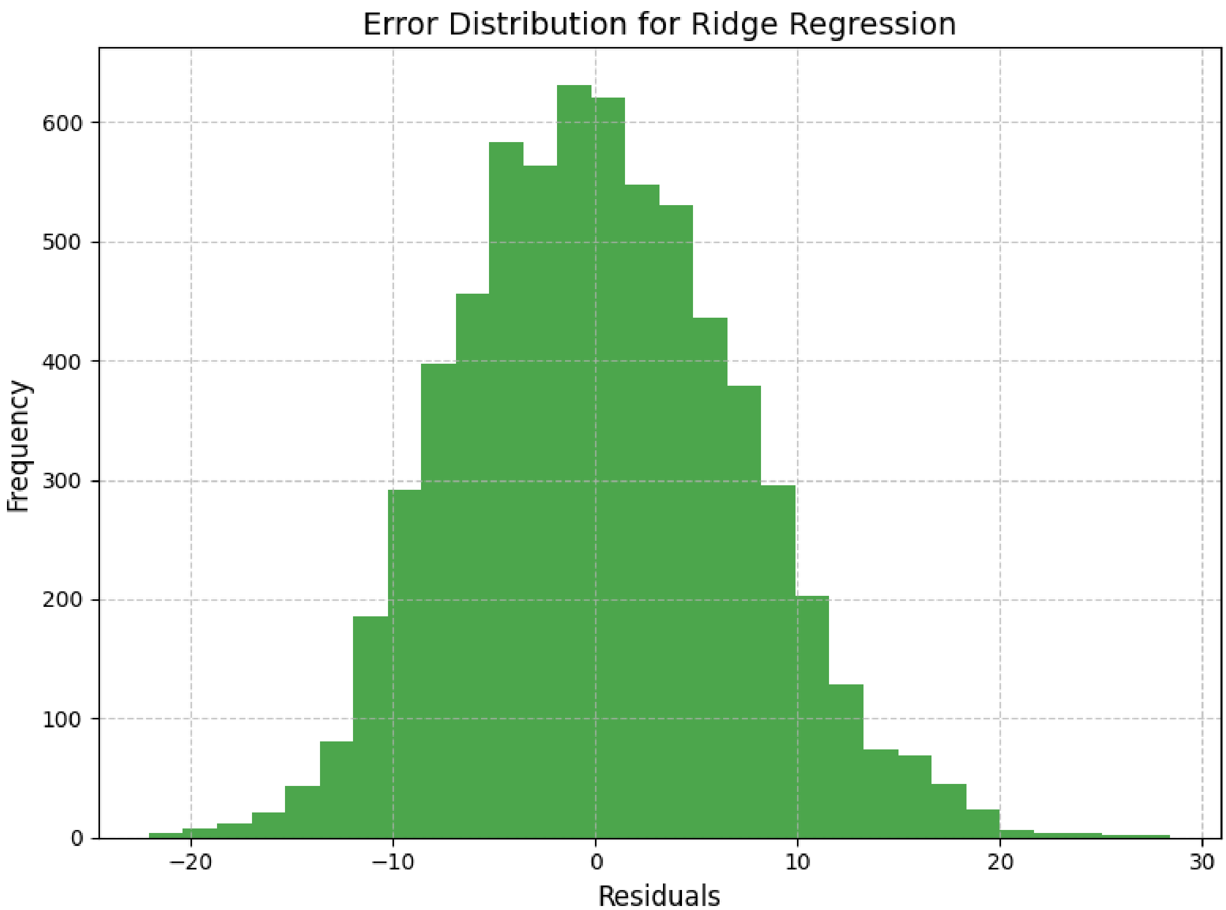
```
Mean Squared Error: 47.96832608237959
Root Mean Squared Error: 6.925916984947162
Mean Absolute Error: 5.57446807178152
R-squared: 0.46868747285738466
Coefficient =  [ 2.62202137e+01  2.20991535e+00 -1.98470165e+00 -
1.53348433e+00
 -1.62516664e+00 -1.89558657e+00  3.79988827e-02 -2.78440755e-01
  2.07655707e+00  1.56835129e+00 -9.54642548e-01 -2.70135738e-02
  2.47582951e+00 -3.65488125e-02  2.50572351e-02 -2.88058639e-03
 -9.73553796e-02 -1.42035516e-01  3.81441687e-02  3.81441688e-02]
```

```
# Find indices of instances with highest absolute errors (extreme
errors)
extreme_error_indices = np.argsort(-np.abs(y_pred - y_val))[:10]

extreme_error_data = []
for idx in extreme_error_indices:
    extreme_error_data.append({
        'Instance Index': idx,
        'True Value': y_val[idx],
        'Predicted Value': y_pred[idx],
        'Absolute Error': np.abs(y_pred[idx] - y_val[idx])
    })

# Plot extreme error instances for Ridge Regression
plt.figure(figsize=(8, 6))
```

```
error_values = [data['Absolute Error'] for data in extreme_error_data]
instance_indices = [data['Instance Index'] for data in
extreme_error_data]
plt.scatter(instance_indices, error_values, color='b', alpha=0.7,
s=80)
plt.xlabel('Instance Index', fontsize=12)
plt.ylabel('Absolute Error', fontsize=12)
plt.title('Extreme Error Instances for Ridge Regression', fontsize=14)
plt.grid(True, linestyle='--', alpha=0.7)
plt.tight_layout()
plt.show()

# Plot error distribution for Ridge Regression
errors = y_val - y_pred

plt.figure(figsize=(8, 6))
plt.hist(errors, bins=30, alpha=0.7, color='g')
plt.xlabel('Residuals', fontsize=12)
plt.ylabel('Frequency', fontsize=12)
plt.title('Error Distribution for Ridge Regression', fontsize=14)
plt.grid(True, linestyle='--', alpha=0.7)
plt.tight_layout()
plt.show()
```



Extreme Error Instances for Ridge Regression
Absolute Error
23
24
25
26
27
28
1000
2000
3000
4000
5000
Instance Index



Decision Tree

```
# Decision tree regressor implementation
class Node:
    def __init__(self, feature_index=None, threshold=None, left=None,
right=None, value=None):
        self.feature_index = feature_index  # Index of feature to
split on
        self.threshold = threshold  # Threshold value to split on
        self.left = left  # Left subtree
        self.right = right  # Right subtree
        self.value = value  # Value to return for leaf nodes

class Decision_Tree_Regressor:
    def __init__(self, max_depth=None):
        self.max_depth = max_depth  # Maximum depth of the tree
        self.tree = None

    def mse(self, y):
        return np.mean((y - np.mean(y)) ** 2)

    def find_best_split(self, X, y):
```

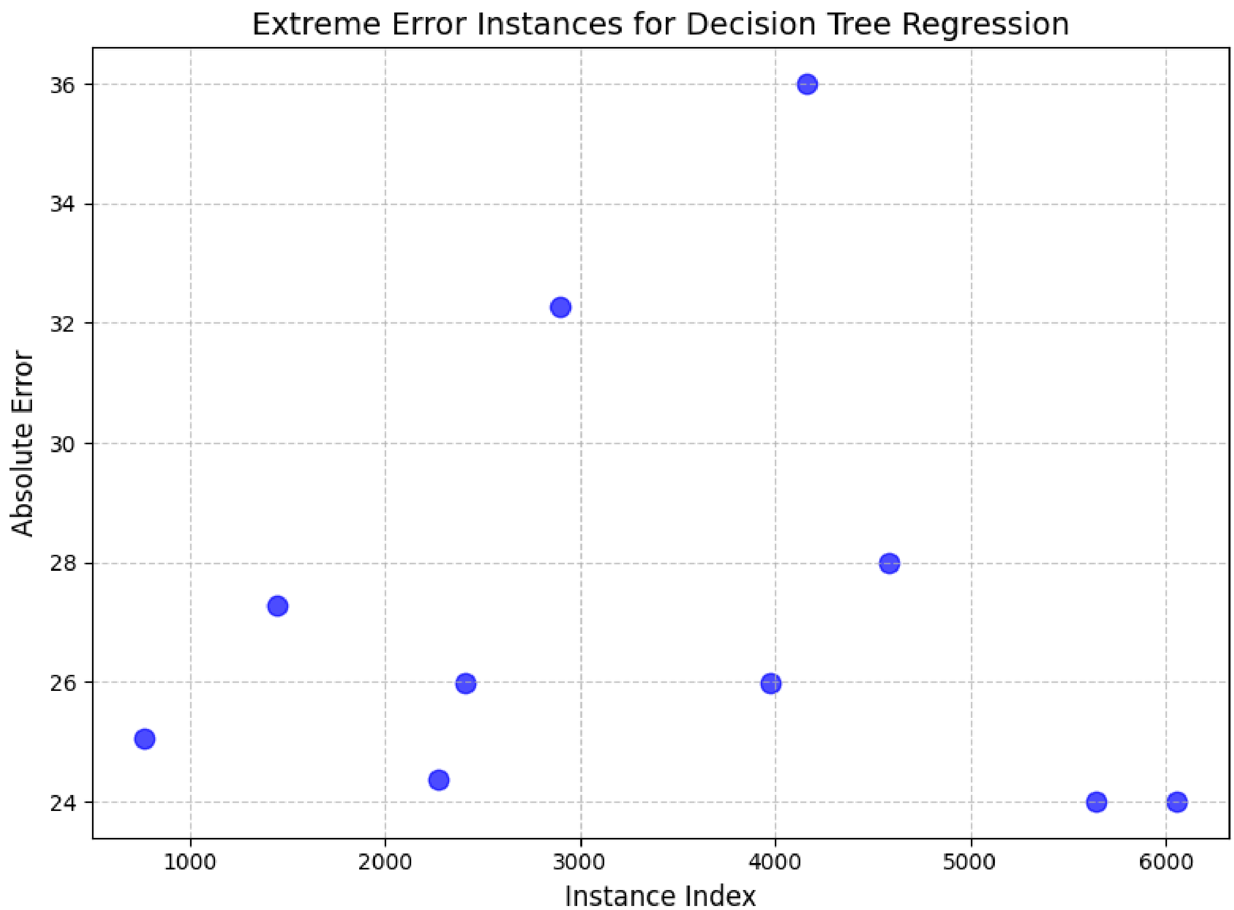
```
        m, n = X.shape
        best_mse = float('inf')
        best_feature_index = None
        best_threshold = None

        for feature_index in range(n):
            thresholds = np.unique(X[:, feature_index])
            for threshold in thresholds:
                left_indices = X[:, feature_index] < threshold
                right_indices = ~left_indices

                if np.sum(left_indices) == 0 or np.sum(right_indices)
== 0:
                    continue

                y_left = y[left_indices]
                y_right = y[right_indices]

                mse = self.mse(y_left) + self.mse(y_right)
                if mse < best_mse:
                    best_mse = mse
                    best_feature_index = feature_index
                    best_threshold = threshold

        return best_feature_index, best_threshold

    def fit(self, X, y):
        self.tree = self._fit_tree(X, y, depth=0)

    def _fit_tree(self, X, y, depth):
        if depth == self.max_depth or len(np.unique(y)) == 1:
            return Node(value=np.mean(y))

        feature_index, threshold = self.find_best_split(X, y)
        if feature_index is None or threshold is None:
            return Node(value=np.mean(y))

        left_indices = X[:, feature_index] < threshold
        X_left, y_left = X[left_indices], y[left_indices]
        X_right, y_right = X[~left_indices], y[~left_indices]

        left_subtree = self._fit_tree(X_left, y_left, depth + 1)
        right_subtree = self._fit_tree(X_right, y_right, depth + 1)

        return Node(feature_index=feature_index, threshold=threshold,
left=left_subtree, right=right_subtree)

    def predict(self, X):
        return np.array([self._predict_tree(sample, self.tree) for
sample in X])
```

```
    def _predict_tree(self, sample, node):
        if node.value is not None:
            return node.value

        if sample[node.feature_index] < node.threshold:
            return self._predict_tree(sample, node.left)
        else:
            return self._predict_tree(sample, node.right)

regressor = Decision_Tree_Regressor(max_depth=27)
regressor.fit(X_train, y_train)


y_pred = regressor.predict(X_val)

# Evaluate the model's performance
mse = mean_squared_error(y_val, y_pred)
rmse = np.sqrt(mse)
mae = mean_absolute_error(y_val, y_pred)
r2 = r2_score(y_val, y_pred)

# Display the performance metrics for Decision Tree Regression model
metrics = {
    'Mean Squared Error (MSE)': mse,
    'Root Mean Squared Error (RMSE)': rmse,
    'Mean Absolute Error (MAE)': mae,
    'R-squared (R2)': r2
}

metrics_df = pd.DataFrame.from_dict(metrics, orient='index')
print(metrics_df)
```

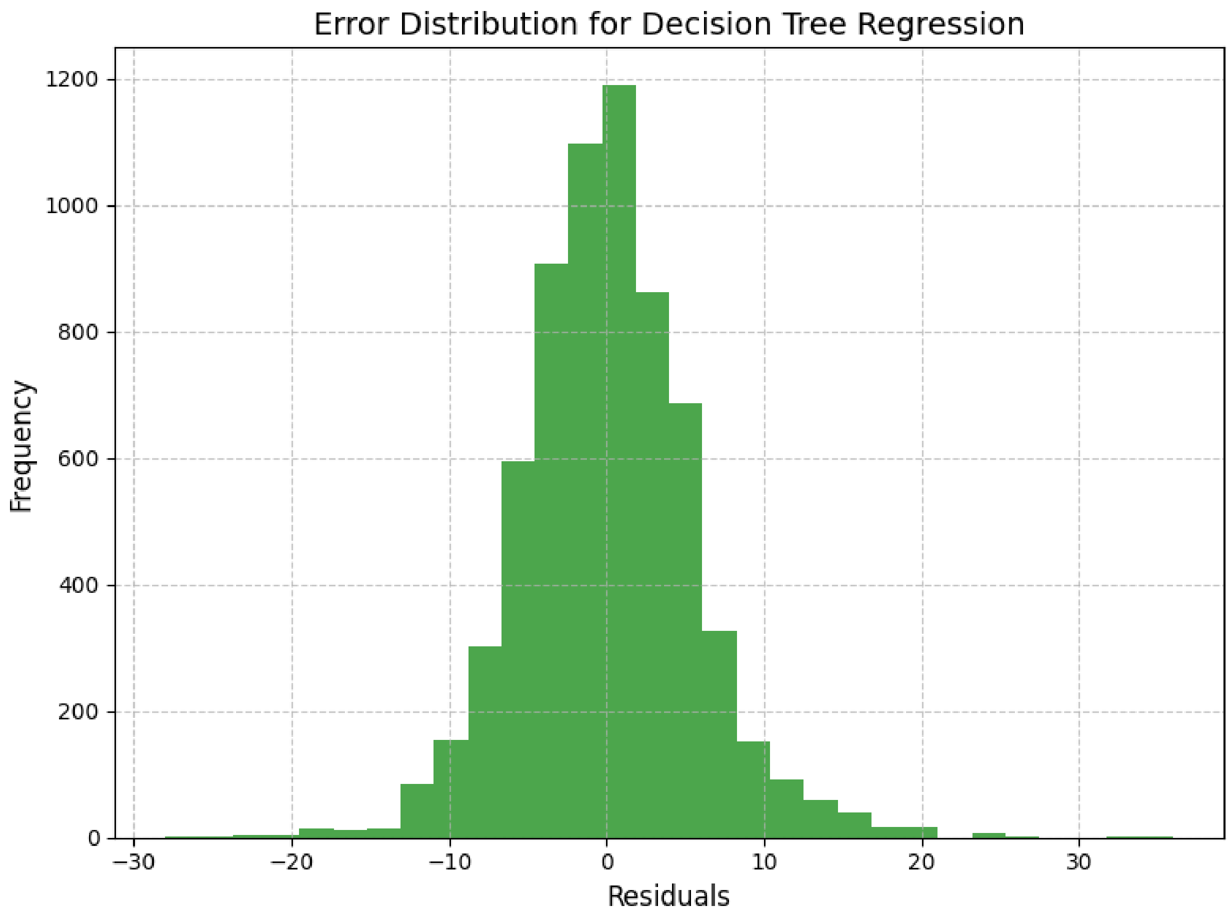
	0
Mean Squared Error (MSE)	30.054892
Root Mean Squared Error (RMSE)	5.482234
Mean Absolute Error (MAE)	4.125896
R-squared (R2)	0.667102

```
extreme_error_indices = np.argsort(-np.abs(y_pred - y_val))[:10]

extreme_error_data = []
for idx in extreme_error_indices:
    extreme_error_data.append({
        'Instance Index': idx,
        'True Value': y_val[idx],
        'Predicted Value': y_pred[idx],
        'Absolute Error': np.abs(y_pred[idx] - y_val[idx])
    })

# Plot extreme error instances for Decision Tree Regression
```

```
plt.figure(figsize=(8, 6))
error_values = [data['Absolute Error'] for data in extreme_error_data]
instance_indices = [data['Instance Index'] for data in
extreme_error_data]
plt.scatter(instance_indices, error_values, color='b', alpha=0.7,
s=80)
plt.xlabel('Instance Index', fontsize=12)
plt.ylabel('Absolute Error', fontsize=12)
plt.title('Extreme Error Instances for Decision Tree Regression',
fontsize=14)
plt.grid(True, linestyle='--', alpha=0.7)
plt.tight_layout()
plt.show()

# Plot error distribution for Decision Tree Regression
errors = y_val - y_pred

plt.figure(figsize=(8, 6))
plt.hist(errors, bins=30, alpha=0.7, color='g')
plt.xlabel('Residuals', fontsize=12)
plt.ylabel('Frequency', fontsize=12)
plt.title('Error Distribution for Decision Tree Regression',
fontsize=14)
plt.grid(True, linestyle='--', alpha=0.7)
plt.tight_layout()
plt.show()
```



Extreme Error Instances for Decision Tree Regression
Absolute Error
Instance Index
36
34
32
30
28
26
24
1000
2000
3000
4000
5000
6000



Implementation using libraries

ANN

```
import numpy as np
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout
from tensorflow.keras.callbacks import EarlyStopping
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error, mean_absolute_error,
r2_score
import pandas as pd

# Create a function to build and train the model
def build_and_train_model(num_layers, units_per_layer):
    model = Sequential()
    model.add(Dense(units_per_layer, activation='relu',
input_shape=(19,)))
    for _ in range(num_layers):
        model.add(Dense(units_per_layer, activation='relu'))
```

```
    model.add(Dense(1))

    model.compile(optimizer='adam', loss='mean_squared_error')

    early_stopping = EarlyStopping(monitor='val_loss', patience=5,
restore_best_weights=True)

    model.fit(X_train, y_train, epochs=100, batch_size=32,
validation_split=0.2, callbacks=[early_stopping])

    y_pred = model.predict(X_val)

    mse = mean_squared_error(y_val, y_pred)
    rmse = np.sqrt(mse)
    mae = mean_absolute_error(y_val, y_pred)
    r2 = r2_score(y_val, y_pred)

    return {'Num Layers': num_layers, 'Units Per Layer':
units_per_layer, 'MSE': mse, 'RMSE': rmse, 'MAE': mae, 'R2': r2}

results = []
for num_layers in range(1, 6):
    for units_per_layer in [64, 128, 264]:
        result = build_and_train_model(num_layers, units_per_layer)
        results.append(result)

ANN_results_df = pd.DataFrame(results)
```

```
Epoch 1/100
665/665 [==============================] - 9s 5ms/step - loss: 97.6576
- val_loss: 43.4507
Epoch 2/100
665/665 [==============================] - 3s 4ms/step - loss: 41.1053
- val_loss: 40.2397
Epoch 3/100
665/665 [==============================] - 3s 4ms/step - loss: 39.2660
- val_loss: 39.0077
Epoch 4/100
665/665 [==============================] - 3s 4ms/step - loss: 37.5916
- val_loss: 36.6585
Epoch 5/100
665/665 [==============================] - 3s 4ms/step - loss: 34.7584
- val_loss: 34.2340
Epoch 6/100
665/665 [==============================] - 3s 5ms/step - loss: 32.6599
- val_loss: 33.4462
Epoch 7/100
665/665 [==============================] - 3s 4ms/step - loss: 31.5556
- val_loss: 32.0863
Epoch 8/100
```

```
665/665 [==============================] - 3s 4ms/step - loss: 30.5452
- val_loss: 31.4211
Epoch 9/100
665/665 [==============================] - 4s 5ms/step - loss: 29.6484
- val_loss: 29.9133
Epoch 10/100
665/665 [==============================] - 5s 7ms/step - loss: 28.7665
- val_loss: 28.9782
Epoch 11/100
665/665 [==============================] - 2s 4ms/step - loss: 27.9707
- val_loss: 29.4707
Epoch 12/100
665/665 [==============================] - 3s 4ms/step - loss: 27.2330
- val_loss: 28.0254
Epoch 13/100
665/665 [==============================] - 2s 4ms/step - loss: 26.6093
- val_loss: 27.8050
Epoch 14/100
665/665 [==============================] - 3s 5ms/step - loss: 26.2182
- val_loss: 27.2075
Epoch 15/100
665/665 [==============================] - 3s 4ms/step - loss: 25.8219
- val_loss: 27.5264
Epoch 16/100
665/665 [==============================] - 2s 4ms/step - loss: 25.5762
- val_loss: 26.4994
Epoch 17/100
665/665 [==============================] - 3s 4ms/step - loss: 25.1566
- val_loss: 26.3840
Epoch 18/100
665/665 [==============================] - 3s 4ms/step - loss: 24.7934
- val_loss: 26.2713
Epoch 19/100
665/665 [==============================] - 4s 5ms/step - loss: 24.4183
- val_loss: 26.0977
Epoch 20/100
665/665 [==============================] - 2s 4ms/step - loss: 24.1821
- val_loss: 25.4080
Epoch 21/100
665/665 [==============================] - 3s 4ms/step - loss: 23.8394
- val_loss: 25.7959
Epoch 22/100
665/665 [==============================] - 2s 4ms/step - loss: 23.6138
- val_loss: 25.2033
Epoch 23/100
665/665 [==============================] - 3s 4ms/step - loss: 23.2818
- val_loss: 24.8303
Epoch 24/100
665/665 [==============================] - 3s 5ms/step - loss: 22.9151
```

```
- val_loss: 24.6041
Epoch 25/100
665/665 [==============================] - 2s 4ms/step - loss: 22.7267
- val_loss: 24.3680
Epoch 26/100
665/665 [==============================] - 2s 4ms/step - loss: 22.3888
- val_loss: 24.6990
Epoch 27/100
665/665 [==============================] - 3s 4ms/step - loss: 22.1960
- val_loss: 23.8248
Epoch 28/100
665/665 [==============================] - 3s 4ms/step - loss: 21.8592
- val_loss: 23.8587
Epoch 29/100
665/665 [==============================] - 3s 4ms/step - loss: 21.6634
- val_loss: 23.4641
Epoch 30/100
665/665 [==============================] - 3s 4ms/step - loss: 21.4566
- val_loss: 23.4155
Epoch 31/100
665/665 [==============================] - 3s 4ms/step - loss: 21.1567
- val_loss: 22.8223
Epoch 32/100
665/665 [==============================] - 3s 4ms/step - loss: 20.9605
- val_loss: 22.9083
Epoch 33/100
665/665 [==============================] - 3s 5ms/step - loss: 20.7077
- val_loss: 23.6973
Epoch 34/100
665/665 [==============================] - 3s 4ms/step - loss: 20.5797
- val_loss: 22.9194
Epoch 35/100
665/665 [==============================] - 3s 4ms/step - loss: 20.3069
- val_loss: 22.6718
Epoch 36/100
665/665 [==============================] - 3s 4ms/step - loss: 20.2316
- val_loss: 22.4639
Epoch 37/100
665/665 [==============================] - 3s 4ms/step - loss: 19.8855
- val_loss: 21.7727
Epoch 38/100
665/665 [==============================] - 3s 5ms/step - loss: 19.8143
- val_loss: 21.9809
Epoch 39/100
665/665 [==============================] - 2s 4ms/step - loss: 19.7257
- val_loss: 23.2507
Epoch 40/100
665/665 [==============================] - 2s 4ms/step - loss: 19.4917
- val_loss: 21.6392
```

```
Epoch 41/100
665/665 [==============================] - 2s 4ms/step - loss: 19.4093
- val_loss: 21.6746
Epoch 42/100
665/665 [==============================] - 3s 5ms/step - loss: 19.3036
- val_loss: 21.4078
Epoch 43/100
665/665 [==============================] - 3s 4ms/step - loss: 19.2090
- val_loss: 21.1511
Epoch 44/100
665/665 [==============================] - 2s 4ms/step - loss: 19.0297
- val_loss: 21.1349
Epoch 45/100
665/665 [==============================] - 3s 4ms/step - loss: 18.9502
- val_loss: 21.8821
Epoch 46/100
665/665 [==============================] - 3s 4ms/step - loss: 18.8295
- val_loss: 21.3821
Epoch 47/100
665/665 [==============================] - 3s 5ms/step - loss: 18.9431
- val_loss: 21.2633
Epoch 48/100
665/665 [==============================] - 3s 4ms/step - loss: 18.6984
- val_loss: 21.0587
Epoch 49/100
665/665 [==============================] - 2s 4ms/step - loss: 18.7884
- val_loss: 21.0959
Epoch 50/100
665/665 [==============================] - 2s 4ms/step - loss: 18.6181
- val_loss: 21.1787
Epoch 51/100
665/665 [==============================] - 3s 4ms/step - loss: 18.4418
- val_loss: 21.2283
Epoch 52/100
665/665 [==============================] - 3s 5ms/step - loss: 18.4438
- val_loss: 21.0754
Epoch 53/100
665/665 [==============================] - 3s 4ms/step - loss: 18.3387
- val_loss: 21.3048
208/208 [==============================] - 0s 2ms/step
Epoch 1/100
665/665 [==============================] - 5s 5ms/step - loss: 80.0577
- val_loss: 41.4823
Epoch 2/100
665/665 [==============================] - 3s 4ms/step - loss: 39.6424
- val_loss: 38.4787
Epoch 3/100
665/665 [==============================] - 2s 4ms/step - loss: 37.6246
- val_loss: 37.0444
```

```
Epoch 4/100
665/665 [==============================] - 2s 4ms/step - loss: 35.2106
- val_loss: 33.8324
Epoch 5/100
665/665 [==============================] - 2s 4ms/step - loss: 32.6475
- val_loss: 31.8277
Epoch 6/100
665/665 [==============================] - 3s 5ms/step - loss: 30.8316
- val_loss: 30.8514
Epoch 7/100
665/665 [==============================] - 2s 4ms/step - loss: 29.9521
- val_loss: 30.1500
Epoch 8/100
665/665 [==============================] - 3s 4ms/step - loss: 28.8288
- val_loss: 29.4050
Epoch 9/100
665/665 [==============================] - 3s 4ms/step - loss: 27.7095
- val_loss: 28.9619
Epoch 10/100
665/665 [==============================] - 3s 4ms/step - loss: 27.2149
- val_loss: 28.4700
Epoch 11/100
665/665 [==============================] - 3s 4ms/step - loss: 26.5721
- val_loss: 27.5995
Epoch 12/100
665/665 [==============================] - 4s 5ms/step - loss: 25.9712
- val_loss: 26.9617
Epoch 13/100
665/665 [==============================] - 3s 4ms/step - loss: 25.4910
- val_loss: 26.8259
Epoch 14/100
665/665 [==============================] - 3s 4ms/step - loss: 24.7854
- val_loss: 25.6955
Epoch 15/100
665/665 [==============================] - 3s 5ms/step - loss: 24.0720
- val_loss: 26.1318
Epoch 16/100
665/665 [==============================] - 3s 4ms/step - loss: 23.3227
- val_loss: 24.8400
Epoch 17/100
665/665 [==============================] - 3s 4ms/step - loss: 22.7170
- val_loss: 24.7070
Epoch 18/100
665/665 [==============================] - 2s 4ms/step - loss: 21.9053
- val_loss: 24.2196
Epoch 19/100
665/665 [==============================] - 3s 5ms/step - loss: 21.3507
- val_loss: 22.6456
Epoch 20/100
```

```
665/665 [==============================] - 3s 4ms/step - loss: 20.8490
- val_loss: 22.3892
Epoch 21/100
665/665 [==============================] - 2s 4ms/step - loss: 20.4828
- val_loss: 22.8678
Epoch 22/100
665/665 [==============================] - 2s 4ms/step - loss: 19.9301
- val_loss: 22.9214
Epoch 23/100
665/665 [==============================] - 2s 4ms/step - loss: 19.7242
- val_loss: 22.3579
Epoch 24/100
665/665 [==============================] - 3s 5ms/step - loss: 19.4431
- val_loss: 21.8320
Epoch 25/100
665/665 [==============================] - 2s 4ms/step - loss: 19.1524
- val_loss: 22.1188
Epoch 26/100
665/665 [==============================] - 2s 4ms/step - loss: 18.8909
- val_loss: 21.7541
Epoch 27/100
665/665 [==============================] - 2s 4ms/step - loss: 18.6739
- val_loss: 21.9056
Epoch 28/100
665/665 [==============================] - 3s 4ms/step - loss: 18.4095
- val_loss: 21.2573
Epoch 29/100
665/665 [==============================] - 3s 5ms/step - loss: 18.1858
- val_loss: 21.0587
Epoch 30/100
665/665 [==============================] - 2s 4ms/step - loss: 18.0132
- val_loss: 21.1535
Epoch 31/100
665/665 [==============================] - 3s 4ms/step - loss: 17.8206
- val_loss: 21.2412
Epoch 32/100
665/665 [==============================] - 2s 4ms/step - loss: 17.6187
- val_loss: 20.9916
Epoch 33/100
665/665 [==============================] - 3s 4ms/step - loss: 17.4140
- val_loss: 22.6134
Epoch 34/100
665/665 [==============================] - 3s 5ms/step - loss: 17.3655
- val_loss: 21.1566
Epoch 35/100
665/665 [==============================] - 2s 4ms/step - loss: 17.1531
- val_loss: 21.0668
Epoch 36/100
665/665 [==============================] - 2s 4ms/step - loss: 17.0082
```

```
- val_loss: 21.1508
Epoch 37/100
665/665 [==============================] - 3s 4ms/step - loss: 16.8762
- val_loss: 20.7618
Epoch 38/100
665/665 [==============================] - 3s 5ms/step - loss: 16.6617
- val_loss: 20.6564
Epoch 39/100
665/665 [==============================] - 2s 4ms/step - loss: 16.4864
- val_loss: 20.9595
Epoch 40/100
665/665 [==============================] - 2s 4ms/step - loss: 16.4255
- val_loss: 20.3112
Epoch 41/100
665/665 [==============================] - 3s 4ms/step - loss: 16.1803
- val_loss: 20.5715
Epoch 42/100
665/665 [==============================] - 3s 4ms/step - loss: 16.1714
- val_loss: 20.2983
Epoch 43/100
665/665 [==============================] - 3s 5ms/step - loss: 15.9304
- val_loss: 20.2594
Epoch 44/100
665/665 [==============================] - 2s 4ms/step - loss: 15.9342
- val_loss: 20.2102
Epoch 45/100
665/665 [==============================] - 2s 4ms/step - loss: 15.8714
- val_loss: 20.5680
Epoch 46/100
665/665 [==============================] - 3s 4ms/step - loss: 15.6935
- val_loss: 20.2773
Epoch 47/100
665/665 [==============================] - 3s 5ms/step - loss: 15.6292
- val_loss: 20.3559
Epoch 48/100
665/665 [==============================] - 3s 4ms/step - loss: 15.5188
- val_loss: 20.1940
Epoch 49/100
665/665 [==============================] - 2s 4ms/step - loss: 15.3144
- val_loss: 20.0887
Epoch 50/100
665/665 [==============================] - 3s 4ms/step - loss: 15.3583
- val_loss: 19.9886
Epoch 51/100
665/665 [==============================] - 3s 4ms/step - loss: 15.1566
- val_loss: 20.5248
Epoch 52/100
665/665 [==============================] - 3s 5ms/step - loss: 15.1347
- val_loss: 20.2692
```

```
Epoch 53/100
665/665 [==============================] - 3s 4ms/step - loss: 15.1417
- val_loss: 20.7255
Epoch 54/100
665/665 [==============================] - 3s 4ms/step - loss: 15.0179
- val_loss: 20.5461
Epoch 55/100
665/665 [==============================] - 2s 4ms/step - loss: 14.7812
- val_loss: 20.7069
208/208 [==============================] - 0s 2ms/step
Epoch 1/100
665/665 [==============================] - 5s 5ms/step - loss: 65.2536
- val_loss: 40.9343
Epoch 2/100
665/665 [==============================] - 3s 4ms/step - loss: 39.2291
- val_loss: 37.6387
Epoch 3/100
665/665 [==============================] - 2s 4ms/step - loss: 35.0581
- val_loss: 33.1223
Epoch 4/100
665/665 [==============================] - 3s 4ms/step - loss: 31.7013
- val_loss: 31.1547
Epoch 5/100
665/665 [==============================] - 3s 4ms/step - loss: 29.9500
- val_loss: 29.4897
Epoch 6/100
665/665 [==============================] - 3s 4ms/step - loss: 28.4384
- val_loss: 29.4822
Epoch 7/100
665/665 [==============================] - 2s 4ms/step - loss: 27.2861
- val_loss: 28.4209
Epoch 8/100
665/665 [==============================] - 3s 4ms/step - loss: 26.2563
- val_loss: 27.0231
Epoch 9/100
665/665 [==============================] - 3s 4ms/step - loss: 25.6678
- val_loss: 26.6848
Epoch 10/100
665/665 [==============================] - 3s 5ms/step - loss: 25.2033
- val_loss: 26.1354
Epoch 11/100
665/665 [==============================] - 3s 4ms/step - loss: 24.6041
- val_loss: 27.6201
Epoch 12/100
665/665 [==============================] - 3s 4ms/step - loss: 24.1078
- val_loss: 25.7179
Epoch 13/100
665/665 [==============================] - 3s 4ms/step - loss: 23.4752
- val_loss: 25.9832
```

```
Epoch 14/100
665/665 [==============================] - 3s 4ms/step - loss: 22.7226
- val_loss: 24.0120
Epoch 15/100
665/665 [==============================] - 3s 5ms/step - loss: 22.0274
- val_loss: 24.2036
Epoch 16/100
665/665 [==============================] - 3s 4ms/step - loss: 21.2748
- val_loss: 24.3216
Epoch 17/100
665/665 [==============================] - 3s 4ms/step - loss: 20.7898
- val_loss: 22.5860
Epoch 18/100
665/665 [==============================] - 2s 4ms/step - loss: 20.3616
- val_loss: 22.4205
Epoch 19/100
665/665 [==============================] - 3s 5ms/step - loss: 19.7254
- val_loss: 21.8486
Epoch 20/100
665/665 [==============================] - 3s 4ms/step - loss: 19.2985
- val_loss: 21.4495
Epoch 21/100
665/665 [==============================] - 3s 4ms/step - loss: 19.0596
- val_loss: 23.0821
Epoch 22/100
665/665 [==============================] - 2s 4ms/step - loss: 18.7053
- val_loss: 21.5665
Epoch 23/100
665/665 [==============================] - 3s 4ms/step - loss: 18.2122
- val_loss: 21.3930
Epoch 24/100
665/665 [==============================] - 3s 5ms/step - loss: 17.9232
- val_loss: 21.4543
Epoch 25/100
665/665 [==============================] - 3s 4ms/step - loss: 17.5128
- val_loss: 21.3027
Epoch 26/100
665/665 [==============================] - 2s 4ms/step - loss: 17.3138
- val_loss: 21.0188
Epoch 27/100
665/665 [==============================] - 3s 4ms/step - loss: 16.9850
- val_loss: 21.2269
Epoch 28/100
665/665 [==============================] - 3s 4ms/step - loss: 16.8682
- val_loss: 20.3841
Epoch 29/100
665/665 [==============================] - 3s 5ms/step - loss: 16.5299
- val_loss: 20.9822
Epoch 30/100
```

```
665/665 [==============================] - 2s 4ms/step - loss: 16.3689
- val_loss: 21.3518
Epoch 31/100
665/665 [==============================] - 2s 4ms/step - loss: 16.2651
- val_loss: 20.5801
Epoch 32/100
665/665 [==============================] - 3s 4ms/step - loss: 16.0067
- val_loss: 20.5992
Epoch 33/100
665/665 [==============================] - 3s 5ms/step - loss: 15.7937
- val_loss: 23.3041
208/208 [==============================] - 0s 2ms/step
Epoch 1/100
665/665 [==============================] - 4s 4ms/step - loss: 87.5114
- val_loss: 41.0746
Epoch 2/100
665/665 [==============================] - 4s 5ms/step - loss: 39.8798
- val_loss: 38.3609
Epoch 3/100
665/665 [==============================] - 3s 4ms/step - loss: 36.6432
- val_loss: 34.6733
Epoch 4/100
665/665 [==============================] - 3s 4ms/step - loss: 33.3991
- val_loss: 34.5304
Epoch 5/100
665/665 [==============================] - 3s 4ms/step - loss: 31.6722
- val_loss: 32.2522
Epoch 6/100
665/665 [==============================] - 3s 5ms/step - loss: 30.2929
- val_loss: 30.4016
Epoch 7/100
665/665 [==============================] - 3s 5ms/step - loss: 29.0871
- val_loss: 29.3514
Epoch 8/100
665/665 [==============================] - 3s 4ms/step - loss: 28.3979
- val_loss: 28.9596
Epoch 9/100
665/665 [==============================] - 3s 4ms/step - loss: 27.6966
- val_loss: 28.4015
Epoch 10/100
665/665 [==============================] - 3s 4ms/step - loss: 27.2711
- val_loss: 27.8326
Epoch 11/100
665/665 [==============================] - 4s 5ms/step - loss: 26.7331
- val_loss: 27.7548
Epoch 12/100
665/665 [==============================] - 3s 4ms/step - loss: 26.3041
- val_loss: 27.9351
Epoch 13/100
```

```
665/665 [==============================] - 3s 4ms/step - loss: 25.7652
- val_loss: 26.6048
Epoch 14/100
665/665 [==============================] - 3s 4ms/step - loss: 25.3019
- val_loss: 27.1790
Epoch 15/100
665/665 [==============================] - 3s 5ms/step - loss: 24.8451
- val_loss: 26.9058
Epoch 16/100
665/665 [==============================] - 3s 5ms/step - loss: 24.4729
- val_loss: 26.7521
Epoch 17/100
665/665 [==============================] - 3s 5ms/step - loss: 23.9987
- val_loss: 25.4524
Epoch 18/100
665/665 [==============================] - 3s 4ms/step - loss: 23.5500
- val_loss: 25.9295
Epoch 19/100
665/665 [==============================] - 4s 6ms/step - loss: 23.1285
- val_loss: 26.4235
Epoch 20/100
665/665 [==============================] - 3s 4ms/step - loss: 22.7326
- val_loss: 24.6687
Epoch 21/100
665/665 [==============================] - 3s 5ms/step - loss: 22.3845
- val_loss: 24.1225
Epoch 22/100
665/665 [==============================] - 3s 5ms/step - loss: 21.8443
- val_loss: 24.9279
Epoch 23/100
665/665 [==============================] - 4s 6ms/step - loss: 21.3999
- val_loss: 24.1667
Epoch 24/100
665/665 [==============================] - 3s 4ms/step - loss: 20.9797
- val_loss: 23.6346
Epoch 25/100
665/665 [==============================] - 3s 4ms/step - loss: 20.4562
- val_loss: 22.8077
Epoch 26/100
665/665 [==============================] - 3s 4ms/step - loss: 20.0114
- val_loss: 22.6650
Epoch 27/100
665/665 [==============================] - 3s 5ms/step - loss: 19.8437
- val_loss: 22.1985
Epoch 28/100
665/665 [==============================] - 3s 5ms/step - loss: 19.2553
- val_loss: 22.6874
Epoch 29/100
665/665 [==============================] - 3s 4ms/step - loss: 19.0324
- val_loss: 22.0259
```

```
Epoch 30/100
665/665 [==============================] - 3s 4ms/step - loss: 18.7258
- val_loss: 21.2454
Epoch 31/100
665/665 [==============================] - 3s 4ms/step - loss: 18.3745
- val_loss: 21.9786
Epoch 32/100
665/665 [==============================] - 4s 5ms/step - loss: 18.2498
- val_loss: 21.5858
Epoch 33/100
665/665 [==============================] - 3s 4ms/step - loss: 17.8746
- val_loss: 21.1577
Epoch 34/100
665/665 [==============================] - 3s 4ms/step - loss: 17.6125
- val_loss: 20.9921
Epoch 35/100
665/665 [==============================] - 3s 4ms/step - loss: 17.5363
- val_loss: 20.3365
Epoch 36/100
665/665 [==============================] - 4s 6ms/step - loss: 17.1450
- val_loss: 20.6446
Epoch 37/100
665/665 [==============================] - 3s 4ms/step - loss: 17.0816
- val_loss: 20.9683
Epoch 38/100
665/665 [==============================] - 3s 4ms/step - loss: 17.0113
- val_loss: 21.1685
Epoch 39/100
665/665 [==============================] - 3s 4ms/step - loss: 16.7872
- val_loss: 20.4842
Epoch 40/100
665/665 [==============================] - 3s 5ms/step - loss: 16.6262
- val_loss: 20.7027
208/208 [==============================] - 0s 2ms/step
Epoch 1/100
665/665 [==============================] - 5s 4ms/step - loss: 63.1456
- val_loss: 38.3750
Epoch 2/100
665/665 [==============================] - 3s 4ms/step - loss: 36.7430
- val_loss: 36.2818
Epoch 3/100
665/665 [==============================] - 3s 4ms/step - loss: 33.1652
- val_loss: 30.7300
Epoch 4/100
665/665 [==============================] - 3s 5ms/step - loss: 30.5174
- val_loss: 29.2702
Epoch 5/100
665/665 [==============================] - 3s 4ms/step - loss: 28.7829
- val_loss: 28.8059
```

```
Epoch 6/100
665/665 [==============================] - 3s 4ms/step - loss: 27.6723
- val_loss: 29.6910
Epoch 7/100
665/665 [==============================] - 3s 4ms/step - loss: 26.7219
- val_loss: 27.5844
Epoch 8/100
665/665 [==============================] - 3s 4ms/step - loss: 25.8304
- val_loss: 26.5382
Epoch 9/100
665/665 [==============================] - 4s 5ms/step - loss: 25.0771
- val_loss: 26.7549
Epoch 10/100
665/665 [==============================] - 3s 4ms/step - loss: 24.1199
- val_loss: 25.5608
Epoch 11/100
665/665 [==============================] - 3s 4ms/step - loss: 23.4765
- val_loss: 24.1065
Epoch 12/100
665/665 [==============================] - 3s 4ms/step - loss: 22.3750
- val_loss: 24.7601
Epoch 13/100
665/665 [==============================] - 3s 5ms/step - loss: 22.0156
- val_loss: 24.8898
Epoch 14/100
665/665 [==============================] - 3s 4ms/step - loss: 21.2931
- val_loss: 23.8151
Epoch 15/100
665/665 [==============================] - 3s 4ms/step - loss: 20.7342
- val_loss: 23.0588
Epoch 16/100
665/665 [==============================] - 3s 4ms/step - loss: 20.2658
- val_loss: 23.2332
Epoch 17/100
665/665 [==============================] - 3s 4ms/step - loss: 19.5816
- val_loss: 22.8922
Epoch 18/100
665/665 [==============================] - 3s 5ms/step - loss: 19.1283
- val_loss: 22.7058
Epoch 19/100
665/665 [==============================] - 3s 4ms/step - loss: 18.6509
- val_loss: 22.3644
Epoch 20/100
665/665 [==============================] - 3s 4ms/step - loss: 17.8842
- val_loss: 21.4086
Epoch 21/100
665/665 [==============================] - 3s 4ms/step - loss: 17.4169
- val_loss: 21.6639
Epoch 22/100
```

```
665/665 [==============================] - 4s 6ms/step - loss: 17.0763
- val_loss: 20.5095
Epoch 23/100
665/665 [==============================] - 3s 4ms/step - loss: 16.4705
- val_loss: 20.6918
Epoch 24/100
665/665 [==============================] - 3s 4ms/step - loss: 16.1957
- val_loss: 19.9848
Epoch 25/100
665/665 [==============================] - 3s 4ms/step - loss: 15.9990
- val_loss: 20.6211
Epoch 26/100
665/665 [==============================] - 3s 5ms/step - loss: 15.6031
- val_loss: 19.5909
Epoch 27/100
665/665 [==============================] - 3s 5ms/step - loss: 15.5341
- val_loss: 19.8413
Epoch 28/100
665/665 [==============================] - 3s 4ms/step - loss: 15.1072
- val_loss: 19.9920
Epoch 29/100
665/665 [==============================] - 3s 5ms/step - loss: 14.8404
- val_loss: 20.1814
Epoch 30/100
665/665 [==============================] - 4s 5ms/step - loss: 14.6471
- val_loss: 19.4449
Epoch 31/100
665/665 [==============================] - 3s 5ms/step - loss: 14.4738
- val_loss: 19.4639
Epoch 32/100
665/665 [==============================] - 3s 5ms/step - loss: 14.1434
- val_loss: 20.7106
Epoch 33/100
665/665 [==============================] - 3s 5ms/step - loss: 13.9808
- val_loss: 20.2163
Epoch 34/100
665/665 [==============================] - 4s 5ms/step - loss: 13.8392
- val_loss: 20.8827
Epoch 35/100
665/665 [==============================] - 3s 5ms/step - loss: 13.5757
- val_loss: 20.0523
208/208 [==============================] - 0s 2ms/step
Epoch 1/100
665/665 [==============================] - 5s 5ms/step - loss: 56.6159
- val_loss: 36.8629
Epoch 2/100
665/665 [==============================] - 3s 5ms/step - loss: 35.6933
- val_loss: 33.1177
Epoch 3/100
```

```
665/665 [==============================] - 3s 5ms/step - loss: 31.6806
- val_loss: 30.9469
Epoch 4/100
665/665 [==============================] - 3s 5ms/step - loss: 29.1052
- val_loss: 28.8351
Epoch 5/100
665/665 [==============================] - 3s 5ms/step - loss: 27.7013
- val_loss: 27.7117
Epoch 6/100
665/665 [==============================] - 4s 6ms/step - loss: 26.3791
- val_loss: 26.3708
Epoch 7/100
665/665 [==============================] - 4s 6ms/step - loss: 24.9871
- val_loss: 26.3075
Epoch 8/100
665/665 [==============================] - 3s 5ms/step - loss: 24.2271
- val_loss: 28.3987
Epoch 9/100
665/665 [==============================] - 3s 5ms/step - loss: 23.1459
- val_loss: 25.4600
Epoch 10/100
665/665 [==============================] - 4s 6ms/step - loss: 21.9545
- val_loss: 23.4467
Epoch 11/100
665/665 [==============================] - 3s 5ms/step - loss: 21.1846
- val_loss: 22.4409
Epoch 12/100
665/665 [==============================] - 3s 5ms/step - loss: 20.1785
- val_loss: 22.7749
Epoch 13/100
665/665 [==============================] - 3s 5ms/step - loss: 19.4589
- val_loss: 23.9704
Epoch 14/100
665/665 [==============================] - 4s 6ms/step - loss: 18.6601
- val_loss: 23.0249
Epoch 15/100
665/665 [==============================] - 3s 5ms/step - loss: 18.2067
- val_loss: 21.3012
Epoch 16/100
665/665 [==============================] - 3s 5ms/step - loss: 17.6025
- val_loss: 21.4725
Epoch 17/100
665/665 [==============================] - 3s 5ms/step - loss: 17.0782
- val_loss: 22.1797
Epoch 18/100
665/665 [==============================] - 4s 6ms/step - loss: 16.6838
- val_loss: 21.7481
Epoch 19/100
665/665 [==============================] - 3s 5ms/step - loss: 16.4219
```

```
- val_loss: 22.0182
Epoch 20/100
665/665 [==============================] - 3s 5ms/step - loss: 16.0122
- val_loss: 21.3447
208/208 [==============================] - 0s 2ms/step
Epoch 1/100
665/665 [==============================] - 7s 5ms/step - loss: 74.2898
- val_loss: 40.6217
Epoch 2/100
665/665 [==============================] - 4s 5ms/step - loss: 37.9251
- val_loss: 37.8762
Epoch 3/100
665/665 [==============================] - 3s 5ms/step - loss: 34.4407
- val_loss: 33.1338
Epoch 4/100
665/665 [==============================] - 5s 7ms/step - loss: 31.5441
- val_loss: 31.1608
Epoch 5/100
665/665 [==============================] - 3s 5ms/step - loss: 29.5297
- val_loss: 29.3950
Epoch 6/100
665/665 [==============================] - 3s 5ms/step - loss: 28.1706
- val_loss: 30.3489
Epoch 7/100
665/665 [==============================] - 5s 7ms/step - loss: 27.0175
- val_loss: 28.0481
Epoch 8/100
665/665 [==============================] - 4s 6ms/step - loss: 26.3014
- val_loss: 26.9019
Epoch 9/100
665/665 [==============================] - 4s 5ms/step - loss: 25.6482
- val_loss: 26.4557
Epoch 10/100
665/665 [==============================] - 4s 5ms/step - loss: 24.7685
- val_loss: 25.4877
Epoch 11/100
665/665 [==============================] - 5s 7ms/step - loss: 23.8286
- val_loss: 26.3902
Epoch 12/100
665/665 [==============================] - 3s 5ms/step - loss: 23.2593
- val_loss: 25.0146
Epoch 13/100
665/665 [==============================] - 3s 5ms/step - loss: 22.5743
- val_loss: 23.6888
Epoch 14/100
665/665 [==============================] - 4s 6ms/step - loss: 22.0090
- val_loss: 23.7054
Epoch 15/100
665/665 [==============================] - 4s 6ms/step - loss: 21.5449
```

```
- val_loss: 23.1112
Epoch 16/100
665/665 [==============================] - 4s 5ms/step - loss: 20.6917
- val_loss: 22.8530
Epoch 17/100
665/665 [==============================] - 4s 5ms/step - loss: 20.3351
- val_loss: 23.1975
Epoch 18/100
665/665 [==============================] - 4s 6ms/step - loss: 19.9192
- val_loss: 21.7101
Epoch 19/100
665/665 [==============================] - 4s 5ms/step - loss: 19.4499
- val_loss: 21.4188
Epoch 20/100
665/665 [==============================] - 4s 5ms/step - loss: 18.9809
- val_loss: 22.0666
Epoch 21/100
665/665 [==============================] - 4s 6ms/step - loss: 18.5213
- val_loss: 21.1112
Epoch 22/100
665/665 [==============================] - 4s 6ms/step - loss: 18.2298
- val_loss: 20.8083
Epoch 23/100
665/665 [==============================] - 3s 5ms/step - loss: 17.7917
- val_loss: 21.2656
Epoch 24/100
665/665 [==============================] - 3s 5ms/step - loss: 17.3526
- val_loss: 21.4195
Epoch 25/100
665/665 [==============================] - 4s 6ms/step - loss: 17.3118
- val_loss: 22.3082
Epoch 26/100
665/665 [==============================] - 4s 5ms/step - loss: 17.0023
- val_loss: 20.5961
Epoch 27/100
665/665 [==============================] - 4s 5ms/step - loss: 16.6997
- val_loss: 22.3830
Epoch 28/100
665/665 [==============================] - 4s 6ms/step - loss: 16.6355
- val_loss: 23.0942
Epoch 29/100
665/665 [==============================] - 4s 6ms/step - loss: 16.4469
- val_loss: 19.7785
Epoch 30/100
665/665 [==============================] - 4s 5ms/step - loss: 16.1892
- val_loss: 21.4052
Epoch 31/100
665/665 [==============================] - 3s 5ms/step - loss: 16.0085
- val_loss: 21.1635
```

```
Epoch 32/100
665/665 [==============================] - 5s 7ms/step - loss: 15.9003
- val_loss: 19.9957
Epoch 33/100
665/665 [==============================] - 3s 5ms/step - loss: 15.5749
- val_loss: 20.0117
Epoch 34/100
665/665 [==============================] - 4s 5ms/step - loss: 15.4347
- val_loss: 19.8284
208/208 [==============================] - 0s 2ms/step
Epoch 1/100
665/665 [==============================] - 7s 6ms/step - loss: 63.4884
- val_loss: 38.3839
Epoch 2/100
665/665 [==============================] - 3s 5ms/step - loss: 36.5405
- val_loss: 33.7090
Epoch 3/100
665/665 [==============================] - 4s 5ms/step - loss: 32.2333
- val_loss: 32.9759
Epoch 4/100
665/665 [==============================] - 4s 6ms/step - loss: 29.8048
- val_loss: 29.3569
Epoch 5/100
665/665 [==============================] - 3s 5ms/step - loss: 28.2982
- val_loss: 28.6773
Epoch 6/100
665/665 [==============================] - 3s 5ms/step - loss: 27.3229
- val_loss: 27.6463
Epoch 7/100
665/665 [==============================] - 4s 5ms/step - loss: 26.1764
- val_loss: 26.5680
Epoch 8/100
665/665 [==============================] - 4s 6ms/step - loss: 25.1764
- val_loss: 27.8824
Epoch 9/100
665/665 [==============================] - 3s 5ms/step - loss: 24.2970
- val_loss: 25.5871
Epoch 10/100
665/665 [==============================] - 3s 5ms/step - loss: 23.4736
- val_loss: 24.9010
Epoch 11/100
665/665 [==============================] - 4s 6ms/step - loss: 22.2596
- val_loss: 25.7570
Epoch 12/100
665/665 [==============================] - 3s 5ms/step - loss: 21.2201
- val_loss: 24.0107
Epoch 13/100
665/665 [==============================] - 3s 5ms/step - loss: 20.2263
- val_loss: 23.1099
```

```
Epoch 14/100
665/665 [==============================] - 3s 5ms/step - loss: 19.5580
- val_loss: 23.4661
Epoch 15/100
665/665 [==============================] - 4s 7ms/step - loss: 19.2076
- val_loss: 22.6788
Epoch 16/100
665/665 [==============================] - 3s 5ms/step - loss: 18.3950
- val_loss: 22.1134
Epoch 17/100
665/665 [==============================] - 4s 6ms/step - loss: 17.9105
- val_loss: 21.7502
Epoch 18/100
665/665 [==============================] - 4s 6ms/step - loss: 17.4941
- val_loss: 21.8384
Epoch 19/100
665/665 [==============================] - 4s 6ms/step - loss: 17.1556
- val_loss: 21.2169
Epoch 20/100
665/665 [==============================] - 3s 5ms/step - loss: 16.8579
- val_loss: 22.1217
Epoch 21/100
665/665 [==============================] - 4s 5ms/step - loss: 16.4651
- val_loss: 21.6477
Epoch 22/100
665/665 [==============================] - 5s 7ms/step - loss: 16.0050
- val_loss: 21.5038
Epoch 23/100
665/665 [==============================] - 3s 5ms/step - loss: 15.7109
- val_loss: 21.6278
Epoch 24/100
665/665 [==============================] - 3s 5ms/step - loss: 15.3609
- val_loss: 21.5515
208/208 [==============================] - 0s 2ms/step
Epoch 1/100
665/665 [==============================] - 5s 5ms/step - loss: 54.0628
- val_loss: 36.5776
Epoch 2/100
665/665 [==============================] - 4s 7ms/step - loss: 34.6253
- val_loss: 32.3764
Epoch 3/100
665/665 [==============================] - 4s 6ms/step - loss: 31.4861
- val_loss: 29.6933
Epoch 4/100
665/665 [==============================] - 3s 5ms/step - loss: 28.9166
- val_loss: 30.9299
Epoch 5/100
665/665 [==============================] - 4s 5ms/step - loss: 27.9967
- val_loss: 27.4436
```

```
Epoch 6/100
665/665 [==============================] - 4s 6ms/step - loss: 26.3207
- val_loss: 32.9797
Epoch 7/100
665/665 [==============================] - 3s 5ms/step - loss: 25.1610
- val_loss: 29.4554
Epoch 8/100
665/665 [==============================] - 4s 6ms/step - loss: 23.8320
- val_loss: 23.8643
Epoch 9/100
665/665 [==============================] - 5s 8ms/step - loss: 22.3567
- val_loss: 23.6060
Epoch 10/100
665/665 [==============================] - 3s 5ms/step - loss: 20.8072
- val_loss: 21.8930
Epoch 11/100
665/665 [==============================] - 3s 5ms/step - loss: 19.8783
- val_loss: 21.9629
Epoch 12/100
665/665 [==============================] - 4s 6ms/step - loss: 18.7994
- val_loss: 21.3377
Epoch 13/100
665/665 [==============================] - 4s 6ms/step - loss: 18.0952
- val_loss: 20.7792
Epoch 14/100
665/665 [==============================] - 4s 6ms/step - loss: 17.8656
- val_loss: 23.3941
Epoch 15/100
665/665 [==============================] - 3s 5ms/step - loss: 17.1692
- val_loss: 20.3295
Epoch 16/100
665/665 [==============================] - 4s 7ms/step - loss: 16.6199
- val_loss: 20.3900
Epoch 17/100
665/665 [==============================] - 4s 5ms/step - loss: 16.2927
- val_loss: 21.7870
Epoch 18/100
665/665 [==============================] - 3s 5ms/step - loss: 15.6386
- val_loss: 21.0915
Epoch 19/100
665/665 [==============================] - 4s 6ms/step - loss: 15.2587
- val_loss: 20.5279
Epoch 20/100
665/665 [==============================] - 4s 6ms/step - loss: 14.9600
- val_loss: 20.4396
208/208 [==============================] - 0s 2ms/step
Epoch 1/100
665/665 [==============================] - 6s 6ms/step - loss: 74.7669
- val_loss: 39.7984
```

```
Epoch 2/100
665/665 [==============================] - 5s 7ms/step - loss: 37.6588
- val_loss: 35.5886
Epoch 3/100
665/665 [==============================] - 4s 6ms/step - loss: 34.6076
- val_loss: 33.6021
Epoch 4/100
665/665 [==============================] - 4s 6ms/step - loss: 31.6558
- val_loss: 31.1712
Epoch 5/100
665/665 [==============================] - 4s 7ms/step - loss: 29.5862
- val_loss: 29.7045
Epoch 6/100
665/665 [==============================] - 4s 6ms/step - loss: 28.2759
- val_loss: 28.8516
Epoch 7/100
665/665 [==============================] - 4s 6ms/step - loss: 27.1169
- val_loss: 27.8087
Epoch 8/100
665/665 [==============================] - 4s 6ms/step - loss: 26.1721
- val_loss: 26.8605
Epoch 9/100
665/665 [==============================] - 4s 7ms/step - loss: 25.3368
- val_loss: 27.2919
Epoch 10/100
665/665 [==============================] - 4s 6ms/step - loss: 24.3215
- val_loss: 27.8383
Epoch 11/100
665/665 [==============================] - 3s 5ms/step - loss: 22.9697
- val_loss: 24.1029
Epoch 12/100
665/665 [==============================] - 4s 7ms/step - loss: 21.7193
- val_loss: 24.2178
Epoch 13/100
665/665 [==============================] - 4s 6ms/step - loss: 20.5001
- val_loss: 23.8817
Epoch 14/100
665/665 [==============================] - 4s 6ms/step - loss: 19.8988
- val_loss: 22.2707
Epoch 15/100
665/665 [==============================] - 4s 6ms/step - loss: 19.1725
- val_loss: 21.6928
Epoch 16/100
665/665 [==============================] - 4s 6ms/step - loss: 18.6889
- val_loss: 20.7288
Epoch 17/100
665/665 [==============================] - 4s 5ms/step - loss: 18.3686
- val_loss: 20.8306
Epoch 18/100
```

```
665/665 [==============================] - 4s 6ms/step - loss: 17.7494
- val_loss: 20.6180
Epoch 19/100
665/665 [==============================] - 5s 7ms/step - loss: 17.5118
- val_loss: 20.4157
Epoch 20/100
665/665 [==============================] - 4s 5ms/step - loss: 17.1310
- val_loss: 20.0922
Epoch 21/100
665/665 [==============================] - 4s 5ms/step - loss: 16.8428
- val_loss: 21.0227
Epoch 22/100
665/665 [==============================] - 5s 7ms/step - loss: 16.5773
- val_loss: 20.0044
Epoch 23/100
665/665 [==============================] - 4s 6ms/step - loss: 16.2673
- val_loss: 20.2580
Epoch 24/100
665/665 [==============================] - 3s 5ms/step - loss: 16.0888
- val_loss: 19.9077
Epoch 25/100
665/665 [==============================] - 4s 6ms/step - loss: 15.8825
- val_loss: 19.4495
Epoch 26/100
665/665 [==============================] - 4s 6ms/step - loss: 15.7167
- val_loss: 20.7919
Epoch 27/100
665/665 [==============================] - 4s 5ms/step - loss: 15.9072
- val_loss: 20.9614
Epoch 28/100
665/665 [==============================] - 4s 5ms/step - loss: 15.4550
- val_loss: 20.3758
Epoch 29/100
665/665 [==============================] - 5s 7ms/step - loss: 15.2622
- val_loss: 19.2857
Epoch 30/100
665/665 [==============================] - 4s 6ms/step - loss: 15.1170
- val_loss: 20.4025
Epoch 31/100
665/665 [==============================] - 3s 5ms/step - loss: 15.0027
- val_loss: 19.5189
Epoch 32/100
665/665 [==============================] - 4s 7ms/step - loss: 14.7546
- val_loss: 19.5162
Epoch 33/100
665/665 [==============================] - 4s 6ms/step - loss: 14.6760
- val_loss: 19.5325
Epoch 34/100
665/665 [==============================] - 4s 5ms/step - loss: 14.5240
- val_loss: 19.6869
```

```
208/208 [==============================] - 0s 2ms/step
Epoch 1/100
665/665 [==============================] - 7s 7ms/step - loss: 57.8843
- val_loss: 37.8447
Epoch 2/100
665/665 [==============================] - 4s 6ms/step - loss: 36.1694
- val_loss: 35.7278
Epoch 3/100
665/665 [==============================] - 4s 6ms/step - loss: 32.3422
- val_loss: 32.6620
Epoch 4/100
665/665 [==============================] - 5s 7ms/step - loss: 30.1933
- val_loss: 29.9475
Epoch 5/100
665/665 [==============================] - 4s 5ms/step - loss: 29.0379
- val_loss: 28.2812
Epoch 6/100
665/665 [==============================] - 4s 5ms/step - loss: 27.1066
- val_loss: 31.8935
Epoch 7/100
665/665 [==============================] - 4s 7ms/step - loss: 26.1275
- val_loss: 27.3044
Epoch 8/100
665/665 [==============================] - 4s 6ms/step - loss: 24.9139
- val_loss: 25.1457
Epoch 9/100
665/665 [==============================] - 4s 6ms/step - loss: 22.9617
- val_loss: 24.4031
Epoch 10/100
665/665 [==============================] - 4s 6ms/step - loss: 21.7321
- val_loss: 24.1233
Epoch 11/100
665/665 [==============================] - 4s 6ms/step - loss: 20.5393
- val_loss: 22.4376
Epoch 12/100
665/665 [==============================] - 4s 5ms/step - loss: 19.4776
- val_loss: 22.6416
Epoch 13/100
665/665 [==============================] - 4s 5ms/step - loss: 18.8759
- val_loss: 21.9189
Epoch 14/100
665/665 [==============================] - 5s 7ms/step - loss: 18.2747
- val_loss: 21.2239
Epoch 15/100
665/665 [==============================] - 4s 6ms/step - loss: 17.8291
- val_loss: 20.5724
Epoch 16/100
665/665 [==============================] - 4s 5ms/step - loss: 17.3040
- val_loss: 20.6002
```

```
Epoch 17/100
665/665 [==============================] - 4s 7ms/step - loss: 16.8316
- val_loss: 22.3983
Epoch 18/100
665/665 [==============================] - 4s 5ms/step - loss: 16.4364
- val_loss: 20.9507
Epoch 19/100
665/665 [==============================] - 4s 5ms/step - loss: 16.3237
- val_loss: 20.4480
Epoch 20/100
665/665 [==============================] - 4s 6ms/step - loss: 15.6678
- val_loss: 20.5070
Epoch 21/100
665/665 [==============================] - 4s 6ms/step - loss: 15.4204
- val_loss: 20.3503
Epoch 22/100
665/665 [==============================] - 4s 5ms/step - loss: 14.8043
- val_loss: 20.9842
Epoch 23/100
665/665 [==============================] - 4s 5ms/step - loss: 14.6962
- val_loss: 21.2597
Epoch 24/100
665/665 [==============================] - 5s 7ms/step - loss: 14.2347
- val_loss: 20.4194
Epoch 25/100
665/665 [==============================] - 5s 7ms/step - loss: 14.1201
- val_loss: 20.6923
Epoch 26/100
665/665 [==============================] - 4s 6ms/step - loss: 13.6230
- val_loss: 22.0961
208/208 [==============================] - 1s 3ms/step
Epoch 1/100
665/665 [==============================] - 6s 6ms/step - loss: 53.4140
- val_loss: 37.1066
Epoch 2/100
665/665 [==============================] - 4s 6ms/step - loss: 35.8396
- val_loss: 33.1133
Epoch 3/100
665/665 [==============================] - 5s 7ms/step - loss: 31.4789
- val_loss: 32.0664
Epoch 4/100
665/665 [==============================] - 4s 6ms/step - loss: 29.3718
- val_loss: 30.3434
Epoch 5/100
665/665 [==============================] - 4s 6ms/step - loss: 27.6923
- val_loss: 27.9937
Epoch 6/100
665/665 [==============================] - 4s 6ms/step - loss: 25.7161
- val_loss: 26.3593
```

```
Epoch 7/100
665/665 [==============================] - 4s 6ms/step - loss: 25.0247
- val_loss: 25.3818
Epoch 8/100
665/665 [==============================] - 4s 6ms/step - loss: 23.0225
- val_loss: 25.2163
Epoch 9/100
665/665 [==============================] - 4s 6ms/step - loss: 22.2282
- val_loss: 26.4445
Epoch 10/100
665/665 [==============================] - 4s 7ms/step - loss: 20.7743
- val_loss: 22.7178
Epoch 11/100
665/665 [==============================] - 4s 6ms/step - loss: 19.9674
- val_loss: 22.0022
Epoch 12/100
665/665 [==============================] - 4s 5ms/step - loss: 18.7485
- val_loss: 22.4122
Epoch 13/100
665/665 [==============================] - 5s 7ms/step - loss: 17.9538
- val_loss: 22.0473
Epoch 14/100
665/665 [==============================] - 4s 6ms/step - loss: 17.4254
- val_loss: 21.4976
Epoch 15/100
665/665 [==============================] - 4s 5ms/step - loss: 17.0299
- val_loss: 20.9800
Epoch 16/100
665/665 [==============================] - 4s 6ms/step - loss: 16.0984
- val_loss: 21.4041
Epoch 17/100
665/665 [==============================] - 4s 6ms/step - loss: 15.7068
- val_loss: 22.3729
Epoch 18/100
665/665 [==============================] - 4s 5ms/step - loss: 15.3472
- val_loss: 22.2113
Epoch 19/100
665/665 [==============================] - 4s 5ms/step - loss: 14.7989
- val_loss: 20.4504
Epoch 20/100
665/665 [==============================] - 5s 7ms/step - loss: 14.1836
- val_loss: 20.8853
Epoch 21/100
665/665 [==============================] - 4s 6ms/step - loss: 13.9390
- val_loss: 21.7824
Epoch 22/100
665/665 [==============================] - 4s 5ms/step - loss: 13.5609
- val_loss: 22.1265
Epoch 23/100
```

```
665/665 [==============================] - 4s 7ms/step - loss: 13.1124
- val_loss: 21.8003
Epoch 24/100
665/665 [==============================] - 4s 6ms/step - loss: 12.6501
- val_loss: 24.5595
208/208 [==============================] - 0s 2ms/step
Epoch 1/100
665/665 [==============================] - 7s 6ms/step - loss: 78.2256
- val_loss: 40.7397
Epoch 2/100
665/665 [==============================] - 5s 7ms/step - loss: 38.3967
- val_loss: 37.1917
Epoch 3/100
665/665 [==============================] - 4s 6ms/step - loss: 35.4497
- val_loss: 35.9864
Epoch 4/100
665/665 [==============================] - 4s 6ms/step - loss: 32.3954
- val_loss: 31.5781
Epoch 5/100
665/665 [==============================] - 4s 7ms/step - loss: 30.0134
- val_loss: 29.0798
Epoch 6/100
665/665 [==============================] - 4s 6ms/step - loss: 28.4867
- val_loss: 27.9748
Epoch 7/100
665/665 [==============================] - 4s 6ms/step - loss: 27.4291
- val_loss: 28.8244
Epoch 8/100
665/665 [==============================] - 4s 6ms/step - loss: 26.5417
- val_loss: 28.8746
Epoch 9/100
665/665 [==============================] - 4s 7ms/step - loss: 25.3806
- val_loss: 26.1570
Epoch 10/100
665/665 [==============================] - 4s 6ms/step - loss: 24.7833
- val_loss: 26.1113
Epoch 11/100
665/665 [==============================] - 4s 6ms/step - loss: 23.9796
- val_loss: 25.9328
Epoch 12/100
665/665 [==============================] - 5s 7ms/step - loss: 22.9700
- val_loss: 26.4315
Epoch 13/100
665/665 [==============================] - 4s 6ms/step - loss: 22.1009
- val_loss: 23.1067
Epoch 14/100
665/665 [==============================] - 4s 6ms/step - loss: 21.1827
- val_loss: 22.3524
Epoch 15/100
```

```
665/665 [==============================] - 5s 7ms/step - loss: 20.3462
- val_loss: 23.3419
Epoch 16/100
665/665 [==============================] - 4s 6ms/step - loss: 19.5392
- val_loss: 21.1650
Epoch 17/100
665/665 [==============================] - 4s 6ms/step - loss: 19.0940
- val_loss: 21.8201
Epoch 18/100
665/665 [==============================] - 5s 7ms/step - loss: 18.5903
- val_loss: 21.0318
Epoch 19/100
665/665 [==============================] - 4s 6ms/step - loss: 18.0988
- val_loss: 20.6840
Epoch 20/100
665/665 [==============================] - 4s 6ms/step - loss: 17.8677
- val_loss: 20.2380
Epoch 21/100
665/665 [==============================] - 5s 7ms/step - loss: 17.4143
- val_loss: 20.5821
Epoch 22/100
665/665 [==============================] - 5s 8ms/step - loss: 17.2420
- val_loss: 20.9622
Epoch 23/100
665/665 [==============================] - 4s 6ms/step - loss: 16.9740
- val_loss: 20.2738
Epoch 24/100
665/665 [==============================] - 4s 6ms/step - loss: 16.7001
- val_loss: 20.4397
Epoch 25/100
665/665 [==============================] - 5s 7ms/step - loss: 16.3444
- val_loss: 19.7303
Epoch 26/100
665/665 [==============================] - 4s 6ms/step - loss: 16.2939
- val_loss: 20.5329
Epoch 27/100
665/665 [==============================] - 4s 6ms/step - loss: 16.1570
- val_loss: 19.7211
Epoch 28/100
665/665 [==============================] - 5s 7ms/step - loss: 15.8504
- val_loss: 20.6641
Epoch 29/100
665/665 [==============================] - 4s 6ms/step - loss: 15.6571
- val_loss: 19.8038
Epoch 30/100
665/665 [==============================] - 4s 6ms/step - loss: 15.6286
- val_loss: 19.7317
Epoch 31/100
665/665 [==============================] - 5s 7ms/step - loss: 15.2671
```

```
- val_loss: 19.3083
Epoch 32/100
665/665 [==============================] - 4s 6ms/step - loss: 15.0968
- val_loss: 19.5896
Epoch 33/100
665/665 [==============================] - 4s 6ms/step - loss: 15.0664
- val_loss: 20.0840
Epoch 34/100
665/665 [==============================] - 4s 7ms/step - loss: 14.9548
- val_loss: 19.4599
Epoch 35/100
665/665 [==============================] - 4s 6ms/step - loss: 14.8552
- val_loss: 20.2042
Epoch 36/100
665/665 [==============================] - 4s 6ms/step - loss: 14.6831
- val_loss: 19.9431
208/208 [==============================] - 1s 3ms/step
Epoch 1/100
665/665 [==============================] - 7s 6ms/step - loss: 59.8637
- val_loss: 37.9760
Epoch 2/100
665/665 [==============================] - 4s 6ms/step - loss: 35.2631
- val_loss: 33.3533
Epoch 3/100
665/665 [==============================] - 5s 7ms/step - loss: 31.1166
- val_loss: 33.4668
Epoch 4/100
665/665 [==============================] - 4s 6ms/step - loss: 29.4972
- val_loss: 28.9017
Epoch 5/100
665/665 [==============================] - 4s 6ms/step - loss: 27.7082
- val_loss: 28.1794
Epoch 6/100
665/665 [==============================] - 5s 7ms/step - loss: 26.8117
- val_loss: 28.8912
Epoch 7/100
665/665 [==============================] - 4s 6ms/step - loss: 26.2095
- val_loss: 27.5275
Epoch 8/100
665/665 [==============================] - 4s 6ms/step - loss: 24.9594
- val_loss: 28.1366
Epoch 9/100
665/665 [==============================] - 5s 7ms/step - loss: 24.0890
- val_loss: 28.6452
Epoch 10/100
665/665 [==============================] - 4s 6ms/step - loss: 22.8268
- val_loss: 25.2426
Epoch 11/100
665/665 [==============================] - 4s 6ms/step - loss: 21.4735
```

```
- val_loss: 23.9456
Epoch 12/100
665/665 [==============================] - 4s 7ms/step - loss: 20.4084
- val_loss: 23.3146
Epoch 13/100
665/665 [==============================] - 4s 6ms/step - loss: 19.4287
- val_loss: 23.6348
Epoch 14/100
665/665 [==============================] - 4s 6ms/step - loss: 18.6325
- val_loss: 22.7063
Epoch 15/100
665/665 [==============================] - 4s 6ms/step - loss: 17.9674
- val_loss: 23.7308
Epoch 16/100
665/665 [==============================] - 5s 7ms/step - loss: 17.6338
- val_loss: 21.6936
Epoch 17/100
665/665 [==============================] - 4s 6ms/step - loss: 17.0244
- val_loss: 26.5659
Epoch 18/100
665/665 [==============================] - 4s 6ms/step - loss: 16.5677
- val_loss: 21.9485
Epoch 19/100
665/665 [==============================] - 5s 7ms/step - loss: 16.0412
- val_loss: 21.7374
Epoch 20/100
665/665 [==============================] - 4s 6ms/step - loss: 15.4979
- val_loss: 22.7557
Epoch 21/100
665/665 [==============================] - 4s 6ms/step - loss: 15.0746
- val_loss: 21.9610
208/208 [==============================] - 1s 2ms/step
Epoch 1/100
665/665 [==============================] - 8s 6ms/step - loss: 52.7185
- val_loss: 41.3698
Epoch 2/100
665/665 [==============================] - 4s 6ms/step - loss: 35.0449
- val_loss: 34.2163
Epoch 3/100
665/665 [==============================] - 5s 7ms/step - loss: 31.2302
- val_loss: 42.9844
Epoch 4/100
665/665 [==============================] - 4s 6ms/step - loss: 29.3864
- val_loss: 31.0551
Epoch 5/100
665/665 [==============================] - 4s 6ms/step - loss: 27.1534
- val_loss: 26.6610
Epoch 6/100
665/665 [==============================] - 5s 7ms/step - loss: 25.8731
```

```
- val_loss: 25.6708
Epoch 7/100
665/665 [==============================] - 4s 7ms/step - loss: 23.6047
- val_loss: 23.6516
Epoch 8/100
665/665 [==============================] - 4s 6ms/step - loss: 21.2713
- val_loss: 22.2452
Epoch 9/100
665/665 [==============================] - 4s 7ms/step - loss: 19.1986
- val_loss: 20.9387
Epoch 10/100
665/665 [==============================] - 4s 7ms/step - loss: 18.8047
- val_loss: 21.1101
Epoch 11/100
665/665 [==============================] - 4s 6ms/step - loss: 17.5272
- val_loss: 19.8323
Epoch 12/100
665/665 [==============================] - 4s 6ms/step - loss: 16.8902
- val_loss: 20.8933
Epoch 13/100
665/665 [==============================] - 6s 8ms/step - loss: 16.1007
- val_loss: 20.6526
Epoch 14/100
665/665 [==============================] - 4s 6ms/step - loss: 15.7951
- val_loss: 20.3841
Epoch 15/100
665/665 [==============================] - 4s 6ms/step - loss: 15.4012
- val_loss: 19.7802
Epoch 16/100
665/665 [==============================] - 5s 8ms/step - loss: 14.8743
- val_loss: 19.7438
Epoch 17/100
665/665 [==============================] - 4s 6ms/step - loss: 14.5214
- val_loss: 19.7682
Epoch 18/100
665/665 [==============================] - 4s 6ms/step - loss: 14.0824
- val_loss: 19.9567
Epoch 19/100
665/665 [==============================] - 5s 7ms/step - loss: 13.5865
- val_loss: 20.9218
Epoch 20/100
665/665 [==============================] - 4s 6ms/step - loss: 13.3137
- val_loss: 19.3768
Epoch 21/100
665/665 [==============================] - 4s 6ms/step - loss: 12.7447
- val_loss: 19.9478
Epoch 22/100
665/665 [==============================] - 5s 7ms/step - loss: 12.2189
- val_loss: 20.2672
```

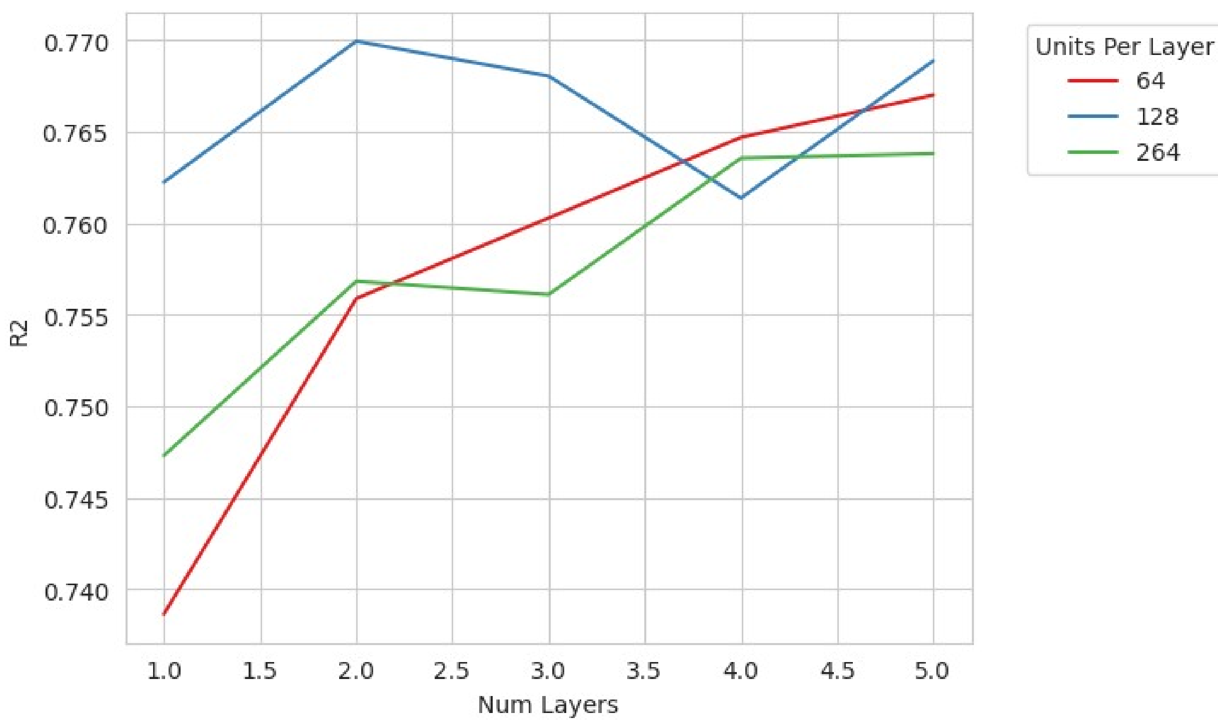
```
Epoch 23/100
665/665 [==============================] - 4s 6ms/step - loss: 11.8647
- val_loss: 20.8215
Epoch 24/100
665/665 [==============================] - 4s 6ms/step - loss: 11.4476
- val_loss: 20.7234
Epoch 25/100
665/665 [==============================] - 5s 7ms/step - loss: 11.0827
- val_loss: 20.5728
208/208 [==============================] - 1s 3ms/step
```

```
ANN_results_df
```

```
    Unnamed: 0  Num Layers  Units Per Layer        MSE      RMSE
MAE  \
0            0           1                64  23.596571  4.857630
3.805371
1            1           1               128  21.466089  4.633151
3.652819
2            2           1               264  22.814865  4.776491
3.756048
3            3           2                64  22.040040  4.694682
3.679674
4            4           2               128  20.770378  4.557453
3.578196
5            5           2               264  21.955023  4.685619
3.682180
6            6           3                64  21.642823  4.652185
3.642992
7            7           3               128  20.942181  4.576263
3.591862
8            8           3               264  22.020138  4.692562
3.650261
9            9           4                64  21.245016  4.609232
3.610318
10          10           4               128  21.544229  4.641576
3.656985
11          11           4               264  21.347487  4.620334
3.622161
12          12           5                64  21.036361  4.586541
3.597410
13          13           5               128  20.867716  4.568120
3.571487
14          14           5               264  21.325292  4.617932
3.592101

          R2
0   0.738637
1   0.762235
2   0.747295
```

```
3   0.755877
4   0.769941
5   0.756819
6   0.760277
7   0.768038
8   0.756098
9   0.764683
10  0.761369
11  0.763548
12  0.766995
13  0.768862
14  0.763794
```

```
color_palette = sns.color_palette("Set1",
n_colors=len(ANN_results_df['Units Per Layer'].unique()))
sns.set_style("whitegrid")
sns.lineplot(y=ANN_results_df['R2'], hue=ANN_results_df['Units Per
Layer'], x=ANN_results_df['Num Layers'], palette=color_palette)
plt.legend(title='Units Per Layer', bbox_to_anchor=(1.05, 1),
loc='upper left')
plt.show()
```



Linear Regression, Lasso Regression, Ridge Regression, Decision Tree Regression, Random Forest Regression, Support Vector Regression Linear, Support Vector Regression RBF, XGBoost Regression, AdaBoost Regression.

```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression, Lasso, Ridge
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor, AdaBoostRegressor
from sklearn.svm import SVR
import xgboost as xgb
from sklearn.metrics import mean_squared_error, mean_absolute_error,
r2_score
import matplotlib.pyplot as plt

y_val = pd.Series(y_val)

# Evaluate the performance of each model
models = {
    'Linear Regression': Linear_Regression(),
    'Lasso Regression': Lasso(alpha=0.01),
    'Ridge Regression': Ridge_Regression(alpha=1.0),
    'Decision Tree Regression': Decision_Tree_Regressor(),
    'Random Forest Regression':
RandomForestRegressor(n_estimators=100, random_state=42),
    'Support Vector Regression Linear': SVR(kernel='linear'),
    'Support Vector Regression RBF': SVR(kernel='rbf'),
    'XGBoost Regression': xgb.XGBRegressor(n_estimators=100,
learning_rate=0.1, random_state=42),
    'AdaBoost Regression': AdaBoostRegressor()
}

metrics = {}
results = []

for model_name, model in models.items():
    model.fit(X_train, y_train)
    y_pred = model.predict(X_val)
    mse = mean_squared_error(y_val, y_pred)
    rmse = np.sqrt(mse)
    mae = mean_absolute_error(y_val, y_pred)
    r2 = r2_score(y_val, y_pred)

    metrics[model_name] = {
        'Mean Squared Error (MSE)': mse,
        'Root Mean Squared Error (RMSE)': rmse,
        'Mean Absolute Error (MAE)': mae,
        'R-squared (R2)': r2
    }
```

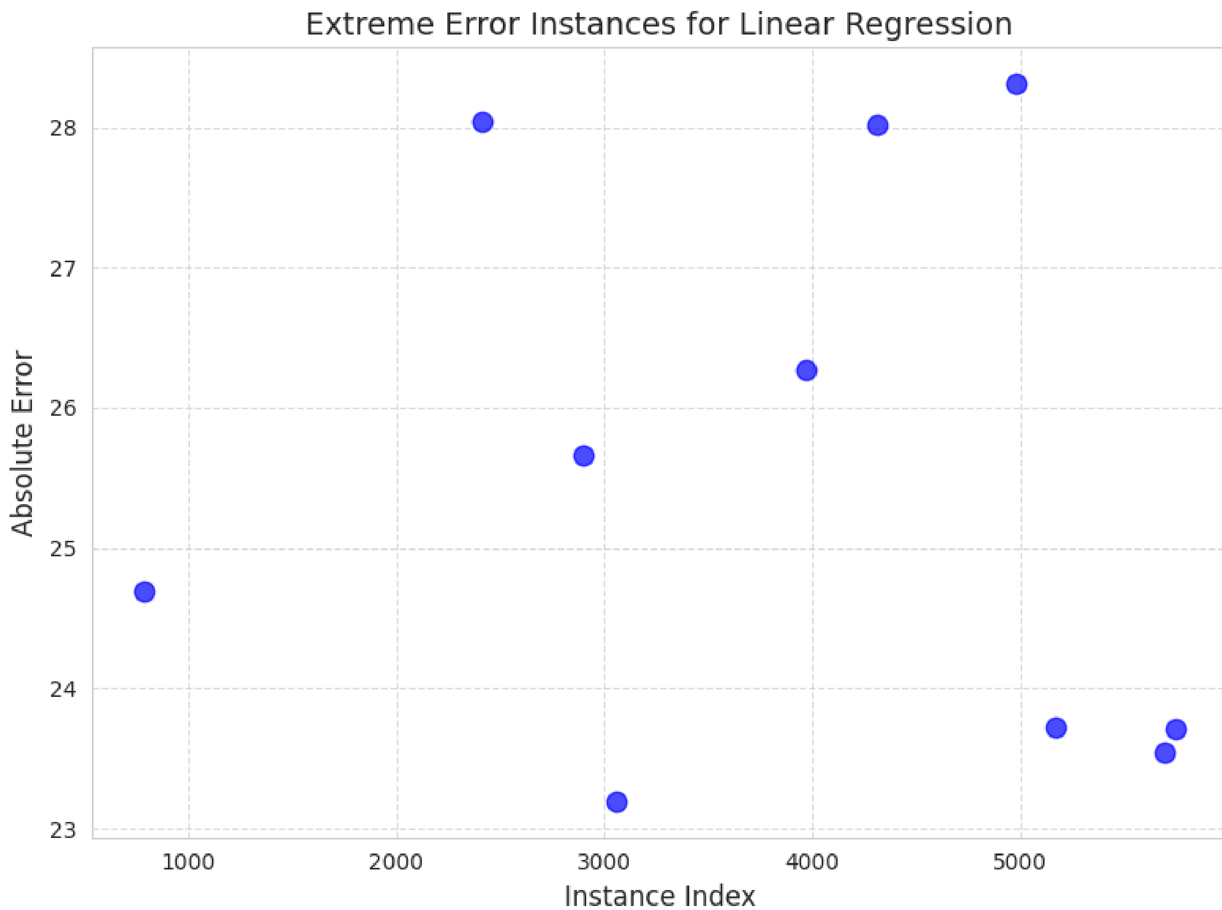
```
    # Find indices of instances with highest MSE (extreme errors)
    extreme_error_indices = np.argsort(-np.abs(y_pred - y_val))[:10]

    extreme_error_data = []
    for idx in extreme_error_indices:
        extreme_error_data.append({
            'Instance Index': idx,
            'True Value': y_val.iloc[idx],
            'Predicted Value': y_pred[idx],
            'Absolute Error': np.abs(y_pred[idx] - y_val.iloc[idx])
        })

    results.append({
        'Model Name': model_name,
        # 'Hyperparameters': model.get_params(),
        'Extreme Error Instances': extreme_error_data
    })

# Display the performance metrics for each model
metrics_df_1 = pd.DataFrame.from_dict(metrics, orient='index')
metrics_df_1
```

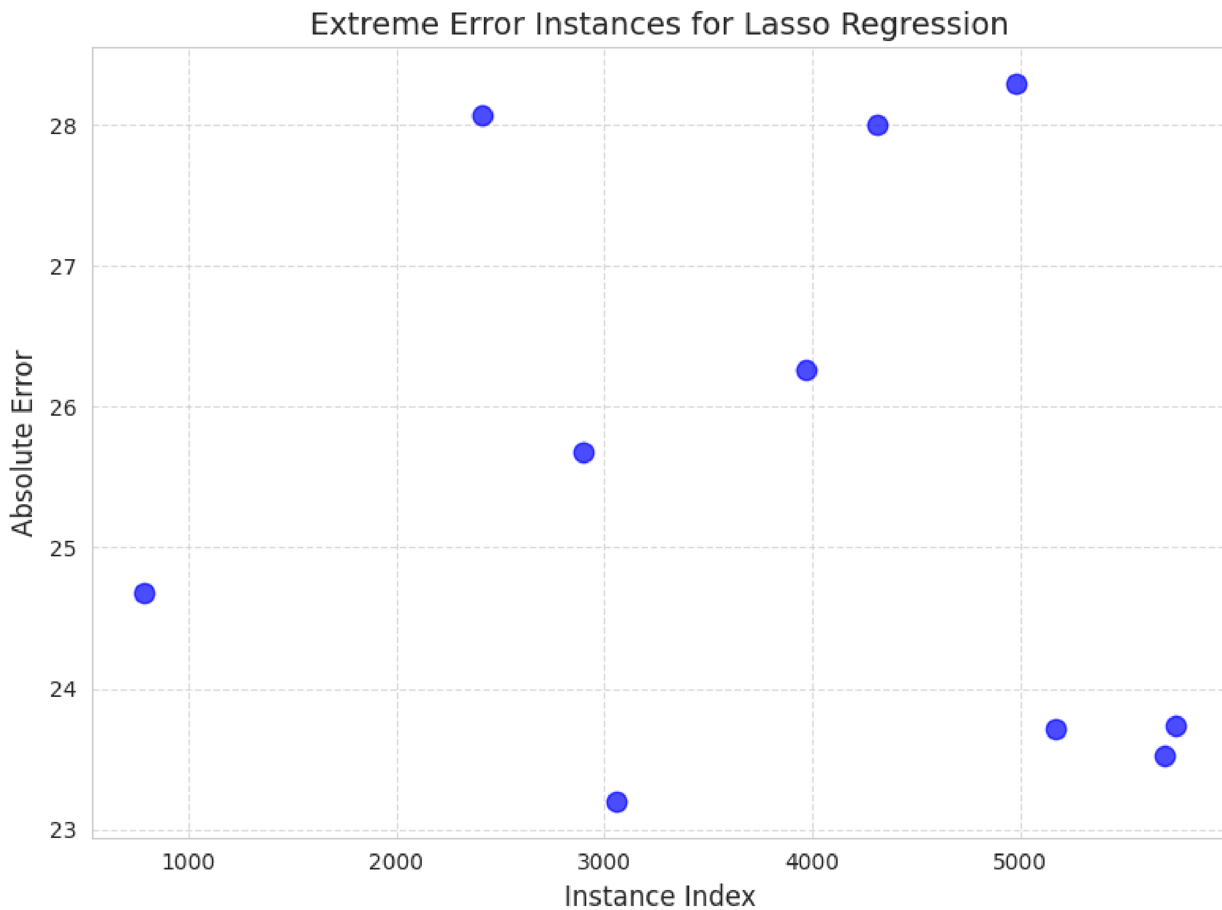
```
                                  Mean Squared Error (MSE)  \
Linear Regression                                47.968322
Lasso Regression                                 47.955343
Ridge Regression                                 47.968780
Decision Tree Regression                         39.900361
Random Forest Regression                         17.310343
Support Vector Regression Linear                 48.593853
Support Vector Regression RBF                    36.198723
XGBoost Regression                               16.780930
AdaBoost Regression                              38.362833

                                  Root Mean Squared Error (RMSE)  \
Linear Regression                                       6.925917
Lasso Regression                                        6.924980
Ridge Regression                                        6.925950
Decision Tree Regression                                6.316673
Random Forest Regression                                4.160570
Support Vector Regression Linear                        6.970929
Support Vector Regression RBF                           6.016537
XGBoost Regression                                      4.096453
AdaBoost Regression                                     6.193774

                                  Mean Absolute Error (MAE)  R-squared
(R2)
Linear Regression                                   5.574468
0.468688
Lasso Regression                                    5.573968
```

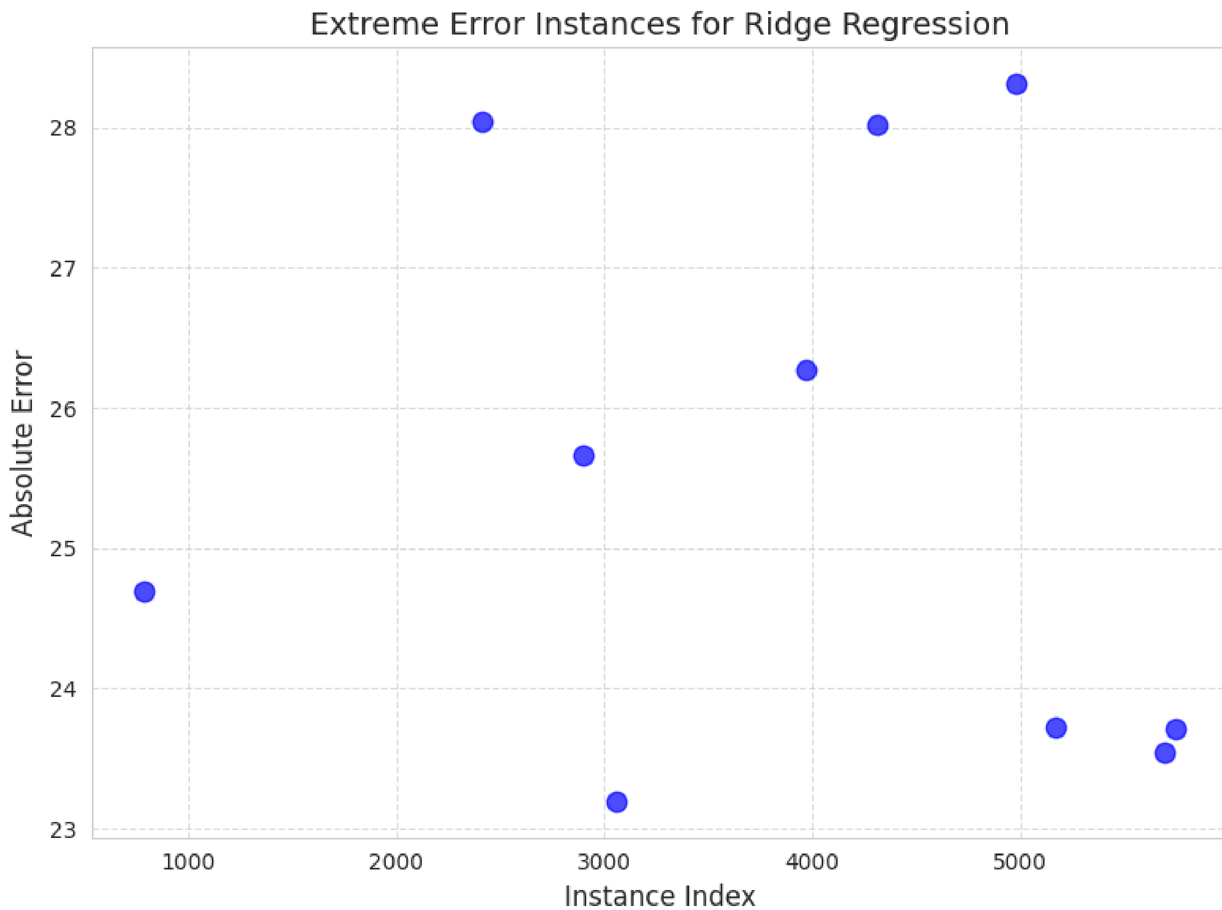
```
0.468831
Ridge Regression                                            5.574463
0.468682
Decision Tree Regression                                    4.751054
0.558051
Random Forest Regression                                    3.280992
0.808265
Support Vector Regression Linear                            5.568677
0.461759
Support Vector Regression RBF                               4.730614
0.599051
XGBoost Regression                                          3.222540
0.814129
AdaBoost Regression                                         5.100050
0.575081
```

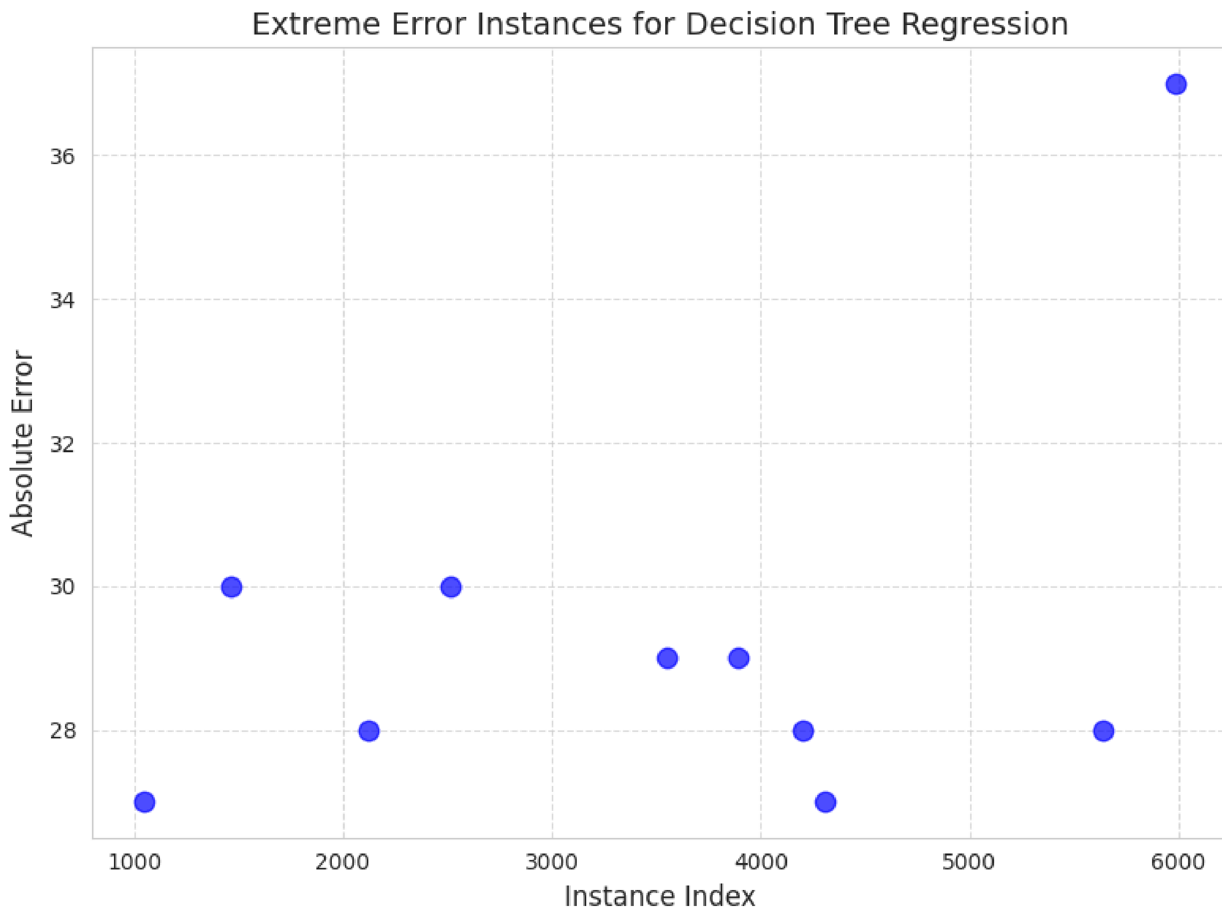
Extreme errors in models

```python
# Plot extreme error instances for each model separately
for idx, model_result in enumerate(results):
    model_name = model_result['Model Name']
    extreme_error_data = model_result['Extreme Error Instances']
    error_values = [data['Absolute Error'] for data in
extreme_error_data]
    instance_indices = [data['Instance Index'] for data in
extreme_error_data]

    plt.figure(figsize=(8, 6))
    plt.scatter(instance_indices, error_values, color='b', alpha=0.7,
s=80)
    plt.xlabel('Instance Index', fontsize=12)
    plt.ylabel('Absolute Error', fontsize=12)
    plt.title(f'Extreme Error Instances for {model_name}',
fontsize=14)
    plt.grid(True, linestyle='--', alpha=0.7)
    plt.tight_layout()
    plt.show()
```

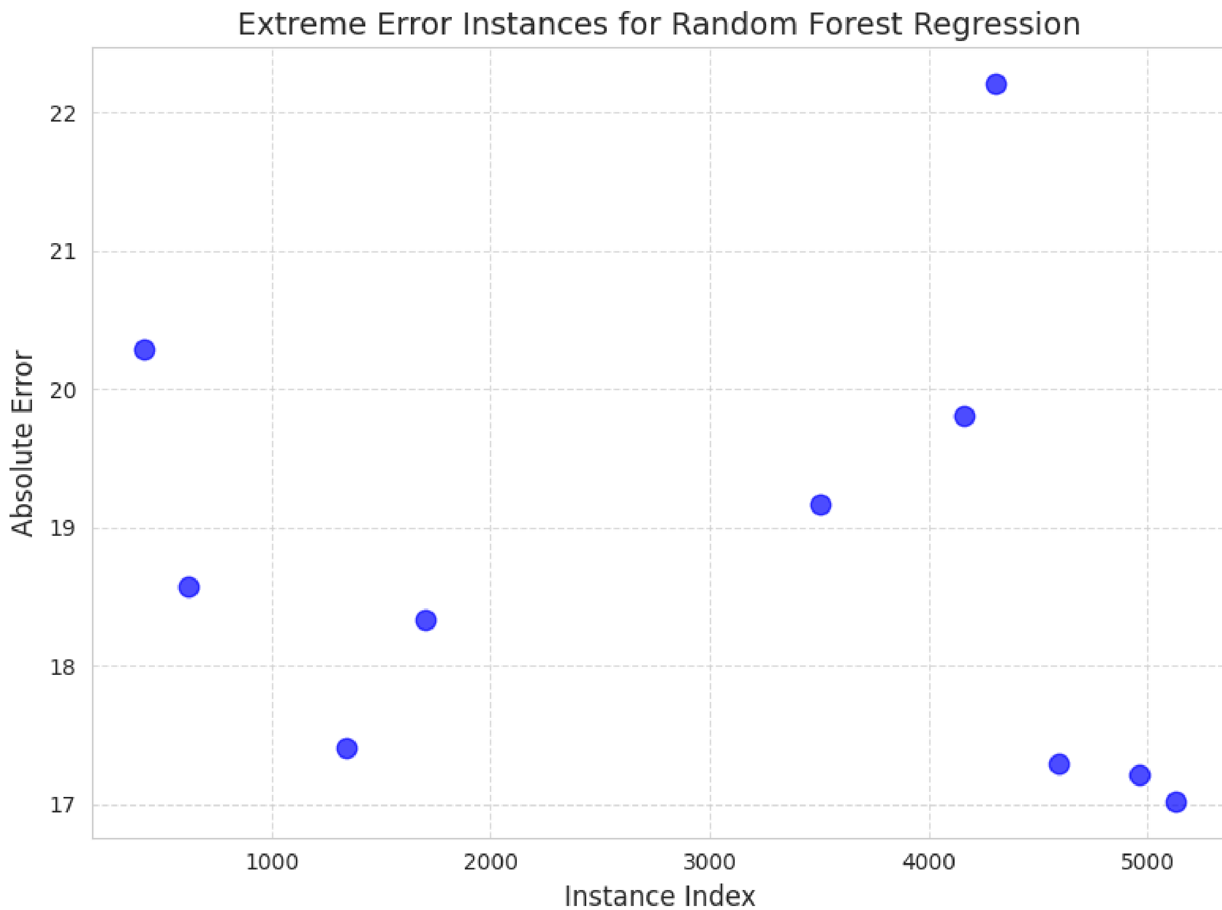

Extreme Error Instances for Linear Regression
Absolute Error
Instance Index
23
24
25
26
27
28
1000
2000
3000
4000
5000


Extreme Error Instances for Lasso Regression
Absolute Error
Instance Index
28
27
26
25
24
23
1000
2000
3000
4000
5000

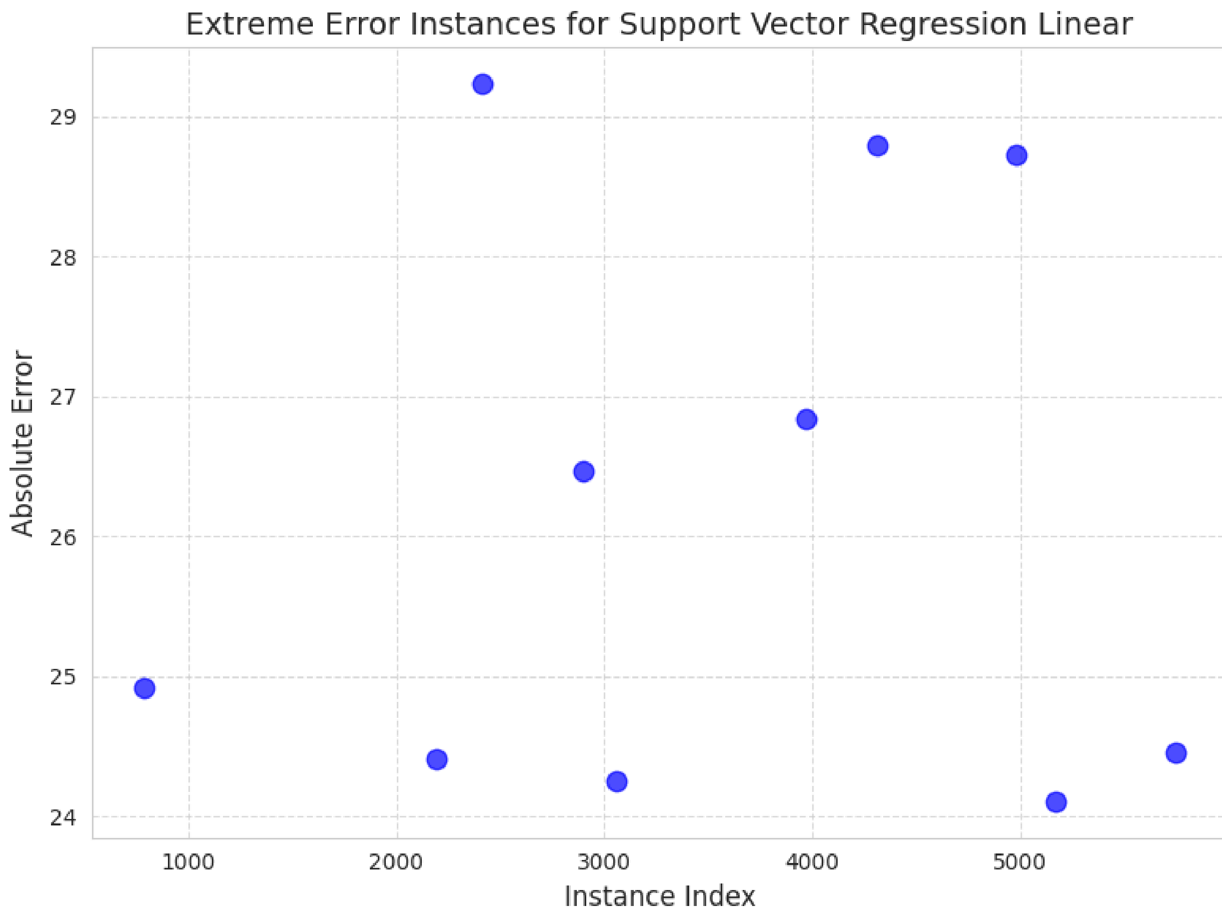

Extreme Error Instances for Ridge Regression
Absolute Error
Instance Index
23
24
25
26
27
28
1000
2000
3000
4000
5000



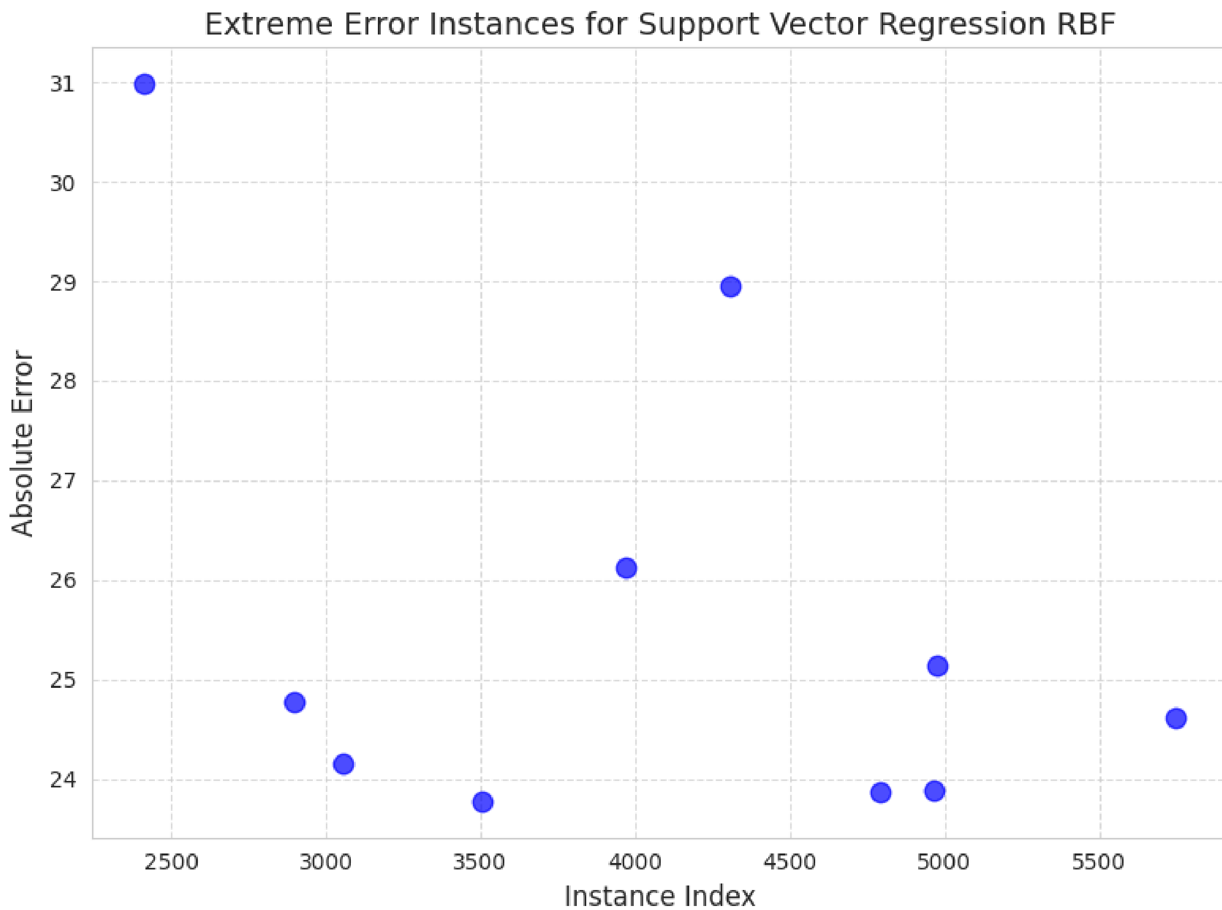
Extreme Error Instances for Decision Tree Regression
Absolute Error
36
34
32
30
28
1000
2000
3000
4000
5000
6000
Instance Index



Extreme Error Instances for Random Forest Regression
Absolute Error
17
18
19
20
21
22
1000
2000
3000
4000
5000
Instance Index

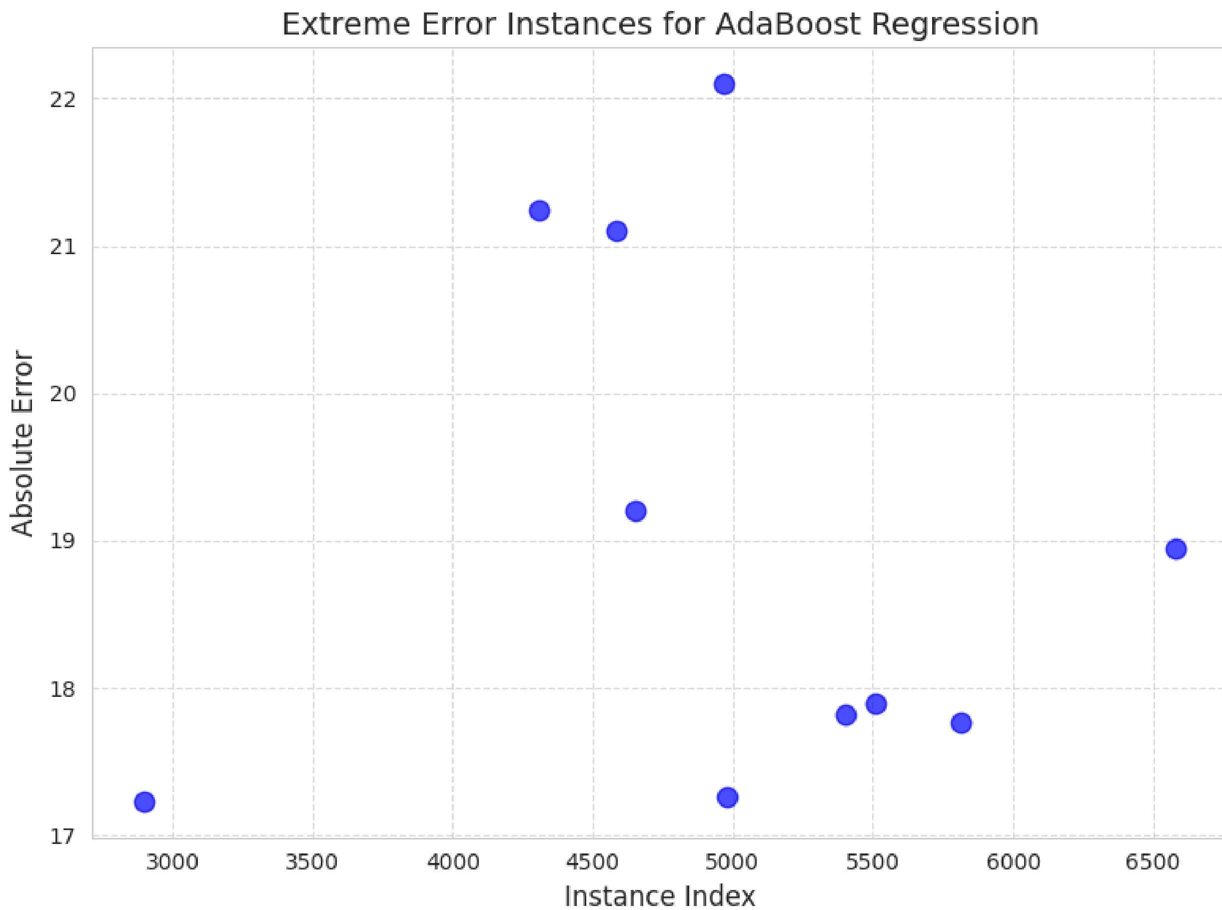


Extreme Error Instances for Support Vector Regression Linear
Absolute Error
29
28
27
26
25
24
1000
2000
3000
4000
5000
Instance Index



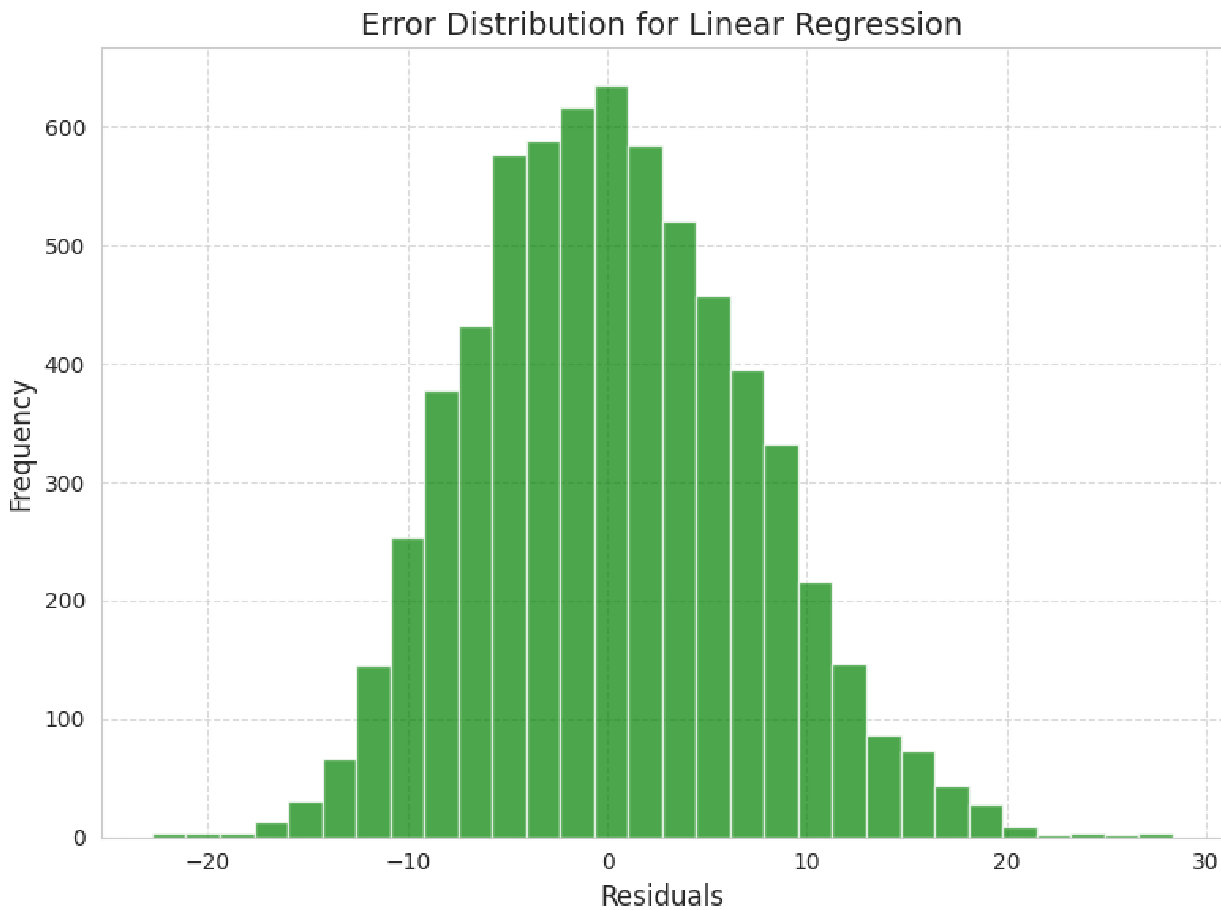
Extreme Error Instances for Support Vector Regression RBF
Absolute Error
31
30
29
28
27
26
25
24
2500
3000
3500
4000
4500
5000
5500
Instance Index

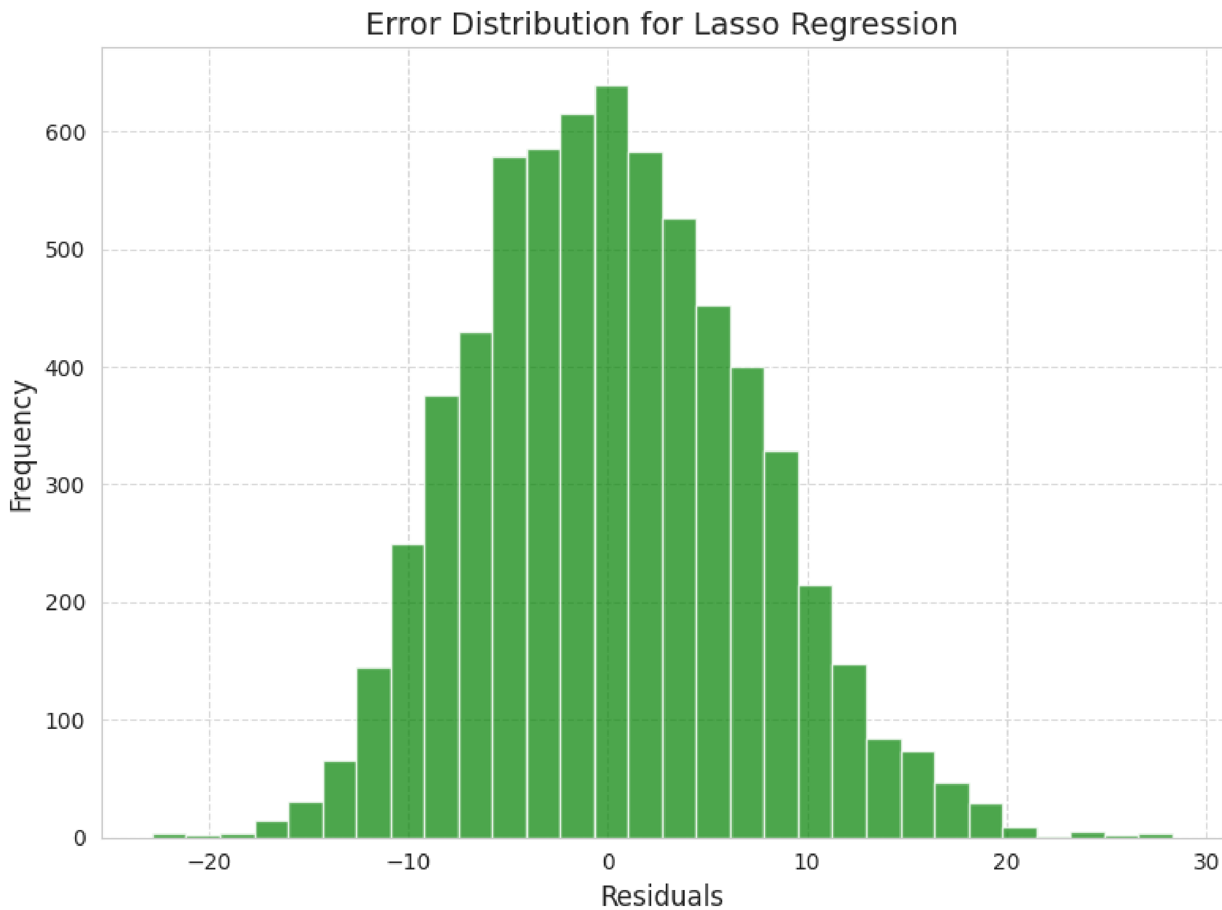

Extreme Error Instances for XGBoost Regression
Absolute Error
Instance Index
23
22
21
20
19
18
17
1000
2000
3000
4000
5000
6000



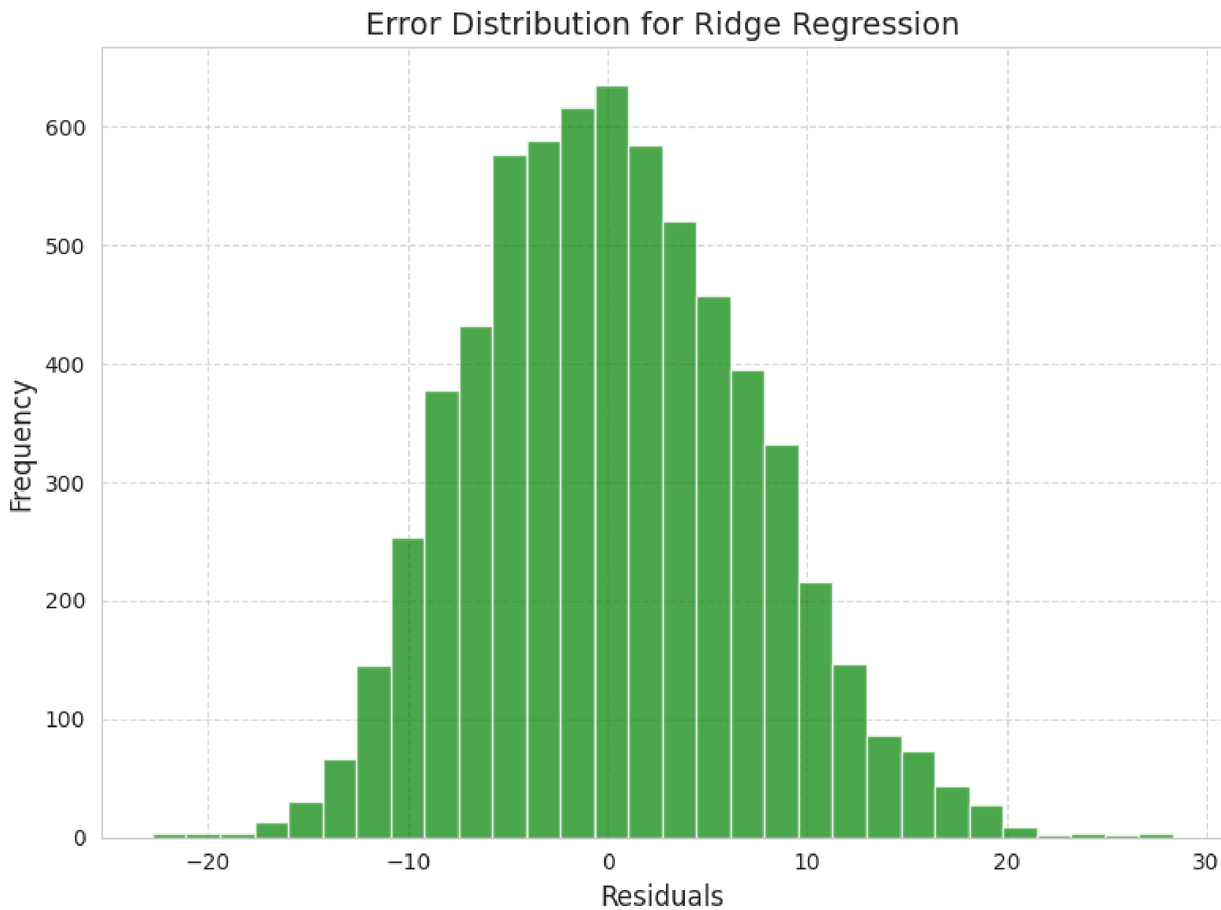
Error Distribution

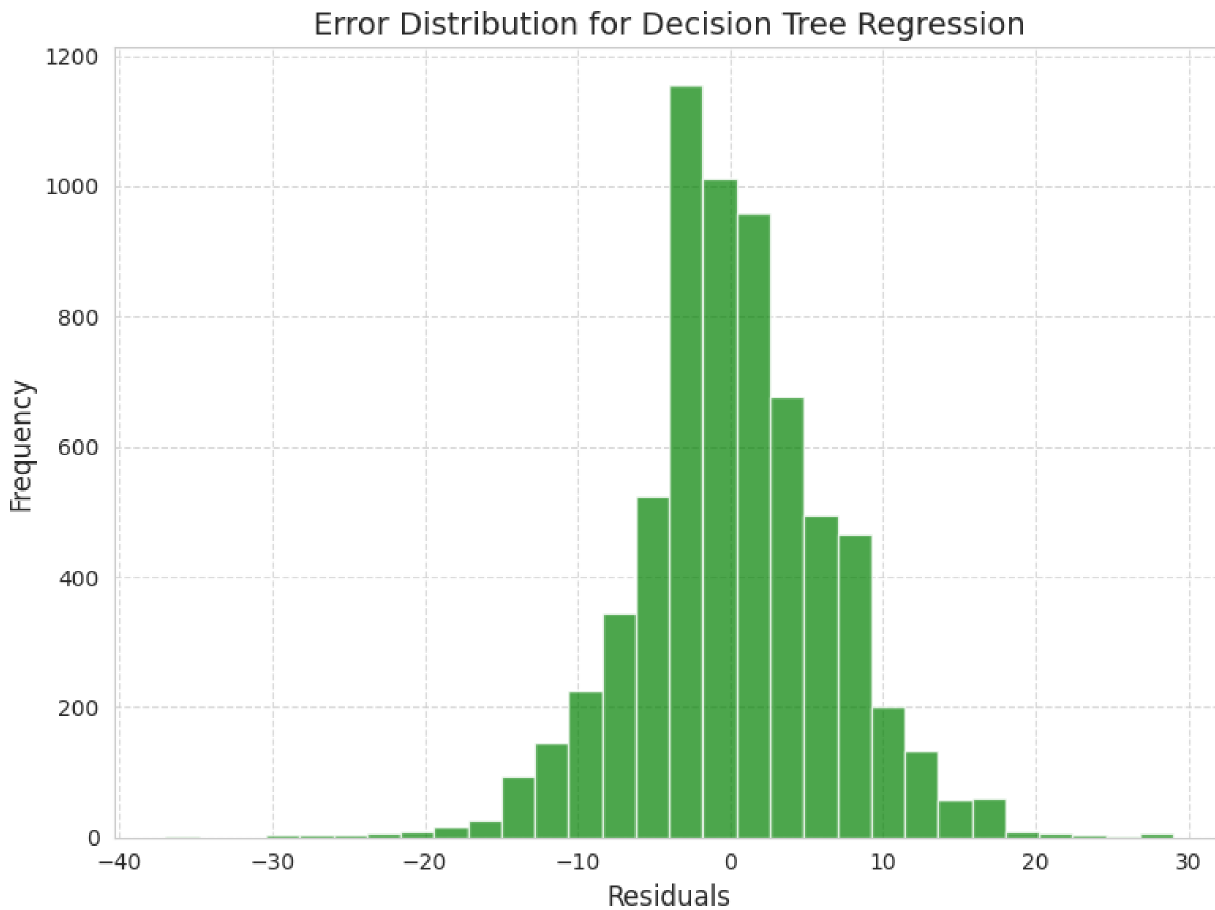
```
# Plot error distribution for each model
for idx, model_result in enumerate(results):
    model_name = model_result['Model Name']
    y_pred = models[model_name].predict(X_val)
    errors = y_val - y_pred

    plt.figure(figsize=(8, 6))
    plt.hist(errors, bins=30, alpha=0.7, color='g')
    plt.xlabel('Residuals', fontsize=12)
    plt.ylabel('Frequency', fontsize=12)
    plt.title(f'Error Distribution for {model_name}', fontsize=14)
    plt.grid(True, linestyle='--', alpha=0.7)
    plt.tight_layout()
    plt.show()
```


Error Distribution for Linear Regression
Frequency
0
100
200
300
400
500
600
−20
−10
0
10
20
30
Residuals

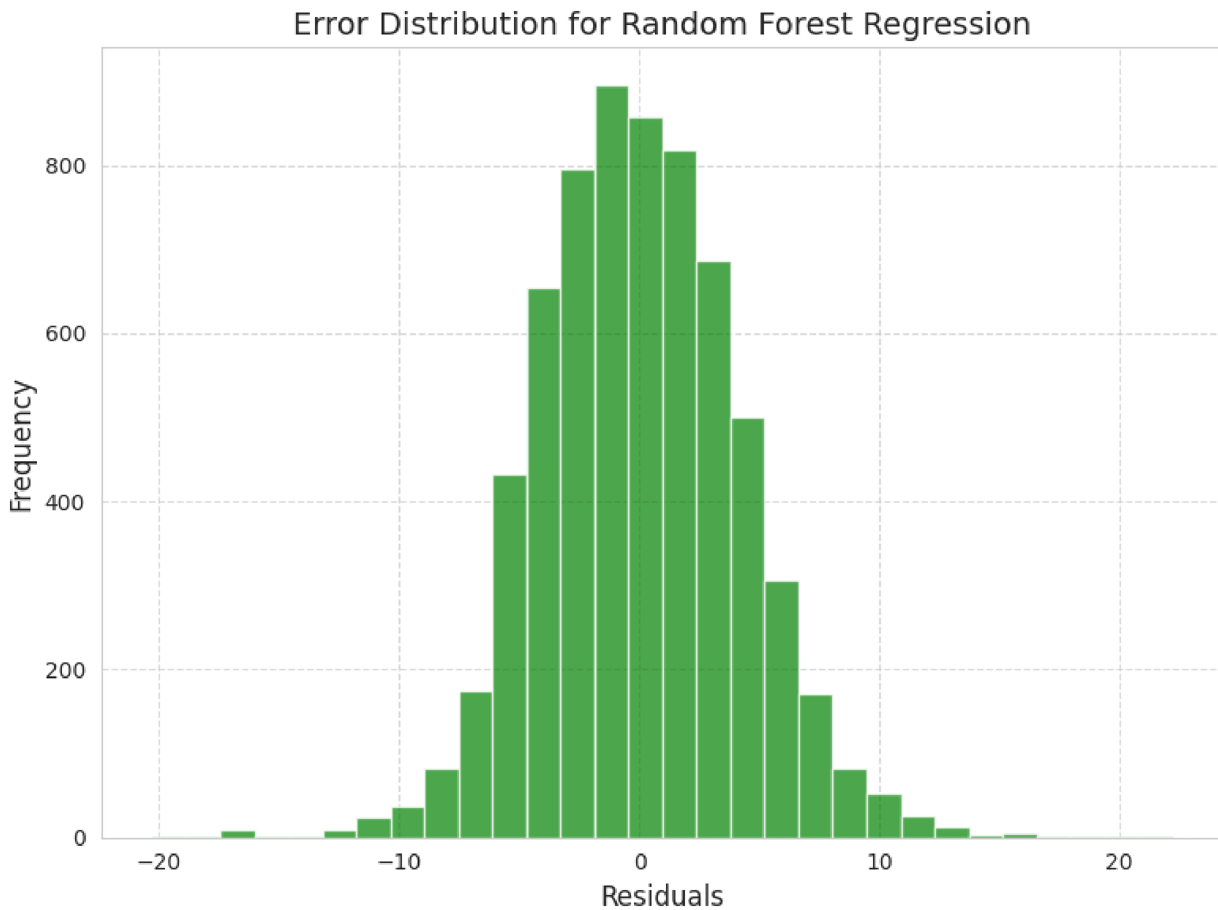


Error Distribution for Lasso Regression
Frequency
Residuals
600
500
400
300
200
100
0
−20
−10
0
10
20
30

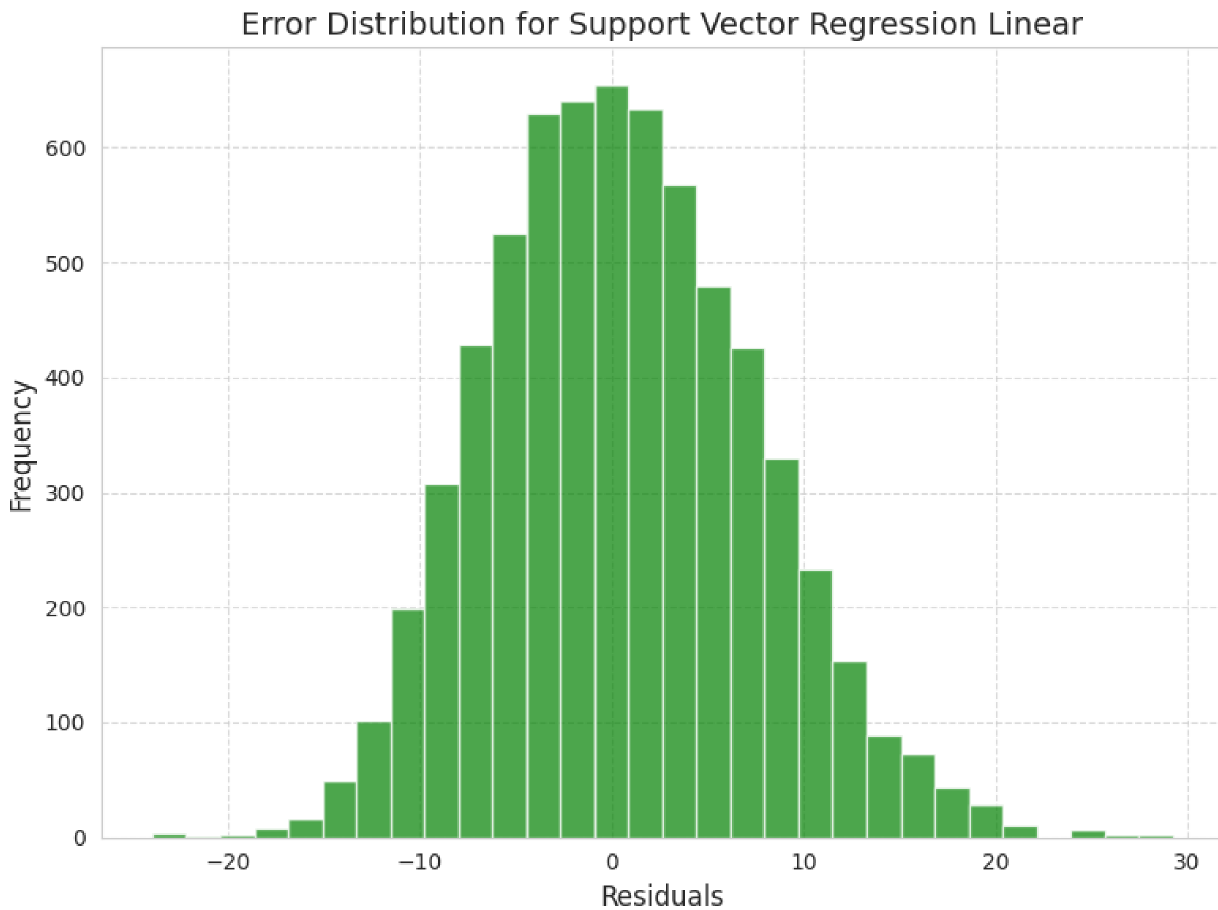

Error Distribution for Ridge Regression
Frequency
0
100
200
300
400
500
600
Residuals
−20
−10
0
10
20
30



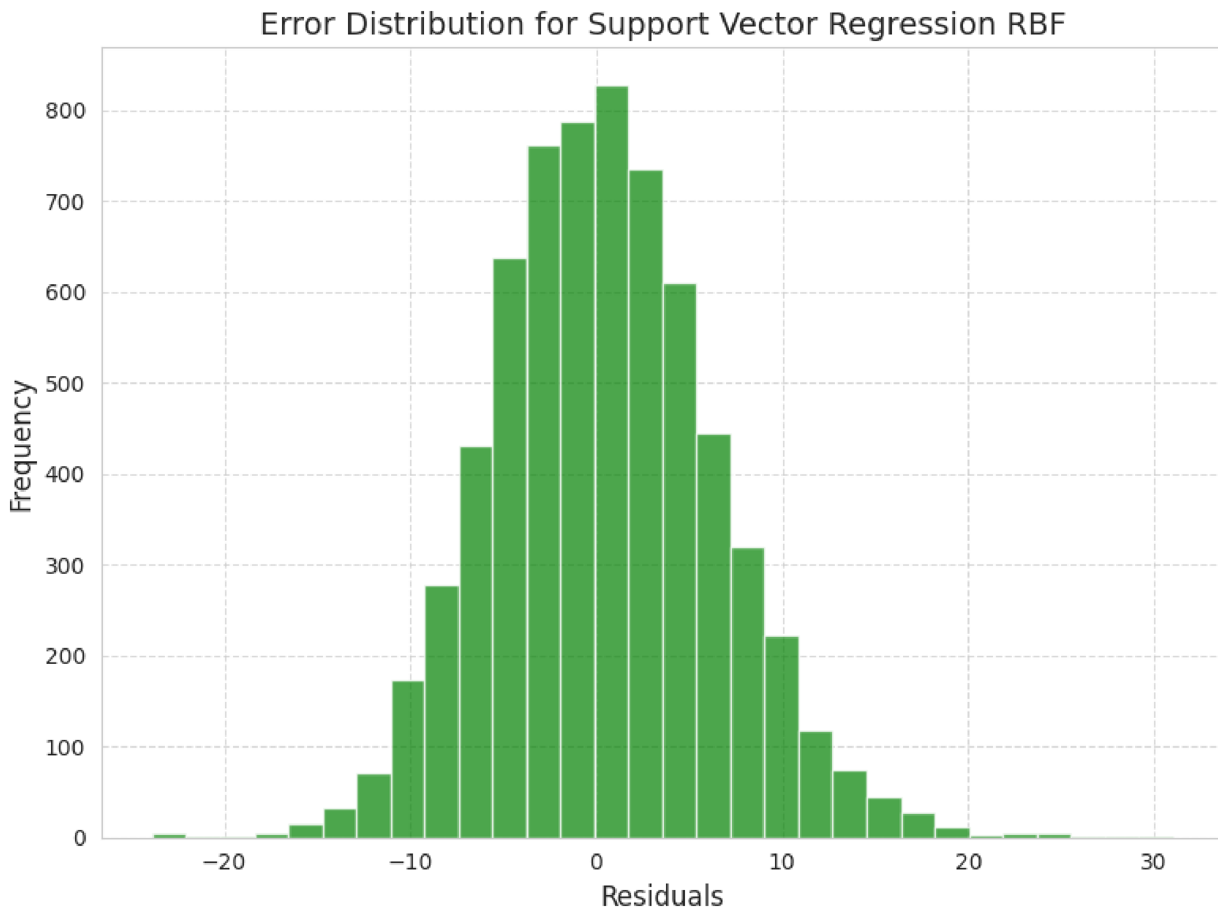
Error Distribution for Decision Tree Regression
Frequency
0
200
400
600
800
1000
1200
−40
−30
−20
−10
0
10
20
30
Residuals

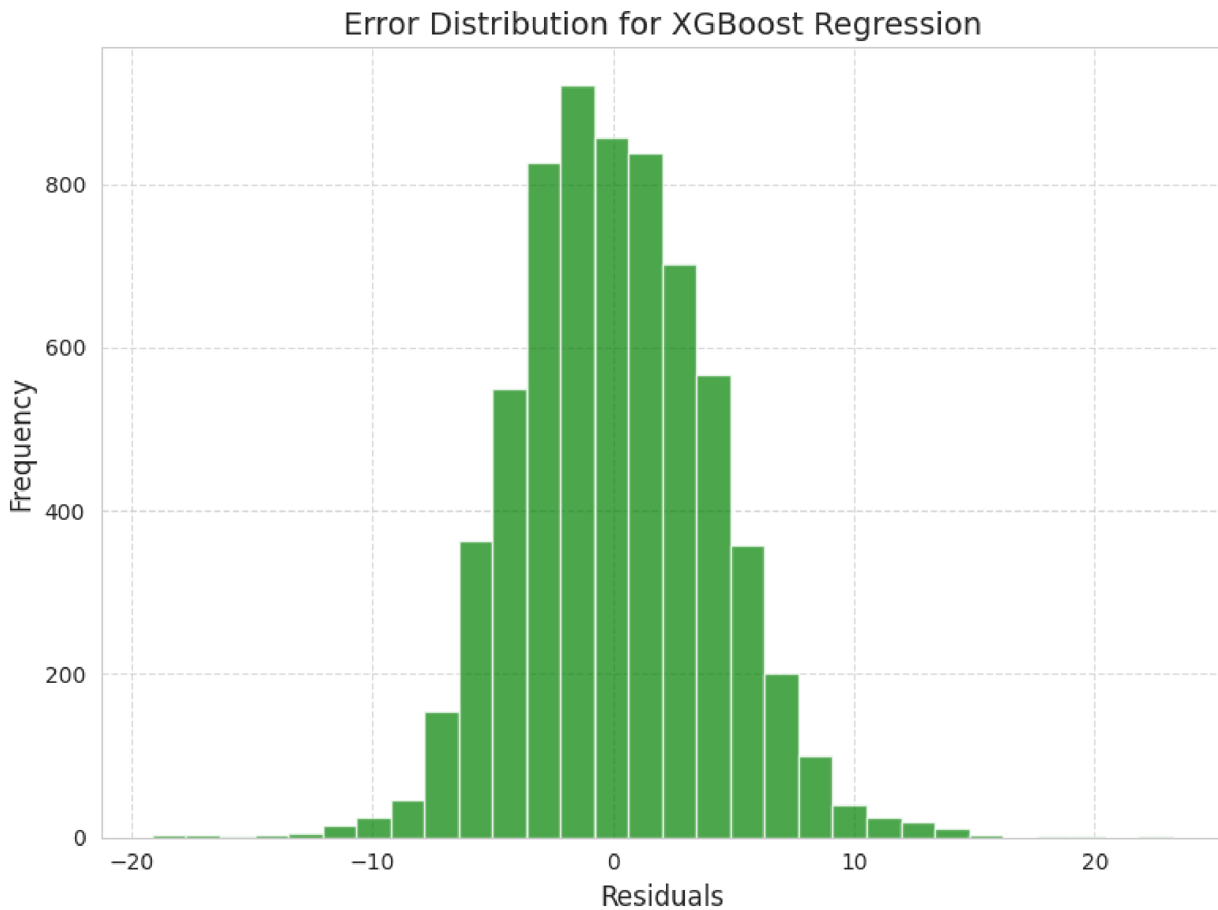


Error Distribution for Random Forest Regression
Frequency
Residuals
0
200
400
600
800
−20
−10
0
10
20

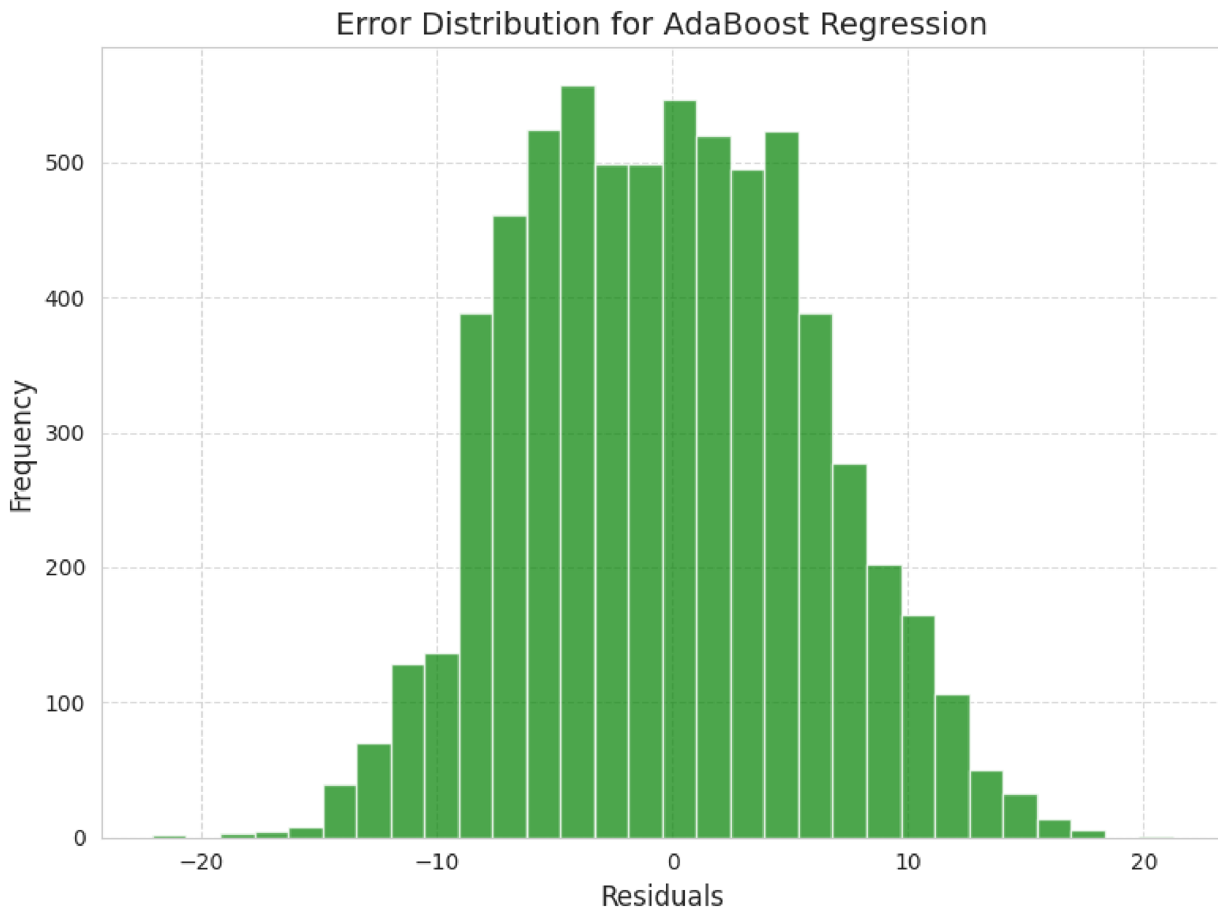


Error Distribution for Support Vector Regression Linear
Frequency
Residuals
0
100
200
300
400
500
600
−20
−10
0
10
20
30


Error Distribution for Support Vector Regression RBF
800
700
600
500
400
300
200
100
0
Frequency
−20
−10
0
10
20
30
Residuals



Error Distribution for XGBoost Regression
Frequency
0
200
400
600
800
−20
−10
0
10
20
Residuals



Error Analysis

- **Linear Regression:** Extreme errors occur due to nonlinear relationships in the data, causing the linear model to fail in capturing the underlying complex patterns.
- **Lasso Regression and Ridge Regression:** Extreme errors in regularization-based models arise due to strong feature selection, which may overlook important predictors or over-penalize some features, leading to substantial prediction errors.
- **Decision Tree Regression:** Extreme errors occur when the decision tree creates deep branches, resulting in overfitting on the training data. Overfitting causes the model to perform poorly on unseen data, leading to significant errors in predictions.
- **Random Forest Regression:** Extreme errors can occur when individual trees in the ensemble overfit certain training data points, impacting the generalization of the random forest model and leading to inaccurate predictions on new data instances.
- **Support Vector Regression (Linear and RBF):** Extreme errors in SVR models result from poor parameter tuning, such as selecting an inappropriate kernel or misinterpreting hyperparameters. These issues can lead to a model that poorly fits the data, resulting in significant errors in predictions.

- **XGBoost Regression:** Extreme errors happen when the learning rate is too high, causing overshooting and instability during training. High learning rates cause the model to miss the optimal predictions, leading to substantial errors.
- **AdaBoost Regression:** Extreme errors occur due to the sensitivity of AdaBoost to outliers in the data. The presence of extreme outliers can exert undue influence on the model, leading to significant errors in predictions.

K-Fold Cross Validation

```
# K-fold cross validation on models implemented using the libraries
new_models = {
    'Linear Regression': LinearRegression(),
    'Lasso Regression': Lasso(alpha=0.01),
    'Ridge Regression': Ridge(alpha=1.0),
    'Decision Tree Regression': DecisionTreeRegressor(),
    'Random Forest Regression':
RandomForestRegressor(n_estimators=100, random_state=42),
    'Support Vector Regression Linear': SVR(kernel='linear'),
    'Support Vector Regression RBF': SVR(kernel='rbf'),
    'XGBoost Regression': xgb.XGBRegressor(n_estimators=100,
learning_rate=0.1, random_state=42),
    'AdaBoost Regression': AdaBoostRegressor()
}

from sklearn.metrics import mean_squared_error, mean_absolute_error,
r2_score
from sklearn.model_selection import KFold

def k_fold_cross_validation(X, y, model, k=5):
    kf = KFold(n_splits=k, shuffle=True, random_state=42)
    mse_scores = []
    rmse_scores = []
    mae_scores = []
    r2_scores = []

    for train_idx, test_idx in kf.split(X):
        X_train, X_test = X[train_idx], X[test_idx]
        y_train, y_test = y[train_idx], y[test_idx]

        model.fit(X_train, y_train)
        y_pred = model.predict(X_test)

        mse = mean_squared_error(y_test, y_pred)
        rmse = np.sqrt(mse)
        mae = mean_absolute_error(y_test, y_pred)
        r2 = r2_score(y_test, y_pred)

        mse_scores.append(mse)
```

```python
        rmse_scores.append(rmse)
        mae_scores.append(mae)
        r2_scores.append(r2)

    return np.mean(mse_scores), np.mean(rmse_scores),
np.mean(mae_scores), np.mean(r2_scores)

print('Models implemented using libraries:\n')

for model_name, model in new_models.items():
  mse_avg, rmse_avg, mae_avg, r2_avg =
k_fold_cross_validation(X_train, y_train, model)
  print("Model = ", model_name)
  print("Mean Squared Error (avg):", mse_avg)
  print("Root Mean Squared Error (avg):", rmse_avg)
  print("Mean Absolute Error (avg):", mae_avg)
  print("R-squared (avg):", r2_avg)
  print()
```

```
Models implemented using libraries:

Model =  Linear Regression
Mean Squared Error (avg): 44.940056741593295
Root Mean Squared Error (avg): 6.703721922150544
Mean Absolute Error (avg): 5.389340959310508
R-squared (avg): 0.4839776185073846

Model =  Lasso Regression
Mean Squared Error (avg): 44.938675027706765
Root Mean Squared Error (avg): 6.703618845619692
Mean Absolute Error (avg): 5.389621836578435
R-squared (avg): 0.48399351763815257

Model =  Ridge Regression
Mean Squared Error (avg): 44.94005206881736
Root Mean Squared Error (avg): 6.70372157075838
Mean Absolute Error (avg): 5.389345315984427
R-squared (avg): 0.48397767634565936

Model =  Decision Tree Regression
Mean Squared Error (avg): 30.593754837768564
Root Mean Squared Error (avg): 5.530765435112734
Mean Absolute Error (avg): 4.173781618763124
R-squared (avg): 0.6485792278130144

Model =  Random Forest Regression
Mean Squared Error (avg): 16.489193689561073
Root Mean Squared Error (avg): 4.060530302046639
Mean Absolute Error (avg): 3.2069290021022816
R-squared (avg): 0.8106129656163311
```

```
Model =  Support Vector Regression Linear
Mean Squared Error (avg): 45.36787520719051
Root Mean Squared Error (avg): 6.735538511978923
Mean Absolute Error (avg): 5.368246454026731
R-squared (avg): 0.47906532116669986

Model =  Support Vector Regression RBF
Mean Squared Error (avg): 34.6080222173148
Root Mean Squared Error (avg): 5.882798989079549
Mean Absolute Error (avg): 4.645223736471295
R-squared (avg): 0.6025875400874912

Model =  XGBoost Regression
Mean Squared Error (avg): 16.04147522149257
Root Mean Squared Error (avg): 4.005144746665882
Mean Absolute Error (avg): 3.1676002083413595
R-squared (avg): 0.8157798663805981

Model =  AdaBoost Regression
Mean Squared Error (avg): 36.74942914770364
Root Mean Squared Error (avg): 6.061908724029225
Mean Absolute Error (avg): 4.9935466984511105
R-squared (avg): 0.5779796960206502
```

```
# K-fold cross validation on models implemented from scratch
scratch_models = {
    'Linear Regression': Linear_Regression(),
    'Ridge Regression': Ridge_Regression(alpha=1.0),
    'Decision Tree Regression': Decision_Tree_Regressor(),
}

print('Models implemented from scratch:\n')

for model_name, model in scratch_models.items():
  mse_avg, rmse_avg, mae_avg, r2_avg =
k_fold_cross_validation(X_train, y_train, model)
  print("Model = ", model_name)
  print("Mean Squared Error (avg):", mse_avg)
  print("Root Mean Squared Error (avg):", rmse_avg)
  print("Mean Absolute Error (avg):", mae_avg)
  print("R-squared (avg):", r2_avg)
  print()
```

```
Models implemented from scratch:

Model =  Linear Regression
Mean Squared Error (avg): 44.940056741593295
Root Mean Squared Error (avg): 6.703721922150544
Mean Absolute Error (avg): 5.389340959310509
```

```
R-squared (avg): 0.4839776185073846

Model =  Ridge Regression
Mean Squared Error (avg): 44.94005632045661
Root Mean Squared Error (avg): 6.7037218432774255
Mean Absolute Error (avg): 5.38929747680306
R-squared (avg): 0.48397767966634514

Model =  Decision Tree Regression
Mean Squared Error (avg): 40.956396901137275
Root Mean Squared Error (avg): 6.399202155446744
Mean Absolute Error (avg): 4.841608360882045
R-squared (avg): 0.5296411809817327
```

Grid Search CV

```
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.linear_model import LinearRegression, Lasso, Ridge
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor, AdaBoostRegressor
from sklearn.svm import SVR
import xgboost as xgb
from sklearn.metrics import mean_squared_error, mean_absolute_error,
r2_score

models = {
    'Linear Regression': Linear_Regression(),
    'Lasso Regression': Lasso(),
    'Ridge Regression': Ridge_Regression(),
    'Decision Tree Regression': Decision_Tree_Regressor(),
    'Random Forest Regression': RandomForestRegressor(),
    'Support Vector Regression Linear': SVR(kernel='linear'),
    'Support Vector Regression RBF': SVR(kernel='rbf'),
    'XGBoost Regression': xgb.XGBRegressor(),
    'AdaBoost Regression': AdaBoostRegressor()
}

param_grids = {
    'Lasso Regression': {'alpha': [0.01, 0.1, 1.0]},
    'Ridge Regression': {'alpha': [0.01, 0.1, 1.0]},
    'Decision Tree Regression': {'max_depth': [None, 5, 10]},
    'Random Forest Regression': {'n_estimators': [50, 100, 200]},
    'Support Vector Regression RBF': {'C': [1, 10, 100], 'gamma':
['scale', 'auto']},
    'XGBoost Regression': {'n_estimators': [50, 100, 200],
```

```
'learning_rate': [0.01, 0.1, 0.2]},
    'AdaBoost Regression': {'n_estimators': [50, 100, 200],
'learning_rate': [0.01, 0.1, 0.2]}
}

results = []

for model_name, model in models.items():
  if model_name in param_grids:
      result = {}
      result['Model Name'] = model_name
      result['Hyperparameters'] = []

      grid_search = GridSearchCV(model, param_grids[model_name],
scoring='neg_mean_squared_error', cv=5)
      grid_search.fit(X_train, y_train)

      for params, score in zip(grid_search.cv_results_['params'],
grid_search.cv_results_['mean_test_score']):
        y_pred = grid_search.best_estimator_.predict(X_val)
        mse_val = mean_squared_error(y_val, y_pred)
        rmse_val = np.sqrt(mse_val)
        mae_val = mean_absolute_error(y_val, y_pred)
        r2_val = r2_score(y_val, y_pred)

        result['Hyperparameters'].append({
            'Parameters': params,
            'Mean Squared Error': -score,
            'Root Mean Squared Error': rmse_val,
            'Mean Absolute Error': mae_val,
            'R-squared': r2_val
        })

      results.append(result)

metrics_df_2 = pd.DataFrame(results)
```

Results before Grid Search CV:

```
metrics_df_1
```

	Mean Squared Error (MSE) \
Linear Regression	47.780250
Lasso Regression	47.765159
Ridge Regression	47.780263
Decision Tree Regression	31.035069
Random Forest Regression	17.317225
Support Vector Regression Linear	48.370209
Support Vector Regression RBF	35.945731
XGBoost Regression	16.774219

```
AdaBoost Regression                                    38.322681

                                  Root Mean Squared Error (RMSE)  \
Linear Regression                                        6.912326
Lasso Regression                                         6.911234
Ridge Regression                                         6.912327
Decision Tree Regression                                 5.570913
Random Forest Regression                                 4.161397
Support Vector Regression Linear                         6.954869
Support Vector Regression RBF                            5.995476
XGBoost Regression                                       4.095634
AdaBoost Regression                                      6.190532

                                  Mean Absolute Error (MAE)  R-squared
(R2)
Linear Regression                                   5.564283
0.470771
Lasso Regression                                    5.563655
0.470938
Ridge Regression                                    5.564287
0.470771
Decision Tree Regression                            4.169326
0.656246
Random Forest Regression                            3.275963
0.808189
Support Vector Regression Linear                    5.558453
0.464236
Support Vector Regression RBF                       4.716017
0.601854
XGBoost Regression                                  3.229385
0.814203
AdaBoost Regression                                 5.101507
0.575526
```

Results after Grid Search CV:

```
metrics_df_2

                      Model Name  \
0               Lasso Regression
1               Ridge Regression
2       Decision Tree Regression
3       Random Forest Regression
4  Support Vector Regression RBF
5             XGBoost Regression
6            AdaBoost Regression

                                     Hyperparameters
0  [{'Parameters': {'alpha': 0.01}, 'Mean Squared...
1  [{'Parameters': {'alpha': 0.01}, 'Mean Squared...
```

```
2  [{'Parameters': {'max_depth': None}, 'Mean Squ...
3  [{'Parameters': {'n_estimators': 50}, 'Mean Sq...
4  [{'Parameters': {'C': 1, 'gamma': 'scale'}, 'M...
5  [{'Parameters': {'learning_rate': 0.01, 'n_est...
6  [{'Parameters': {'learning_rate': 0.01, 'n_est...
```

```
metrics_df_1.to_csv('metrics_df_1.csv')
metrics_df_2.to_csv('metrics_df_2.csv')

metrics_df_1 = pd.read_csv('metrics_df_1.csv', index_col=False)
metrics_df_2 = pd.read_csv('metrics_df_2.csv', index_col=False)

metrics_df_2.head()
```

```
   Unnamed: 0                    Model Name  \
0           1              Lasso Regression
1           2              Ridge Regression
2           3      Decision Tree Regression
3           4      Random Forest Regression
4           5  Support Vector Regression RBF

                                     Hyperparameters
0  [{'Parameters': {'alpha': 0.01}, 'Mean Squared...
1  [{'Parameters': {'alpha': 0.01}, 'Mean Squared...
2  [{'Parameters': {'max_depth': None}, 'Mean Squ...
3  [{'Parameters': {'n_estimators': 50}, 'Mean Sq...
4  [{'Parameters': {'C': 1, 'gamma': 'scale'}, 'M...
```

```
# Get hyper parameters which performed the best for each model after 
grid search cv
import ast

data = metrics_df_2
model_names = data['Model Name'].unique()
dfs = {model_name: pd.DataFrame(columns=['Parameters', 'Mean Squared 
Error', 'Root Mean Squared Error', 'Mean Absolute Error', 'R-
squared']) for model_name in model_names}

for index, row in data.iterrows():
  model_name = row['Model Name']
  results = ast.literal_eval(row['Hyperparameters'])
  for result in results:
    parameters = result['Parameters']
    mse = result['Mean Squared Error']
    rmse = result['Root Mean Squared Error']
    mae = result['Mean Absolute Error']
    r_squared = result['R-squared']
    dfs[model_name] = dfs[model_name].append({'Parameters': 
parameters, 'Mean Squared Error': mse, 'Root Mean Squared Error': 
rmse, 'Mean Absolute Error': mae, 'R-squared': r_squared}, 
ignore_index=True)
```

```
best_results = []
for model_name, df in dfs.items():
    best_row = df.loc[df['Mean Squared Error'].idxmin()]
    best_results.append({'Model Name': model_name, **best_row})

best_df = pd.DataFrame(best_results)
best_df.to_csv('Best_Model_Performance.csv', index=False)
```

```
<ipython-input-173-7e38b0e3a0a1>:19: FutureWarning: The frame.append
method is deprecated and will be removed from pandas in a future
version. Use pandas.concat instead.
  dfs[model_name] = dfs[model_name].append({'Parameters': parameters,
'Mean Squared Error': mse, 'Root Mean Squared Error': rmse, 'Mean
Absolute Error': mae, 'R-squared': r_squared}, ignore_index=True)
<ipython-input-173-7e38b0e3a0a1>:19: FutureWarning: The frame.append
method is deprecated and will be removed from pandas in a future
version. Use pandas.concat instead.
  dfs[model_name] = dfs[model_name].append({'Parameters': parameters,
'Mean Squared Error': mse, 'Root Mean Squared Error': rmse, 'Mean
Absolute Error': mae, 'R-squared': r_squared}, ignore_index=True)
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'Mean Squared Error': mse, 'Root Mean Squared Error': rmse, 'Mean
Absolute Error': mae, 'R-squared': r_squared}, ignore_index=True)
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version. Use pandas.concat instead.
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version. Use pandas.concat instead.
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```

```
'Mean Squared Error': mse, 'Root Mean Squared Error': rmse, 'Mean
Absolute Error': mae, 'R-squared': r_squared}, ignore_index=True)
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Absolute Error': mae, 'R-squared': r_squared}, ignore_index=True)
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Absolute Error': mae, 'R-squared': r_squared}, ignore_index=True)
<ipython-input-173-7e38b0e3a0a1>:19: FutureWarning: The frame.append
method is deprecated and will be removed from pandas in a future
version. Use pandas.concat instead.
  dfs[model_name] = dfs[model_name].append({'Parameters': parameters,
'Mean Squared Error': mse, 'Root Mean Squared Error': rmse, 'Mean
```

```
Absolute Error': mae, 'R-squared': r_squared}, ignore_index=True)
<ipython-input-173-7e38b0e3a0a1>:19: FutureWarning: The frame.append
method is deprecated and will be removed from pandas in a future
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'Mean Squared Error': mse, 'Root Mean Squared Error': rmse, 'Mean
Absolute Error': mae, 'R-squared': r_squared}, ignore_index=True)
<ipython-input-173-7e38b0e3a0a1>:19: FutureWarning: The frame.append
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  dfs[model_name] = dfs[model_name].append({'Parameters': parameters,
'Mean Squared Error': mse, 'Root Mean Squared Error': rmse, 'Mean
Absolute Error': mae, 'R-squared': r_squared}, ignore_index=True)
```

```
<ipython-input-173-7e38b0e3a0a1>:19: FutureWarning: The frame.append method is deprecated and will be removed from pandas in a future version. Use pandas.concat instead.
  dfs[model_name] = dfs[model_name].append({'Parameters': parameters, 'Mean Squared Error': mse, 'Root Mean Squared Error': rmse, 'Mean Absolute Error': mae, 'R-squared': r_squared}, ignore_index=True)
<ipython-input-173-7e38b0e3a0a1>:19: FutureWarning: The frame.append method is deprecated and will be removed from pandas in a future version. Use pandas.concat instead.
  dfs[model_name] = dfs[model_name].append({'Parameters': parameters, 'Mean Squared Error': mse, 'Root Mean Squared Error': rmse, 'Mean Absolute Error': mae, 'R-squared': r_squared}, ignore_index=True)
<ipython-input-173-7e38b0e3a0a1>:19: FutureWarning: The frame.append method is deprecated and will be removed from pandas in a future version. Use pandas.concat instead.
  dfs[model_name] = dfs[model_name].append({'Parameters': parameters, 'Mean Squared Error': mse, 'Root Mean Squared Error': rmse, 'Mean Absolute Error': mae, 'R-squared': r_squared}, ignore_index=True)
<ipython-input-173-7e38b0e3a0a1>:19: FutureWarning: The frame.append method is deprecated and will be removed from pandas in a future version. Use pandas.concat instead.
  dfs[model_name] = dfs[model_name].append({'Parameters': parameters, 'Mean Squared Error': mse, 'Root Mean Squared Error': rmse, 'Mean Absolute Error': mae, 'R-squared': r_squared}, ignore_index=True)
<ipython-input-173-7e38b0e3a0a1>:19: FutureWarning: The frame.append method is deprecated and will be removed from pandas in a future version. Use pandas.concat instead.
  dfs[model_name] = dfs[model_name].append({'Parameters': parameters, 'Mean Squared Error': mse, 'Root Mean Squared Error': rmse, 'Mean Absolute Error': mae, 'R-squared': r_squared}, ignore_index=True)
<ipython-input-173-7e38b0e3a0a1>:19: FutureWarning: The frame.append method is deprecated and will be removed from pandas in a future version. Use pandas.concat instead.
  dfs[model_name] = dfs[model_name].append({'Parameters': parameters, 'Mean Squared Error': mse, 'Root Mean Squared Error': rmse, 'Mean Absolute Error': mae, 'R-squared': r_squared}, ignore_index=True)
<ipython-input-173-7e38b0e3a0a1>:19: FutureWarning: The frame.append method is deprecated and will be removed from pandas in a future version. Use pandas.concat instead.
  dfs[model_name] = dfs[model_name].append({'Parameters': parameters, 'Mean Squared Error': mse, 'Root Mean Squared Error': rmse, 'Mean Absolute Error': mae, 'R-squared': r_squared}, ignore_index=True)
<ipython-input-173-7e38b0e3a0a1>:19: FutureWarning: The frame.append method is deprecated and will be removed from pandas in a future version. Use pandas.concat instead.
  dfs[model_name] = dfs[model_name].append({'Parameters': parameters, 'Mean Squared Error': mse, 'Root Mean Squared Error': rmse, 'Mean Absolute Error': mae, 'R-squared': r_squared}, ignore_index=True)
<ipython-input-173-7e38b0e3a0a1>:19: FutureWarning: The frame.append
```

```
method is deprecated and will be removed from pandas in a future
version. Use pandas.concat instead.
  dfs[model_name] = dfs[model_name].append({'Parameters': parameters,
'Mean Squared Error': mse, 'Root Mean Squared Error': rmse, 'Mean
Absolute Error': mae, 'R-squared': r_squared}, ignore_index=True)
<ipython-input-173-7e38b0e3a0a1>:19: FutureWarning: The frame.append
method is deprecated and will be removed from pandas in a future
version. Use pandas.concat instead.
  dfs[model_name] = dfs[model_name].append({'Parameters': parameters,
'Mean Squared Error': mse, 'Root Mean Squared Error': rmse, 'Mean
Absolute Error': mae, 'R-squared': r_squared}, ignore_index=True)
<ipython-input-173-7e38b0e3a0a1>:19: FutureWarning: The frame.append
method is deprecated and will be removed from pandas in a future
version. Use pandas.concat instead.
  dfs[model_name] = dfs[model_name].append({'Parameters': parameters,
'Mean Squared Error': mse, 'Root Mean Squared Error': rmse, 'Mean
Absolute Error': mae, 'R-squared': r_squared}, ignore_index=True)
<ipython-input-173-7e38b0e3a0a1>:19: FutureWarning: The frame.append
method is deprecated and will be removed from pandas in a future
version. Use pandas.concat instead.
  dfs[model_name] = dfs[model_name].append({'Parameters': parameters,
'Mean Squared Error': mse, 'Root Mean Squared Error': rmse, 'Mean
Absolute Error': mae, 'R-squared': r_squared}, ignore_index=True)
<ipython-input-173-7e38b0e3a0a1>:19: FutureWarning: The frame.append
method is deprecated and will be removed from pandas in a future
version. Use pandas.concat instead.
  dfs[model_name] = dfs[model_name].append({'Parameters': parameters,
'Mean Squared Error': mse, 'Root Mean Squared Error': rmse, 'Mean
Absolute Error': mae, 'R-squared': r_squared}, ignore_index=True)
```

Best Hyperparameters and Results:

```
best_df
```

```
                      Model Name
Parameters  \
0               Lasso Regression
{'alpha': 0.01}
1               Ridge Regression
{'alpha': 1.0}
2       Decision Tree Regression
{'max_depth': 10}
3       Random Forest Regression
{'n_estimators': 200}
4  Support Vector Regression RBF                   {'C': 10, 'gamma':
'auto'}
5             XGBoost Regression  {'learning_rate': 0.1,
'n_estimators': 100}
```

```
6            AdaBoost Regression   {'learning_rate': 0.2,
'n_estimators': 50}

   Mean Squared Error  Root Mean Squared Error  Mean Absolute Error
R-squared
0           44.974013                 6.911234             5.563655
0.470938
1           44.979415                 6.912327             5.564287
0.470771
2           17.462015                 4.293587             3.308838
0.795809
3           16.639106                 4.147538             3.266604
0.809464
4           30.028610                 5.603102             4.395774
0.652262
5           16.117282                 4.095634             3.229385
0.814203
6           37.351728                 6.233168             5.116572
0.569659
```

```python
metrics_df_1.drop('Linear Regression', axis=0)
```

```
                               Mean Squared Error (MSE)  \
Lasso Regression                              47.765159
Ridge Regression                              47.780263
Decision Tree Regression                      31.035069
Random Forest Regression                      17.317225
Support Vector Regression RBF                 35.945731
XGBoost Regression                            16.774219
AdaBoost Regression                           38.322681

                               Root Mean Squared Error (RMSE)  \
Lasso Regression                                     6.911234
Ridge Regression                                     6.912327
Decision Tree Regression                             5.570913
Random Forest Regression                             4.161397
Support Vector Regression RBF                        5.995476
XGBoost Regression                                   4.095634
AdaBoost Regression                                  6.190532

                               Mean Absolute Error (MAE)  R-squared
(R2)
Lasso Regression                                5.563655
0.470938
Ridge Regression                                5.564287
0.470771
Decision Tree Regression                        4.169326
0.656246
Random Forest Regression                        3.275963
0.808189
```

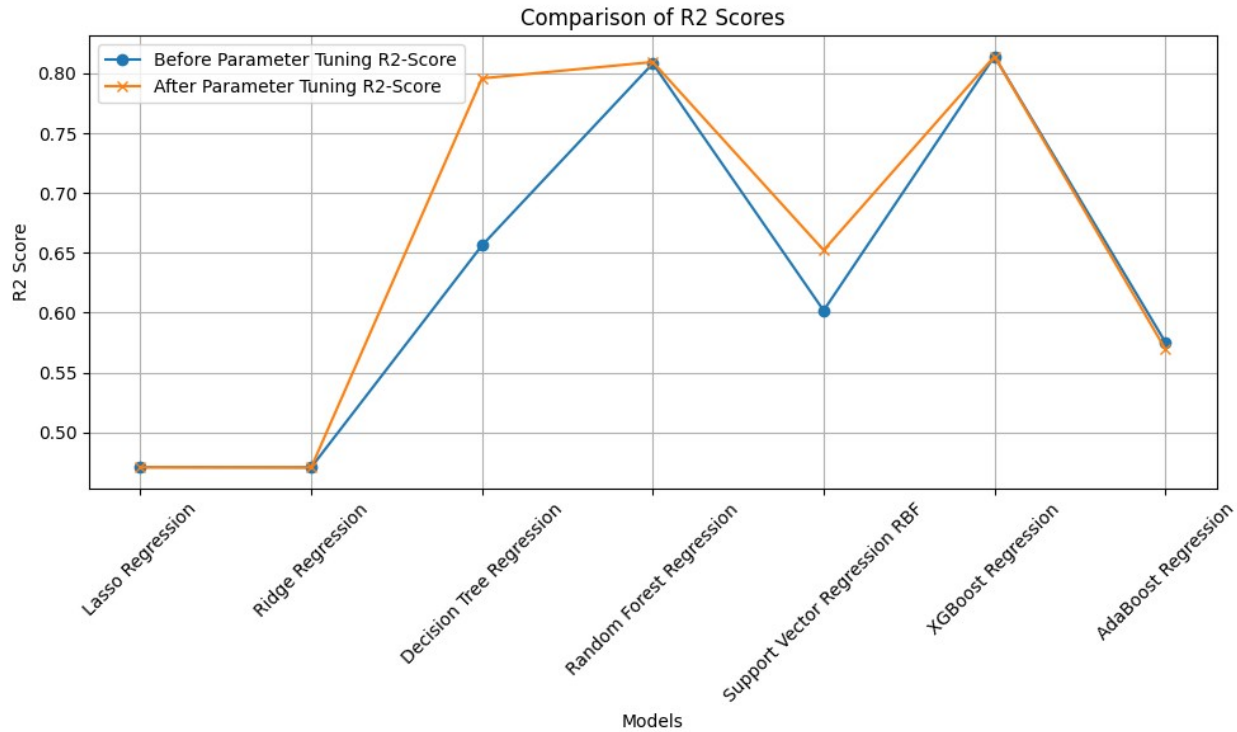
```
Support Vector Regression RBF                          4.716017
0.601854
XGBoost Regression                                     3.229385
0.814203
AdaBoost Regression                                    5.101507
0.575526
```

```
# Compare the R2 scores
metrics_df_1 = pd.read_csv('metrics_df_1.csv', index_col=0)
metrics_df_1.drop('Linear Regression', inplace=True, axis=0)
metrics_df_2 = pd.read_csv('Best_Model_Performance.csv')
models = metrics_df_2['Model Name']
plt.figure(figsize=(10, 6))
plt.title('Comparison of R2 Scores')
plt.xlabel('Models')
plt.ylabel('R2 Score')

metrics_df_1 = metrics_df_1.drop('Support Vector Regression Linear')
plt.plot(models, metrics_df_1['R-squared (R2)'], marker='o',
label='Before Parameter Tuning R2-Score')
plt.plot(models, metrics_df_2['R-squared'], marker='x', label='After
Parameter Tuning R2-Score')
# plt.plot(models, metrics_df_2['Validation R2'], marker='x',
linestyle='dashed', label='DF2 Validation R2')

plt.xticks(rotation=45)
plt.legend()
plt.grid()

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



Conclusion:

Based on the evaluation of various regression models using the engineered features, we have observed the following results:

- Xgboost stands out as the top-performing model with an impressive R2 score of 0.81. This indicates a strong ability to capture the variance in the target variable.
- Linear, ridge, and lasso regression models demonstrate similar performance, with an R2 score of 0.47. Interestingly, the inclusion of L1 and L2 regularization (lasso and ridge) did not significantly impact the model's performance.
- Random forest regression also performs exceptionally well, achieving an R2 score of 0.8. Its ensemble approach proves to be effective in capturing the complex relationships within the data.
- The Decision tree regressor, SVR (Support Vector Regression), and AdaBoost models deliver satisfactory R2 scores, indicating reasonable predictive capabilities.
- Support Vector Regression with a radial basis function kernel (SVR rbf) outperformed SVR with a linear kernel. The SVR rbf achieved a higher R2 score, demonstrating its superiority in capturing complex nonlinear patterns in the data.

- Surprisingly, the custom implementations of linear regression, ridge regression, and decision tree models yield R2 scores similar to those obtained using standard libraries, proving their correctness and reliability.
- For Artificial Neural Network (ANN), the R2 score was best when using 2 hidden layers, each with 128 neurons. This configuration achieved the highest predictive performance among the ANN models tested.
- By implementing Grid Search CV for hyperparameter tuning, we achieved notable performance improvements for the Decision tree regressor and Support vector regression models. However, other models showed limited enhancement even with hyperparameter tuning.