In [1]:
```python
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings('ignore')
from sklearn.model_selection import train_test_split
```

In [3]:
```python
df = pd.read_csv(r"C:\Users\Sandeep\OneDrive\Desktop\Coching\Resume Projects\Bus
df.head(8)
```

Out[3]:

	Unnamed: 0	key	fare_amount	pickup_datetime	pickup_longitude	pick
0	24238194	2015-05-07 19:52:06.0000003	7.5	2015-05-07 19:52:06 UTC	-73.999817	
1	27835199	2009-07-17 20:04:56.0000002	7.7	2009-07-17 20:04:56 UTC	-73.994355	
2	44984355	2009-08-24 21:45:00.00000061	12.9	2009-08-24 21:45:00 UTC	-74.005043	
3	25894730	2009-06-26 08:22:21.0000001	5.3	2009-06-26 08:22:21 UTC	-73.976124	
4	17610152	2014-08-28 17:47:00.000000188	16.0	2014-08-28 17:47:00 UTC	-73.925023	
5	44470845	2011-02-12 02:27:09.0000006	4.9	2011-02-12 02:27:09 UTC	-73.969019	
6	48725865	2014-10-12 07:04:00.0000002	24.5	2014-10-12 07:04:00 UTC	-73.961447	
7	44195482	2012-12-11 13:52:00.00000029	2.5	2012-12-11 13:52:00 UTC	0.000000	

In [4]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200000 entries, 0 to 199999
Data columns (total 9 columns):
 #   Column             Non-Null Count   Dtype  
---  ------             --------------   -----  
 0   Unnamed: 0         200000 non-null  int64  
 1   key                200000 non-null  object 
 2   fare_amount        200000 non-null  float64
 3   pickup_datetime    200000 non-null  object 
 4   pickup_longitude   200000 non-null  float64
 5   pickup_latitude    200000 non-null  float64
 6   dropoff_longitude  199999 non-null  float64
 7   dropoff_latitude   199999 non-null  float64
 8   passenger_count    200000 non-null  int64  
dtypes: float64(5), int64(2), object(2)
memory usage: 13.7+ MB
```

In [5]:
```
df.columns
```

Out[5]:
```
Index(['Unnamed: 0', 'key', 'fare_amount', 'pickup_datetime',
       'pickup_longitude', 'pickup_latitude', 'dropoff_longitude',
       'dropoff_latitude', 'passenger_count'],
      dtype='object')
```

In [6]:
```
df=df.drop(['Unnamed: 0','key','pickup_datetime'],axis=1)
df
```

Out[6]:

	fare_amount	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_lati
0	7.5	-73.999817	40.738354	-73.999512	40.72
1	7.7	-73.994355	40.728225	-73.994710	40.75
2	12.9	-74.005043	40.740770	-73.962565	40.77
3	5.3	-73.976124	40.790844	-73.965316	40.80
4	16.0	-73.925023	40.744085	-73.973082	40.76
...	...	...	...	...	
199995	3.0	-73.987042	40.739367	-73.986525	40.74
199996	7.5	-73.984722	40.736837	-74.006672	40.73
199997	30.9	-73.986017	40.756487	-73.858957	40.69
199998	14.5	-73.997124	40.725452	-73.983215	40.69
199999	14.1	-73.984395	40.720077	-73.985508	40.76

200000 rows × 6 columns

In [7]:
```
df.shape
```

Out[7]:
```
(200000, 6)
```

In [8]:
```
df.describe()
```

Out[8]:

	fare_amount	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_lati
count	200000.000000	200000.000000	200000.000000	199999.000000	199999.00
mean	11.359955	-72.527638	39.935885	-72.525292	39.92
std	9.901776	11.437787	7.720539	13.117408	6.79
min	-52.000000	-1340.648410	-74.015515	-3356.666300	-881.98
25%	6.000000	-73.992065	40.734796	-73.991407	40.73
50%	8.500000	-73.981823	40.752592	-73.980093	40.75
75%	12.500000	-73.967154	40.767158	-73.963658	40.76
max	499.000000	57.418457	1644.421482	1153.572603	872.69

In [9]:
```
df.dtypes
```

Out[9]:
```
fare_amount          float64
pickup_longitude     float64
pickup_latitude      float64
dropoff_longitude    float64
dropoff_latitude     float64
passenger_count        int64
dtype: object
```

In [10]:
```
df.isna().sum()
```

Out[10]:
```
fare_amount          0
pickup_longitude     0
pickup_latitude      0
dropoff_longitude    1
dropoff_latitude     1
passenger_count      0
dtype: int64
```

In [11]:
```
# missing values in 'dropoff_longitude' & 'dropoff_latitude'
df['dropoff_longitude']=df['dropoff_longitude'].fillna(df['dropoff_longitude'].m
df['dropoff_latitude']=df['dropoff_latitude'].fillna(df['dropoff_latitude'].mean
```

In [12]:
```
df.isna().sum()
```

Out[12]:
```
fare_amount          0
pickup_longitude     0
pickup_latitude      0
dropoff_longitude    0
dropoff_latitude     0
passenger_count      0
dtype: int64
```

In [13]:
```
df.to_csv('preprocessed_uber_data.csv', index=False)
```

In [15]:
```
# Haversine formula to calculate distance
def haversine(lon1, lat1, lon2, lat2):
    lon1, lat1, lon2, lat2 = map(np.radians, [lon1, lat1, lon2, lat2])
    dlon = lon2 - lon1
    dlat = lat2 - lat1
```

```
    a = np.sin(dlat/2)**2 + np.cos(lat1) * np.cos(lat2) * np.sin(dlon/2)**2
    c = 2 * np.arctan2(np.sqrt(a), np.sqrt(1-a))
    r = 6371 # Radius of earth in kilometers. Use 3956 for miles.
    return c * r
```

In [16]:
```
# Calculate distance for each row
df['distance_km'] = df.apply(lambda row: haversine(row['pickup_longitude'], row[
                                                   row['dropoff_longitude'], row
```

In [18]:
```
df.head(6)
```

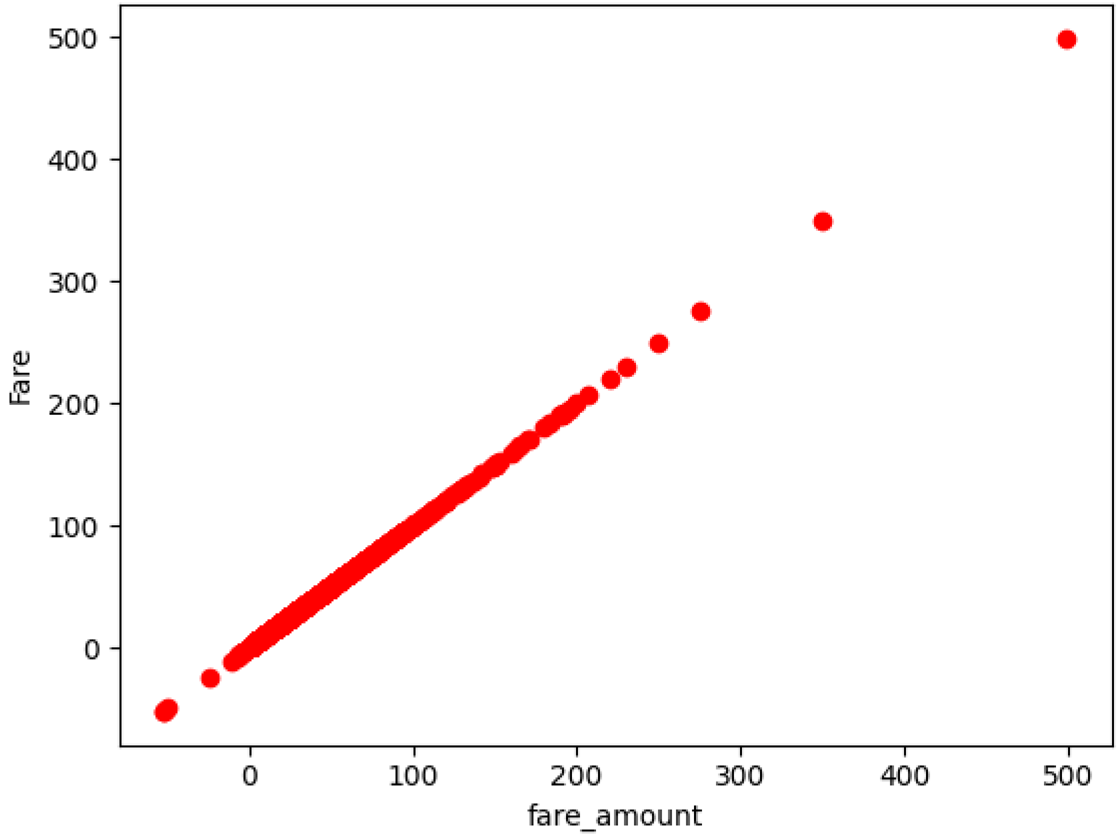
Out[18]:

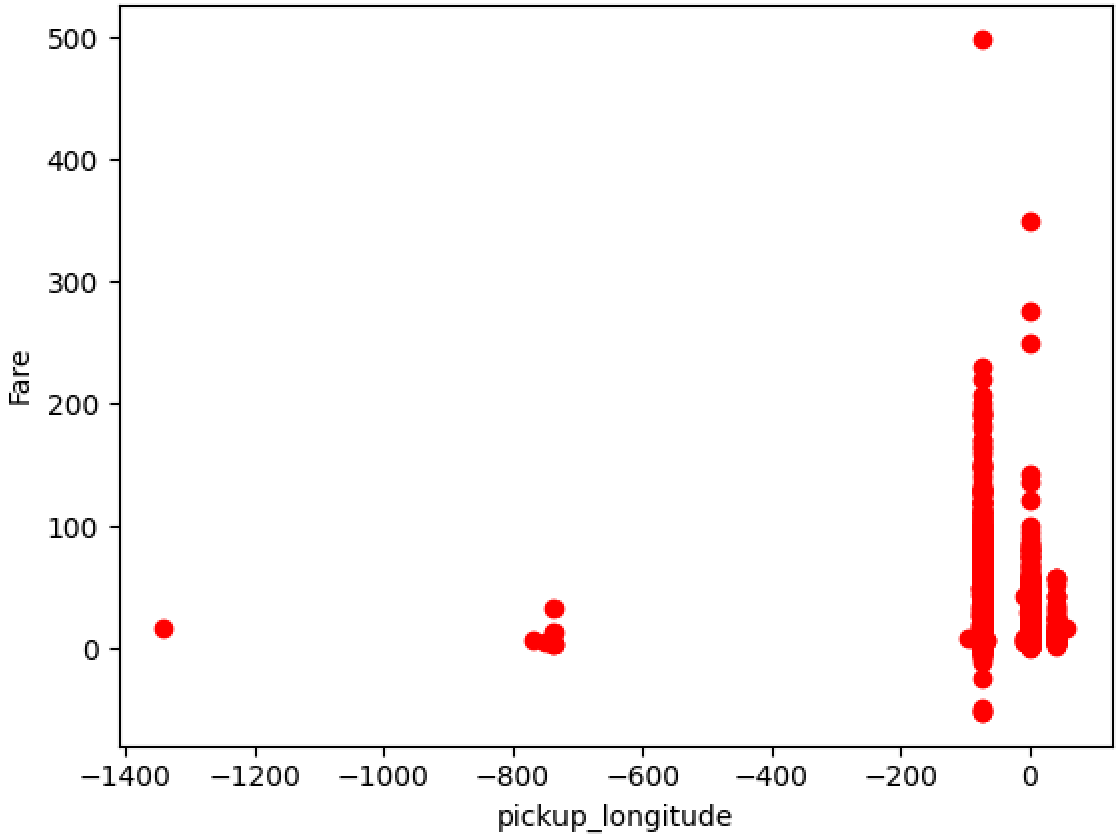
	fare_amount	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude
0	7.5	-73.999817	40.738354	-73.999512	40.723217
1	7.7	-73.994355	40.728225	-73.994710	40.750325
2	12.9	-74.005043	40.740770	-73.962565	40.772647
3	5.3	-73.976124	40.790844	-73.965316	40.803349
4	16.0	-73.925023	40.744085	-73.973082	40.761247
5	4.9	-73.969019	40.755910	-73.969019	40.755910

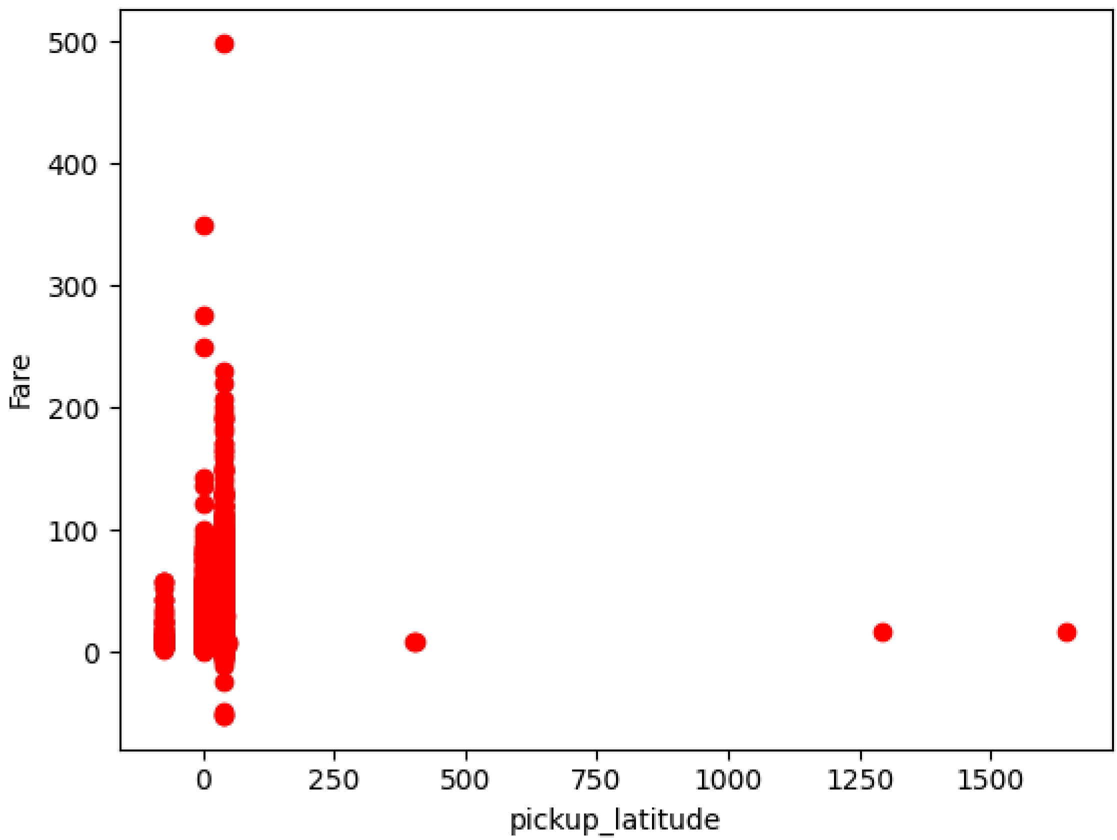
EDA(Exploratory data analysis)

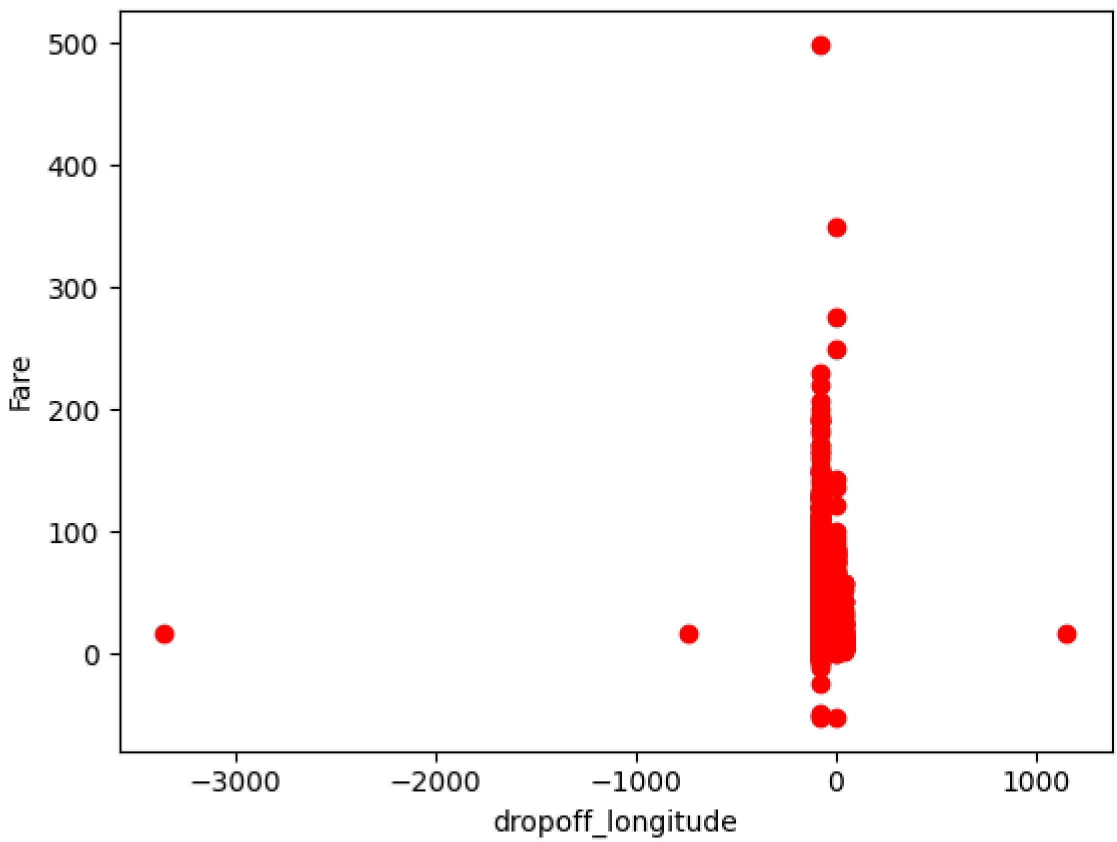
In [15]:
```
import seaborn as sns
import matplotlib.pyplot as plt
```

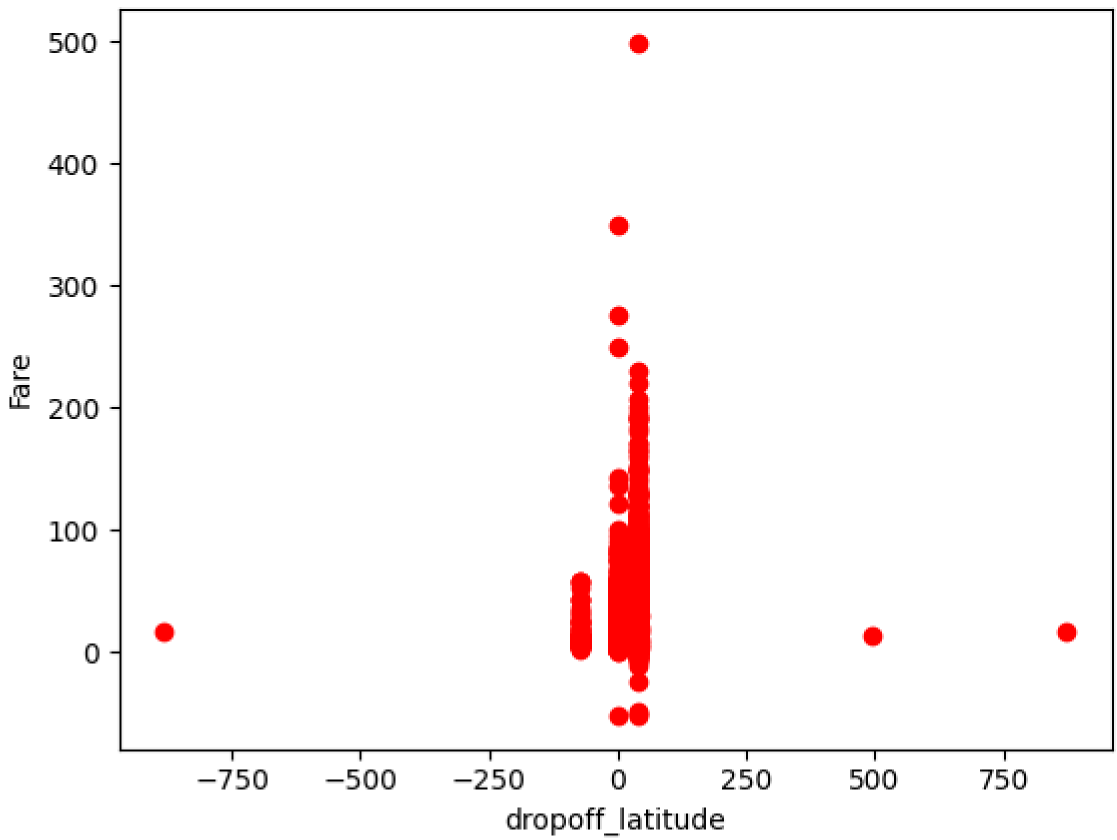
In [17]:
```
for i in df.columns:
    plt.xlabel(i)
    plt.ylabel("Fare")
    plt.scatter(df[i],df["fare_amount"],color='red')
    plt.show()
```

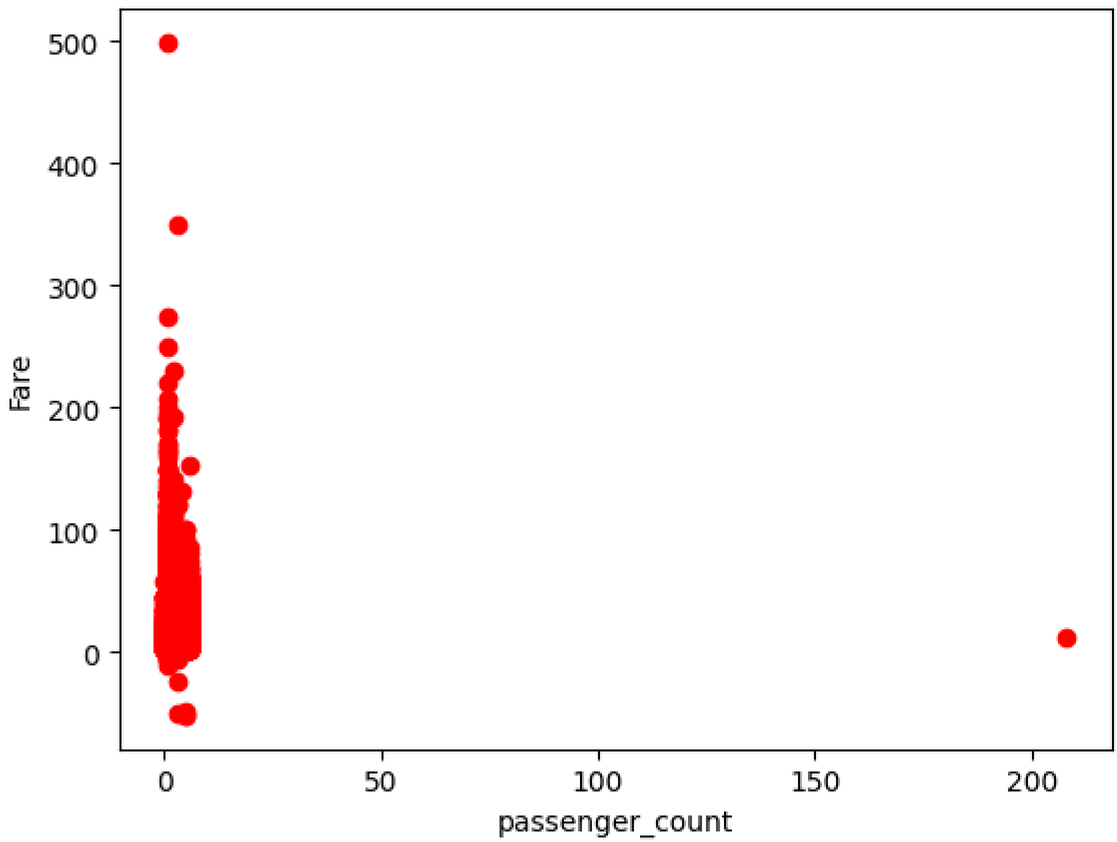

Fare
fare_amount
0
100
200
300
400
500

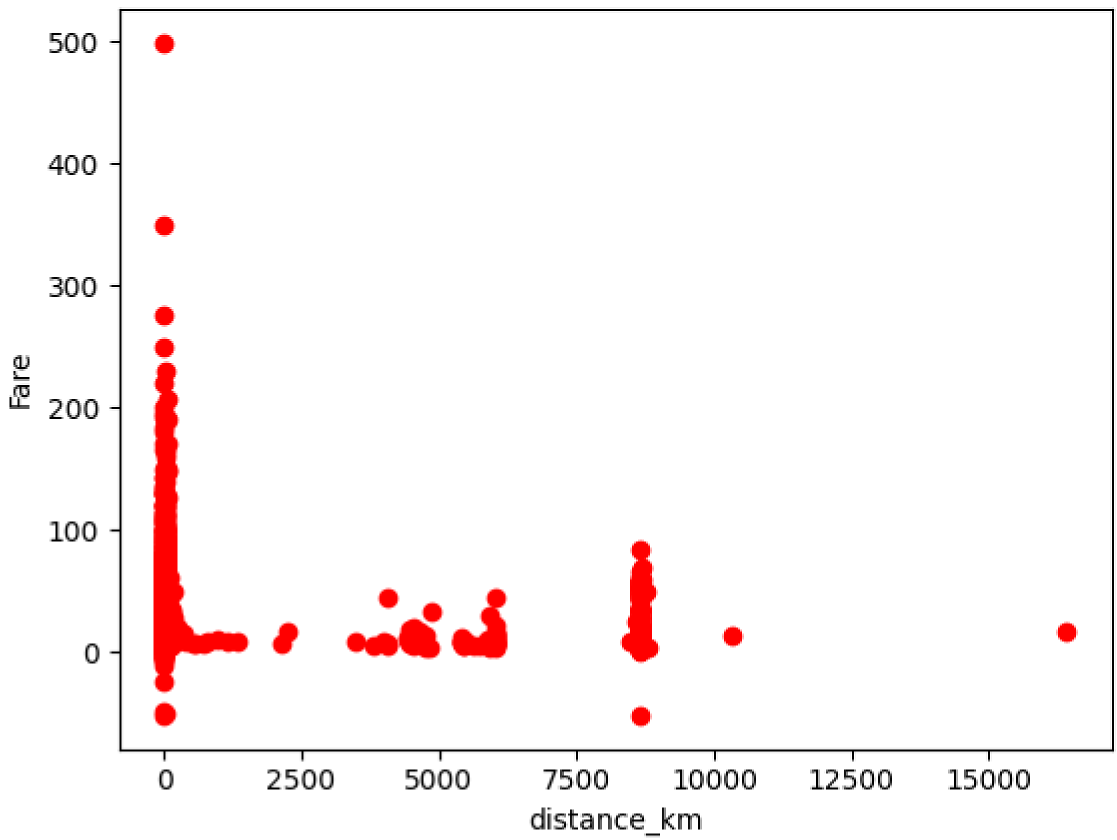

Fare
pickup_longitude
−1400
−1200
−1000
−800
−600
−400
−200
0
100
200
300
400
500


500
400
300
200
100
0
Fare
0
250
500
750
1000
1250
1500
pickup_latitude

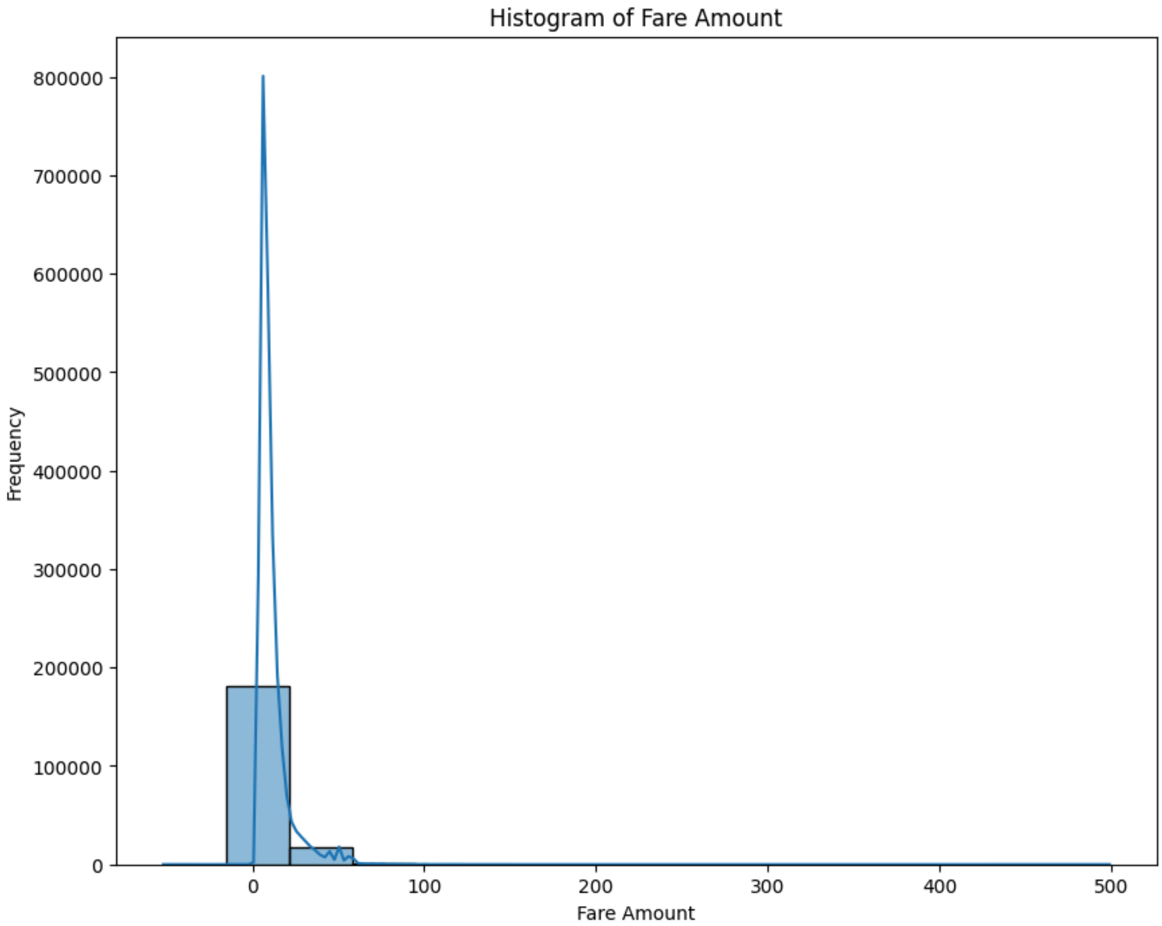

500
400
300
200
100
0
Fare
−3000
−2000
−1000
0
1000
dropoff_longitude


500
400
300
200
100
0
Fare
−750
−500
−250
0
250
500
750
dropoff_latitude

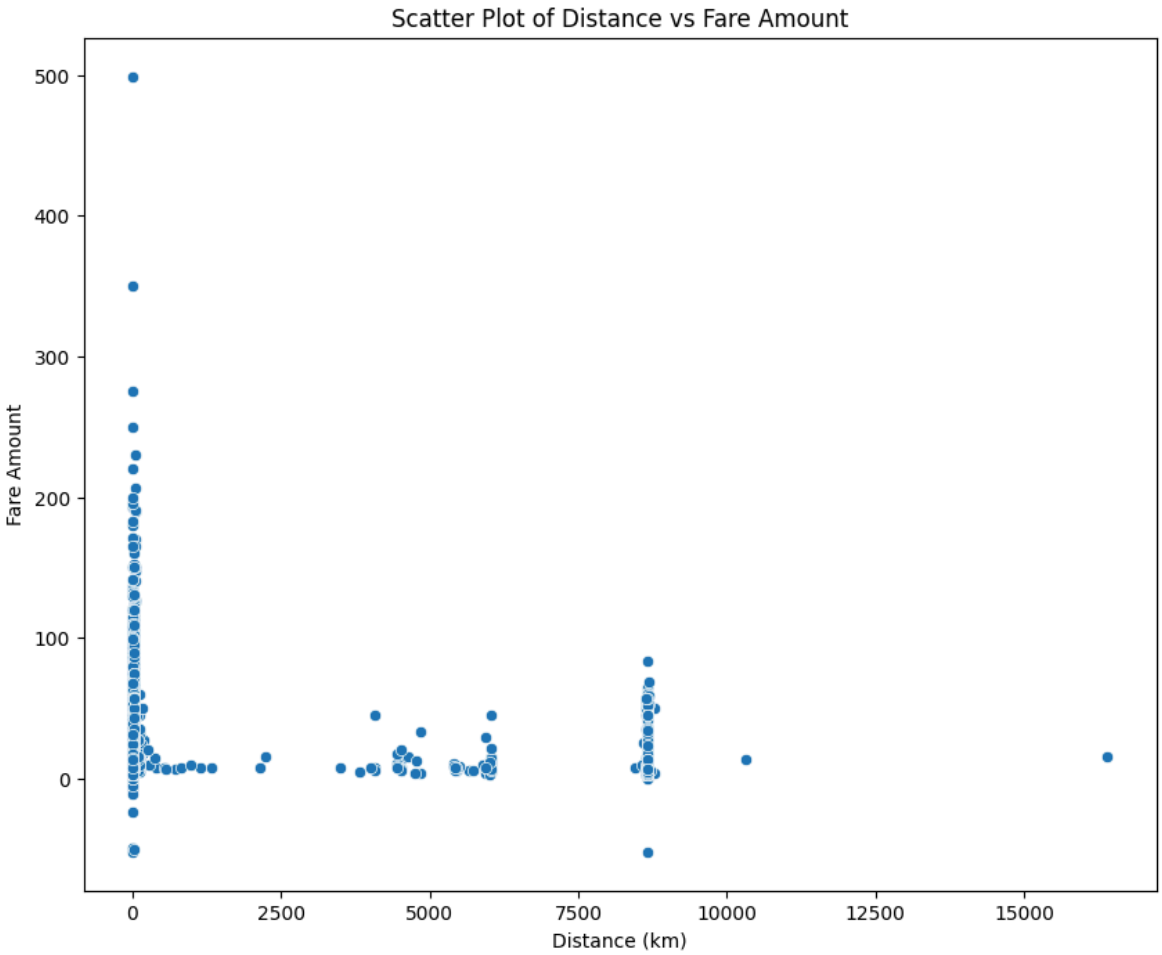

500
400
300
200
100
0
Fare
0
50
100
150
200
passenger_count



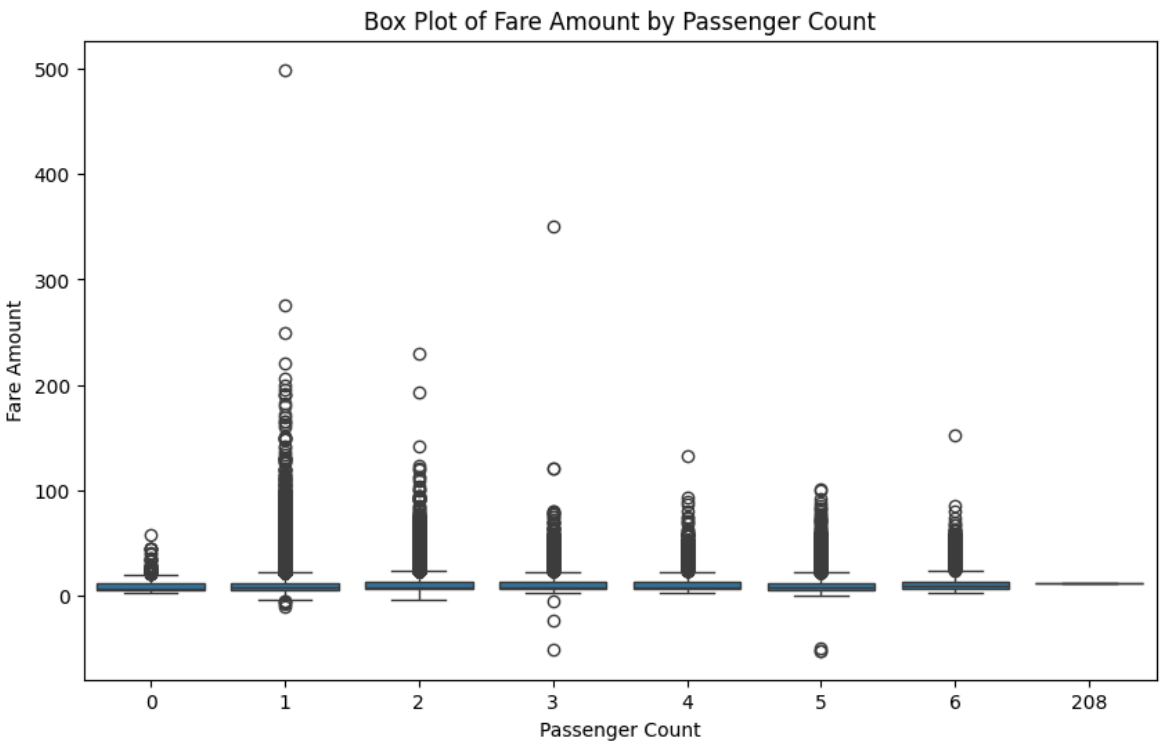
In [22]:
```
# Histogram of fare_amount
plt.figure(figsize=(10, 8))
sns.histplot(df['fare_amount'], bins=15, kde=True)
plt.title('Histogram of Fare Amount')
plt.xlabel('Fare Amount')
plt.ylabel('Frequency')
plt.show()
```



In [23]:
```
# Scatter plot of distance vs fare_amount
plt.figure(figsize=(10, 8))
sns.scatterplot(x='distance_km', y='fare_amount', data=df)
plt.title('Scatter Plot of Distance vs Fare Amount')
plt.xlabel('Distance (km)')
plt.ylabel('Fare Amount')
plt.show()
```

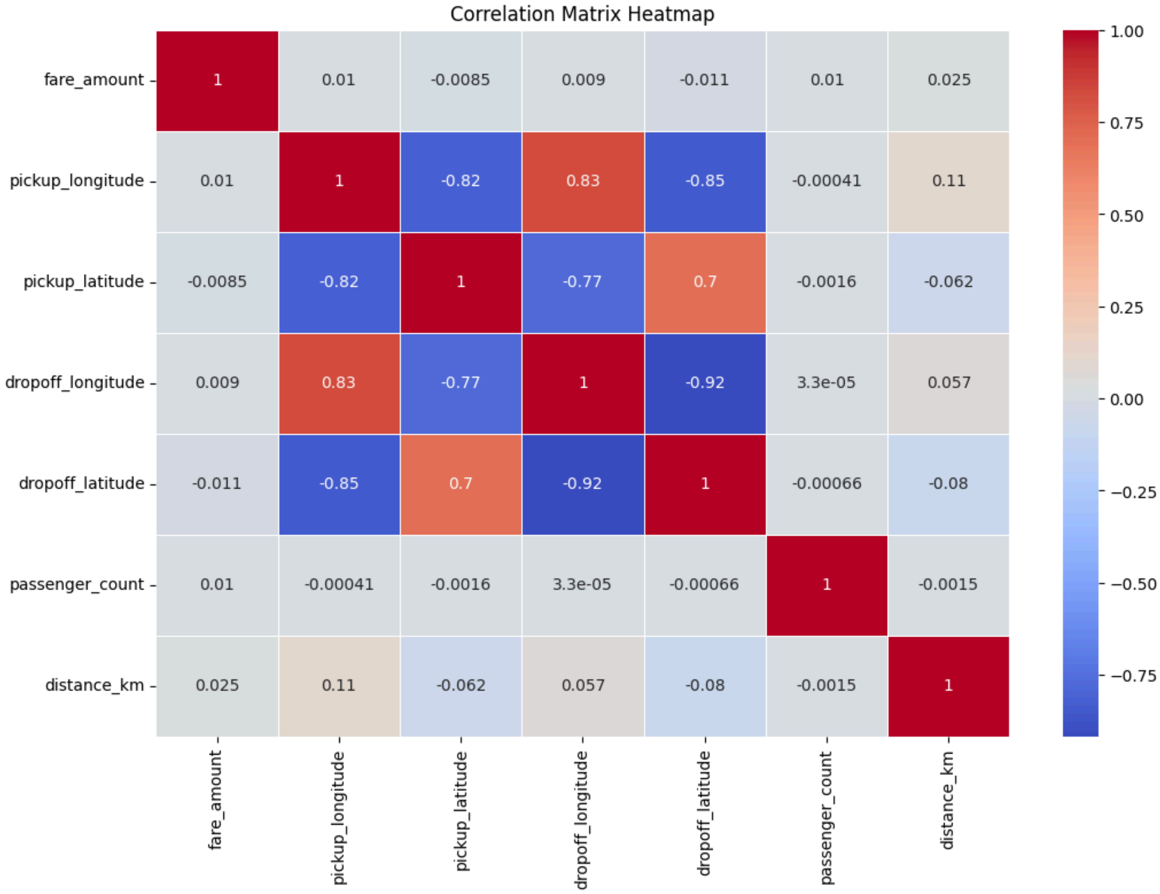


In [24]:
```python
# Box plot of fare_amount by passenger_count
plt.figure(figsize=(10, 6))
sns.boxplot(x='passenger_count', y='fare_amount', data=df)
plt.title('Box Plot of Fare Amount by Passenger Count')
plt.xlabel('Passenger Count')
plt.ylabel('Fare Amount')
plt.show()
```



In [25]:

```python
# Correlation matrix heatmap
plt.figure(figsize=(12, 8))
corr_matrix = df.corr()
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', linewidths=0.5)
plt.title('Correlation Matrix Heatmap')
plt.show()
```

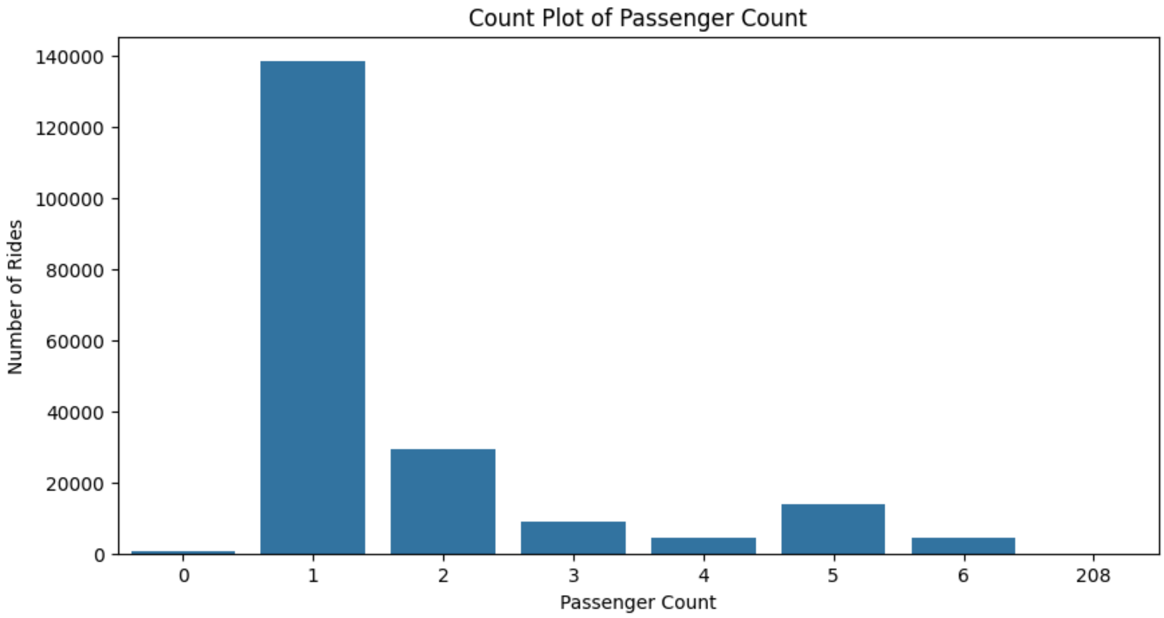


In [26]:

```python
# Pair plot
#sns.pairplot(df[['fare_amount', 'pickup_longitude', 'pickup_latitude',
#                  'dropoff_longitude', 'dropoff_latitude', 'passenger_count', 'di
#plt.suptitle('Pair Plot', y=1.02)
#plt.show()
```

In [28]:

```python
# Count plot of passenger_count
plt.figure(figsize=(10, 5))
sns.countplot(x='passenger_count', data=df)
plt.title('Count Plot of Passenger Count')
plt.xlabel('Passenger Count')
plt.ylabel('Number of Rides')
plt.show()
```



Outlier Detection and Removal Code

In [29]:
```
features = ['fare_amount', 'pickup_longitude', 'pickup_latitude', 'dropoff_longi
```

In [30]:
```
# Calculate IQR for each feature
Q1 = df[features].quantile(0.25)
Q3 = df[features].quantile(0.75)
IQR = Q3 - Q1

# Identify outliers
outliers = ((df[features] < (Q1 - 1.5 * IQR)) | (df[features] > (Q3 + 1.5 * IQR)
```

In [31]:
```
outliers
```

Out[31]:

	fare_amount	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_lati
0	False	False	False	False	
1	False	False	False	False	
2	False	False	False	False	
3	False	False	False	False	
4	False	True	False	False	
...	...	...	...	...	
199995	False	False	False	False	
199996	False	False	False	False	
199997	True	False	False	True	
199998	False	False	False	False	
199999	False	False	False	False	

200000 rows × 7 columns

In [32]:
```
df = df[~outliers.any(axis=1)]
df
```

Out[32]:

	fare_amount	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_lati
0	7.5	-73.999817	40.738354	-73.999512	40.72
1	7.7	-73.994355	40.728225	-73.994710	40.75
2	12.9	-74.005043	40.740770	-73.962565	40.77
3	5.3	-73.976124	40.790844	-73.965316	40.80
5	4.9	-73.969019	40.755910	-73.969019	40.75
...	...	...	...	...	
199994	12.0	-73.983070	40.760770	-73.972972	40.75
199995	3.0	-73.987042	40.739367	-73.986525	40.74
199996	7.5	-73.984722	40.736837	-74.006672	40.73
199998	14.5	-73.997124	40.725452	-73.983215	40.69
199999	14.1	-73.984395	40.720077	-73.985508	40.76

149726 rows × 7 columns

In [33]:
```
# splitting x(inputs) and y(outputs)

X=df.drop(['fare_amount'],axis=1)
```

```
Y=df["fare_amount"]
X
```

Out[33]:

	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passeng
0	-73.999817	40.738354	-73.999512	40.723217	
1	-73.994355	40.728225	-73.994710	40.750325	
2	-74.005043	40.740770	-73.962565	40.772647	
3	-73.976124	40.790844	-73.965316	40.803349	
5	-73.969019	40.755910	-73.969019	40.755910	
...	...	...	...	...	
199994	-73.983070	40.760770	-73.972972	40.754177	
199995	-73.987042	40.739367	-73.986525	40.740297	
199996	-73.984722	40.736837	-74.006672	40.739620	
199998	-73.997124	40.725452	-73.983215	40.695415	
199999	-73.984395	40.720077	-73.985508	40.768793	

149726 rows × 6 columns

In [35]:

```
Y
```

Out[35]:

```
0          7.5
1          7.7
2         12.9
3          5.3
5          4.9
          ...
199994    12.0
199995     3.0
199996     7.5
199998    14.5
199999    14.1
Name: fare_amount, Length: 149726, dtype: float64
```

Implementing Training and Testing

In [36]:

```
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.2, random_
```

In [37]:

```
# Preprocessing Steps

from sklearn.preprocessing import StandardScaler
scalar=StandardScaler()

scalar.fit(X_train)
```

```
X_train=scalar.fit_transform(X_train)
X_test=scalar.fit_transform(X_test)
```

In [38]:
```
# Display the sizes of the resulting datasets
print("Training set size (X_train):", X_train.shape)
print("Training set size (Y_train):", Y_train.shape)
print("Testing set size (X_test):", X_test.shape)
print("Testing set size (Y_test):", Y_test.shape)
```

```
Training set size (X_train): (119780, 6)
Training set size (Y_train): (119780,)
Testing set size (X_test): (29946, 6)
Testing set size (Y_test): (29946,)
```

In [39]:
```
from sklearn.linear_model import LinearRegression, Ridge, Lasso,ElasticNet
from sklearn.tree import DecisionTreeRegressor
from sklearn.svm import SVR
from sklearn.ensemble import RandomForestRegressor, AdaBoostRegressor, GradientB
from xgboost import XGBRegressor
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score
```

In [40]:
```
# Initialize regression models
models = {
    'Linear Regression': LinearRegression(),
    'Ridge Regression': Ridge(),
    'Lasso Regression': Lasso(),
    'ElasticNet Regression': ElasticNet(),
    'Decision Tree': DecisionTreeRegressor(random_state=0),
    'SVR': SVR(),
    'Random Forest': RandomForestRegressor(random_state=0),
    'AdaBoost': AdaBoostRegressor(random_state=0),
    'Gradient Boosting': GradientBoostingRegressor(random_state=0),
    'XGBoost': XGBRegressor(random_state=0)
}
```

In [38]:
```
# Train and evaluate each model
results = []

for name, model in models.items():
    model.fit(X_train, Y_train)
    Y_pred = model.predict(X_test)

    # Evaluate the model
    mse = mean_squared_error(Y_test, Y_pred)
    mae = mean_absolute_error(Y_test, Y_pred)
    r2 = r2_score(Y_test, Y_pred)

    # Store results
    results.append({
        'Model': name,
        'MSE': mse,
        'MAE': mae,
        'R2': r2
    })
```

In [35]:
```
# Create a DataFrame to display results
results_df = pd.DataFrame(results)

print(results_df)
```

```
                    Model        MSE       MAE        R2
0       Linear Regression   5.143903  1.629572  0.650986
1        Ridge Regression   5.143902  1.629575  0.650986
2        Lasso Regression   6.208723  1.885407  0.578738
3   ElasticNet Regression   7.063728  2.038231  0.520726
4           Decision Tree   8.891783  2.082801  0.396692
5                     SVR   4.583332  1.438178  0.689021
6           Random Forest   4.489802  1.500253  0.695367
7                AdaBoost  15.392177  3.501342 -0.044360
8       Gradient Boosting   4.718500  1.553017  0.679849
9                 XGBoost   4.274019  1.461890  0.710007
```

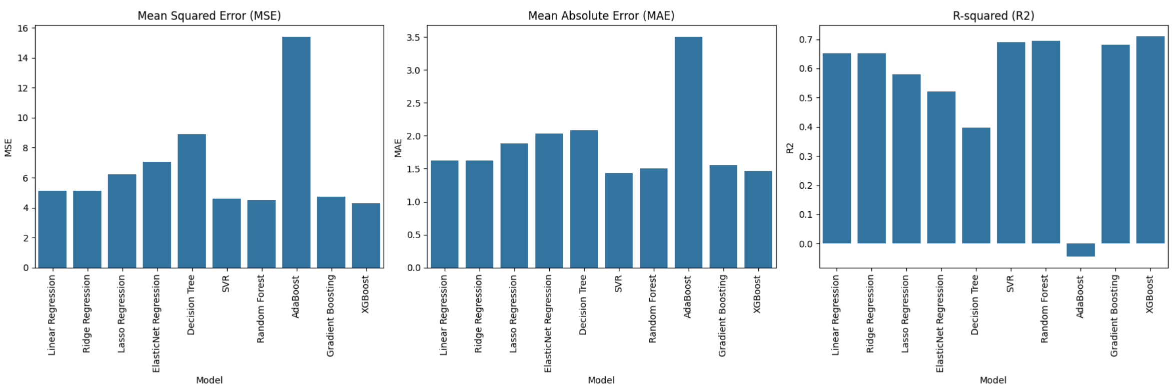
In [36]:
```python
# Visualization of performance metrics
plt.figure(figsize=(18, 6))

# Plot MSE
plt.subplot(1, 3, 1)
sns.barplot(x='Model', y='MSE', data=results_df)
plt.xticks(rotation=90)
plt.title('Mean Squared Error (MSE)')
plt.xlabel('Model')
plt.ylabel('MSE')

# Plot MAE
plt.subplot(1, 3, 2)
sns.barplot(x='Model', y='MAE', data=results_df)
plt.xticks(rotation=90)
plt.title('Mean Absolute Error (MAE)')
plt.xlabel('Model')
plt.ylabel('MAE')

# Plot R-squared
plt.subplot(1, 3, 3)
sns.barplot(x='Model', y='R2', data=results_df)
plt.xticks(rotation=90)
plt.title('R-squared (R2)')
plt.xlabel('Model')
plt.ylabel('R2')

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



In [37]:
```python
import pickle

# Assuming best_model is your trained XGBRegressor
model = RandomForestRegressor(random_state=42)
model.fit(X_train, Y_train)
```

```python
# Save the model to a file
with open('best_model.pkl', 'wb') as f:
    pickle.dump(model, f)
```