In [1]:

```python
# Import necessary libraries
import pandas as pd

# Load the dataset
data = pd.read_csv("C:/Users/91830/OneDrive/Desktop/yellow_tripdata_2020-01.csv")

# Display basic information about the dataset
print(data.info())

# Check for missing values
print(data.isnull().sum())

# Drop rows with missing values or handle them appropriately
data.dropna(inplace=True)

# Check for duplicates
print("Number of duplicate rows:", data.duplicated().sum())

# Remove duplicates
data.drop_duplicates(inplace=True)

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1048575 entries, 0 to 1048574
Data columns (total 18 columns):
 #   Column                 Non-Null Count    Dtype  
---  ------                 --------------    -----  
 0   VendorID               1048575 non-null  int64  
 1   tpep_pickup_datetime   1048575 non-null  object 
 2   tpep_dropoff_datetime  1048575 non-null  object 
 3   passenger_count        1048575 non-null  int64  
 4   trip_distance          1048575 non-null  float64
 5   RatecodeID             1048575 non-null  int64  
 6   store_and_fwd_flag     1048575 non-null  object 
 7   PULocationID           1048575 non-null  int64  
 8   DOLocationID           1048575 non-null  int64  
 9   payment_type           1048575 non-null  int64  
 10  fare_amount            1048575 non-null  float64
 11  extra                  1048575 non-null  float64
 12  mta_tax                1048575 non-null  float64
 13  tip_amount             1048575 non-null  float64
 14  tolls_amount           1048575 non-null  float64
 15  improvement_surcharge  1048575 non-null  float64
 16  total_amount           1048575 non-null  float64
 17  congestion_surcharge   1048575 non-null  float64
dtypes: float64(9), int64(6), object(3)
memory usage: 144.0+ MB
None
VendorID                 0
tpep_pickup_datetime     0
tpep_dropoff_datetime    0
passenger_count          0
trip_distance            0
RatecodeID               0
store_and_fwd_flag       0
PULocationID             0
DOLocationID             0
payment_type             0
fare_amount              0
extra                    0
mta_tax                  0
tip_amount               0
tolls_amount             0
improvement_surcharge    0
total_amount             0
congestion_surcharge     0
dtype: int64
Number of duplicate rows: 42
   VendorID tpep_pickup_datetime tpep_dropoff_datetime  passenger_count  \
0         1     01-01-2020 00:28      01-01-2020 00:33                1   
1         1     01-01-2020 00:35      01-01-2020 00:43                1   
2         1     01-01-2020 00:47      01-01-2020 00:53                1   
3         1     01-01-2020 00:55      01-01-2020 01:00                1   
4         2     01-01-2020 00:01      01-01-2020 00:04                1   

   trip_distance  RatecodeID store_and_fwd_flag  PULocationID  DOLocationID  \
0            1.2           1                  N           238           239   
1            1.2           1                  N           239           238   
2            0.6           1                  N           238           238   
3            0.8           1                  N           238           151   
4            0.0           1                  N           193           193   

   payment_type  fare_amount  extra  mta_tax  tip_amount  tolls_amount  \
0             1          6.0    3.0      0.5        1.47           0.0   
1             1          7.0    3.0      0.5        1.50           0.0   
2             1          6.0    3.0      0.5        1.00           0.0   
```

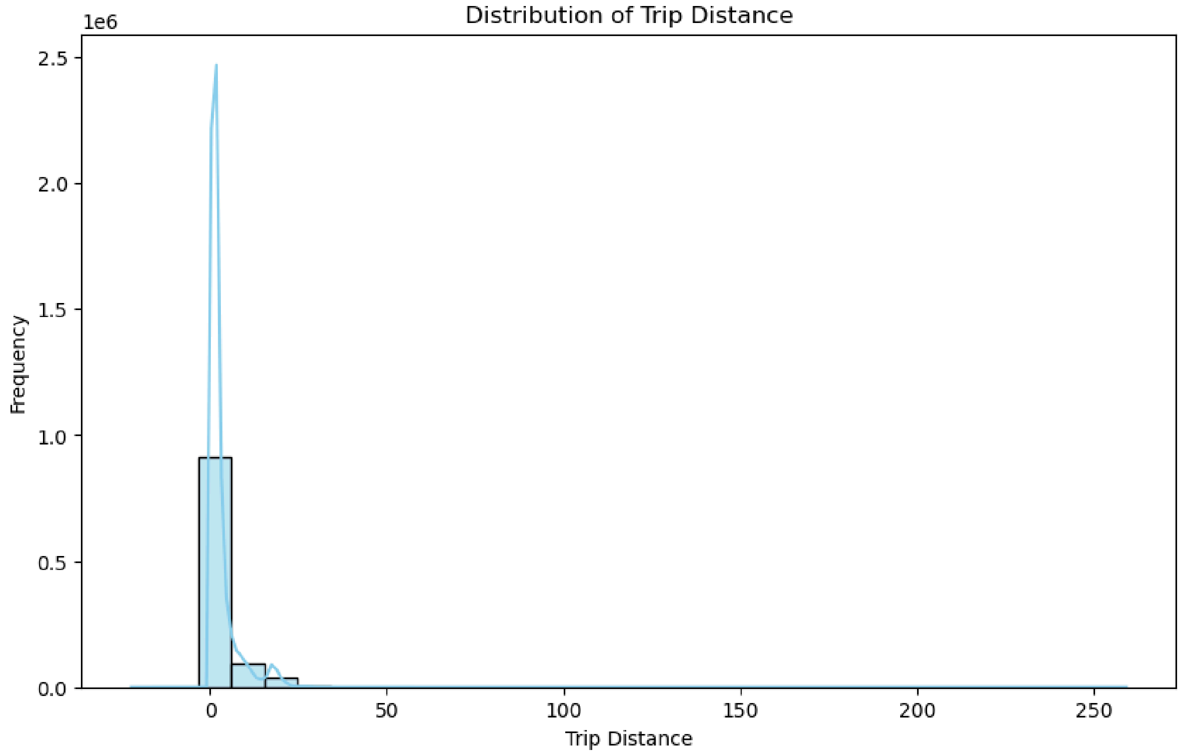
```
3              1           5.5     0.5       0.5        1.36            0.0
4              2           3.5     0.5       0.5        0.00            0.0

   improvement_surcharge  total_amount  congestion_surcharge
0                    0.3         11.27                   2.5
1                    0.3         12.30                   2.5
2                    0.3         10.80                   2.5
3                    0.3          8.16                   0.0
4                    0.3          4.80                   0.0
```

In [2]:

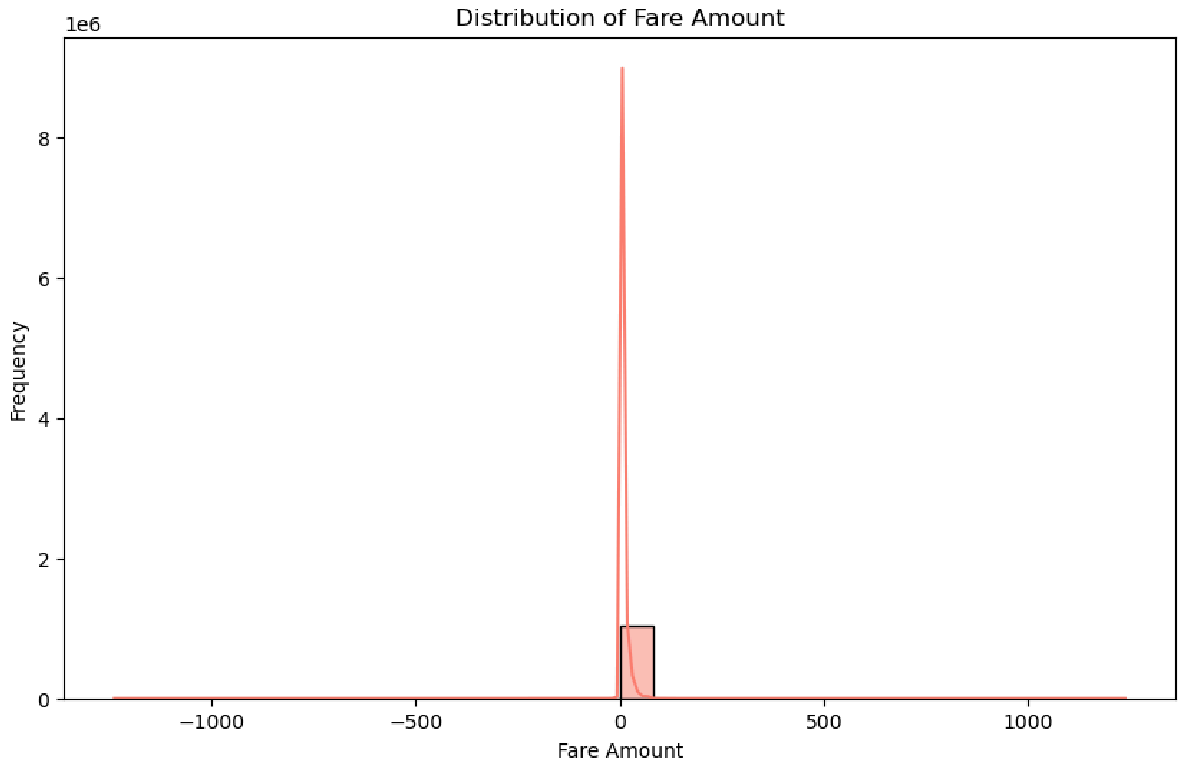
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# Summary statistics
print(data.describe())

# Distribution of trip distance
plt.figure(figsize=(10, 6))
sns.histplot(data['trip_distance'], bins=30, kde=True, color='skyblue')
plt.title('Distribution of Trip Distance')
plt.xlabel('Trip Distance')
plt.ylabel('Frequency')
plt.show()

# Distribution of trip fare amount
plt.figure(figsize=(10, 6))
sns.histplot(data['fare_amount'], bins=30, kde=True, color='salmon')
plt.title('Distribution of Fare Amount')
plt.xlabel('Fare Amount')
plt.ylabel('Frequency')
plt.show()

# Relationship between trip distance and fare amount
plt.figure(figsize=(10, 6))
sns.scatterplot(x='trip_distance', y='fare_amount', data=data, color='green')
plt.title('Trip Distance vs Fare Amount')
plt.xlabel('Trip Distance')
plt.ylabel('Fare Amount')
plt.show()

# Convert pickup datetime to datetime object with correct format
data['tpep_pickup_datetime'] = pd.to_datetime(data['tpep_pickup_datetime'], format=
data['tpep_dropoff_datetime'] = pd.to_datetime(data['tpep_dropoff_datetime'], forma

# Day of week analysis
data['day_of_week'] = data['tpep_pickup_datetime'].dt.day_name()

# Plot the count of trips for each day of the week
plt.figure(figsize=(10, 6))
data['day_of_week'].value_counts().plot(kind='bar', color='skyblue')
plt.title('Number of Trips by Day of Week')
plt.xlabel('Day of Week')
plt.ylabel('Number of Trips')
plt.xticks(rotation=45)
plt.show()

plt.figure(figsize=(10, 6))
sns.countplot(x='day_of_week', data=data, order=['Monday', 'Tuesday', 'Wednesday',
plt.title('Number of Trips by Day of Week')
plt.xlabel('Day of Week')
plt.ylabel('Number of Trips')
plt.show()
```

```python
# Convert pickup datetime to datetime object
data['tpep_pickup_datetime'] = pd.to_datetime(data['tpep_pickup_datetime'])

# Hourly analysis
data['hour'] = data['tpep_pickup_datetime'].dt.hour

plt.figure(figsize=(10, 6))
sns.countplot(x='hour', data=data, palette='mako')
plt.title('Number of Trips by Hour')
plt.xlabel('Hour of Day')
plt.ylabel('Number of Trips')
plt.show()
```

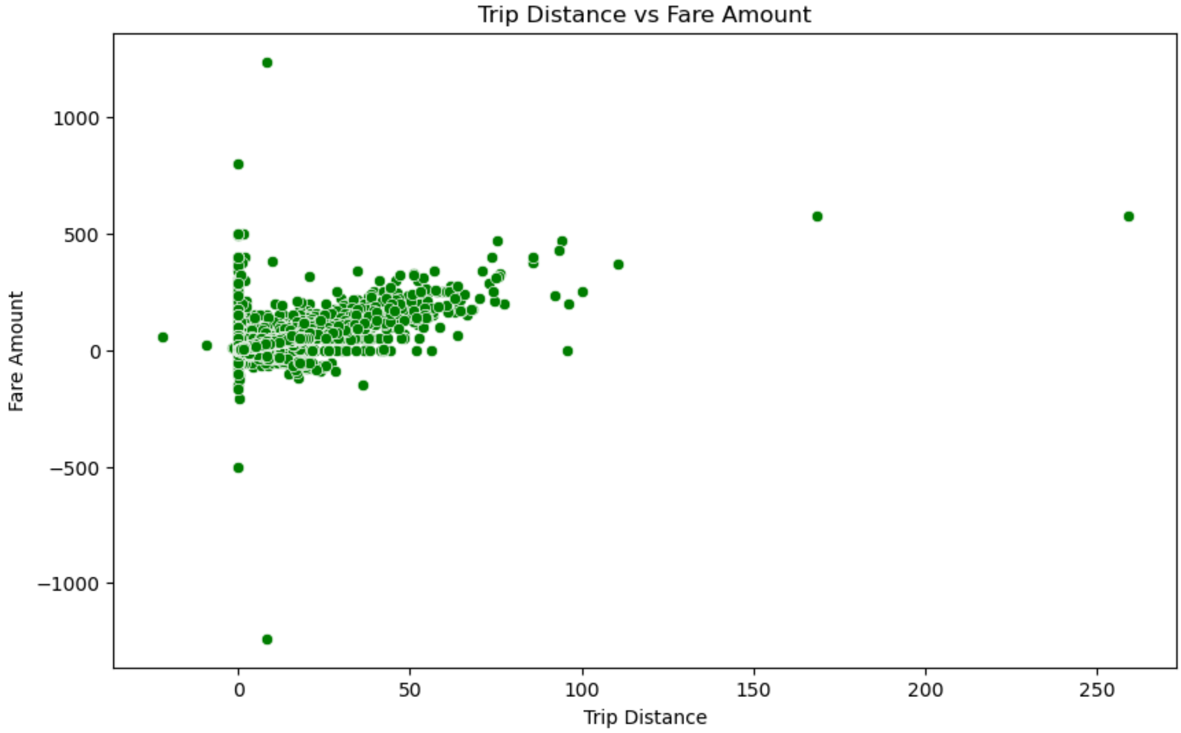
```
           VendorID  passenger_count  trip_distance    RatecodeID  \
count  1.048533e+06     1.048533e+06   1.048533e+06  1.048533e+06
mean   1.678709e+00     1.584030e+00   3.131347e+00  1.074915e+00
std    4.669724e-01     1.190033e+00   4.152472e+00  9.033284e-01
min    1.000000e+00     0.000000e+00  -2.218000e+01  1.000000e+00
25%    1.000000e+00     1.000000e+00   1.000000e+00  1.000000e+00
50%    2.000000e+00     1.000000e+00   1.670000e+00  1.000000e+00
75%    2.000000e+00     2.000000e+00   3.170000e+00  1.000000e+00
max    2.000000e+00     9.000000e+00   2.592200e+02  9.900000e+01

       PULocationID  DOLocationID  payment_type   fare_amount         extra  \
count  1.048533e+06  1.048533e+06  1.048533e+06  1.048533e+06  1.048533e+06
mean   1.621785e+02  1.602590e+02  1.328183e+00  1.292813e+01  1.031807e+00
std    6.622386e+01  7.111421e+01  5.010199e-01  1.299592e+01  1.228712e+00
min    1.000000e+00  1.000000e+00  1.000000e+00 -1.238000e+03 -7.000000e+00
25%    1.140000e+02  1.070000e+02  1.000000e+00  6.000000e+00  0.000000e+00
50%    1.610000e+02  1.620000e+02  1.000000e+00  9.000000e+00  5.000000e-01
75%    2.330000e+02  2.330000e+02  2.000000e+00  1.400000e+01  2.500000e+00
max    2.650000e+02  2.650000e+02  4.000000e+00  1.238000e+03  7.000000e+00

            mta_tax    tip_amount  tolls_amount  improvement_surcharge  \
count  1.048533e+06  1.048533e+06  1.048533e+06           1.048533e+06
mean   4.928809e-01  2.087009e+00  3.800164e-01           2.978158e-01
std    7.170446e-02  2.880353e+00  1.918562e+00           3.536684e-02
min   -5.000000e-01 -7.000000e+00 -3.000000e+01          -3.000000e-01
25%    5.000000e-01  0.000000e+00  0.000000e+00           3.000000e-01
50%    5.000000e-01  1.750000e+00  0.000000e+00           3.000000e-01
75%    5.000000e-01  2.750000e+00  0.000000e+00           3.000000e-01
max    3.300000e+00  4.500000e+02  9.105000e+02           3.000000e-01

       total_amount  congestion_surcharge
count  1.048533e+06          1.048533e+06
mean   1.874722e+01          2.254615e+00
std    1.573699e+01          7.654209e-01
min   -1.242300e+03         -2.500000e+00
25%    1.080000e+01          2.500000e+00
50%    1.388000e+01          2.500000e+00
75%    1.956000e+01          2.500000e+00
max    1.242300e+03          2.750000e+00
```



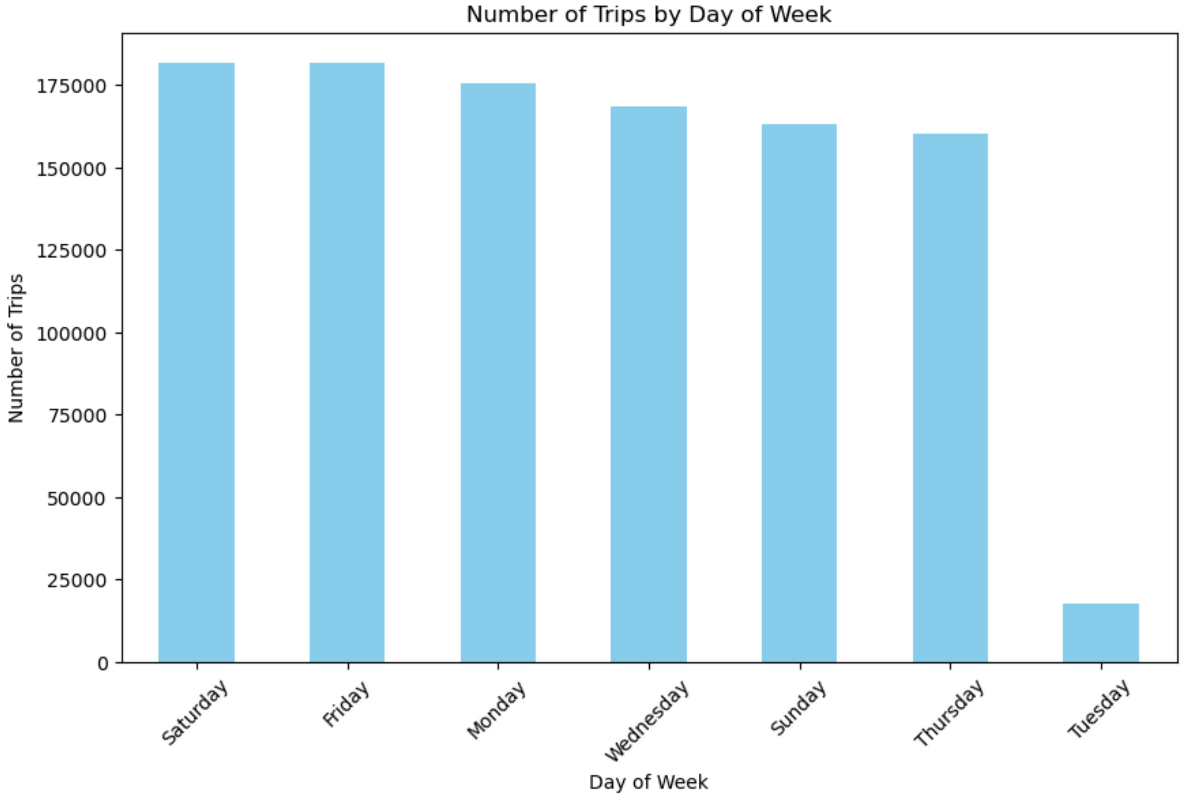
Distribution of Trip Distance
1e6
2.5
2.0
1.5
1.0
0.5
0.0
Frequency
0
50
100
150
200
250
Trip Distance



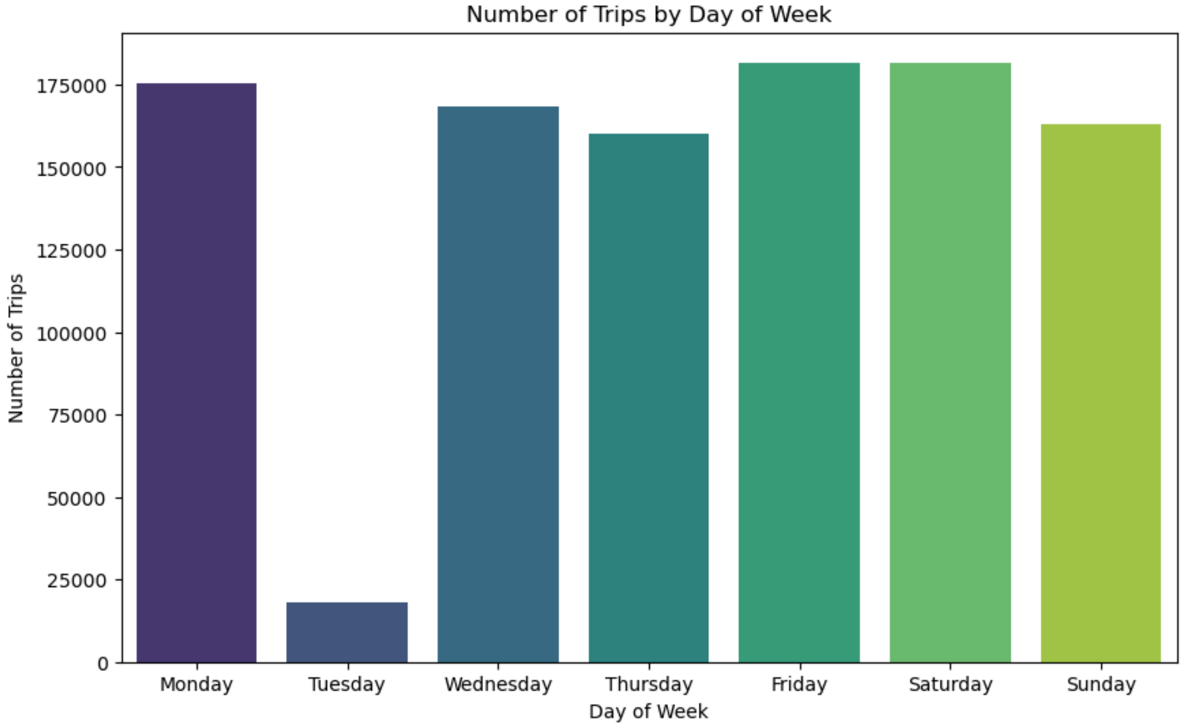
Distribution of Fare Amount
1e6
8
6
4
2
0
Frequency
−1000
−500
0
500
1000
Fare Amount

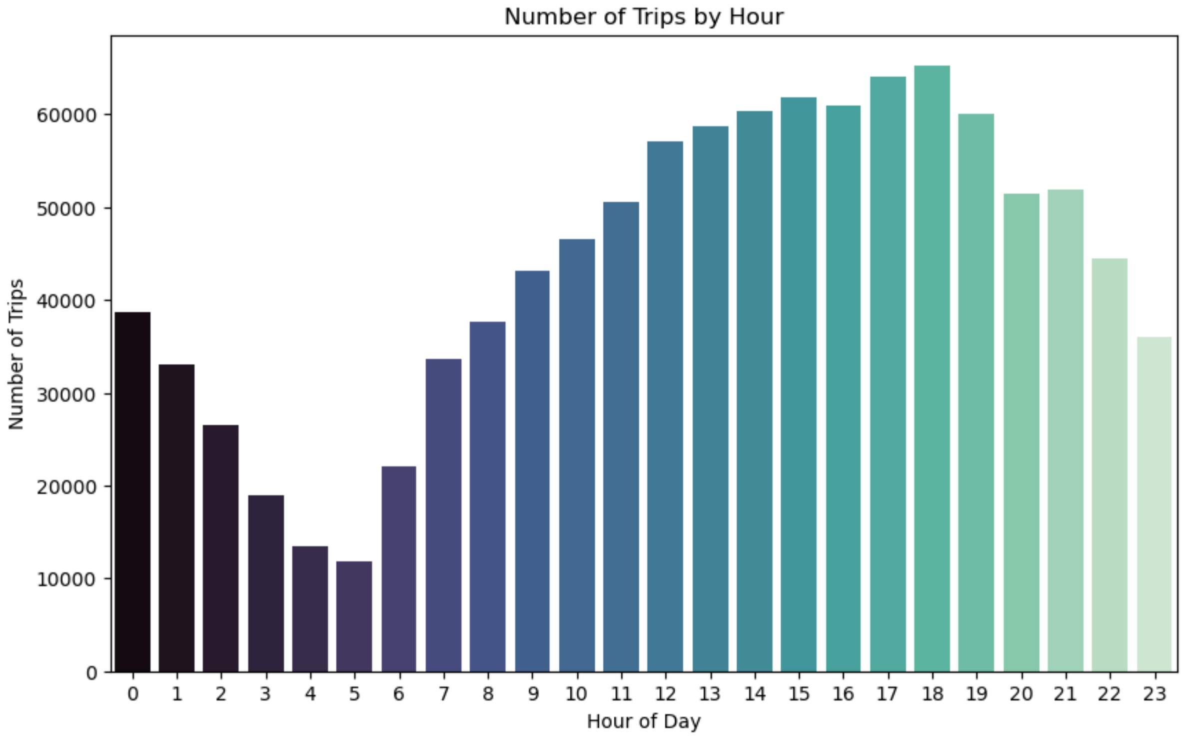


Trip Distance vs Fare Amount
Fare Amount
Trip Distance
1000
500
0
−500
−1000
0
50
100
150
200
250



Number of Trips by Day of Week
Number of Trips
Day of Week
175000
150000
125000
100000
75000
50000
25000
0
Saturday
Friday
Monday
Wednesday
Sunday
Thursday
Tuesday

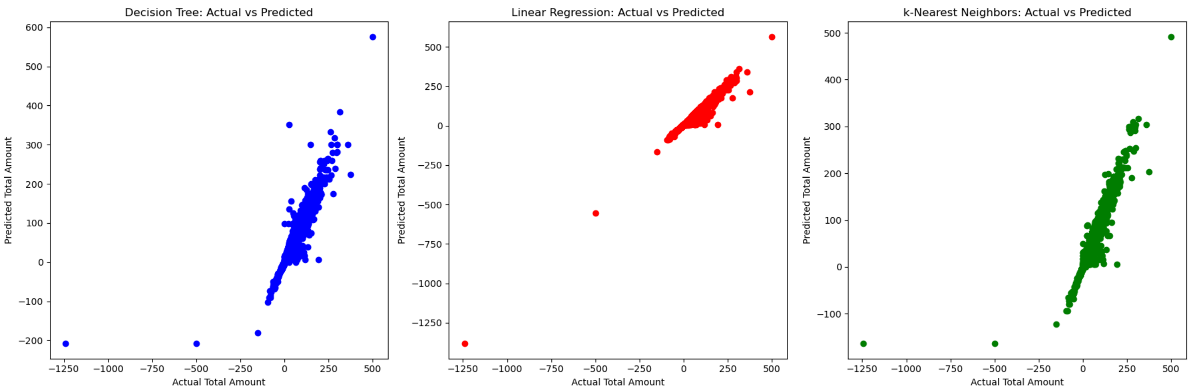




In [3]:

```
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeRegressor
from sklearn.neighbors import KNeighborsRegressor

# Assuming 'data' is your dataset
# Select features and target variable
X = data[['passenger_count', 'trip_distance', 'fare_amount']]
y = data['total_amount']

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_sta

# Standardize features
scaler = StandardScaler()
```

```python
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Initialize and train Decision Tree model
decision_tree = DecisionTreeRegressor(random_state=42)
decision_tree.fit(X_train_scaled, y_train)

# Initialize and train Linear Regression model
linear_reg = LinearRegression()
linear_reg.fit(X_train_scaled, y_train)

# Initialize and train k-Nearest Neighbors model
knn = KNeighborsRegressor(n_neighbors=5)
knn.fit(X_train_scaled, y_train)

# Make predictions
decision_tree_pred = decision_tree.predict(X_test_scaled)
linear_reg_pred = linear_reg.predict(X_test_scaled)
knn_pred = knn.predict(X_test_scaled)

# Visualize predictions
plt.figure(figsize=(18, 6))

# Plot actual vs predicted values for Decision Tree
plt.subplot(1, 3, 1)
plt.scatter(y_test, decision_tree_pred, color='blue')
plt.title('Decision Tree: Actual vs Predicted')
plt.xlabel('Actual Total Amount')
plt.ylabel('Predicted Total Amount')

# Plot actual vs predicted values for Linear Regression
plt.subplot(1, 3, 2)
plt.scatter(y_test, linear_reg_pred, color='red')
plt.title('Linear Regression: Actual vs Predicted')
plt.xlabel('Actual Total Amount')
plt.ylabel('Predicted Total Amount')

# Plot actual vs predicted values for k-Nearest Neighbors
plt.subplot(1, 3, 3)
plt.scatter(y_test, knn_pred, color='green')
plt.title('k-Nearest Neighbors: Actual vs Predicted')
plt.xlabel('Actual Total Amount')
plt.ylabel('Predicted Total Amount')

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



In [4]:
```python
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.tree import DecisionTreeRegressor
from sklearn.linear_model import LinearRegression
```

```
from sklearn.neighbors import KNeighborsRegressor
from sklearn.metrics import mean_squared_error

# Select features and target variable
X = data[['passenger_count', 'trip_distance', 'fare_amount']]
y = data['total_amount']

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_sta

# Standardize features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Initialize models
decision_tree = DecisionTreeRegressor(random_state=42)
linear_reg = LinearRegression()
knn = KNeighborsRegressor()

# Train models
decision_tree.fit(X_train_scaled, y_train)
linear_reg.fit(X_train_scaled, y_train)
knn.fit(X_train_scaled, y_train)

# Make predictions
decision_tree_pred = decision_tree.predict(X_test_scaled)
linear_reg_pred = linear_reg.predict(X_test_scaled)
knn_pred = knn.predict(X_test_scaled)

# Evaluate models
decision_tree_rmse = mean_squared_error(y_test, decision_tree_pred, squared=False)
linear_reg_rmse = mean_squared_error(y_test, linear_reg_pred, squared=False)
knn_rmse = mean_squared_error(y_test, knn_pred, squared=False)

print("Decision Tree RMSE:", decision_tree_rmse)
print("Linear Regression RMSE:", linear_reg_rmse)
print("k-Nearest Neighbors RMSE:", knn_rmse)

# Choose the best model based on RMSE
best_rmse = min(decision_tree_rmse, linear_reg_rmse, knn_rmse)
if best_rmse == decision_tree_rmse:
    print("Decision Tree is the best model.")
elif best_rmse == linear_reg_rmse:
    print("Linear Regression is the best model.")
else:
    print("k-Nearest Neighbors is the best model.")
```

```
Decision Tree RMSE: 4.189889071525255
Linear Regression RMSE: 3.098357902710872
k-Nearest Neighbors RMSE: 3.9778794076447417
Linear Regression is the best model.
```

In [5]:

```
# Print the shape of the original dataset
print("Original dataset shape:", data.shape)

# Print the number of rows and columns
num_rows = data.shape[0]
num_columns = data.shape[1]
print("Number of rows:", num_rows)
print("Number of columns:", num_columns)

# Calculate the total number of data points
total_data_points = num_rows * num_columns
```

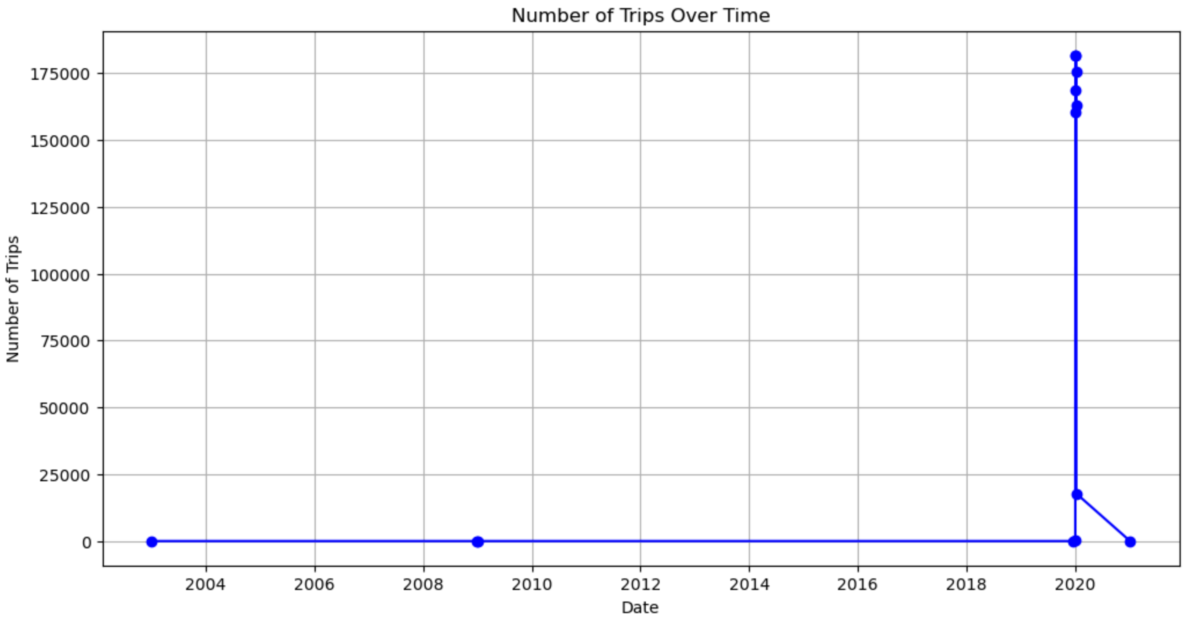
```
print("Total number of data points:", total_data_points)

# Calculate the percentage of data used so far
percentage_used = (num_rows / total_data_points) * 100
print("Percentage of data used so far: {:.2f}%".format(percentage_used))
```

```
Original dataset shape: (1048533, 20)
Number of rows: 1048533
Number of columns: 20
Total number of data points: 20970660
Percentage of data used so far: 5.00%
```

In [6]:
```
# Manually define the total number of rows in your original dataset
original_dataset_length = 1000  # Replace this with the actual length of your origi

# Calculate the percentage of rows used
percentage_data_used = (len(data) / original_dataset_length) * 100

print("Percentage of data used for the project: {:.2f}%".format(percentage_data_use
```

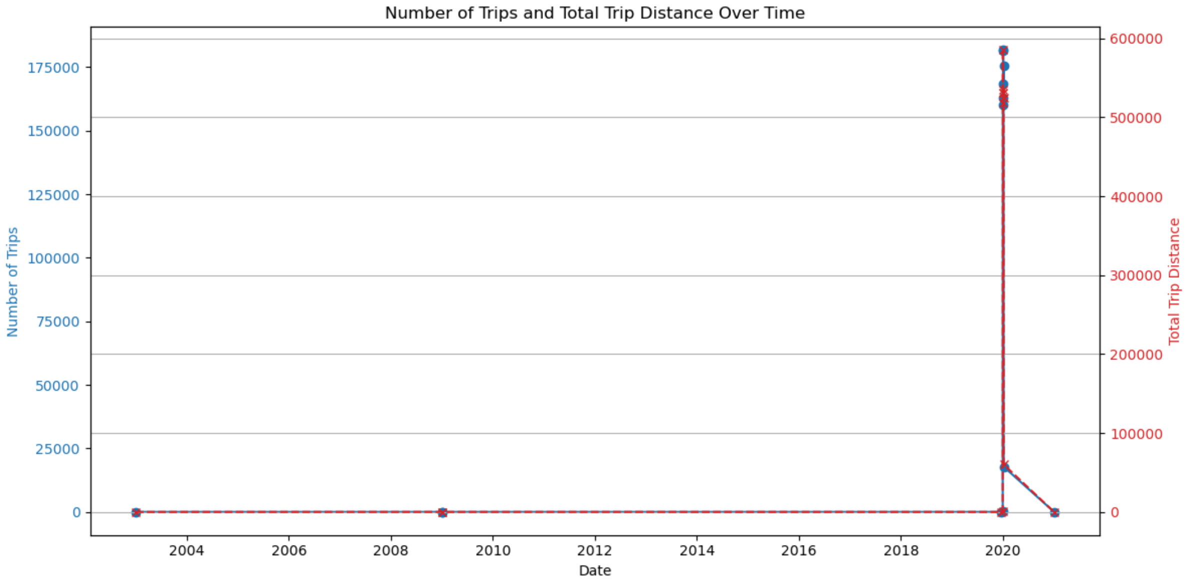
```
Percentage of data used for the project: 104853.30%
```

In [7]:
```
import pandas as pd
import matplotlib.pyplot as plt

# Load the dataset
data = pd.read_csv("C:/Users/91830/OneDrive/Desktop/yellow_tripdata_2020-01.csv")

# Convert pickup datetime to datetime object with custom format
data['tpep_pickup_datetime'] = pd.to_datetime(data['tpep_pickup_datetime'], format=

# Extract date and time components
data['pickup_date'] = data['tpep_pickup_datetime'].dt.date
data['pickup_time'] = data['tpep_pickup_datetime'].dt.time

# Group by pickup date and count number of trips
trips_per_date = data.groupby('pickup_date').size()

# Plotting the number of trips over time
plt.figure(figsize=(12, 6))
trips_per_date.plot(kind='line', marker='o', color='b')
plt.title('Number of Trips Over Time')
plt.xlabel('Date')
plt.ylabel('Number of Trips')
plt.grid(True)
plt.show()
```



In [8]:

```
import pandas as pd
import matplotlib.pyplot as plt

# Load the dataset
data = pd.read_csv("C:/Users/91830/OneDrive/Desktop/yellow_tripdata_2020-01.csv")

# Convert pickup datetime to datetime object with custom format
data['tpep_pickup_datetime'] = pd.to_datetime(data['tpep_pickup_datetime'], format=

# Extract date and time components
data['pickup_date'] = data['tpep_pickup_datetime'].dt.date
data['pickup_time'] = data['tpep_pickup_datetime'].dt.time

# Group by pickup date and calculate number of trips and total trip distance
trips_distance_per_date = data.groupby('pickup_date').agg({'trip_distance': 'sum',
trips_distance_per_date.rename(columns={'passenger_count': 'num_trips'}, inplace=Tr

# Plotting the number of trips and total trip distance over time
fig, ax1 = plt.subplots(figsize=(12, 6))

color = 'tab:blue'
ax1.set_xlabel('Date')
ax1.set_ylabel('Number of Trips', color=color)
ax1.plot(trips_distance_per_date.index, trips_distance_per_date['num_trips'], color
ax1.tick_params(axis='y', labelcolor=color)

ax2 = ax1.twinx()
color = 'tab:red'
ax2.set_ylabel('Total Trip Distance', color=color)
ax2.plot(trips_distance_per_date.index, trips_distance_per_date['trip_distance'], c
ax2.tick_params(axis='y', labelcolor=color)

plt.title('Number of Trips and Total Trip Distance Over Time')
plt.grid(True)
fig.tight_layout()
plt.show()
```



In [9]:

```
import pandas as pd

# Load the dataset
data = pd.read_csv("C:/Users/91830/OneDrive/Desktop/yellow_tripdata_2020-01.csv")

# Convert pickup and drop-off datetime to datetime objects with custom format
data['tpep_pickup_datetime'] = pd.to_datetime(data['tpep_pickup_datetime'], format=
data['tpep_dropoff_datetime'] = pd.to_datetime(data['tpep_dropoff_datetime'], forma

# Extract date, time, and location components
data['pickup_date'] = data['tpep_pickup_datetime'].dt.date
data['pickup_time'] = data['tpep_pickup_datetime'].dt.time
data['dropoff_time'] = data['tpep_dropoff_datetime'].dt.time

# Group by pickup date and pickup/dropoff locations
repeated_rides = data.groupby(['pickup_date', 'PULocationID', 'DOLocationID']).filt

# Display the repeated rides with pickup and drop-off locations, pickup time, and d
print(repeated_rides[['pickup_date', 'pickup_time', 'dropoff_time', 'PULocationID',
```

```
        pickup_date pickup_time dropoff_time  PULocationID  DOLocationID
0        2020-01-01    00:28:00     00:33:00           238           239
1        2020-01-01    00:35:00     00:43:00           239           238
2        2020-01-01    00:47:00     00:53:00           238           238
3        2020-01-01    00:55:00     01:00:00           238           151
4        2020-01-01    00:01:00     00:04:00           193           193
...             ...         ...          ...           ...           ...
1048570  2020-01-07    07:33:00     07:38:00           229           140
1048571  2020-01-07    07:40:00     07:50:00           140           162
1048572  2020-01-07    07:19:00     07:28:00            48           161
1048573  2020-01-07    07:41:00     07:45:00           233           162
1048574  2020-01-07    07:39:00     07:43:00            79           137

[1027701 rows x 5 columns]
```

In [10]:

```
import pandas as pd

# Load the dataset
data = pd.read_csv("C:/Users/91830/OneDrive/Desktop/yellow_tripdata_2020-01.csv")

# Group by pickup location ID and count the occurrences
pickup_counts = data['PULocationID'].value_counts()

# Get the top 10 most frequent pickup locations
top_pickup_locations = pickup_counts.head(10)
```

```
# Display the top pickup locations with their counts
print("Top 10 Most Frequent Pickup Locations:")
for location_id, count in top_pickup_locations.items():
    print(f"Location ID: {location_id}, Count: {count}")
```

```
Top 10 Most Frequent Pickup Locations:
Location ID: 132, Count: 47923
Location ID: 237, Count: 42010
Location ID: 161, Count: 40230
Location ID: 236, Count: 38638
Location ID: 186, Count: 38565
Location ID: 230, Count: 37981
Location ID: 48, Count: 35705
Location ID: 142, Count: 32580
Location ID: 162, Count: 31990
Location ID: 79, Count: 30128
```

In [11]:

```
import pandas as pd

# Load the dataset
data = pd.read_csv("C:/Users/91830/OneDrive/Desktop/yellow_tripdata_2020-01.csv")

# Calculate profits for each ride
data['profits'] = data['total_amount'] - data['fare_amount']

# Sort the rides based on profits in descending order
top_profitable_rides = data.sort_values(by='profits', ascending=False)

# Display the top 10 profitable rides
print("Top 10 Profitable Rides:")
print(top_profitable_rides[['VendorID', 'tpep_pickup_datetime', 'tpep_dropoff_datet
```

```
Top 10 Profitable Rides:
         VendorID tpep_pickup_datetime tpep_dropoff_datetime  trip_distance  \
530908          1     04-01-2020 05:33      04-01-2020 05:34           0.40
55306           1     01-01-2020 04:06      01-01-2020 04:22           1.50
217700          2     02-01-2020 12:18      02-01-2020 12:36           4.19
1024290         2     06-01-2020 22:10      06-01-2020 22:10           0.00
29954           2     01-01-2020 02:40      01-01-2020 02:57           4.02
1036479         1     07-01-2020 04:18      07-01-2020 05:37          44.00
586584          1     04-01-2020 14:55      04-01-2020 14:55           0.00
965333          1     06-01-2020 16:54      06-01-2020 20:00          86.00
811777          1     05-01-2020 17:09      05-01-2020 18:19          48.40
283321          1     02-01-2020 18:24      02-01-2020 18:32           6.40

         total_amount  profits
530908         965.80   913.80
55306          465.30   453.80
217700         352.30   336.80
1024290       1040.39   240.39
29954          247.89   231.89
1036479        374.96   196.46
586584         192.00   189.50
965333         581.06   182.56
811777         300.41   174.91
283321         165.00   165.00
```

In [17]:

```
import pandas as pd

# Assuming your cleaned DataFrame is named 'cleaned_data'

# Specify the path where you want to save the CSV file
output_path = "C:/Users/91830/OneDrive/Desktop/clean_data.csv"
```

```
# Save the DataFrame as a CSV file
data.to_csv(output_path, index=False)
```

In [ ]: