In [1]:
```
!pip install pandas numpy matplotlib seaborn scikit-learn
```

```
Requirement already satisfied: pandas in /home/sargam/.conda/envs/notebook
s/lib/python3.10/site-packages (2.3.3)
Requirement already satisfied: numpy in /home/sargam/.conda/envs/notebook
s/lib/python3.10/site-packages (2.2.6)
Requirement already satisfied: matplotlib in /home/sargam/.conda/envs/note
books/lib/python3.10/site-packages (3.10.6)
Requirement already satisfied: seaborn in /home/sargam/.conda/envs/noteboo
ks/lib/python3.10/site-packages (0.13.2)
Requirement already satisfied: scikit-learn in /home/sargam/.conda/envs/no
tebooks/lib/python3.10/site-packages (1.7.2)
Requirement already satisfied: python-dateutil>=2.8.2 in /home/sargam/.con
da/envs/notebooks/lib/python3.10/site-packages (from pandas) (2.9.0.post0)
Requirement already satisfied: pytz>=2020.1 in /home/sargam/.conda/envs/no
tebooks/lib/python3.10/site-packages (from pandas) (2025.2)
Requirement already satisfied: tzdata>=2022.7 in /home/sargam/.conda/envs/
notebooks/lib/python3.10/site-packages (from pandas) (2025.2)
Requirement already satisfied: contourpy>=1.0.1 in /home/sargam/.conda/env
s/notebooks/lib/python3.10/site-packages (from matplotlib) (1.3.2)
Requirement already satisfied: cycler>=0.10 in /home/sargam/.conda/envs/no
tebooks/lib/python3.10/site-packages (from matplotlib) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in /home/sargam/.conda/en
vs/notebooks/lib/python3.10/site-packages (from matplotlib) (4.60.1)
Requirement already satisfied: kiwisolver>=1.3.1 in /home/sargam/.conda/en
vs/notebooks/lib/python3.10/site-packages (from matplotlib) (1.4.9)
Requirement already satisfied: packaging>=20.0 in /home/sargam/.conda/env
s/notebooks/lib/python3.10/site-packages (from matplotlib) (25.0)
Requirement already satisfied: pillow>=8 in /home/sargam/.conda/envs/noteb
ooks/lib/python3.10/site-packages (from matplotlib) (11.3.0)
Requirement already satisfied: pyparsing>=2.3.1 in /home/sargam/.conda/env
s/notebooks/lib/python3.10/site-packages (from matplotlib) (3.2.5)
Requirement already satisfied: scipy>=1.8.0 in /home/sargam/.conda/envs/no
tebooks/lib/python3.10/site-packages (from scikit-learn) (1.15.3)
Requirement already satisfied: joblib>=1.2.0 in /home/sargam/.conda/envs/n
otebooks/lib/python3.10/site-packages (from scikit-learn) (1.5.2)
Requirement already satisfied: threadpoolctl>=3.1.0 in /home/sargam/.cond
a/envs/notebooks/lib/python3.10/site-packages (from scikit-learn) (3.6.0)
Requirement already satisfied: six>=1.5 in /home/sargam/.conda/envs/notebo
oks/lib/python3.10/site-packages (from python-dateutil>=2.8.2->pandas) (1.
17.0)
```

In [2]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error, r2_score
```

In [5]:
```
data = pd.read_csv('/home/sargam/things/college/daa/lp3/ml/uber/uber.csv'
```

In [6]:
```
print("Dataset shape:", data.shape)
print(data.info())
print(data.head())
```

```
Dataset shape: (200000, 9)
<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
None
   Unnamed: 0                            key  fare_amount  \
0    24238194    2015-05-07 19:52:06.0000003          7.5
1    27835199    2009-07-17 20:04:56.0000002          7.7
2    44984355   2009-08-24 21:45:00.00000061         12.9
3    25894730    2009-06-26 08:22:21.0000001          5.3
4    17610152  2014-08-28 17:47:00.000000188         16.0

           pickup_datetime  pickup_longitude  pickup_latitude  \
0  2015-05-07 19:52:06 UTC        -73.999817        40.738354
1  2009-07-17 20:04:56 UTC        -73.994355        40.728225
2  2009-08-24 21:45:00 UTC        -74.005043        40.740770
3  2009-06-26 08:22:21 UTC        -73.976124        40.790844
4  2014-08-28 17:47:00 UTC        -73.925023        40.744085

   dropoff_longitude  dropoff_latitude  passenger_count
0         -73.999512         40.723217                1
1         -73.994710         40.750325                1
2         -73.962565         40.772647                1
3         -73.965316         40.803349                3
4         -73.973082         40.761247                5
```

In [7]:
```
data.isnull().sum()
```

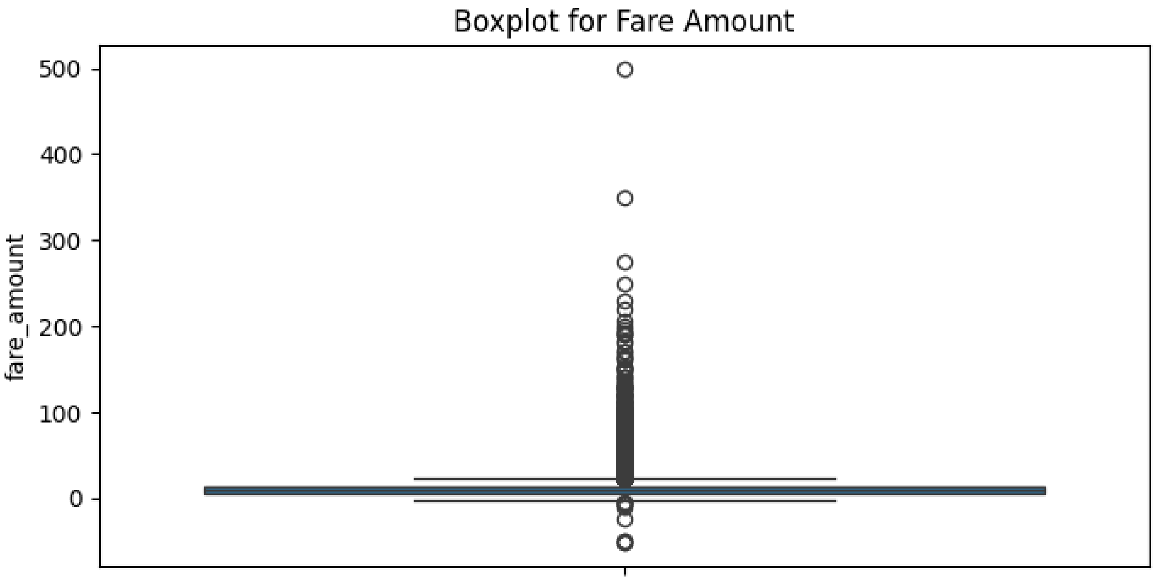
Out[7]:
```
Unnamed: 0           0
key                  0
fare_amount          0
pickup_datetime      0
pickup_longitude     0
pickup_latitude      0
dropoff_longitude    1
dropoff_latitude     1
passenger_count      0
dtype: int64
```

In [8]:
```
data['pickup_datetime'] = pd.to_datetime(data['pickup_datetime'], utc=Tru
```

In [9]:
```
data.dropna(inplace=True)
```

In [10]:
```
plt.figure(figsize=(8, 4))
sns.boxplot(data['fare_amount'])
```

```
plt.title('Boxplot for Fare Amount')
plt.show()
```

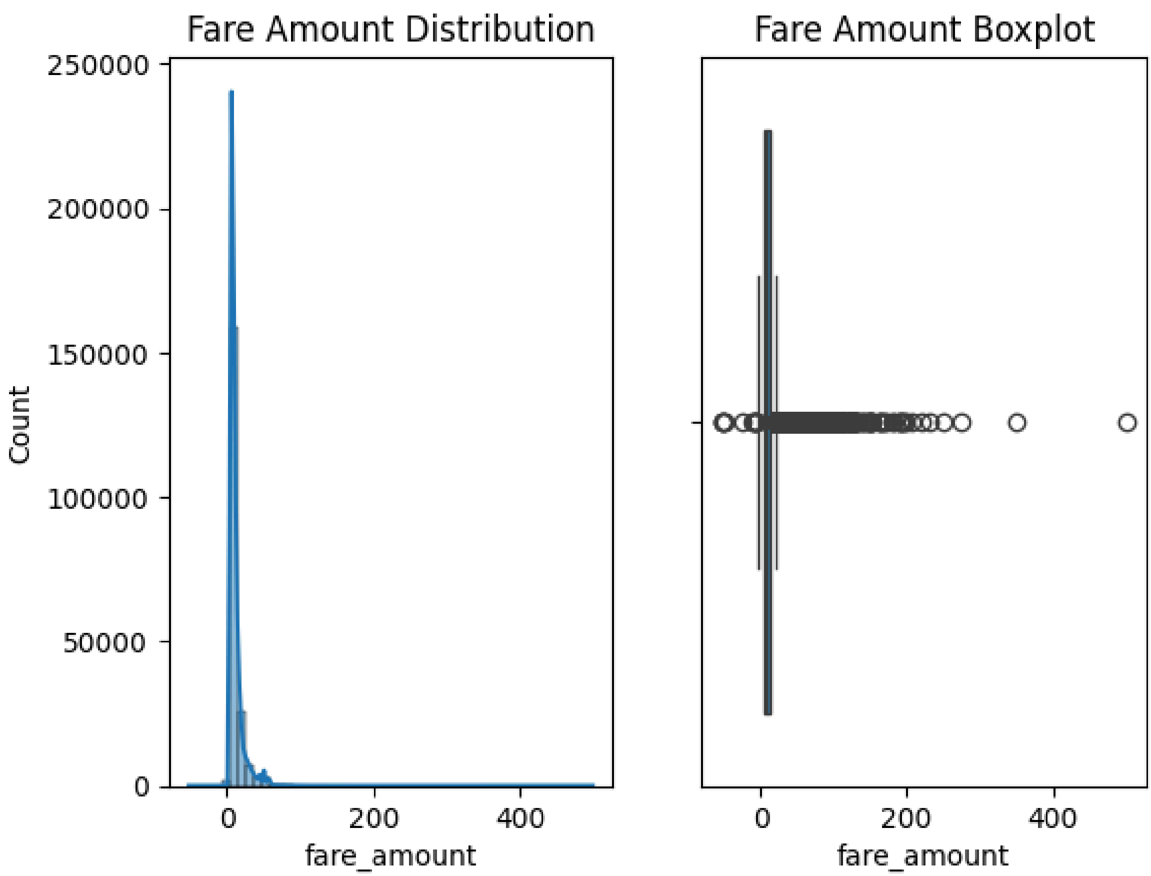



In [11]:
```
import matplotlib.pyplot as plt
import seaborn as sns

# Plot the distribution and boxplot of fare_amount to identify outliers
plt.figure(figsize=(14, 6))
```

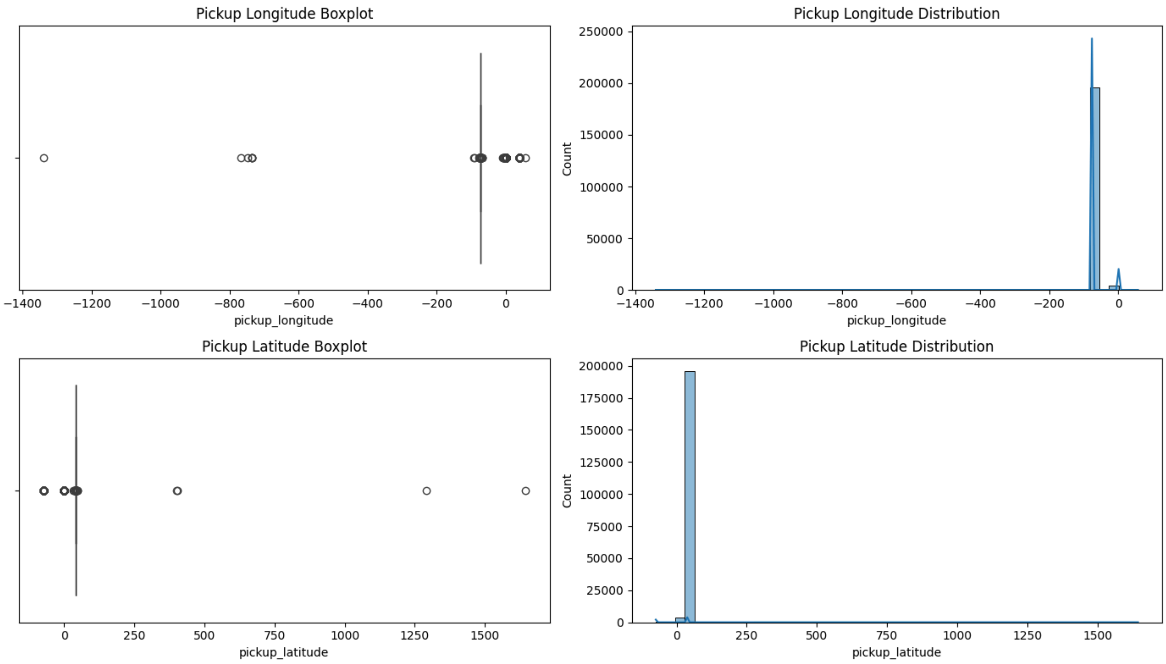
Out[11]:
```
<Figure size 1400x600 with 0 Axes>
```

```
<Figure size 1400x600 with 0 Axes>
```

In [12]:
```
plt.subplot(1, 2, 1)
sns.histplot(data['fare_amount'], bins=50, kde=True)
plt.title('Fare Amount Distribution')

plt.subplot(1, 2, 2)
sns.boxplot(x=data['fare_amount'])
plt.title('Fare Amount Boxplot')

plt.show()
```




```
In [13]: plt.figure(figsize=(14, 8))

         plt.subplot(2, 2, 1)
         sns.boxplot(x=data['pickup_longitude'])
         plt.title('Pickup Longitude Boxplot')

         plt.subplot(2, 2, 2)
         sns.histplot(data['pickup_longitude'], bins=50, kde=True)
         plt.title('Pickup Longitude Distribution')

         plt.subplot(2, 2, 3)
         sns.boxplot(x=data['pickup_latitude'])
         plt.title('Pickup Latitude Boxplot')

         plt.subplot(2, 2, 4)
         sns.histplot(data['pickup_latitude'], bins=50, kde=True)
         plt.title('Pickup Latitude Distribution')

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

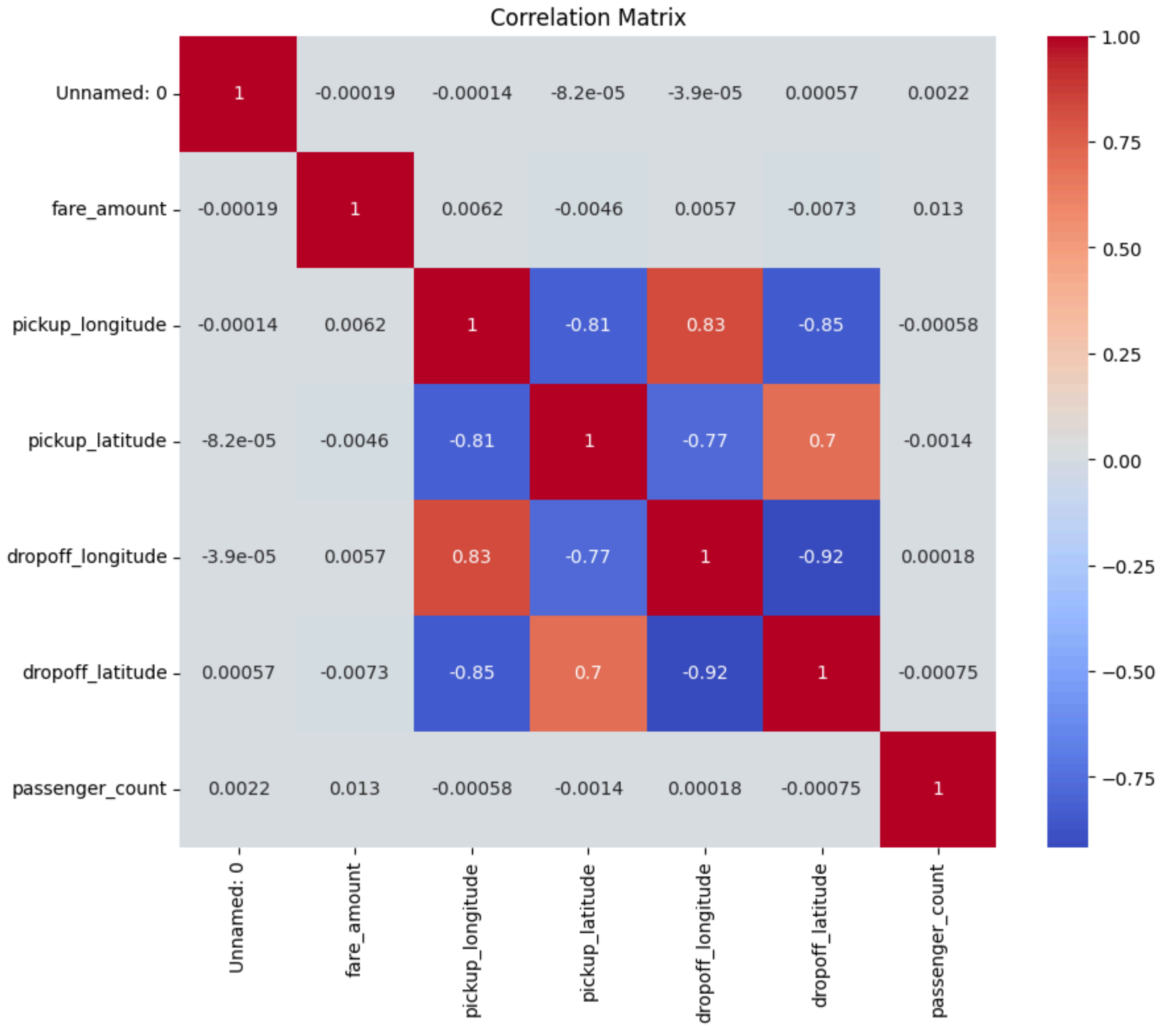



In [14]:

```
# Remove outliers outside 1st and 99th percentile
low_fare = data['fare_amount'].quantile(0.01)
high_fare = data['fare_amount'].quantile(0.99)
data = data[(data['fare_amount'] >= low_fare) & (data['fare_amount'] <= h
```

In [15]:

```
# Step 5: Correlation analysis
numeric_features = data.select_dtypes(include=[np.number])
corr = numeric_features.corr()
plt.figure(figsize=(10, 8))
sns.heatmap(corr, annot=True, cmap='coolwarm')
plt.title('Correlation Matrix')
plt.show()
```




| | Unnamed: 0 | fare_amount | pickup_longitude | pickup_latitude | dropoff_longitude | dropoff_latitude | passenger_count |
|---|---|---|---|---|---|---|---|
| Unnamed: 0 | 1 | -0.00019 | -0.00014 | -8.2e-05 | -3.9e-05 | 0.00057 | 0.0022 |
| fare_amount | -0.00019 | 1 | 0.0062 | -0.0046 | 0.0057 | -0.0073 | 0.013 |
| pickup_longitude | -0.00014 | 0.0062 | 1 | -0.81 | 0.83 | -0.85 | -0.00058 |
| pickup_latitude | -8.2e-05 | -0.0046 | -0.81 | 1 | -0.77 | 0.7 | -0.0014 |
| dropoff_longitude | -3.9e-05 | 0.0057 | 0.83 | -0.77 | 1 | -0.92 | 0.00018 |
| dropoff_latitude | 0.00057 | -0.0073 | -0.85 | 0.7 | -0.92 | 1 | -0.00075 |
| passenger_count | 0.0022 | 0.013 | -0.00058 | -0.0014 | 0.00018 | -0.00075 | 1 |

In [16]:
```
# Step 6: Feature Engineering
# Convert datetime to numerical features such as hour, day, weekday
data['pickup_hour'] = data['pickup_datetime'].dt.hour
data['pickup_day'] = data['pickup_datetime'].dt.day
data['pickup_weekday'] = data['pickup_datetime'].dt.weekday
```

In [17]:
```
# Step 7: Select Features and Target
# Drop columns that are not useful or contain identifiers
X = data.drop(columns=['fare_amount', 'pickup_datetime', 'key', 'Unnamed:
y = data['fare_amount']
```

In [18]:
```
# Step 8: Split dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
```

In [19]:
```
# Step 9: Implement Linear Regression Model
lr_model = LinearRegression()
lr_model.fit(X_train, y_train)
y_pred_lr = lr_model.predict(X_test)
```

In [20]:
```
# Step 10: Implement Random Forest Regression Model
rf_model = RandomForestRegressor(n_estimators=100, random_state=42)
rf_model.fit(X_train, y_train)
y_pred_rf = rf_model.predict(X_test)
```

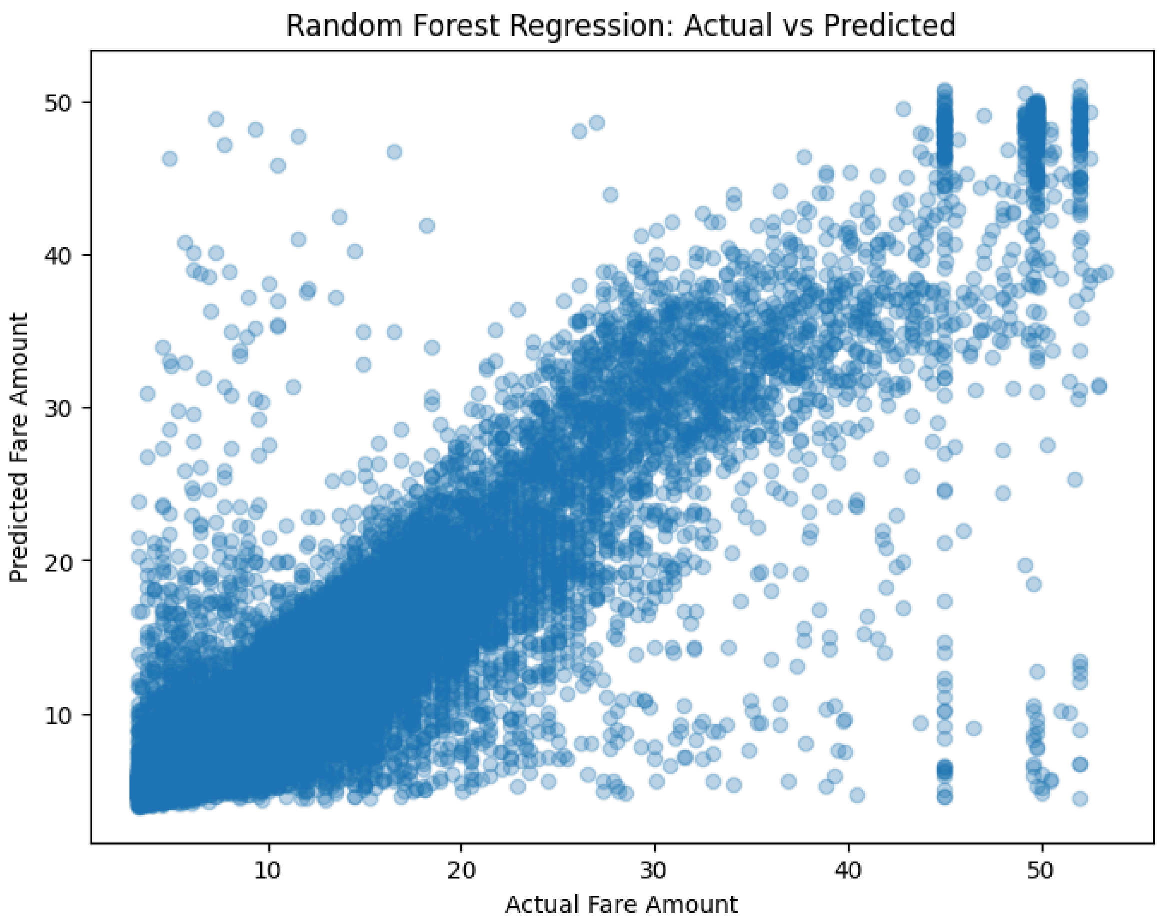
In [21]:
```
# Step 11: Evaluate models with RMSE and R2 Score
def evaluate_model(true, pred, model_name):
    rmse = np.sqrt(mean_squared_error(true, pred))
```

```
    r2 = r2_score(true, pred)
    print(f"{model_name} RMSE: {rmse:.4f}")
    print(f"{model_name} R2 Score: {r2:.4f}")
```

In [22]:
```
evaluate_model(y_test, y_pred_lr, "Linear Regression")
evaluate_model(y_test, y_pred_rf, "Random Forest Regression")
```

```
Linear Regression RMSE: 8.0621
Linear Regression R2 Score: 0.0004
Random Forest Regression RMSE: 3.5102
Random Forest Regression R2 Score: 0.8105
```

In [23]:
```
# Optional: Visualize actual vs predicted for the best model
plt.figure(figsize=(8, 6))
plt.scatter(y_test, y_pred_rf, alpha=0.3)
plt.xlabel("Actual Fare Amount")
plt.ylabel("Predicted Fare Amount")
plt.title("Random Forest Regression: Actual vs Predicted")
plt.show()
```




In [ ]: