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In [ ]: import pandas as pd
import numpy as np
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
from geopy.distance import geodesic
```

```
In [2]: # --- 1. Load the dataset ---
# Dataset Link: https://www.kaggle.com/datasets/yasserh/uber-fares-dataset
data = pd.read_csv("uber.csv")

print("Original Dataset Shape:", data.shape)
print(data.head())
```

Original Dataset Shape: (200000, 9)

	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 [3]: # --- 2. Basic cleaning ---
data = data.dropna(subset=["pickup_longitude", "pickup_latitude",
                           "dropoff_longitude", "dropoff_latitude", "fare_amount"])
```

```
In [4]: # Remove invalid or unrealistic values
data = data[(data["fare_amount"] > 0) & (data["fare_amount"] < 500)]
data = data[(data["pickup_longitude"].between(-180, 180)) &
             (data["dropoff_longitude"].between(-180, 180)) &
             (data["pickup_latitude"].between(-90, 90)) &
             (data["dropoff_latitude"].between(-90, 90))]
```

```
In [5]: # --- 3. Feature Engineering ---
# Calculate distance between pickup and dropoff points using geodesic (km)
def calculate_distance(row):
    pickup = (row["pickup_latitude"], row["pickup_longitude"])
    dropoff = (row["dropoff_latitude"], row["dropoff_longitude"])
    return geodesic(pickup, dropoff).km

data["distance_km"] = data.apply(calculate_distance, axis=1)
data = data[data["distance_km"] < 100] # remove extreme long trips
```

```
In [6]: # --- 4. Prepare data ---
X = data[["distance_km"]]
y = data["fare_amount"]

# Split into train-test
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42
)

print("\nData Ready for Training:")
print("Training Samples:", len(X_train))
print("Testing Samples:", len(X_test))
```

Data Ready for Training:
 Training Samples: 159605
 Testing Samples: 39902

```
In [7]: # --- 5. Train Linear Regression ---
lr_model = LinearRegression()
lr_model.fit(X_train, y_train)
lr_pred = lr_model.predict(X_test)
```

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In [8]: # --- 6. Train Random Forest Regressor ---
rf_model = RandomForestRegressor(n_estimators=100, random_state=42)
rf_model.fit(X_train, y_train)
rf_pred = rf_model.predict(X_test)
```

```
In [9]: # --- 7. Evaluate Models ---
print("\n--- Model Evaluation ---")

lr_r2 = r2_score(y_test, lr_pred)
lr_rmse = np.sqrt(mean_squared_error(y_test, lr_pred))
print(f"Linear Regression -> R2: {lr_r2:.4f}, RMSE: {lr_rmse:.4f}")

rf_r2 = r2_score(y_test, rf_pred)
rf_rmse = np.sqrt(mean_squared_error(y_test, rf_pred))
print(f"Random Forest      -> R2: {rf_r2:.4f}, RMSE: {rf_rmse:.4f}")
```

--- Model Evaluation ---
 Linear Regression -> R2: 0.6078, RMSE: 6.3253
 Random Forest -> R2: 0.5969, RMSE: 6.4124

```
In [10]: # --- 8. Compare Models ---
if rf_r2 > lr_r2:
    print("\nConclusion: ✅ Random Forest performs better.")
else:
    print("\nConclusion: ✅ Linear Regression performs better.")
```

Conclusion: ✅ Linear Regression performs better.

```
In [11]: # --- 9. Show sample predictions ---
results = pd.DataFrame({
    "Actual": y_test.values[:10],
    "LR_Predicted": lr_pred[:10],
    "RF_Predicted": rf_pred[:10]
})
print("\nSample Predictions:")
print(results)
```

Sample Predictions:

	Actual	LR_Predicted	RF_Predicted
0	11.3	4.331917	11.535748
1	9.3	8.224941	7.377000
2	45.0	50.388414	56.449600
3	17.5	14.334062	12.444000
4	5.0	6.568458	4.129000
5	12.1	15.512883	15.350000
6	5.7	6.008335	4.219000
7	5.7	6.753152	5.447000
8	7.3	4.331917	11.535748
9	10.9	8.451748	8.583000

In []: