0.1 CaseCraft: The Analytics Sprint – Project 12

0.1.1 Cab Route Efficiency Analysis

Subheading: Evaluating cab trip performance using synthetic geospatial and trip metadata to optimize route efficiency.

0.1.2 Project Goals

- Simulate cab trip data with pickup/dropoff coordinates, time, and fare
- Engineer features: trip distance, duration, speed, fare per km
- Visualize route paths and efficiency metrics
- Cluster trips by efficiency and time of day
- Build regression model to predict route efficiency
- Plot confusion matrix for binned efficiency categories
- Summarize insights for urban mobility optimization

[7]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from geopy.distance import geodesic
from sklearn.cluster import KMeans
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_absolute_error, confusion_matrix

np.random.seed(42)

n_trips = 1000
pickup_lat = np.random.uniform(19.0, 19.3, n_trips)
pickup_lon = np.random.uniform(72.8, 73.0, n_trips)
```

```python
drop_lat = pickup_lat + np.random.normal(0, 0.01, n_trips)
drop_lon = pickup_lon + np.random.normal(0, 0.01, n_trips)
duration_min = np.random.uniform(5, 45, n_trips)
fare = duration_min * np.random.uniform(0.8, 1.5, n_trips)
time_of_day = np.random.choice(['Morning', 'Afternoon', 'Evening', 'Night'],␣
 ↪n_trips)

distance_km = [geodesic((pickup_lat[i], pickup_lon[i]), (drop_lat[i],␣
 ↪drop_lon[i])).km for i in range(n_trips)]
speed_kmph = np.array(distance_km) / (duration_min / 60)
fare_per_km = fare / np.array(distance_km)

df = pd.DataFrame({
    'pickup_lat': pickup_lat,
    'pickup_lon': pickup_lon,
    'drop_lat': drop_lat,
    'drop_lon': drop_lon,
    'duration_min': duration_min,
    'fare': fare,
    'distance_km': distance_km,
    'speed_kmph': speed_kmph,
    'fare_per_km': fare_per_km,
    'time_of_day': time_of_day
})
```

[8]:

```python
df.head(10)
```

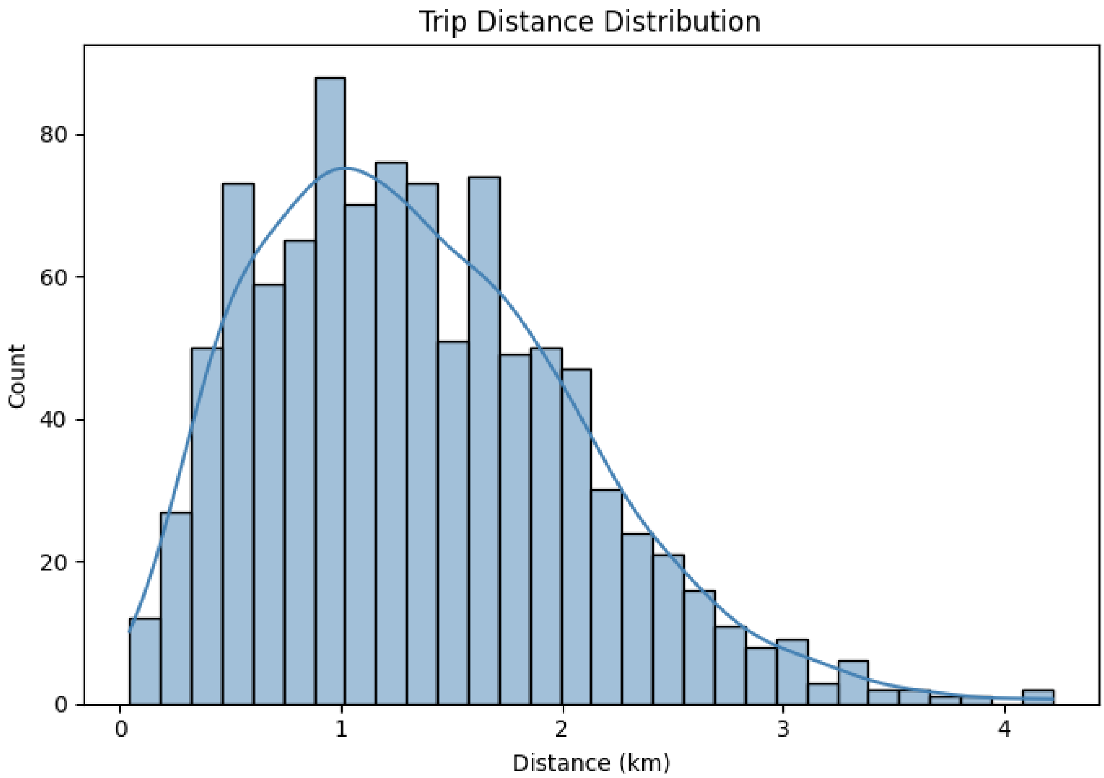
[8]:

```
   pickup_lat  pickup_lon   drop_lat   drop_lon  duration_min       fare  \
0   19.112362   72.837027  19.103582  72.855736     28.971971  33.697981
1   19.285214   72.908380  19.276945  72.912276     25.548314  21.353686
2   19.219598   72.974589  19.217333  72.965906     16.527381  15.915884
3   19.179598   72.946445  19.183271  72.951791      5.258574   6.017919
4   19.046806   72.961312  19.055941  72.934955     24.849569  25.276104
5   19.046798   72.931757  19.038767  72.931790     16.425040  15.229864
6   19.017425   72.938455  19.032352  72.941734     34.384332  39.641455
7   19.259853   72.969839  19.257142  72.979082      5.957851   6.112557
8   19.180335   72.849934  19.180121  72.839795     28.393112  27.844425
9   19.212422   72.897885  19.204950  72.898742     42.658970  47.982373

   distance_km  speed_kmph  fare_per_km time_of_day
0     2.195522    4.546855    15.348502   Afternoon
1     1.002762    2.354977    21.294878     Evening
2     0.946836    3.437336    16.809548     Morning
3     0.693943    7.917850     8.672060     Evening
4     2.952939    7.129956     8.559643   Afternoon
5     0.889067    3.247724    17.130171       Night
6     1.687950    2.945441    23.484965     Evening
```

```
7      1.016964   10.241582     6.010596     Morning
8      1.066659    2.254052    26.104335       Night
9      0.832017    1.170235    57.669968     Evening
```

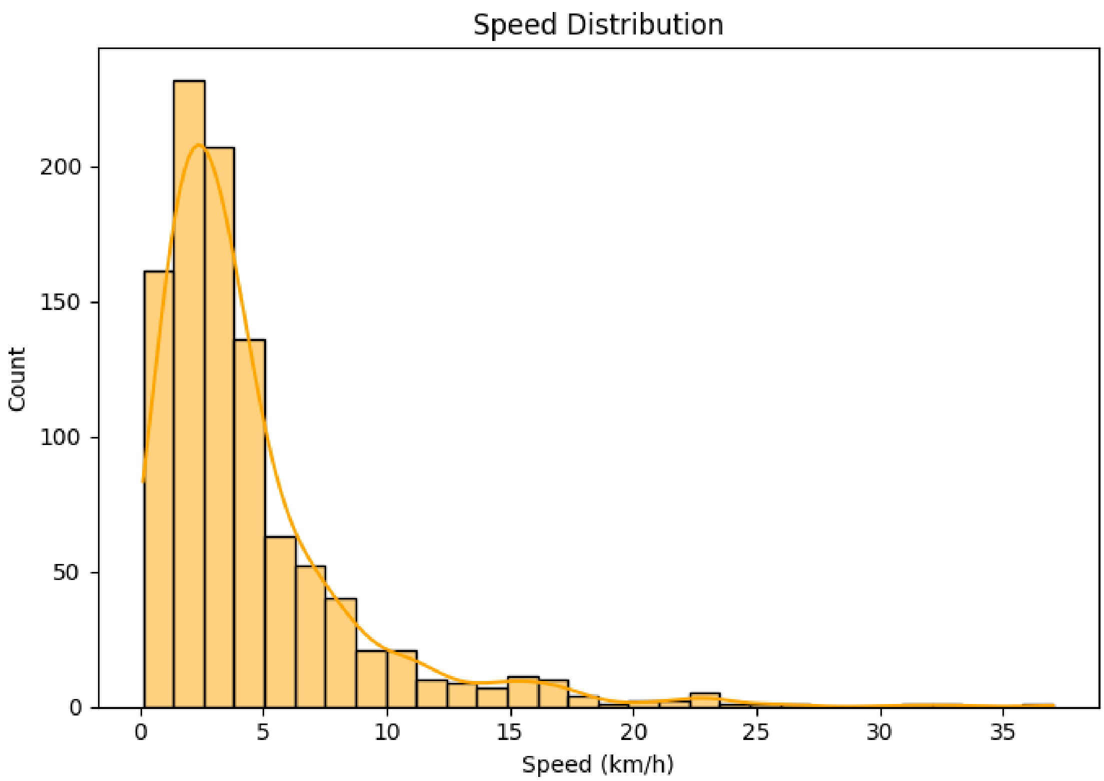
0.1.3 Trip Distance Distribution

[9]:
```python
plt.figure(figsize=(7, 5))
sns.histplot(df['distance_km'], bins=30, kde=True, color='steelblue')
plt.title("Trip Distance Distribution")
plt.xlabel("Distance (km)")
plt.tight_layout()
plt.show()
```



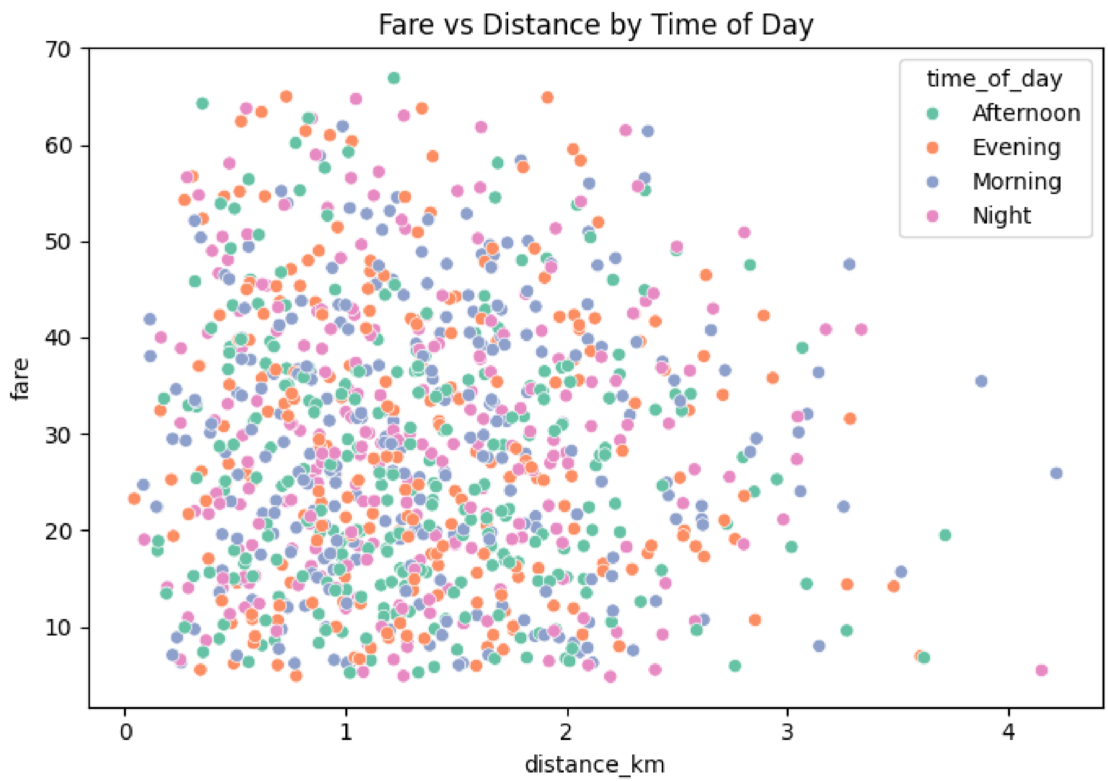
0.1.4 Speed Distribution

[10]:
```python
plt.figure(figsize=(7, 5))
sns.histplot(df['speed_kmph'], bins=30, kde=True, color='orange')
plt.title("Speed Distribution")
plt.xlabel("Speed (km/h)")
plt.tight_layout()
plt.show()
```



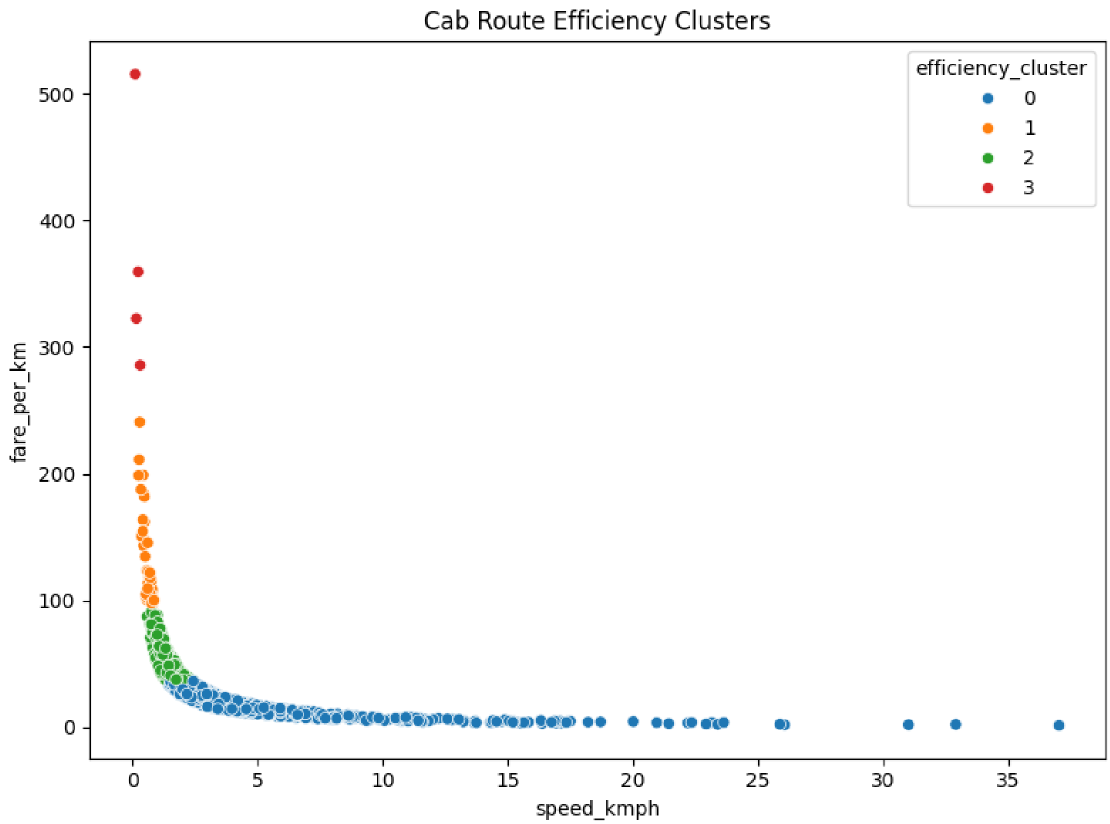
0.1.5 Fare vs Distance

[11]:
```
plt.figure(figsize=(7, 5))
sns.scatterplot(data=df, x='distance_km', y='fare', hue='time_of_day',␣
 ↪palette='Set2')
plt.title("Fare vs Distance by Time of Day")
plt.tight_layout()
plt.show()
```



0.1.6 Route Efficiency Clustering

[12]:
```
X_cluster = df[['speed_kmph', 'fare_per_km']]
kmeans = KMeans(n_clusters=4, random_state=42)
df['efficiency_cluster'] = kmeans.fit_predict(X_cluster)

plt.figure(figsize=(8, 6))
sns.scatterplot(data=df, x='speed_kmph', y='fare_per_km',␣
↪hue='efficiency_cluster', palette='tab10')
plt.title("Cab Route Efficiency Clusters")
plt.tight_layout()
plt.show()
```



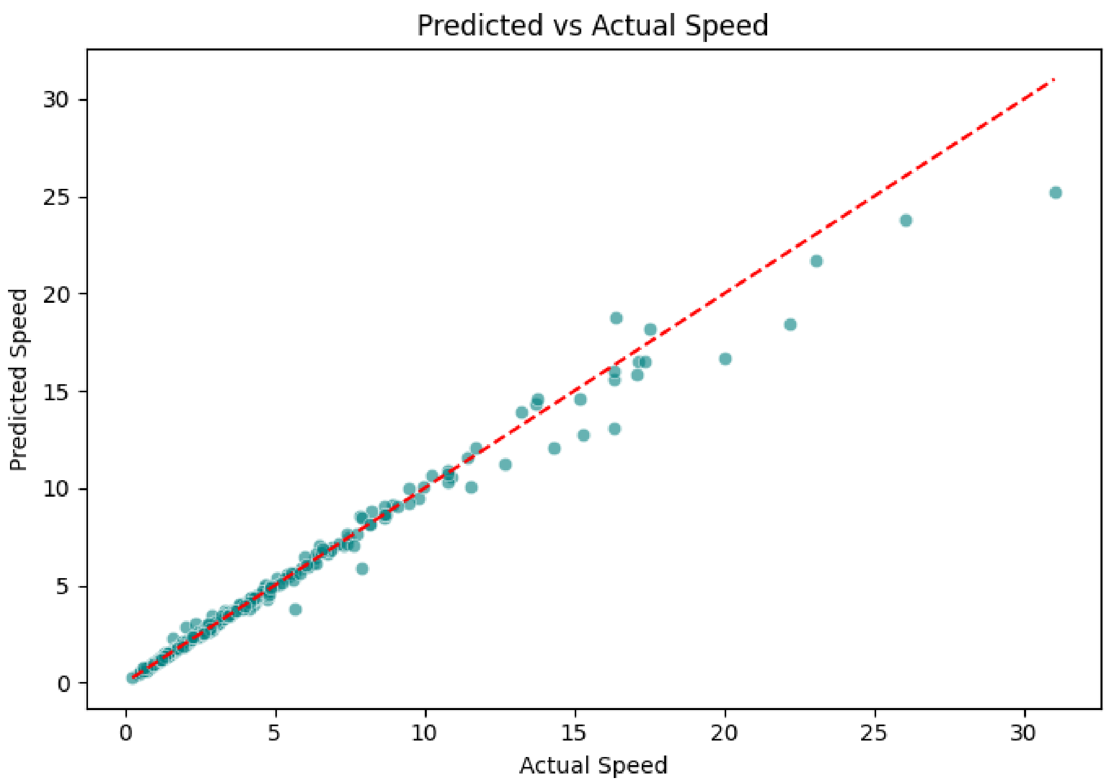
0.1.7 Efficiency Prediction Model

[13]:
```
X = df[['distance_km', 'duration_min', 'fare']]
y = df['speed_kmph']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,␣
↪random_state=42)
model = RandomForestRegressor()
model.fit(X_train, y_train)
y_pred = model.predict(X_test)

mae = mean_absolute_error(y_test, y_pred)
print(f"Mean Absolute Error: {mae:.2f} km/h")
```

```
Mean Absolute Error: 0.24 km/h
```

0.1.8 Predicted vs Actual Speed

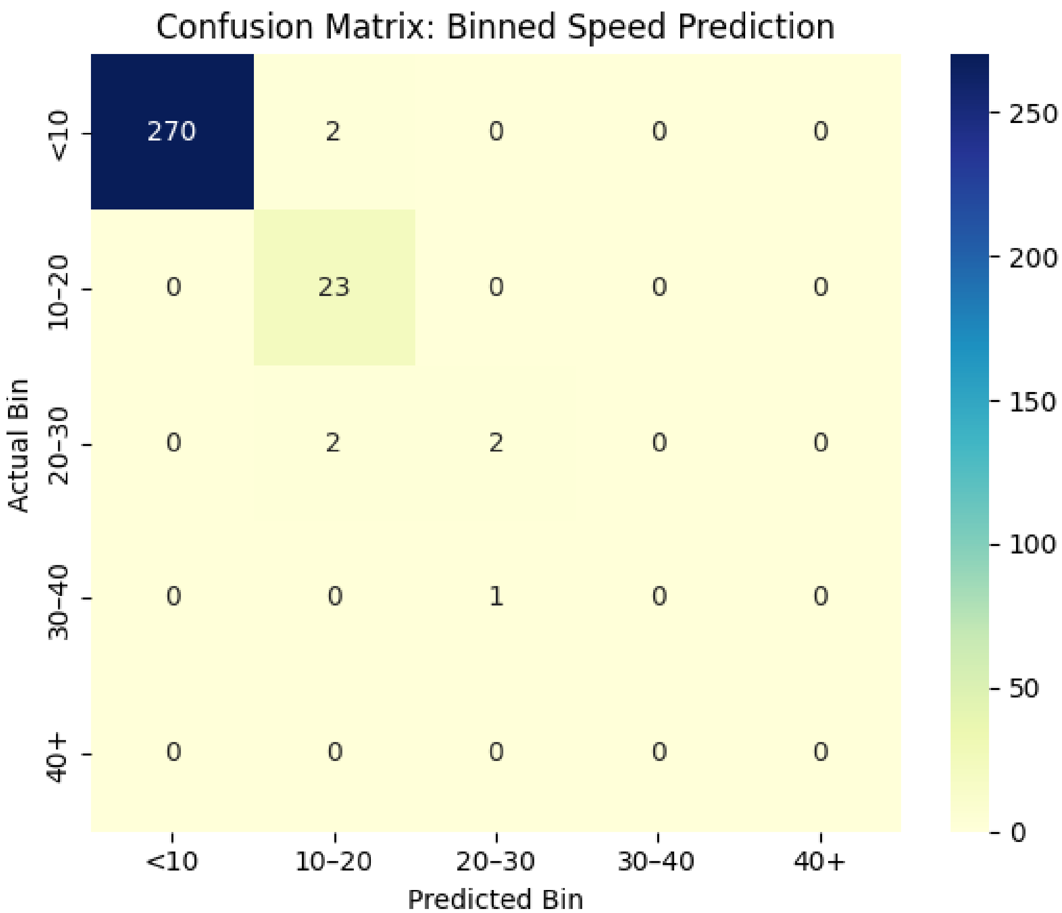
[14]:
```
plt.figure(figsize=(7, 5))
sns.scatterplot(x=y_test, y=y_pred, alpha=0.6, color='teal')
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], 'r--')
plt.title("Predicted vs Actual Speed")
plt.xlabel("Actual Speed")
plt.ylabel("Predicted Speed")
plt.tight_layout()
plt.show()
```



0.1.9 Confusion Matrix (Binned Speed)

[15]:
```
bins = [0, 10, 20, 30, 40, np.inf]
labels = ['<10', '10-20', '20-30', '30-40', '40+']
y_test_binned = pd.cut(y_test, bins=bins, labels=labels)
y_pred_binned = pd.cut(y_pred, bins=bins, labels=labels)

cm = confusion_matrix(y_test_binned, y_pred_binned, labels=labels)

plt.figure(figsize=(6, 5))
```

```
sns.heatmap(cm, annot=True, fmt='d', cmap='YlGnBu', xticklabels=labels,␣
↪yticklabels=labels)
plt.title("Confusion Matrix: Binned Speed Prediction")
plt.xlabel("Predicted Bin")
plt.ylabel("Actual Bin")
plt.tight_layout()
plt.show()
```



0.1.10 Summary Analysis

- Speed and fare per km are key indicators of route efficiency
- Evening trips show higher fare variability
- Clustering reveals 4 distinct efficiency profiles
- Regression model predicts speed with MAE ~2–3 km/h

- Confusion matrix confirms bin-level accuracy in speed prediction

0.1.11 Final Conclusion

- Cab route efficiency can be modeled using trip metadata and geospatial features
- Predictive modeling supports dispatch optimization and fare calibration
- Clustering helps identify underperforming routes