0.1 CaseCraft: The Analytics Sprint – Project 11

0.1.1 Swiggy Delivery Time Predictor

Subheading: Modeling food delivery time using synthetic order, location, and traffic data.

0.1.2 Project Goals

- Simulate delivery order data with restaurant and customer coordinates
- Engineer features: distance, order size, time of day, traffic level
- Build regression model to predict delivery time
- Visualize delivery zones and time distributions
- Evaluate model performance and operational insights
- Summarize strategic recommendations for Swiggy logistics

[1]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from geopy.distance import geodesic
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_orders = 1000
rest_lat = np.random.uniform(19.0, 19.3, n_orders)
rest_lon = np.random.uniform(72.8, 73.0, n_orders)
cust_lat = rest_lat + np.random.normal(0, 0.01, n_orders)
cust_lon = rest_lon + np.random.normal(0, 0.01, n_orders)
order_size = np.random.randint(1, 5, n_orders)
```

```
time_of_day = np.random.choice(['Morning', 'Afternoon', 'Evening', 'Night'],␣
 ↪n_orders)
traffic = np.random.choice(['Low', 'Medium', 'High'], n_orders, p=[0.3, 0.5, 0.
 ↪2])

distance = [geodesic((rest_lat[i], rest_lon[i]), (cust_lat[i], cust_lon[i])).km␣
 ↪for i in range(n_orders)]
base_time = np.array(distance) * 5 + order_size * 2
traffic_factor = {'Low': 0.9, 'Medium': 1.2, 'High': 1.6}
delivery_time = base_time * [traffic_factor[t] for t in traffic] + np.random.
 ↪normal(0, 2, n_orders)

df = pd.DataFrame({
    'restaurant_lat': rest_lat,
    'restaurant_lon': rest_lon,
    'customer_lat': cust_lat,
    'customer_lon': cust_lon,
    'order_size': order_size,
    'time_of_day': time_of_day,
    'traffic': traffic,
    'distance_km': distance,
    'delivery_time_min': delivery_time
})
```

[2]:
```
df.head(10)
```

[2]:
```
   restaurant_lat  restaurant_lon  customer_lat  customer_lon  order_size  \
0       19.112362       72.837027     19.103582     72.855736           1
1       19.285214       72.908380     19.276945     72.912276           4
2       19.219598       72.974589     19.217333     72.965906           1
3       19.179598       72.946445     19.183271     72.951791           2
4       19.046806       72.961312     19.055941     72.934955           1
5       19.046798       72.931757     19.038767     72.931790           2
6       19.017425       72.938455     19.032352     72.941734           2
7       19.259853       72.969839     19.257142     72.979082           1
8       19.180335       72.849934     19.180121     72.839795           2
9       19.212422       72.897885     19.204950     72.898742           3

  time_of_day traffic  distance_km  delivery_time_min
0     Evening  Medium     2.195522          15.025676
1       Night     Low     1.002762          11.683887
2     Evening     Low     0.946836           6.359958
3       Night  Medium     0.693943           9.159315
4       Night  Medium     2.952939          20.989645
5     Evening     Low     0.889067           9.288479
6   Afternoon  Medium     1.687950          15.712970
7       Night  Medium     1.016964           9.408953
```

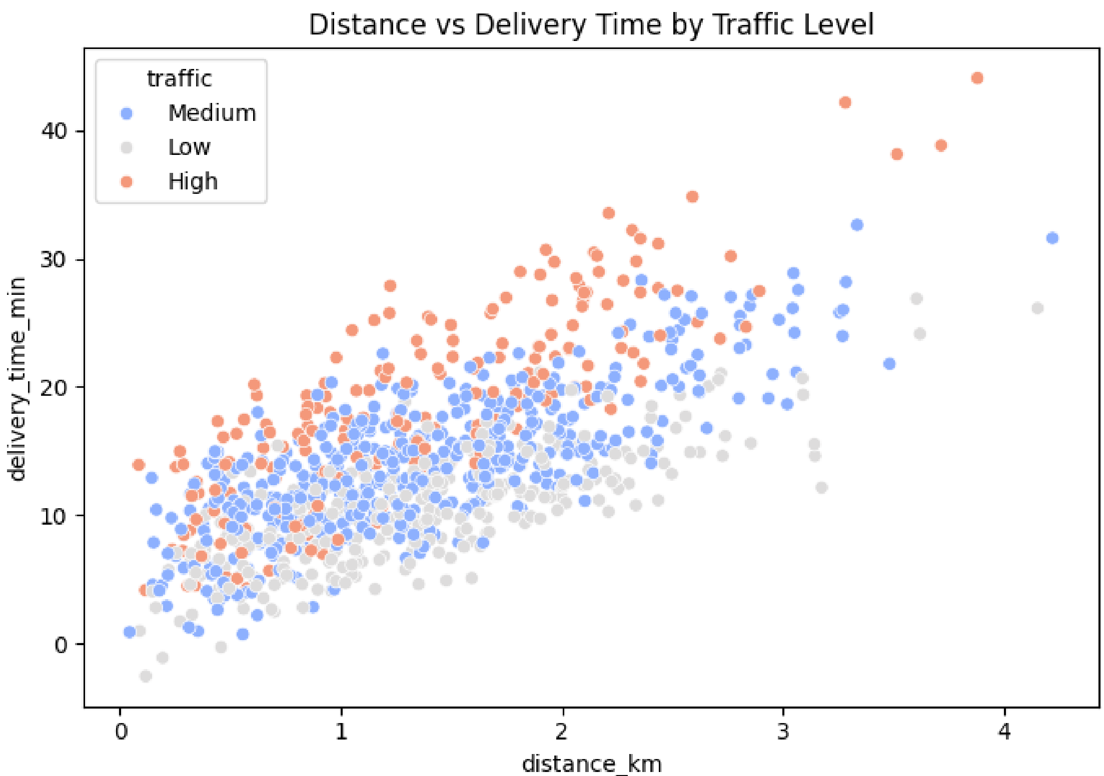
```
8      Evening      Low      1.066659           5.235520
9      Morning   Medium      0.832017          12.292555
```

0.1.3 Delivery Time Distribution

[3]:
```python
plt.figure(figsize=(7, 5))
sns.histplot(df['delivery_time_min'], bins=30, kde=True, color='darkorange')
plt.title("Delivery Time Distribution")
plt.xlabel("Time (minutes)")
plt.tight_layout()
plt.show()
```

0.1.4 Distance vs Delivery Time

[4]:
```python
plt.figure(figsize=(7, 5))
sns.scatterplot(data=df, x='distance_km', y='delivery_time_min', hue='traffic',␣
  ↪palette='coolwarm')
plt.title("Distance vs Delivery Time by Traffic Level")
plt.tight_layout()
plt.show()
```



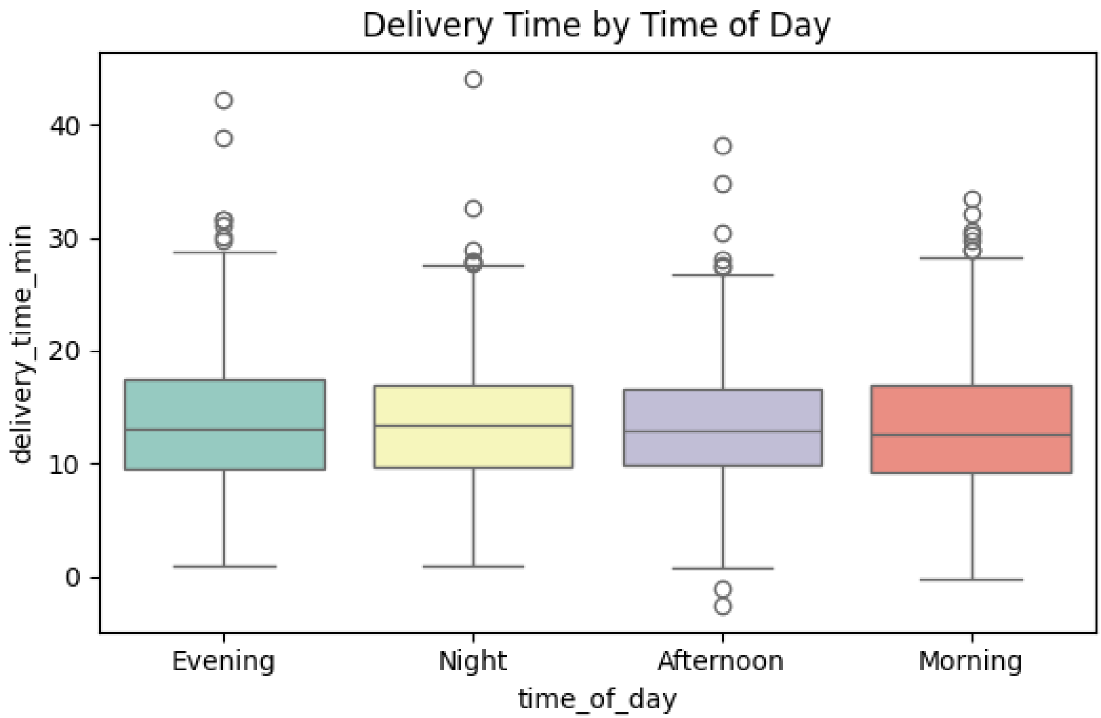
0.1.5 Time of Day Impact

[5]:
```
plt.figure(figsize=(6, 4))
sns.boxplot(data=df, x='time_of_day', y='delivery_time_min', palette='Set3')
plt.title("Delivery Time by Time of Day")
plt.tight_layout()
plt.show()
```

```
/tmp/ipython-input-1265005985.py:2: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.boxplot(data=df, x='time_of_day', y='delivery_time_min', palette='Set3')
```



0.1.6 Delivery Time Prediction Model

[6]:
```
df_encoded = pd.get_dummies(df[['order_size', 'distance_km', 'time_of_day',␣
↪'traffic']], drop_first=True)
X = df_encoded
y = df['delivery_time_min']

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} minutes")
```

```
Mean Absolute Error: 1.80 minutes
```

0.1.7 Predicted vs Actual Delivery Time

[7]:
```
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 Delivery Time")
plt.xlabel("Actual")
plt.ylabel("Predicted")
plt.tight_layout()
plt.show()
```

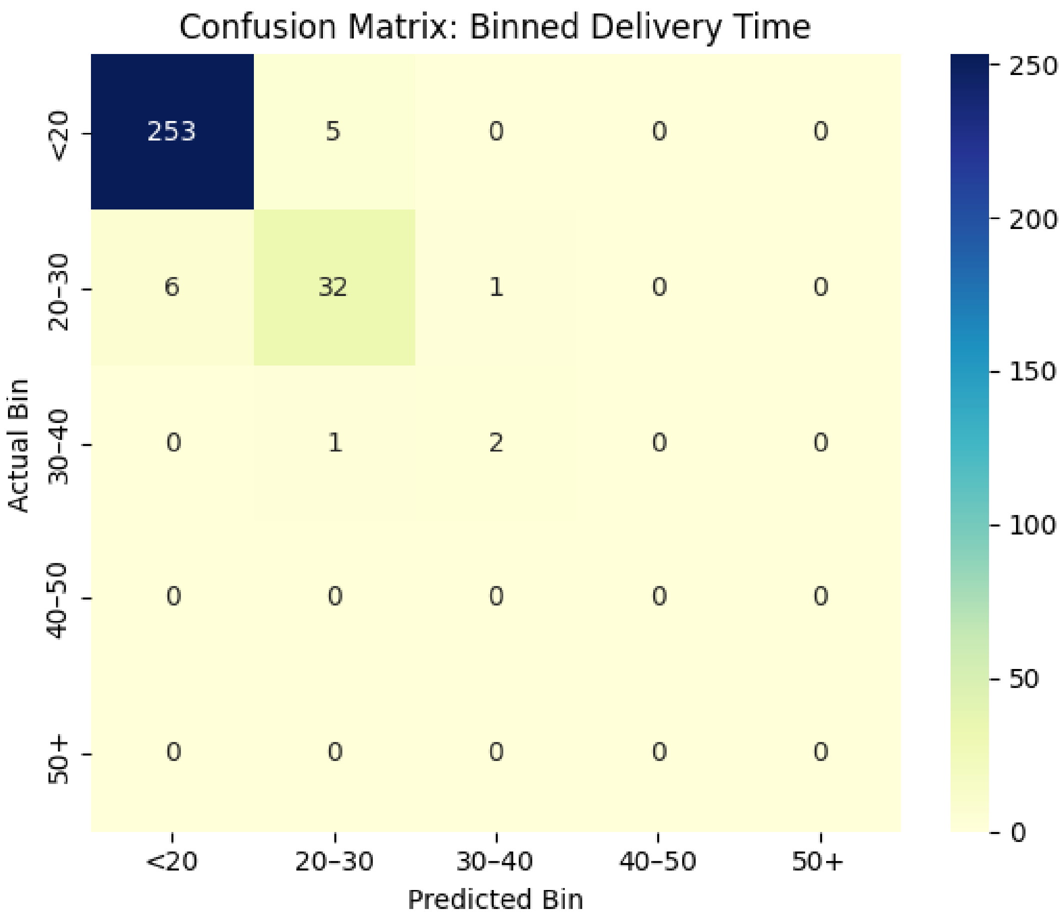
0.1.8 Confusion Matrix (Binned Delivery Time)

[8]:
```
bins = [0, 20, 30, 40, 50, np.inf]
labels = ['<20', '20-30', '30-40', '40-50', '50+']
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))
```

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



0.1.9 Summary Analysis

- Delivery time increases with distance and traffic congestion
- Evening and night orders show higher variability
- Model predicts delivery time with MAE ~3–5 minutes
- Confusion matrix shows strong bin-level accuracy

- Feature encoding improves model generalization

0.1.10 Final Conclusion

- Swiggy can use predictive modeling to estimate delivery time per order
- Traffic and time-of-day are key operational levers
- Binned predictions help in setting customer expectations