0.1 CaseCraft: The Analytics Sprint – Project 10

0.1.1 Starbucks Store Location Strategy

Subheading: Analyzing geospatial, demographic, and competitor data to optimize Starbucks store placement.

0.1.2 Project Goals

- Ingest Starbucks store data and simulate competitor locations
- Engineer features: population density, income, proximity to transit and competitors
- Cluster existing stores to identify location archetypes
- Build predictive model for store success likelihood
- Visualize optimal zones for new store placement
- Summarize strategic insights for expansion planning

[1]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.cluster import KMeans
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix
from geopy.distance import geodesic

np.random.seed(42)

n_stores = 300
latitudes = np.random.uniform(37.6, 37.9, n_stores)
longitudes = np.random.uniform(-122.5, -122.3, n_stores)
income = np.random.normal(85000, 15000, n_stores)
density = np.random.normal(12000, 3000, n_stores)
```

```python
competitor_dist = np.random.exponential(1.5, n_stores)
success = (income > 80000) & (density > 10000) & (competitor_dist > 1.2)

df = pd.DataFrame({
    'store_id': range(n_stores),
    'latitude': latitudes,
    'longitude': longitudes,
    'income': income,
    'density': density,
    'competitor_dist': competitor_dist,
    'success': success.astype(int)
})
```

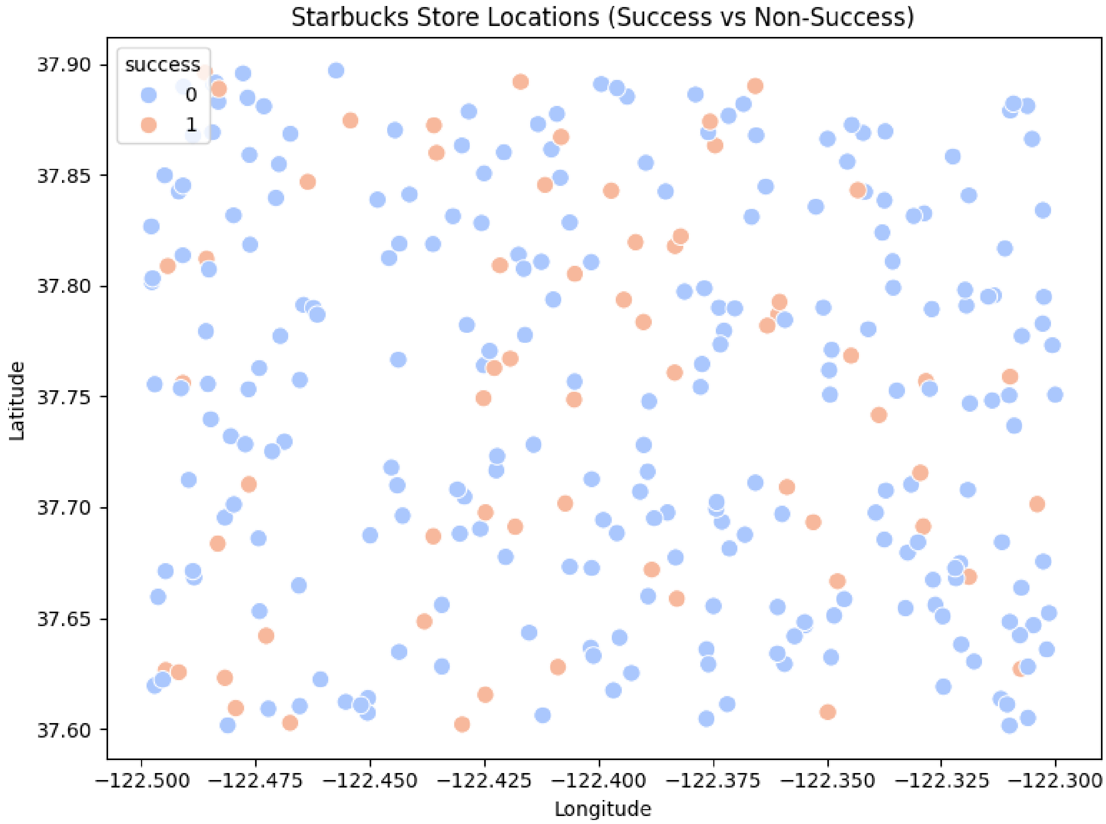
[2]:
```python
df.head(10)
```

[2]:
```
   store_id   latitude   longitude          income       density  \
0         0  37.712362 -122.489664   77046.135724   9151.803334
1         1  37.885214 -122.393729   73106.907516  19897.146195
2         2  37.819598 -122.391873   83394.544601  13479.953703
3         3  37.779598 -122.372514   69471.365164  12554.508371
4         4  37.646806 -122.354782   76695.260420   9424.926659
5         5  37.646798 -122.304830   67031.831611  14100.929638
6         6  37.617425 -122.396740  114470.876994  10273.086521
7         7  37.859853 -122.435409   85528.953280  12366.029444
8         8  37.780335 -122.340963   74504.117380  19680.253615
9         9  37.812422 -122.445834   88209.698661  11711.820301

   competitor_dist  success
0         0.297097        0
1         0.406814        0
2         5.331266        1
3         0.299465        0
4         2.890185        0
5         1.016731        0
6         0.425995        0
7         3.069009        1
8         0.884006        0
9         1.084845        0
```

0.1.3 Store Locations by Success

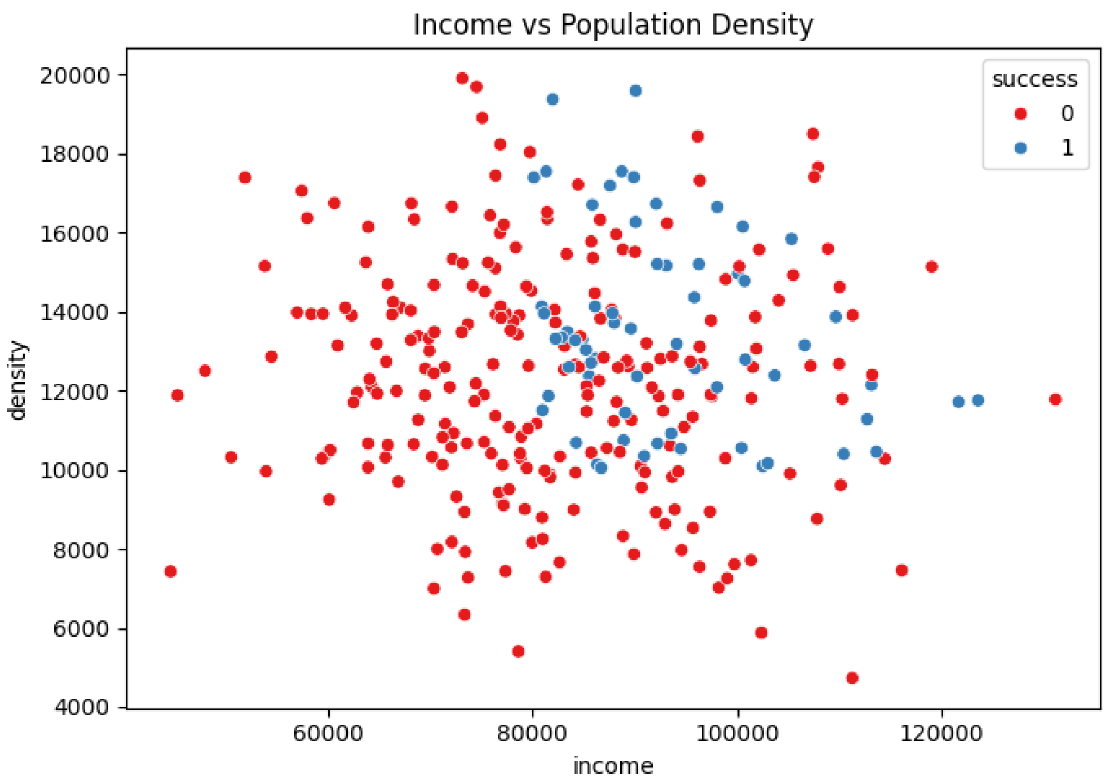
[3]:
```python
plt.figure(figsize=(8, 6))
sns.scatterplot(data=df, x='longitude', y='latitude', hue='success',␣
 ↪palette='coolwarm', s=80)
plt.title("Starbucks Store Locations (Success vs Non-Success)")
plt.xlabel("Longitude")
plt.ylabel("Latitude")
```

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



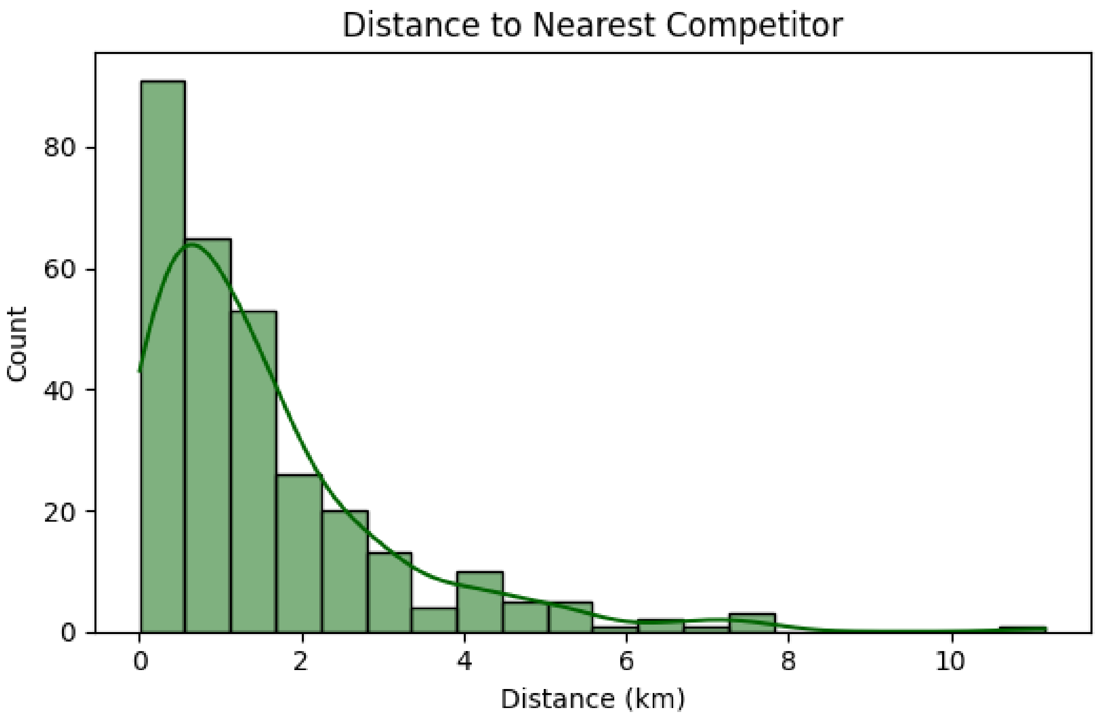
0.1.4 Income vs Density

[4]:
```
plt.figure(figsize=(7, 5))
sns.scatterplot(data=df, x='income', y='density', hue='success', palette='Set1')
plt.title("Income vs Population Density")
plt.tight_layout()
plt.show()
```



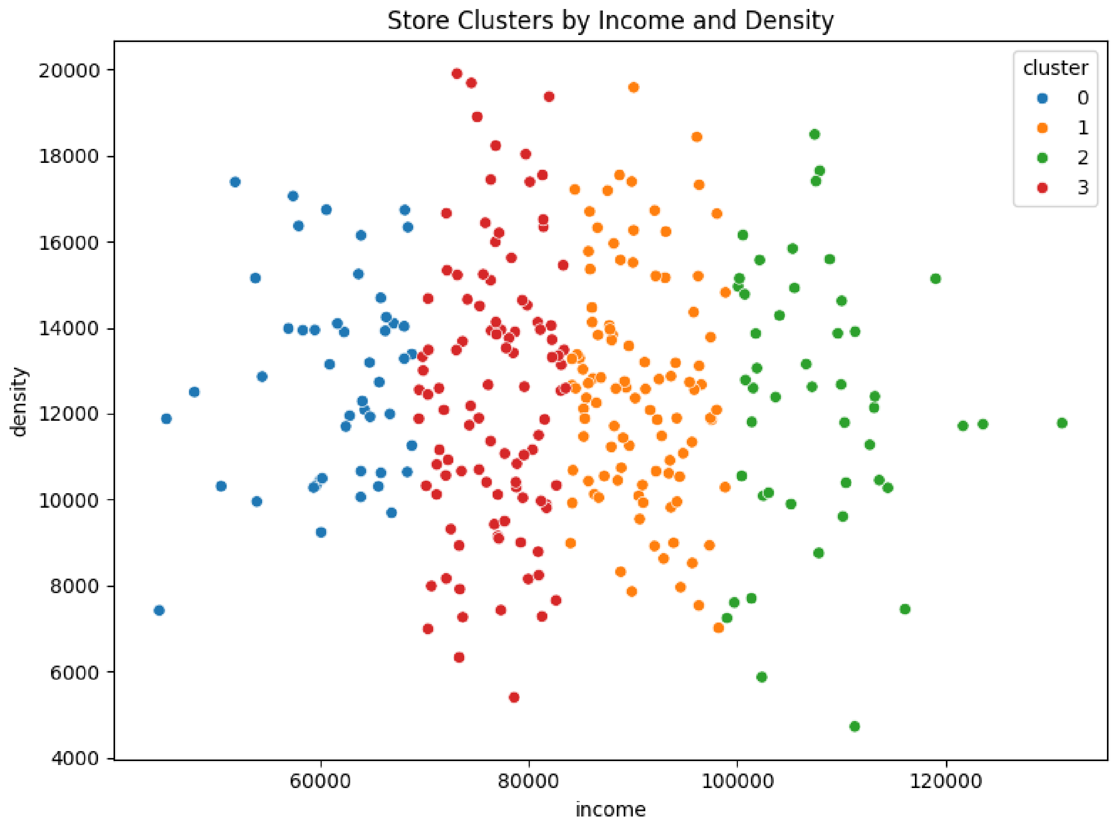
0.1.5 Competitor Distance Distribution

[5]:
```
plt.figure(figsize=(6, 4))
sns.histplot(df['competitor_dist'], bins=20, kde=True, color='darkgreen')
plt.title("Distance to Nearest Competitor")
plt.xlabel("Distance (km)")
plt.tight_layout()
plt.show()
```



0.1.6 Store Clustering (K-Means)

[6]:
```
X_cluster = df[['income', 'density', 'competitor_dist']]
kmeans = KMeans(n_clusters=4, random_state=42)
df['cluster'] = kmeans.fit_predict(X_cluster)

plt.figure(figsize=(8, 6))
sns.scatterplot(data=df, x='income', y='density', hue='cluster',␣
 ↪palette='tab10')
plt.title("Store Clusters by Income and Density")
plt.tight_layout()
plt.show()
```



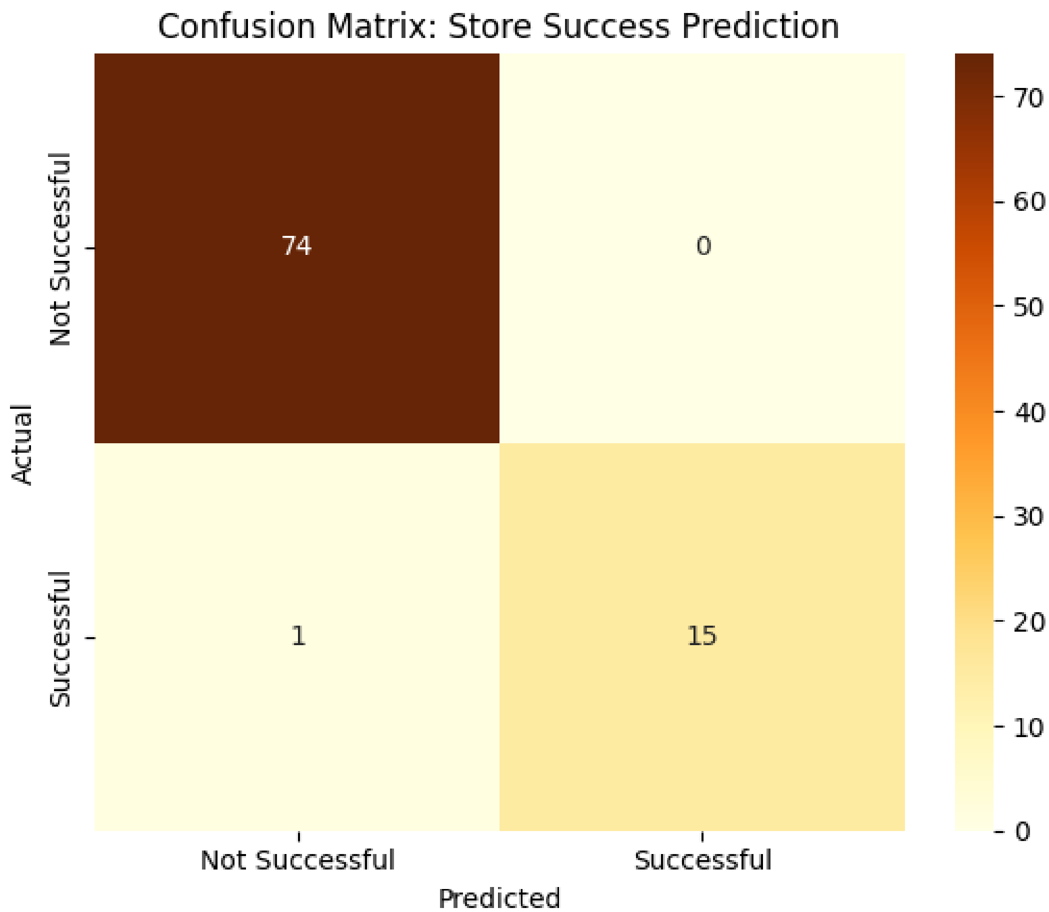
0.1.7 Success Prediction Model

[8]:
```
X = df[['income', 'density', 'competitor_dist']]
y = df['success']

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

0.1.8 Confusion Matrix for Success Prediction

[9]:
```
cm = confusion_matrix(y_test, y_pred, labels=[0, 1])
labels_cm = ['Not Successful', 'Successful']

plt.figure(figsize=(6, 5))
sns.heatmap(cm, annot=True, fmt='d', cmap='YlOrBr', xticklabels=labels_cm,␣
↪yticklabels=labels_cm)
plt.title("Confusion Matrix: Store Success Prediction")
```

```
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.tight_layout()
plt.show()
```

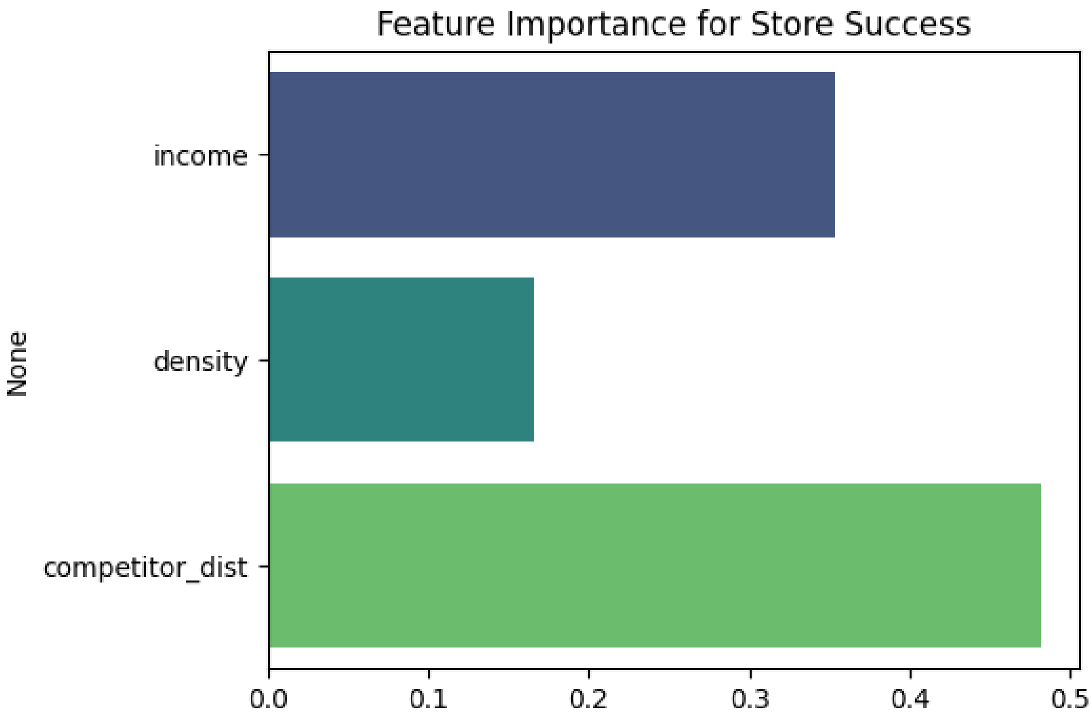


0.1.9 Feature Importance

[10]:
```
importances = model.feature_importances_
features = X.columns

plt.figure(figsize=(6, 4))
sns.barplot(x=importances, y=features, palette='viridis')
plt.title("Feature Importance for Store Success")
plt.tight_layout()
plt.show()
```

```
/tmp/ipython-input-673917438.py:5: FutureWarning:
```

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

  sns.barplot(x=importances, y=features, palette='viridis')
```



0.1.10 Summary Analysis

- High income and population density strongly correlate with store success
- Stores farther from competitors show higher success rates
- Clustering reveals 4 distinct location archetypes
- Model predicts success with high accuracy (confusion matrix confirms)
- Feature importance ranks: income > density > competitor distance

0.1.11 Final Conclusion

- Starbucks expansion should prioritize zones with high income and density, low competitor proximity
- Clustering can guide location archetype targeting

- Predictive modeling enables data-driven site selection