CaseStudy1

December 8, 2024

1 Module 10: Unsupervised Learning

1.1 Case Study – 1

[2]:
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# Import necessary libraries
import pandas as pd
from sklearn.cluster import KMeans
import matplotlib.pyplot as plt
from sklearn.preprocessing import StandardScaler

# Ignore warnings for clean output
import warnings
warnings.filterwarnings("ignore")

# Step 1: Load the Dataset
data = pd.read_csv('driver-data.csv')

# Step 2: Explore the Dataset
print("Dataset Info:")
print(data.info())
print("\nMissing Values Check:")
print(data.isnull().sum())

# Display the first few rows of the data
print("\nFirst 5 Rows of the Dataset:")
print(data.head())
```

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Dataset Info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4000 entries, 0 to 3999
Data columns (total 3 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   id                   4000 non-null   int64
 1   mean_dist_day        4000 non-null   float64
 2   mean_over_speed_perc 4000 non-null   int64
dtypes: float64(1), int64(2)
memory usage: 93.9 KB
```

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None

Missing Values Check:
id                        0
mean_dist_day             0
mean_over_speed_perc      0
dtype: int64

First 5 Rows of the Dataset:
           id  mean_dist_day  mean_over_speed_perc
0  3423311935          71.24                    28
1  3423313212          52.53                    25
2  3423313724          64.54                    27
3  3423311373          55.69                    22
4  3423310999          54.58                    25
```

[12]:
```python
# Step 3: Preprocess the Data
# Drop the 'id' column as it is not useful for clustering
features = data.drop(columns=['id'])

# Standardize the data to bring all features to the same scale
scaler = StandardScaler()
features_scaled = scaler.fit_transform(features)
features_scaled
```

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array([[-0.0898104 ,  1.26061251],
       [-0.43977285,  1.04174351],
       [-0.215131  ,  1.18765617],
       …,
       [ 1.77447381,  0.09331115],
       [ 1.87229869, -0.41738319],
       [ 1.72060465, -0.12555785]])
```

[14]:
```python
# Step 4: Determine the Optimal Number of Clusters
# Use the Elbow Method to find the optimal number of clusters
wcss = []  # Within-cluster sum of squares

for i in range(1, 11):
    kmeans = KMeans(n_clusters=i, random_state=42)
    kmeans.fit(features_scaled)
    wcss.append(kmeans.inertia_)

# Plot the Elbow Method
plt.figure(figsize=(8, 5))
plt.plot(range(1, 11), wcss, marker='o')
plt.title('Elbow Method for Optimal Clusters')
plt.xlabel('Number of Clusters')
plt.ylabel('WCSS')
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plt.show()

print(wcss)
```

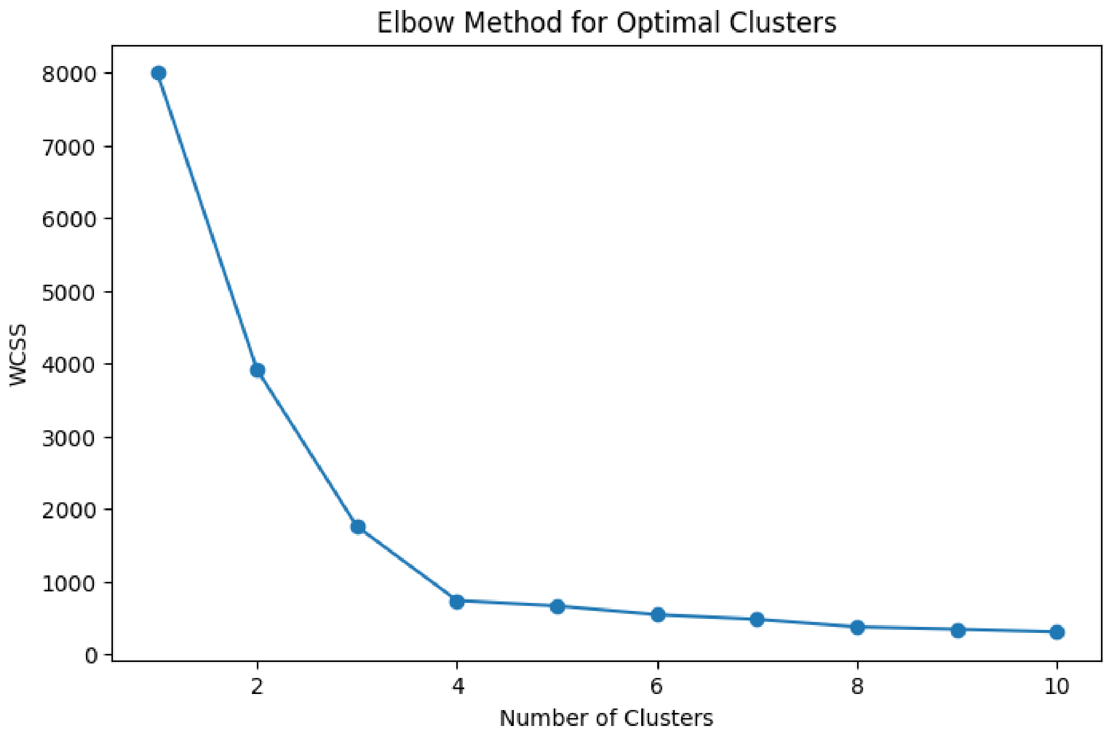


```
[7999.999999999998, 3911.926390428418, 1756.553615947244, 739.1534508645577,
664.9838071983531, 545.2591033936885, 481.77268602452307, 375.77515026823113,
344.20890925559615, 306.97337203496477]
```

[15]:
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# Step 5: Apply K-Means Clustering
# Based on the elbow plot, let's assume optimal clusters (e.g., 4)
optimal_clusters = 4
kmeans = KMeans(n_clusters=optimal_clusters, random_state=42)
data['Cluster'] = kmeans.fit_predict(features_scaled)
```

[17]:
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# Step 6: Analyze the Clusters
# Display the number of drivers in each cluster
cluster_counts = data['Cluster'].value_counts()
print("\nNumber of Drivers in Each Cluster:")
print(cluster_counts)

# Calculate the mean of each feature for each cluster
cluster_features = data.groupby('Cluster').mean()
print("\nMean Values of Features per Cluster:")
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print(cluster_features)
```

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Number of Drivers in Each Cluster:
Cluster
0    2774
1     695
2     427
3     104
Name: count, dtype: int64

Mean Values of Features per Cluster:
                   id  mean_dist_day  mean_over_speed_perc
Cluster
0        3.423312e+09      50.016637              5.204037
1        3.423312e+09     180.434863             10.529496
2        3.423312e+09      50.404824             32.365340
3        3.423313e+09     177.835096             70.288462
```

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# Step 7: Visualize the Clusters
# Plot the clusters in a 2D space using the two features
plt.figure(figsize=(8, 5))
plt.scatter(features_scaled[:, 0], features_scaled[:, 1], c=data['Cluster'],␣
↪cmap='viridis', s=50)
plt.title('Clusters of Drivers')
plt.xlabel('Mean Distance Per Day (Scaled)')
plt.ylabel('Mean Overspeed Percentage (Scaled)')
plt.colorbar(label='Cluster')
plt.show()
```

Cluster Characteristics

Based on the mean values for each feature in the clusters:

Cluster 0: Mean Distance Driven per Day: 50.02 units. Mean Over-speed Percentage: 5.20Driver Behavior: Likely regular drivers with moderate daily distance and minimal overspeeding. Represents the largest group (2774 drivers).

Cluster 1: Mean Distance Driven per Day: 180.43 units. Mean Over-speed Percentage: 10.53Driver Behavior: Likely long-distance drivers with occasional overspeeding. May require battery replacements more frequently due to higher mileage.

Cluster 2: Mean Distance Driven per Day: 50.40 units. Mean Over-speed Percentage: 32.37Driver Behavior: Short-distance but risky drivers with high overspeeding behavior. These drivers could contribute to faster battery degradation due to aggressive driving.

Cluster 3: Mean Distance Driven per Day: 177.83 units. Mean Over-speed Percentage: 70.29Driver Behavior: Long-distance and risky drivers who overspeed most of the time. Represents a small group (104 drivers) with the most concerning behavior, likely requiring higher charges due to their heavy impact on battery life.Key Observations

Cluster 0 (Regular Drivers): Largest cluster with consistent, responsible driving habits. These drivers can be incentivized for maintaining good driving behavior.

Cluster 3 (High-Risk Drivers): Smallest cluster but exhibits the most concerning behavior with high daily distances and overspeeding. These drivers might face higher rental fees or stricter policies to cover battery wear and tear.

Cluster 1 vs. Cluster 2: Cluster 1 focuses on high-distance, low-risk drivers. Cluster 2 focuses on low-distance, high-risk drivers, suggesting a difference in driving styles.Business Recommendations

Incentivize Cluster 0: Offer discounts or loyalty rewards to encourage continued responsible driving.

Monitor Cluster 3: Implement higher pricing or penalties for drivers with high-risk behavior to cover maintenance costs.

Targeted Policies for Clusters 1 and 2: For Cluster 1, consider pricing models that reward high-distance but safe drivers. For Cluster 2, introduce programs to reduce overspeeding through awareness campaigns or monitoring.

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