clustering_primary

October 22, 2024

[2]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from minisom import MiniSom
from sklearn.preprocessing import MinMaxScaler
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import silhouette_score
from sklearn.cluster import KMeans
```

1 Clustering Algorithms for Primary Dataset

[3]:
```
dataset = 'primary'
data = pd.read_csv(f'../dataset/mapped_{dataset}.csv', sep=',')
data = data.drop(columns=['uuid'])
variable_names = data.columns.tolist()

# need to normalize data from SOMs
scaler = MinMaxScaler()
norm_data = pd.DataFrame(scaler.fit_transform(data), columns=data.columns)

print(norm_data)
```

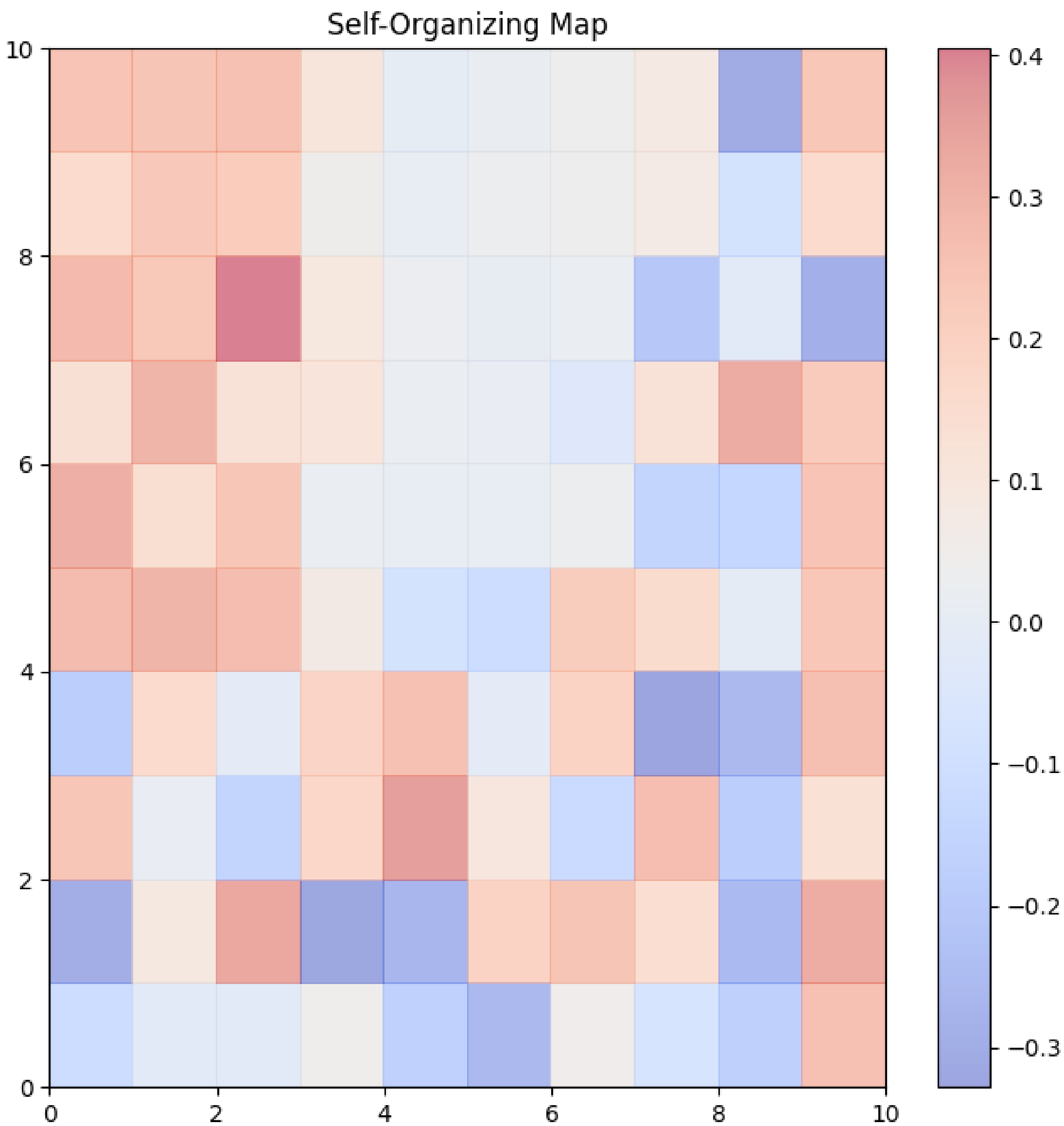
```
          price    artist  cardFinish  colorIdentity    colors  edhrecRank  \
0      0.002581  0.773243         1.0       0.766667  0.766667    0.760212
1      0.063226  0.773243         0.5       0.766667  0.766667    0.760212
2      0.167742  0.773243         1.0       0.766667  0.766667    0.760212
3      0.018065  0.773243         1.0       0.766667  0.766667    0.760212
4      0.126452  0.773243         1.0       0.766667  0.766667    0.760212
…           …         …         …              …         …           …
15209  0.056774  0.621315         1.0       0.533333  0.533333    0.200869
15210  0.024516  0.621315         0.5       0.533333  0.533333    0.200869
15211  0.229677  0.621315         1.0       0.533333  0.533333    0.200869
15212  0.126452  0.621315         0.5       0.533333  0.533333    0.200869
15213  0.218065  0.621315         1.0       0.533333  0.533333    0.200869

       edhrecSaltiness  gameAvailability  isReprint  layout  …  \
0             0.027668               0.0        0.0     0.8  …
```

```
1              0.027668               0.0        0.0      0.8  …
2              0.027668               1.0        0.0      0.8  …
3              0.027668               1.0        0.0      0.8  …
4              0.027668               1.0        0.0      0.8  …
…                 …                …        …        …   …
15209          0.169960               1.0        1.0      0.8  …
15210          0.169960               1.0        1.0      0.8  …
15211          0.169960               1.0        1.0      0.8  …
15212          0.169960               1.0        1.0      0.8  …
15213          0.169960               1.0        1.0      0.8  …

       originalType     power  priceProvider  providerListing  rarity  \
0          1.000000  0.461538       0.000000              0.0     0.5
1          1.000000  0.461538       0.000000              0.0     0.5
2          1.000000  0.461538       1.000000              0.0     0.5
3          1.000000  0.461538       0.333333              1.0     0.5
4          1.000000  0.461538       0.333333              0.0     0.5
…               …         …            …                …      …
15209      0.238754  0.461538       0.333333              1.0     0.5
15210      0.238754  0.461538       0.333333              1.0     0.5
15211      0.238754  0.461538       0.333333              0.0     0.5
15212      0.238754  0.461538       0.333333              0.0     0.5
15213      0.238754  0.461538       0.666667              0.0     0.5

        setCode  supertypes  toughness      type     types
0      0.621053         0.0   0.500000  0.463466  0.666667
1      0.621053         0.0   0.500000  0.463466  0.666667
2      0.621053         0.0   0.500000  0.463466  0.666667
3      0.621053         0.0   0.500000  0.463466  0.666667
4      0.621053         0.0   0.500000  0.463466  0.666667
…           …         …         …         …         …
15209  0.768421         0.0   0.416667  0.062630  0.666667
15210  0.768421         0.0   0.416667  0.062630  0.666667
15211  0.768421         0.0   0.416667  0.062630  0.666667
15212  0.768421         0.0   0.416667  0.062630  0.666667
15213  0.768421         0.0   0.416667  0.062630  0.666667

[15214 rows x 24 columns]
```

[4]:

```
som_size = 10
som = MiniSom(som_size, som_size, norm_data.shape[1], sigma=1.0,␣
↪learning_rate=0.5)

som.train(norm_data.values, num_iteration=1000)

plt.figure(figsize=(8, 8))
plt.pcolor(som.get_weights()[:, :, 0], cmap='coolwarm', alpha=0.5)
```

```
plt.colorbar()
plt.title('Self-Organizing Map')
plt.show()
```



[5]:
```
win_map = som.win_map(norm_data.values)
cluster_characteristics = {}
```

[6]:
```
def plt_som(win_map,col):

    cluster_characteristics = {}
```

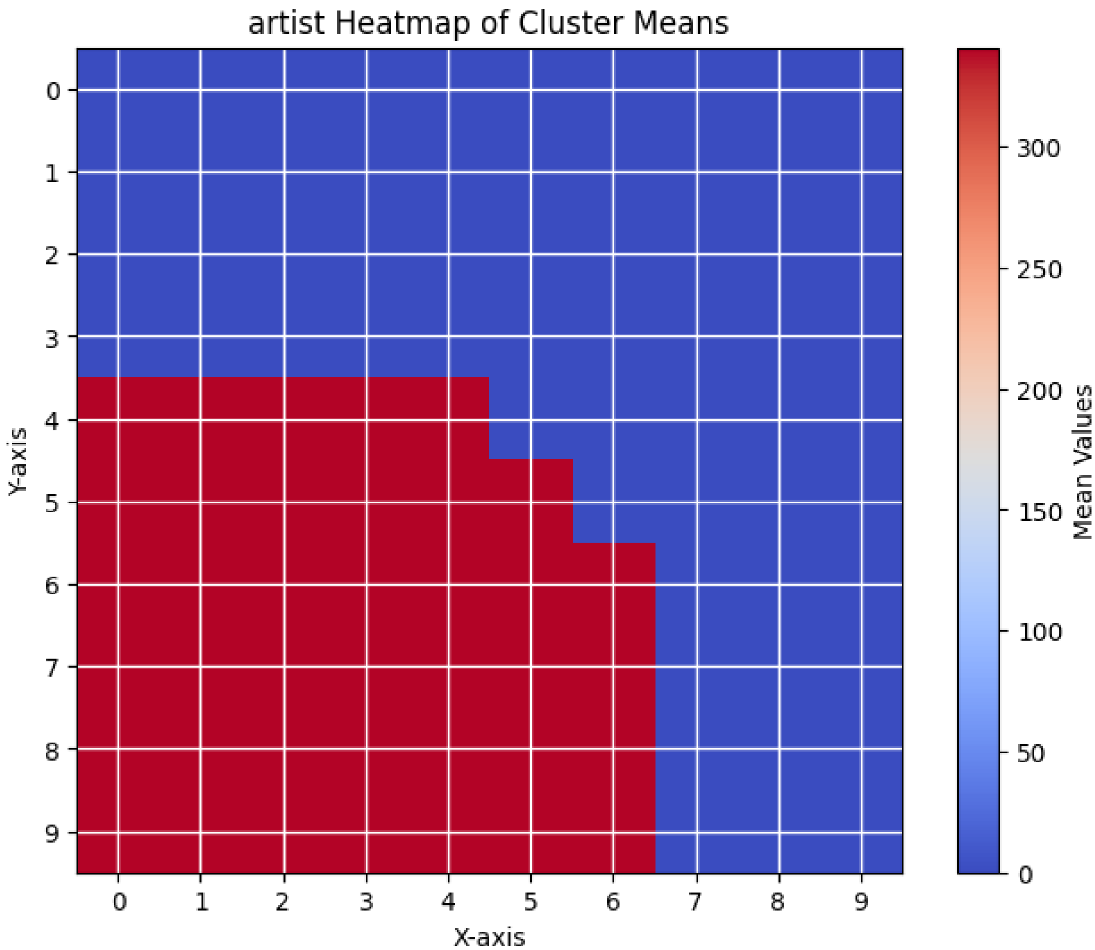
```
    # Loop through the win map to calculate mean prices for each cluster
    for (x, y), indices in win_map.items():
        for i in indices:
            values = data.iloc[i][col].values

        # Calculate mean price for the cluster
        mean_col = np.mean(values) if len(values) > 0 else 0
        median_col = np.median(values) if len(values) > 0 else 0
        std_col = np.std(values) if len(values) > 0 else 0

        # Store in the dictionary
        cluster_characteristics[(x, y)] = {f'mean_{col}': mean_col,␣
↪f'median_{col}': median_col, f'std_{col}': std_col}

    mean_values = np.zeros((10, 10))

    for (x, y), values in cluster_characteristics.items():
        mean_values[x, y] = values[f'mean_{col}']

    # Plotting the heatmap
    plt.figure(figsize=(8, 6))
    plt.imshow(mean_values, cmap='coolwarm', interpolation='nearest')
    plt.colorbar(label='Mean Values')
    plt.title(f'{col} Heatmap of Cluster Means')
    plt.xlabel('X-axis')
    plt.ylabel('Y-axis')

    # Optionally, add grid lines and labels
    plt.xticks(ticks=np.arange(10), labels=np.arange(10))
    plt.yticks(ticks=np.arange(10), labels=np.arange(10))
    plt.grid(color='white', linestyle='-', linewidth=1)

    plt.show()
```

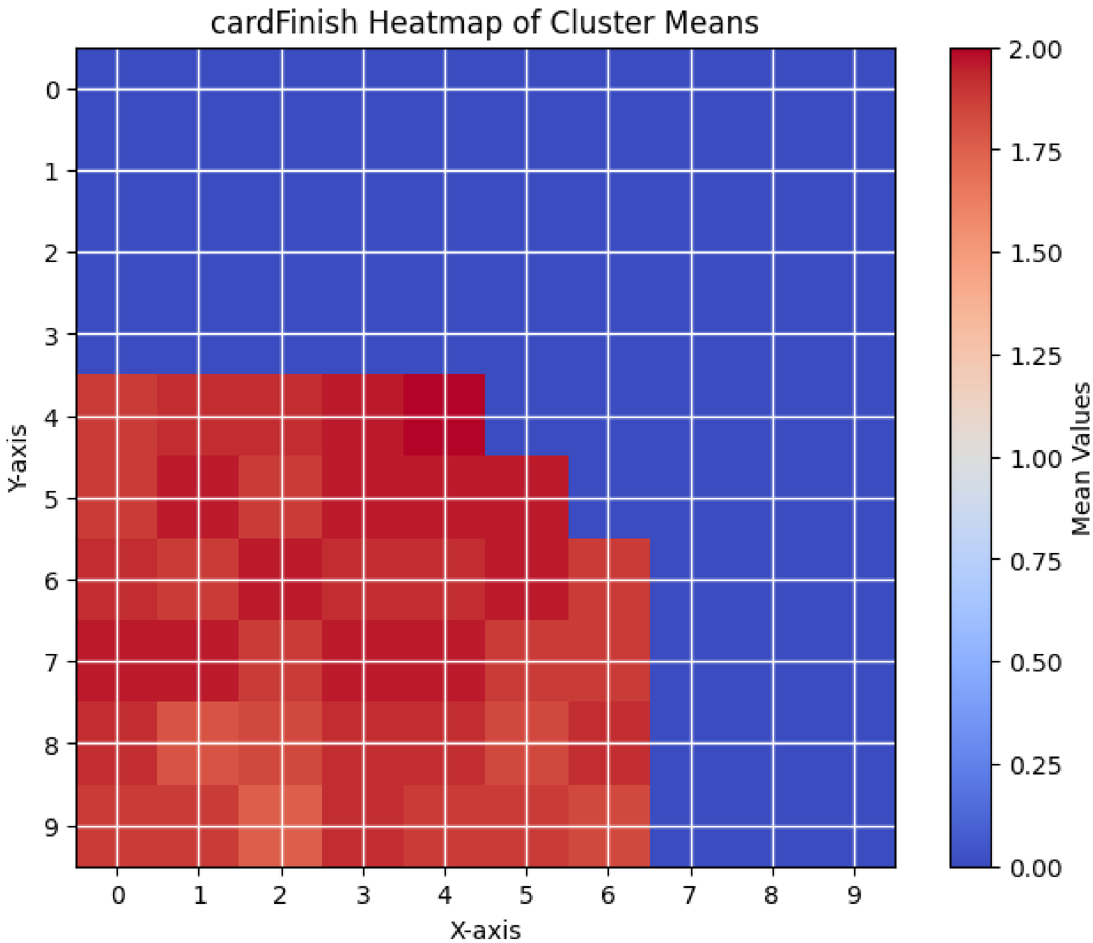
[7]:
```
print(len(data.columns))
```

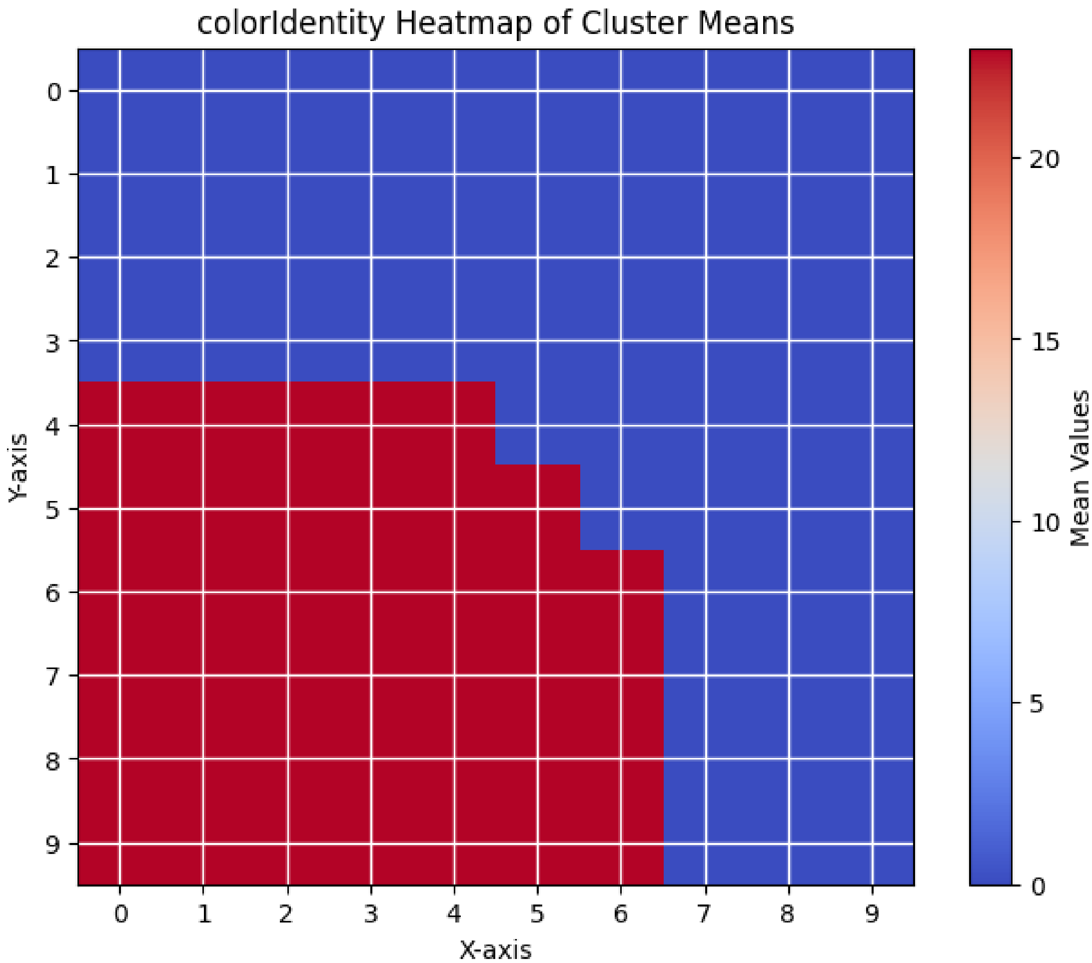
24

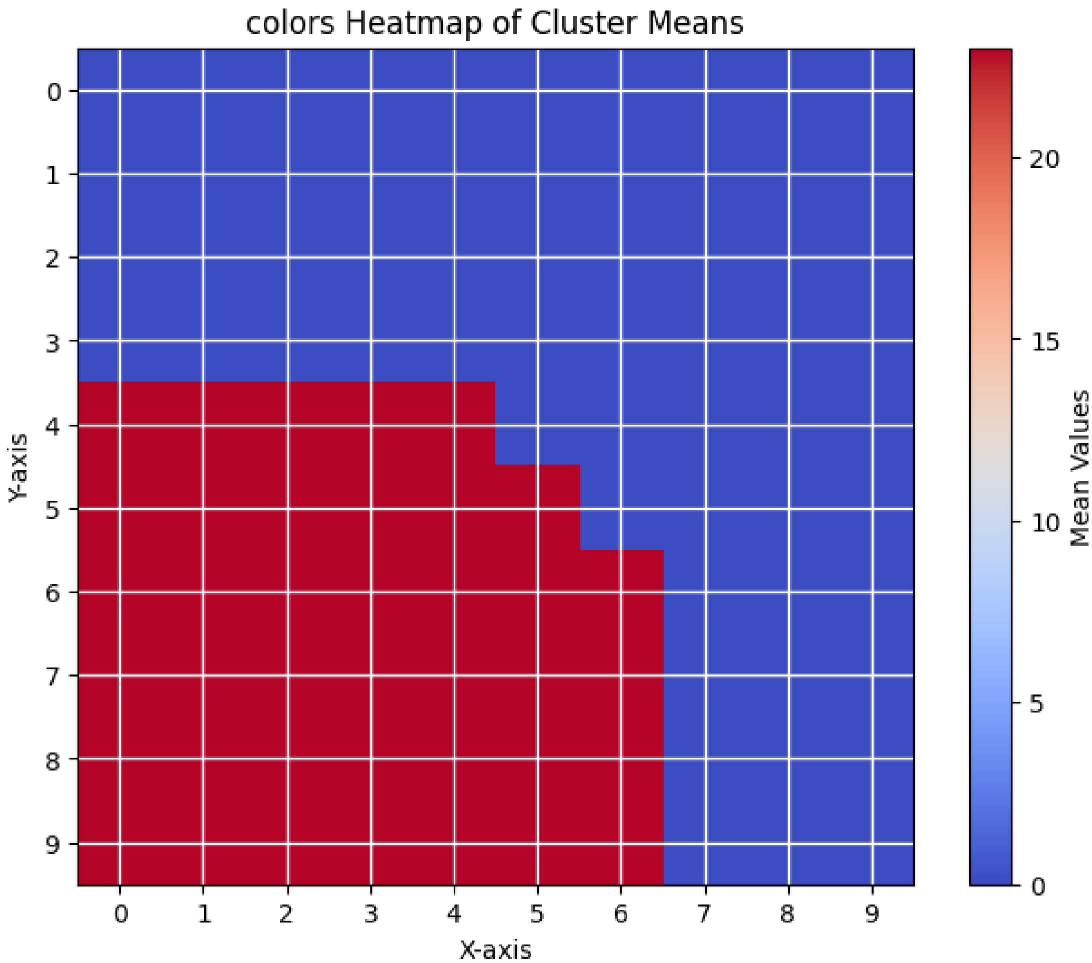
[8]:
```
for i in data.columns:
    plt_som(win_map, i)
```

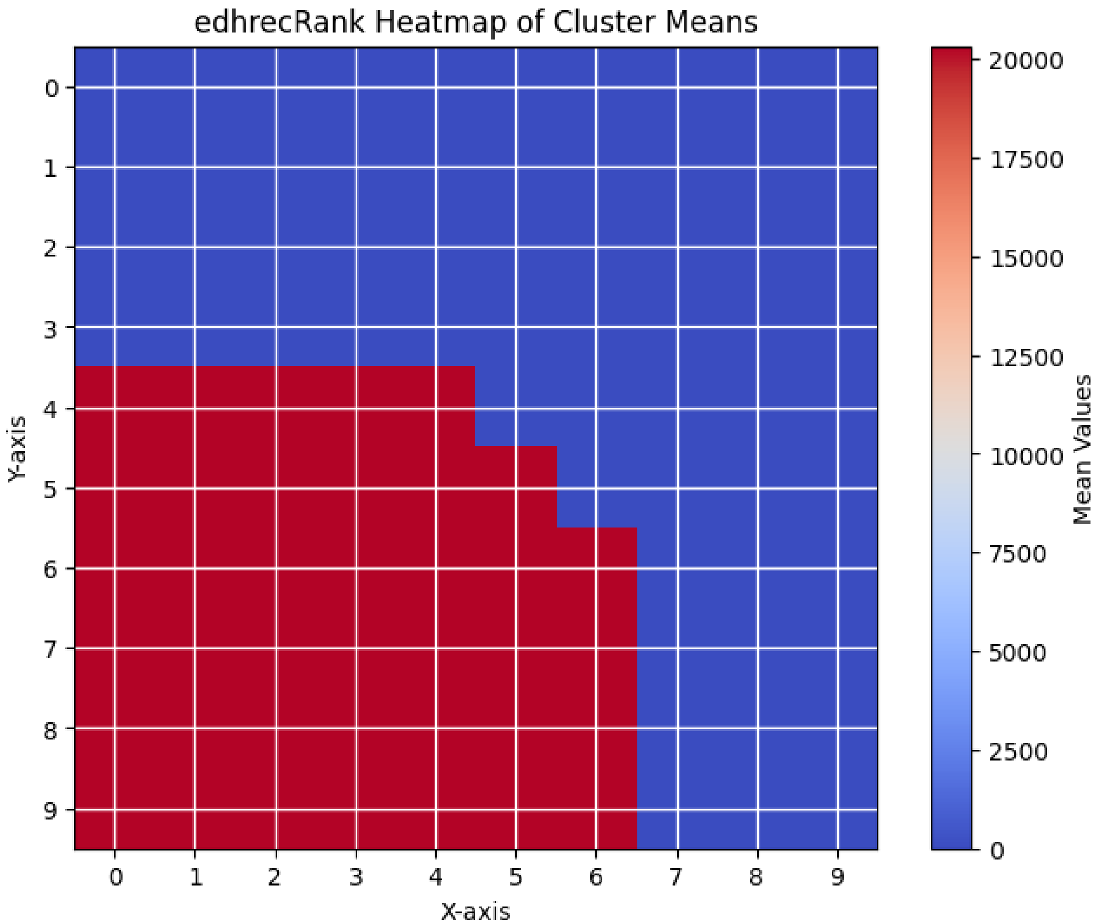

price Heatmap of Cluster Means
Y-axis
X-axis
0
1
2
3
4
5
6
7
8
9
Mean Values
0.00
0.02
0.04
0.06
0.08
0.10
0.12
0.14


artist Heatmap of Cluster Means
Y-axis
X-axis
0
1
2
3
4
5
6
7
8
9
Mean Values
0
50
100
150
200
250
300

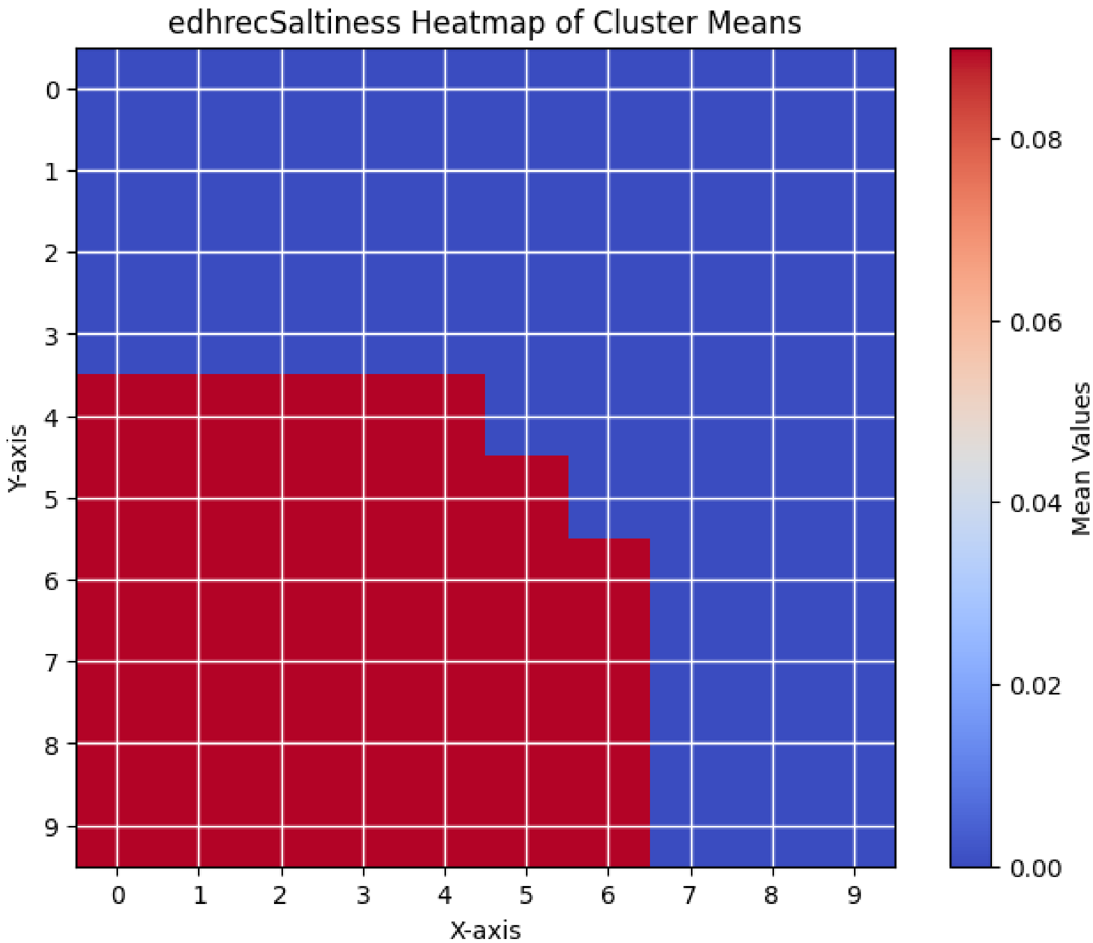

cardFinish Heatmap of Cluster Means
Y-axis
X-axis
Mean Values
0
1
2
3
4
5
6
7
8
9
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00

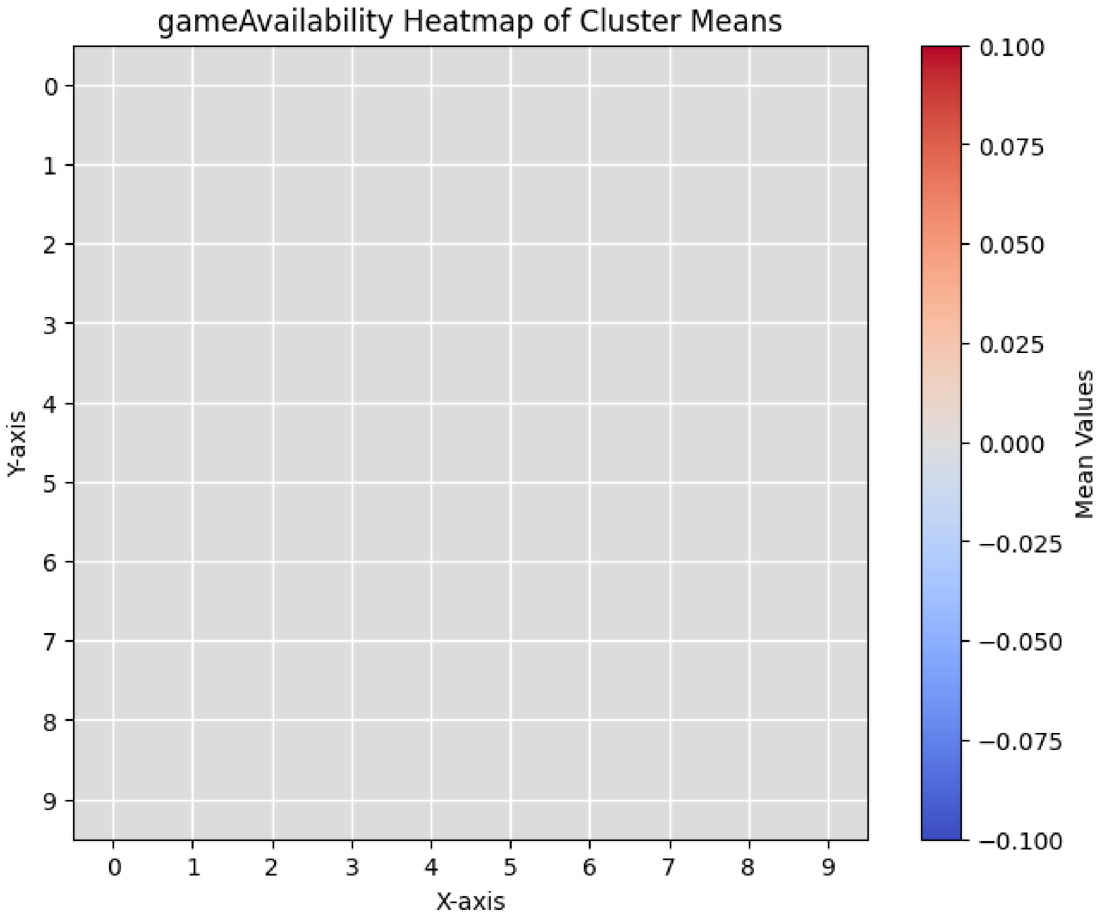

colorIdentity Heatmap of Cluster Means
Y-axis
X-axis
0
1
2
3
4
5
6
7
8
9
Mean Values
0
5
10
15
20

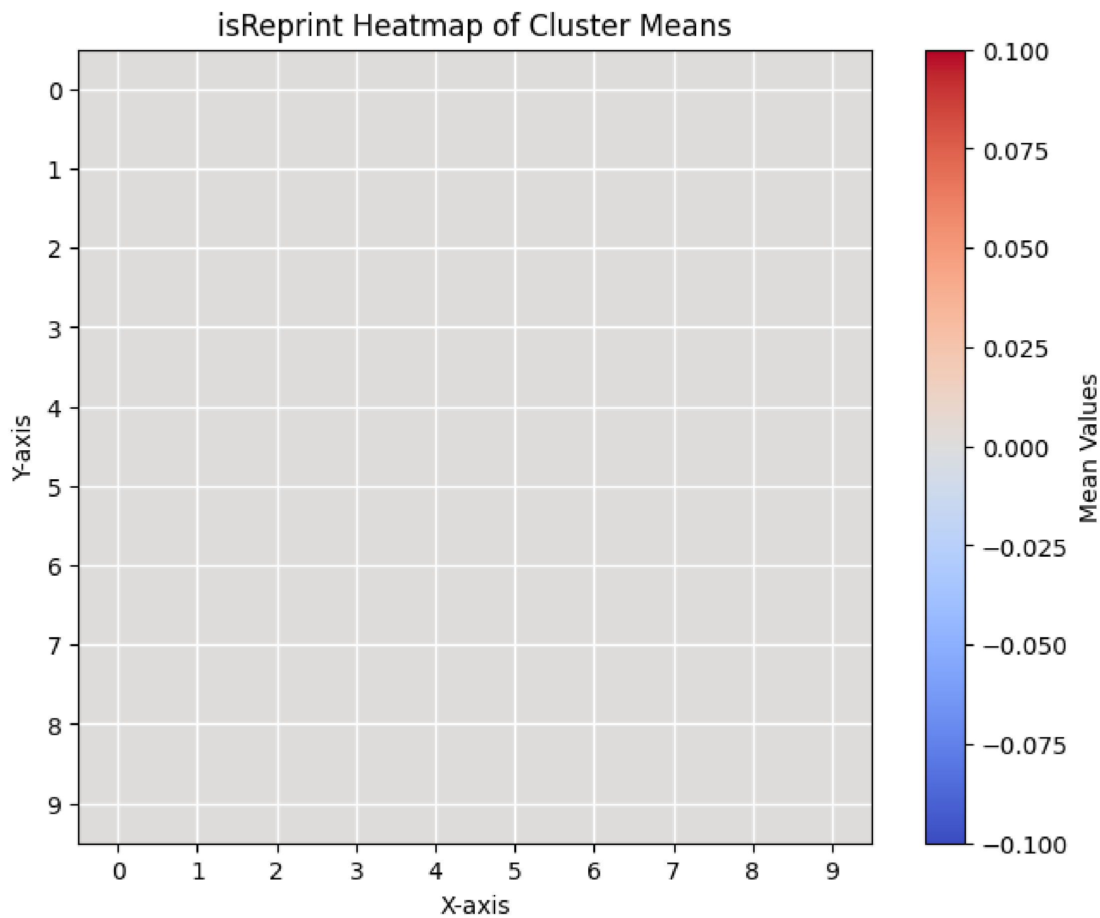

colors Heatmap of Cluster Means
Y-axis
X-axis
Mean Values
0
1
2
3
4
5
6
7
8
9
0
5
10
15
20

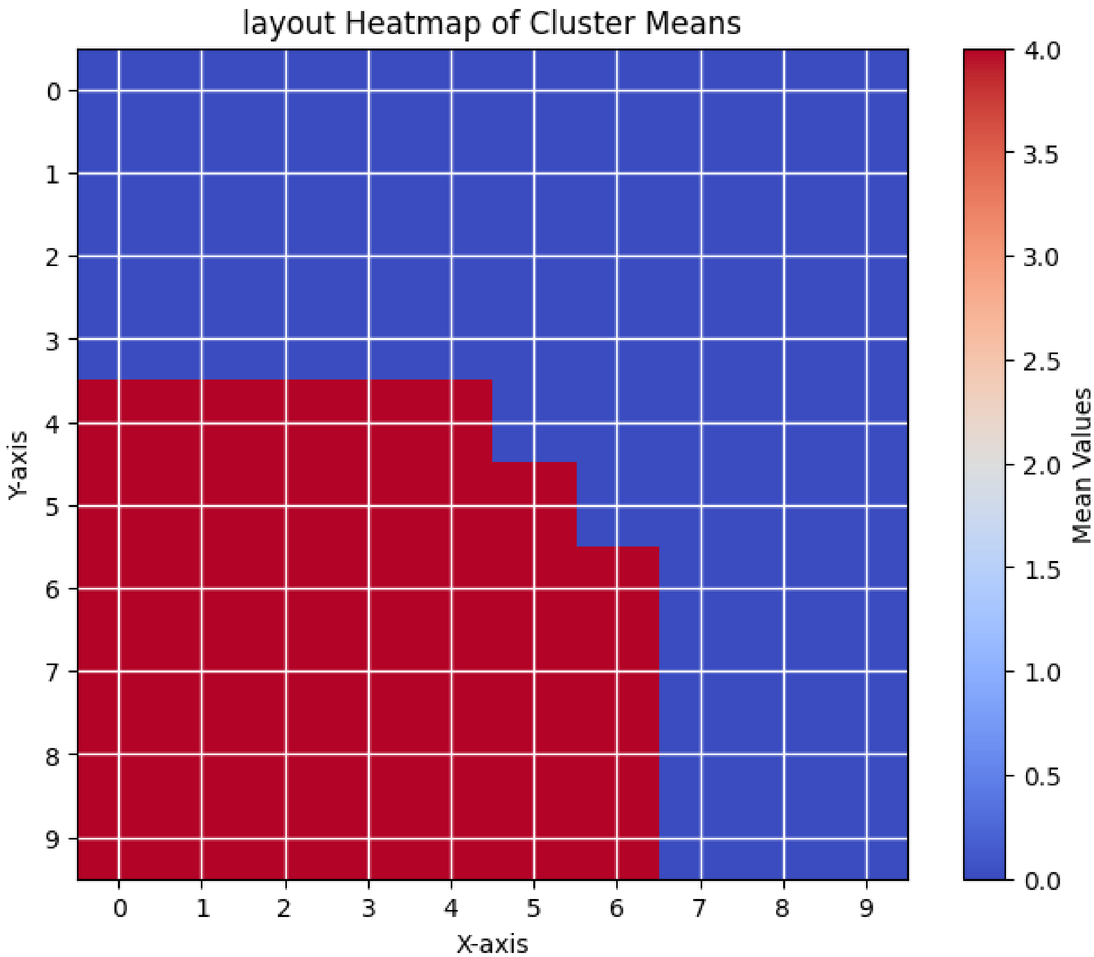


edhrecRank Heatmap of Cluster Means
Y-axis
X-axis
Mean Values
0
1
2
3
4
5
6
7
8
9
2500
5000
7500
10000
12500
15000
17500
20000

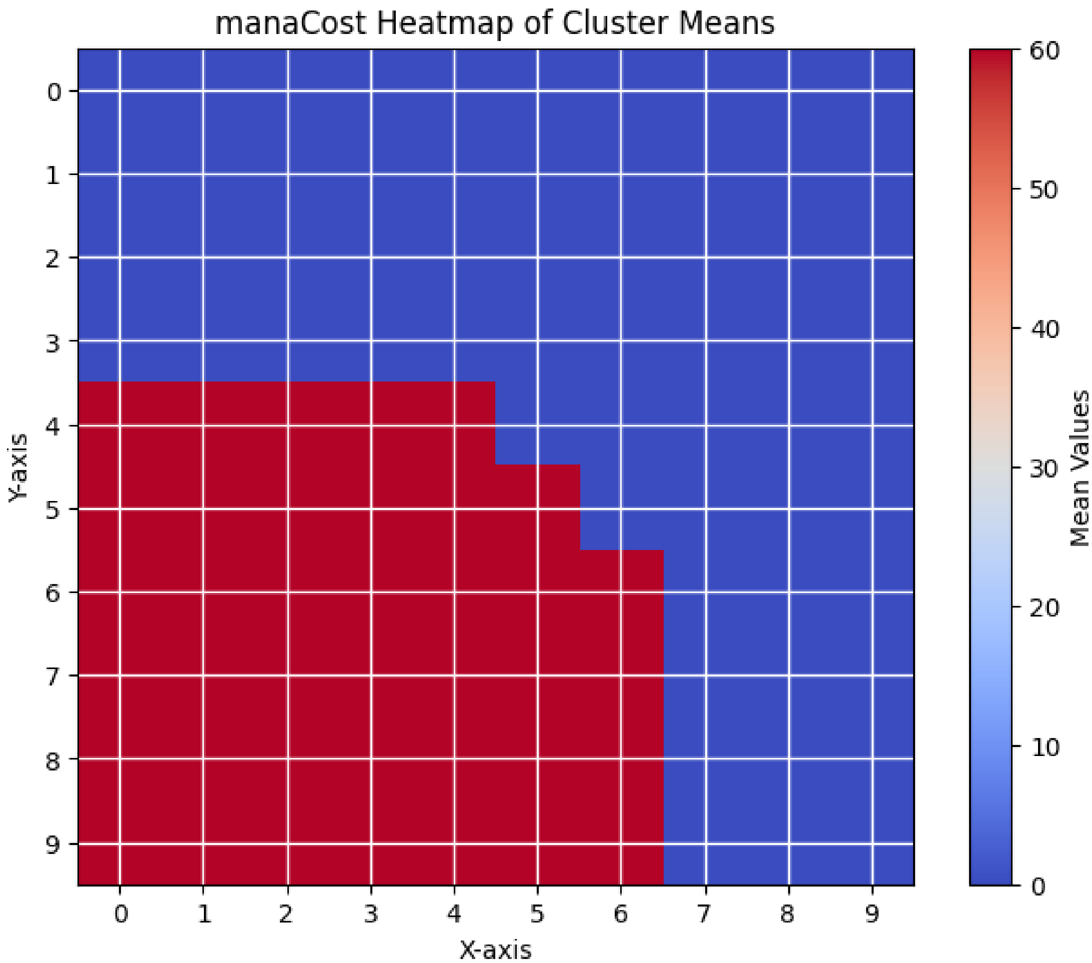

edhrecSaltiness Heatmap of Cluster Means
Y-axis
X-axis
Mean Values
0
1
2
3
4
5
6
7
8
9
0.00
0.02
0.04
0.06
0.08

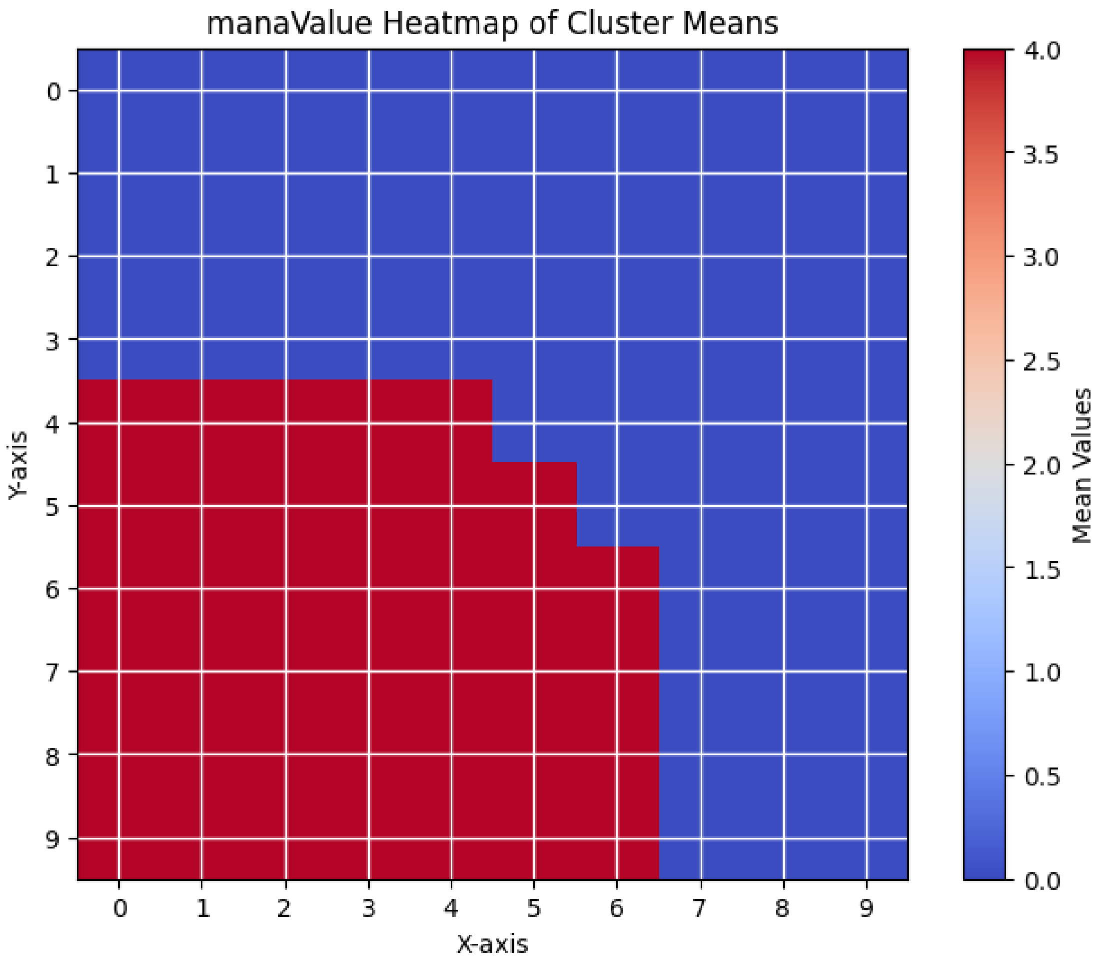

gameAvailability Heatmap of Cluster Means
Y-axis
X-axis
Mean Values
0
1
2
3
4
5
6
7
8
9
0.100
0.075
0.050
0.025
0.000
−0.025
−0.050
−0.075
−0.100

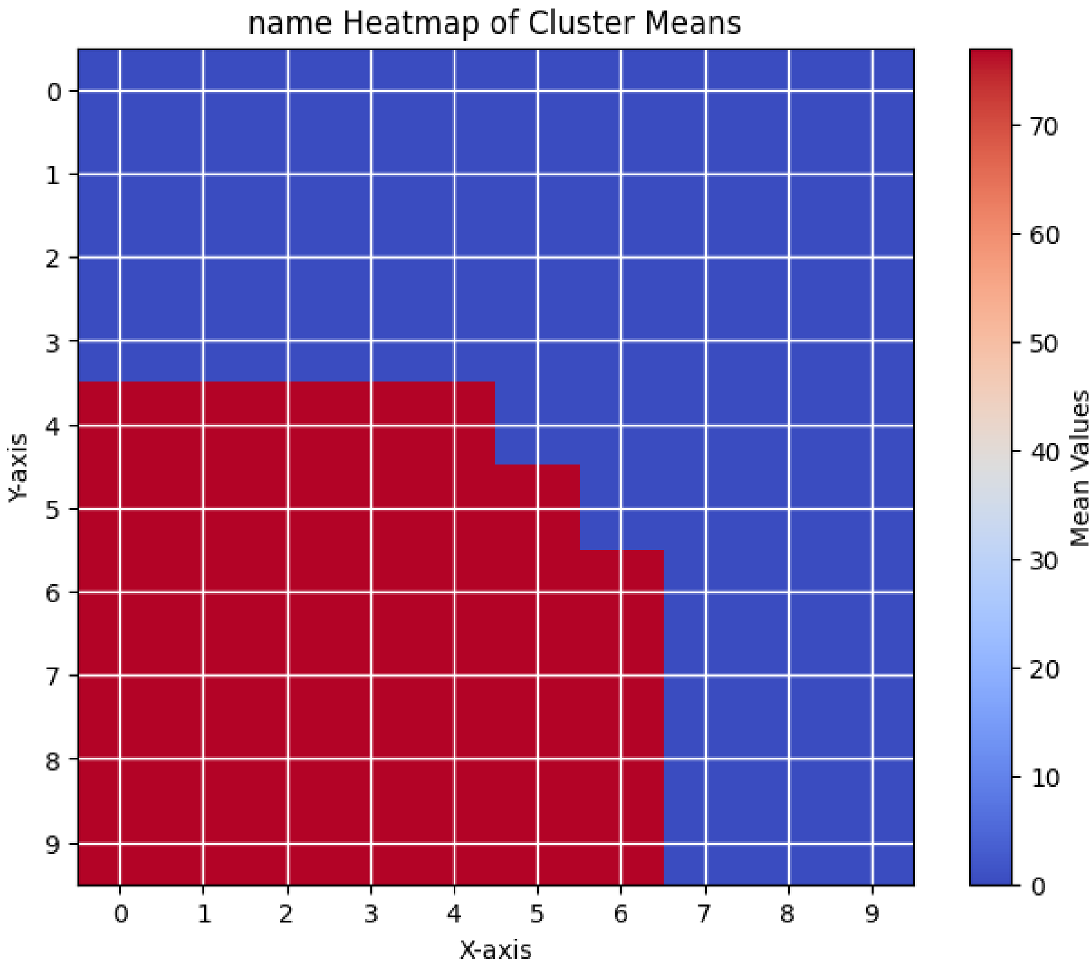

isReprint Heatmap of Cluster Means
Y-axis
X-axis
0
1
2
3
4
5
6
7
8
9
Mean Values
0.100
0.075
0.050
0.025
0.000
−0.025
−0.050
−0.075
−0.100

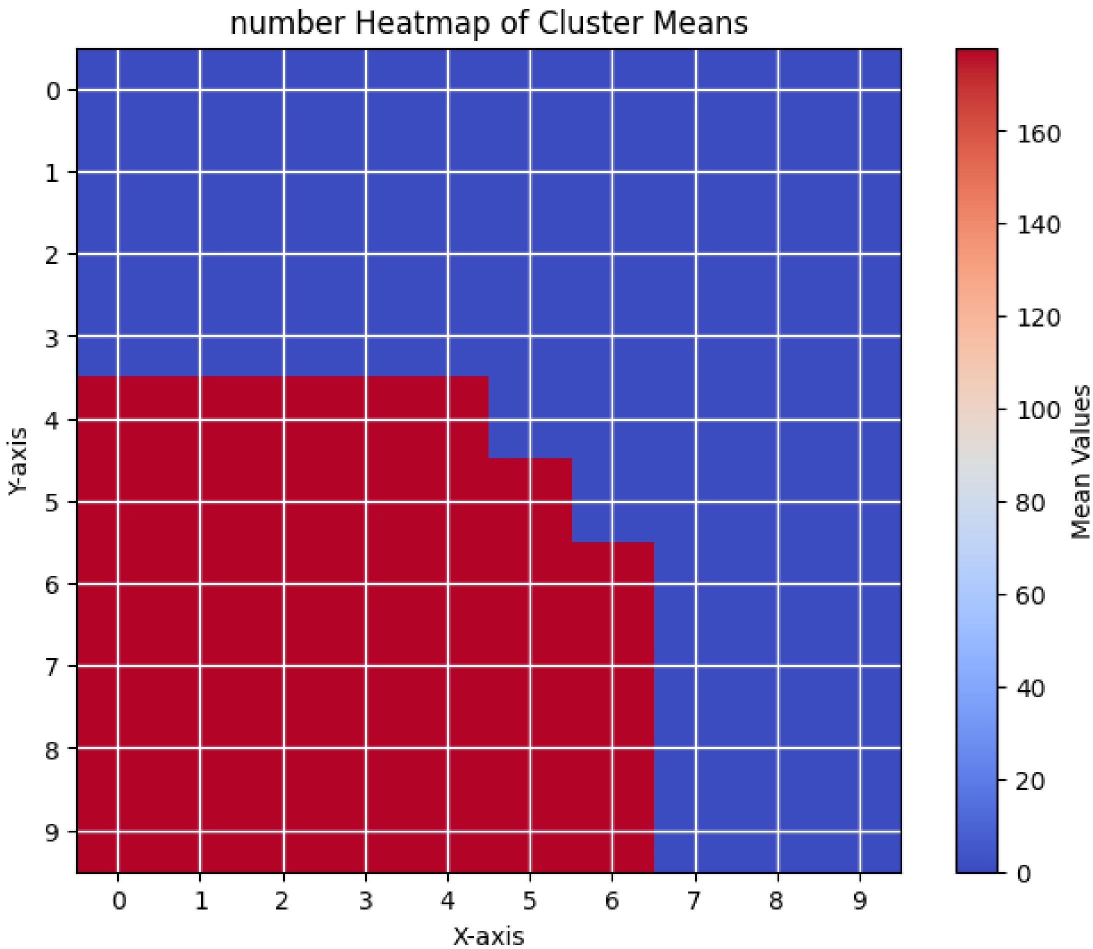


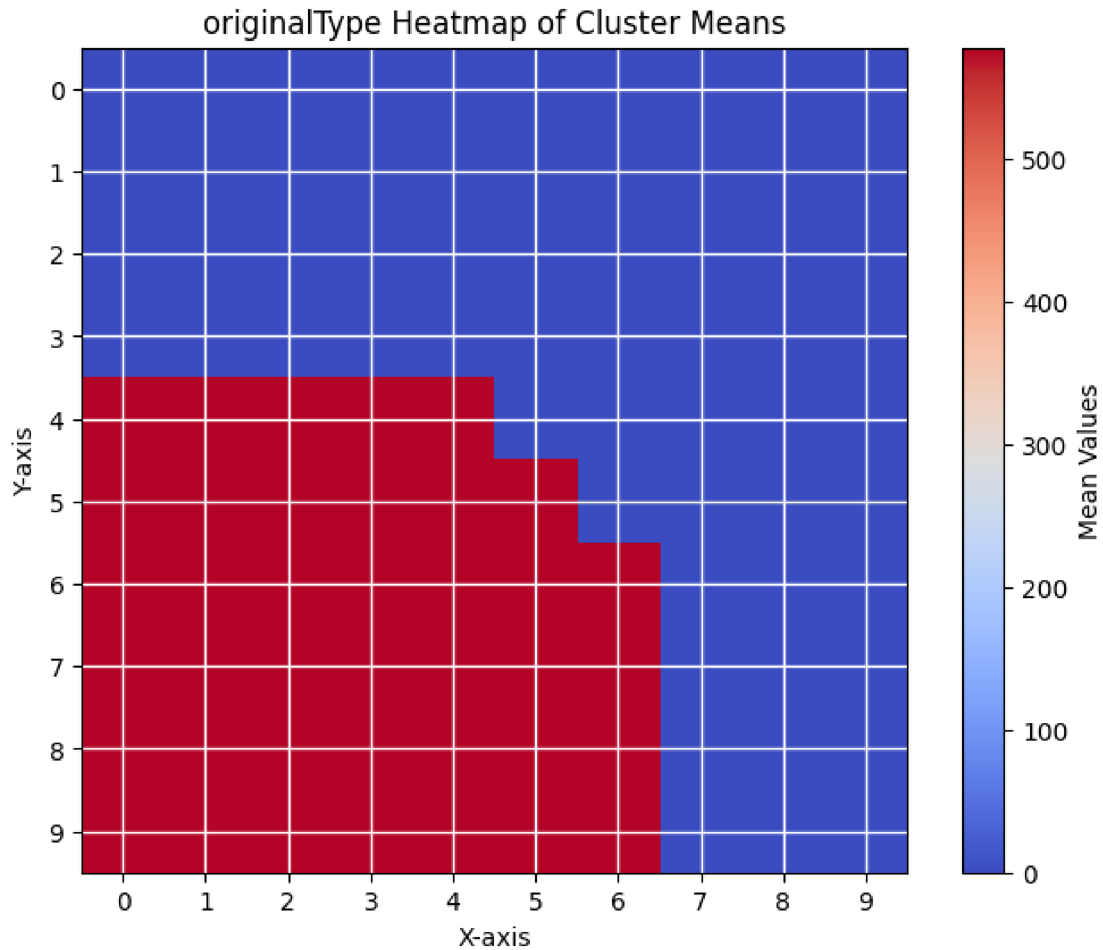
layout Heatmap of Cluster Means
Y-axis
X-axis
0
1
2
3
4
5
6
7
8
9
Mean Values
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0

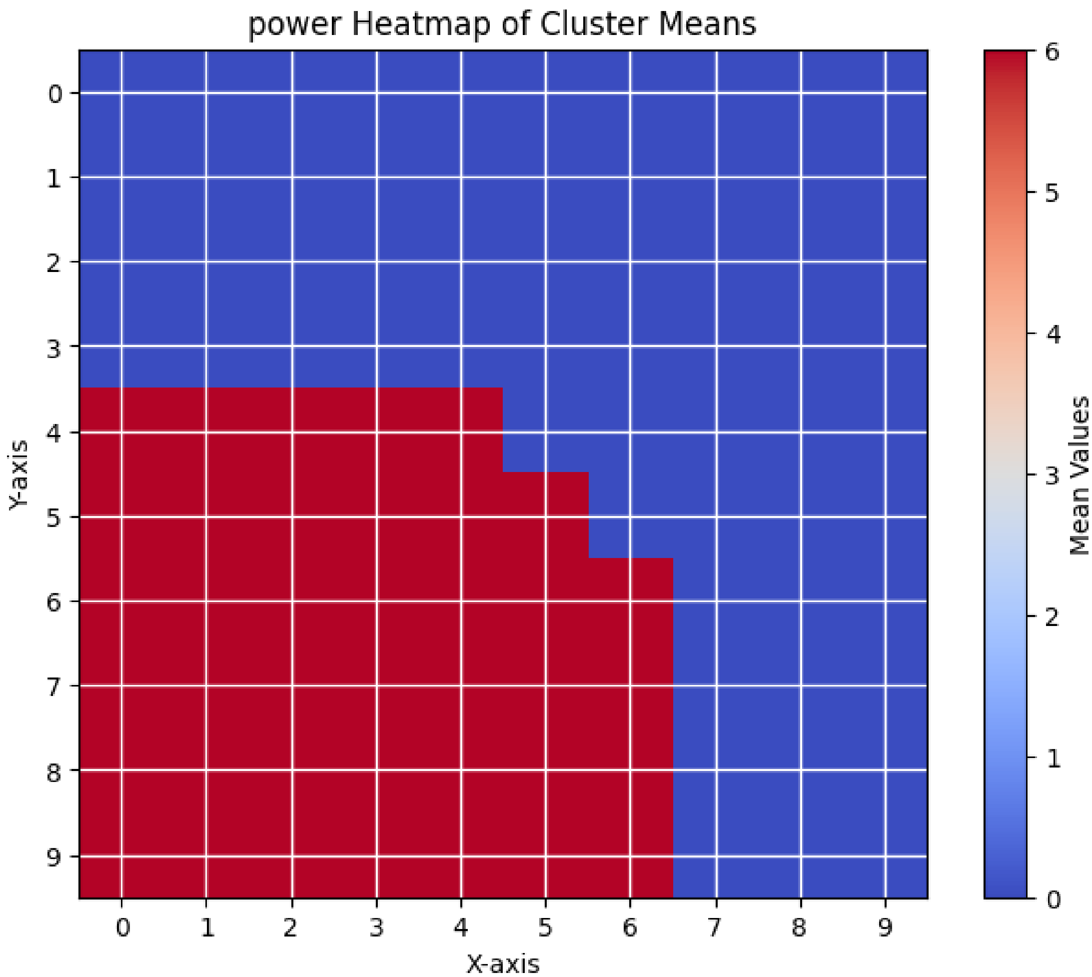

manaCost Heatmap of Cluster Means
Y-axis
X-axis
Mean Values
0
1
2
3
4
5
6
7
8
9
10
20
30
40
50
60

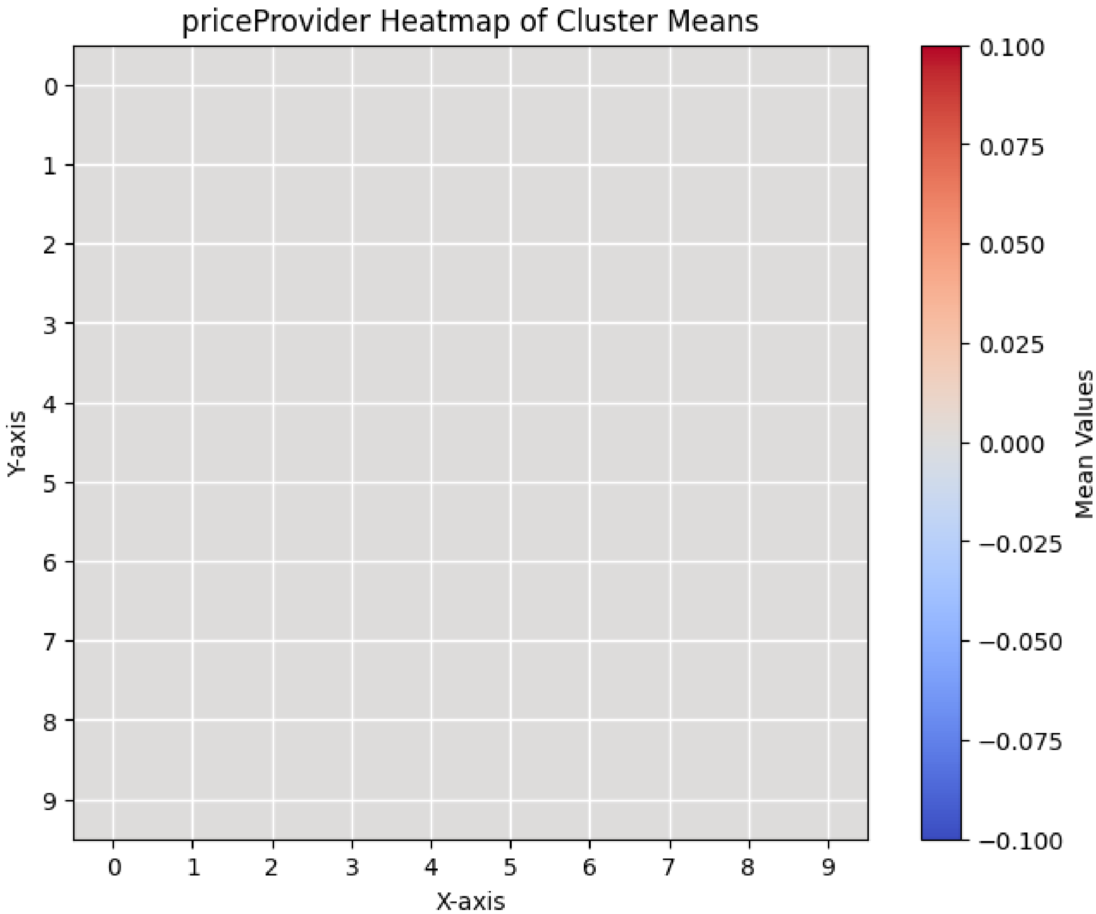

manaValue Heatmap of Cluster Means
Y-axis
X-axis
Mean Values
0
1
2
3
4
5
6
7
8
9
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0

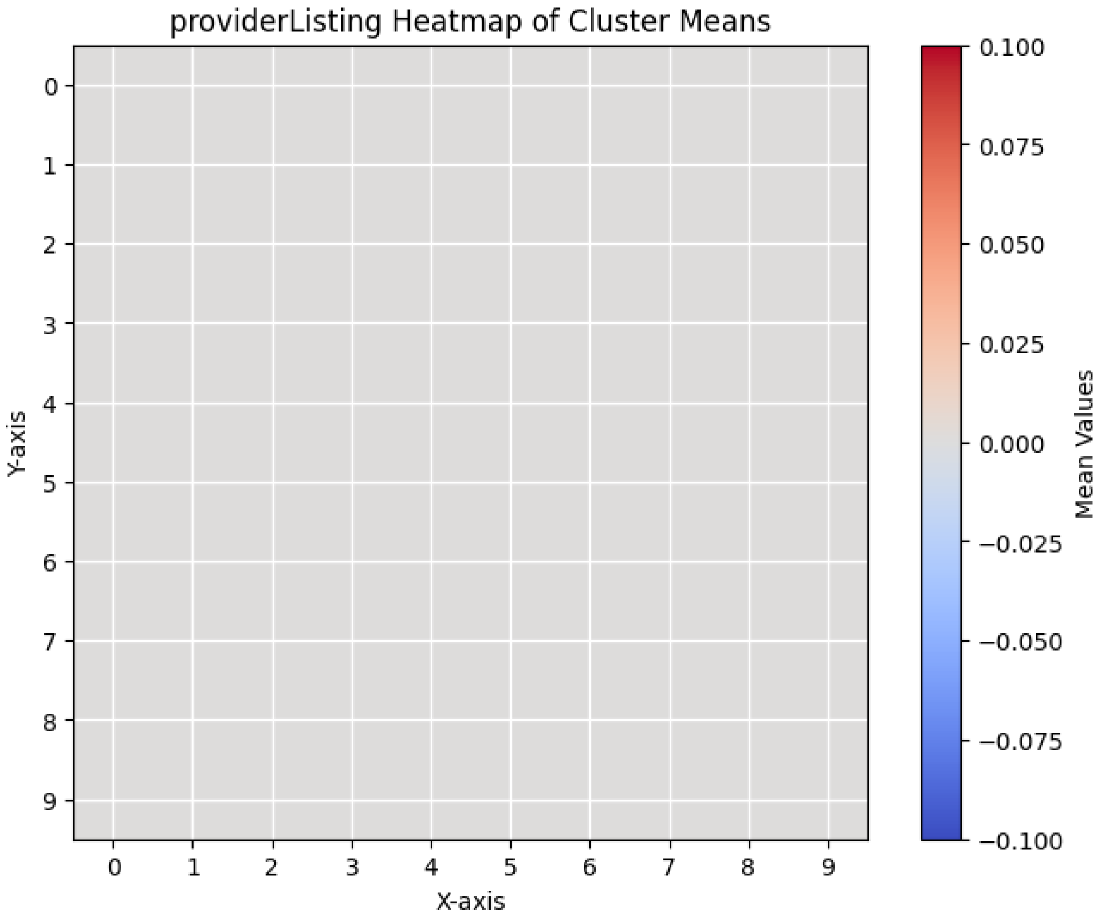

name Heatmap of Cluster Means
Y-axis
X-axis
Mean Values
0
1
2
3
4
5
6
7
8
9
0
10
20
30
40
50
60
70

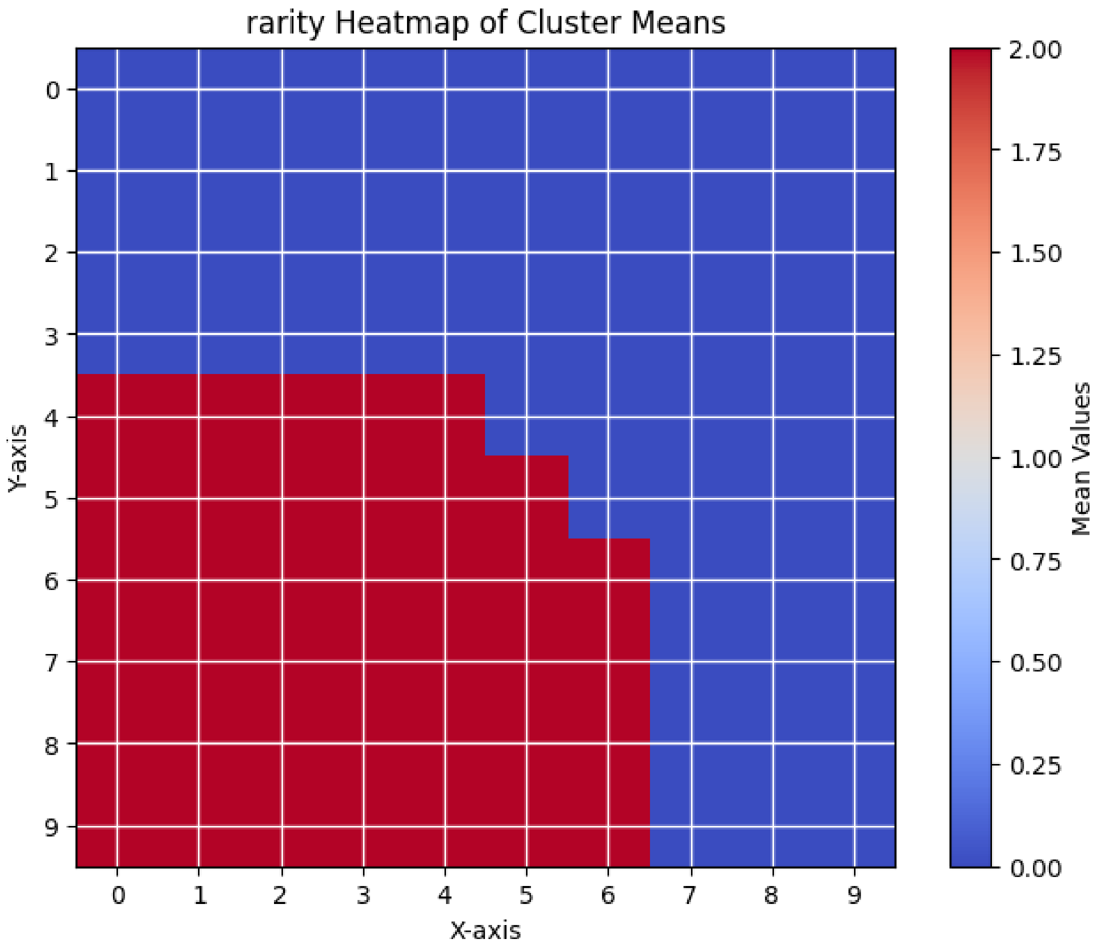

number Heatmap of Cluster Means
Y-axis
X-axis
Mean Values
0
1
2
3
4
5
6
7
8
9
0
20
40
60
80
100
120
140
160

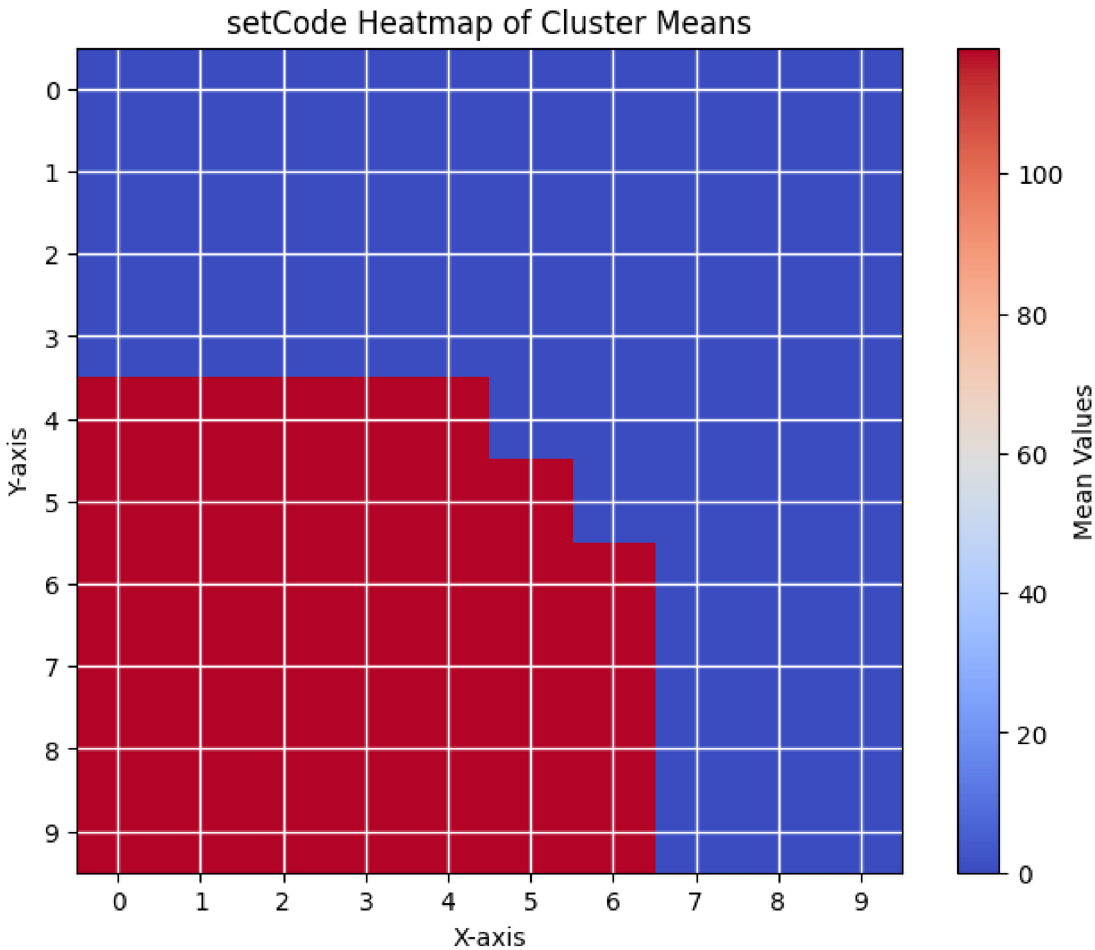

originalType Heatmap of Cluster Means
Y-axis
X-axis
Mean Values
0
1
2
3
4
5
6
7
8
9
0
100
200
300
400
500

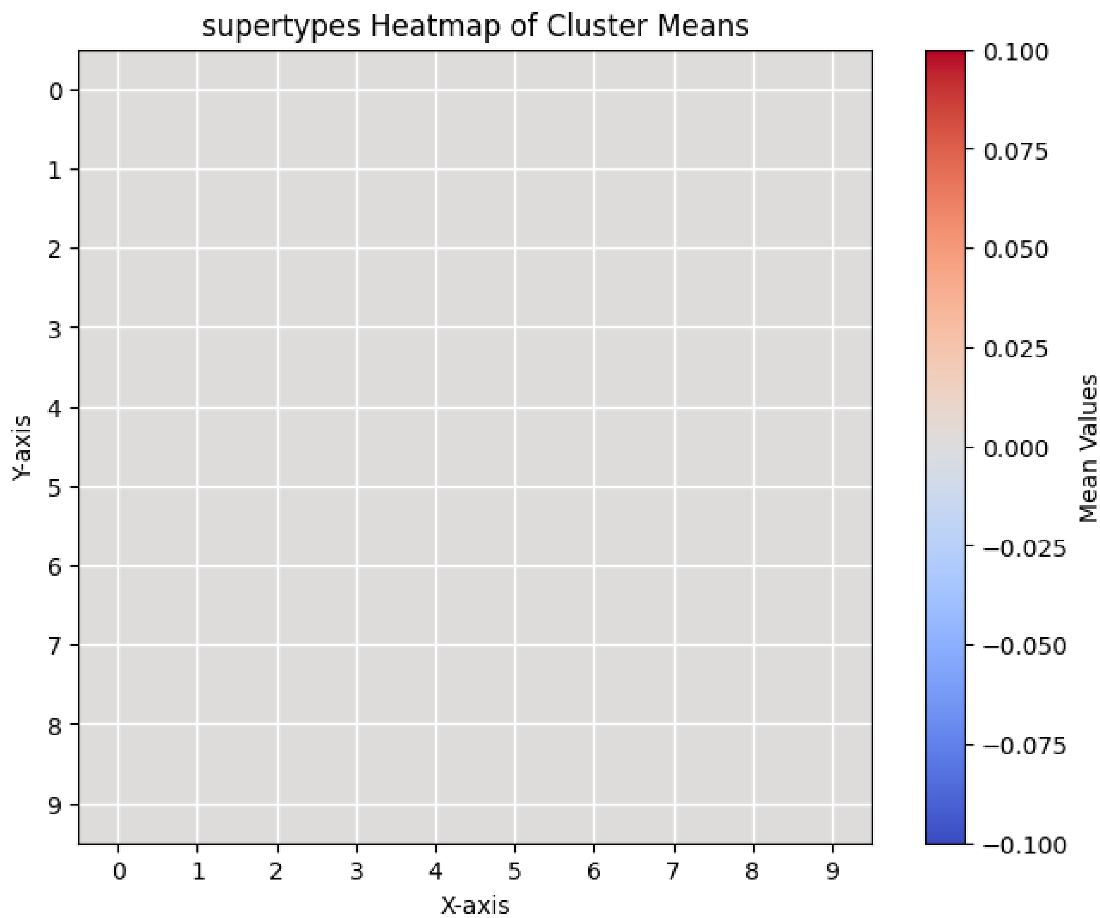

power Heatmap of Cluster Means
Y-axis
X-axis
Mean Values
0
1
2
3
4
5
6
7
8
9

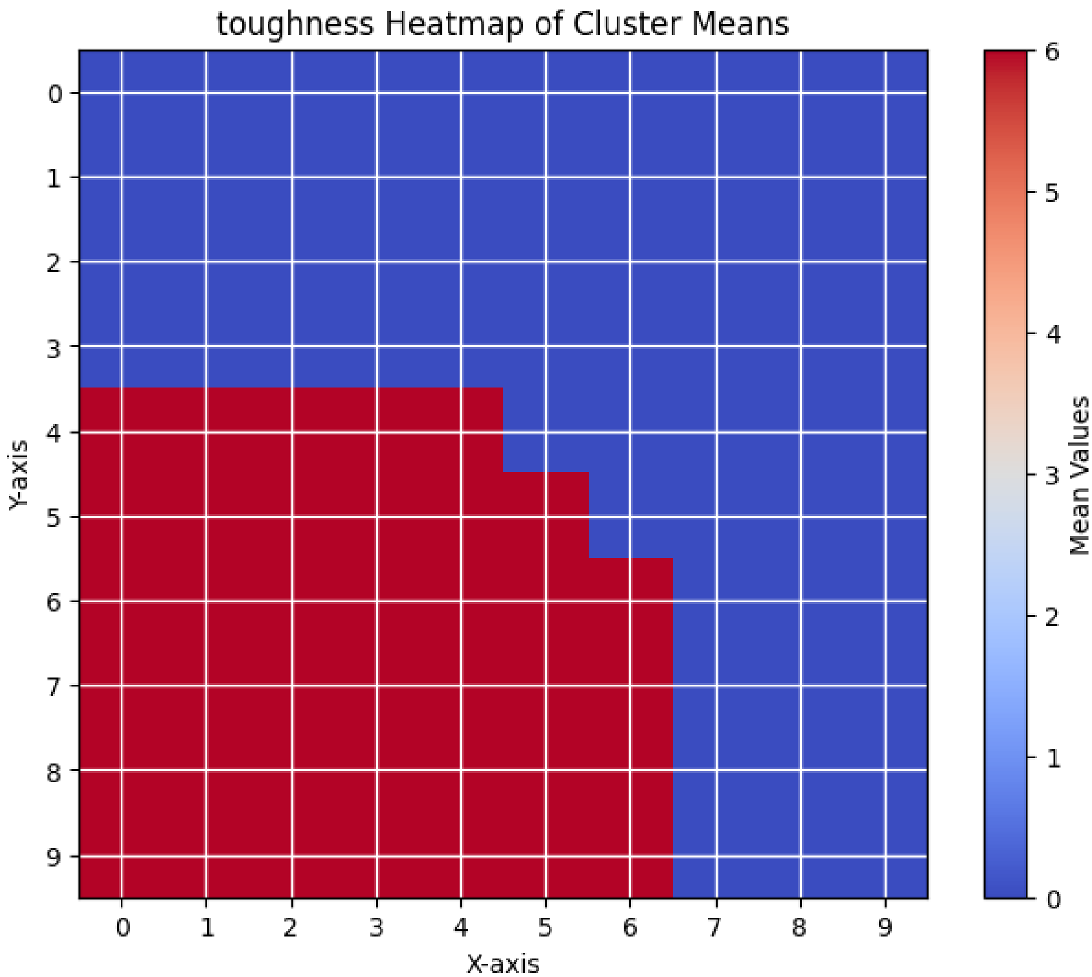

priceProvider Heatmap of Cluster Means
0
1
2
3
4
5
6
7
8
9
Y-axis
X-axis
0.100
0.075
0.050
0.025
0.000
−0.025
−0.050
−0.075
−0.100
Mean Values

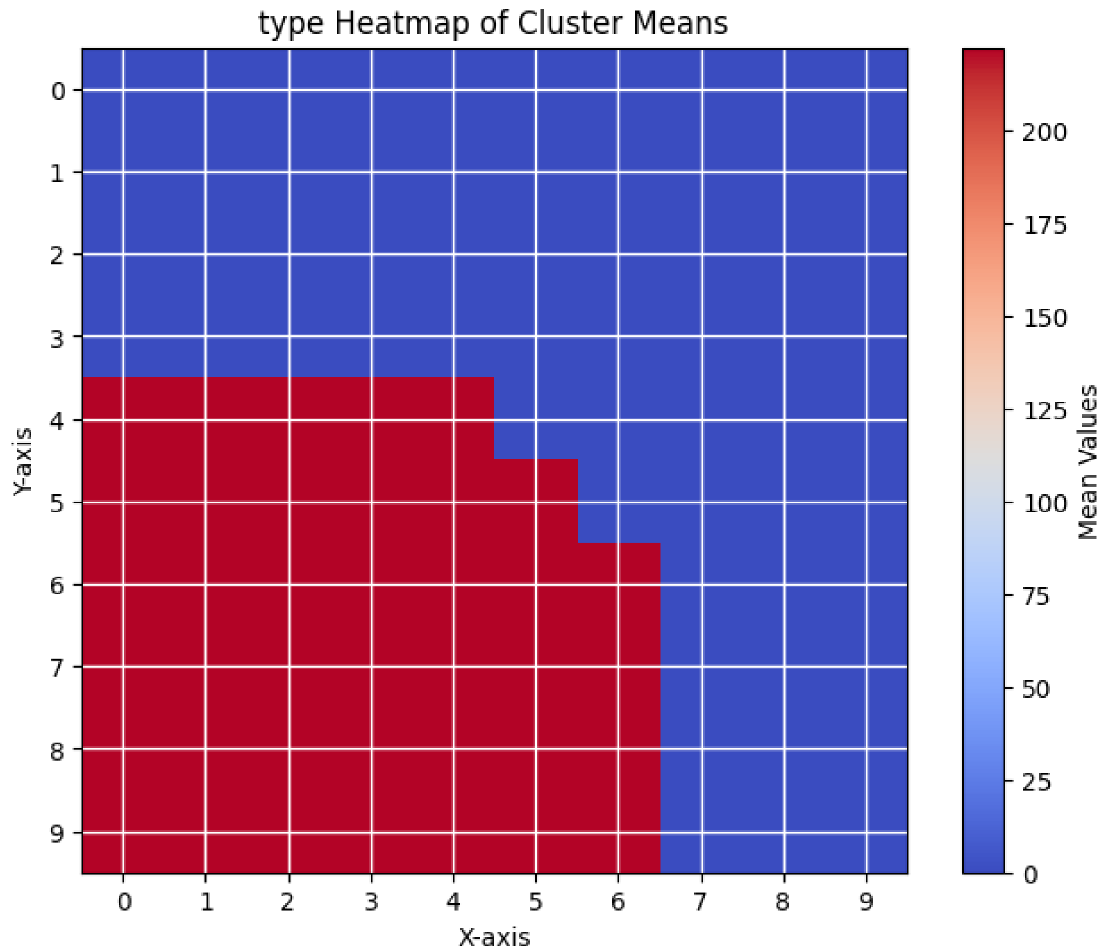

providerListing Heatmap of Cluster Means
Y-axis
X-axis
Mean Values
0
1
2
3
4
5
6
7
8
9
0.100
0.075
0.050
0.025
0.000
−0.025
−0.050
−0.075
−0.100

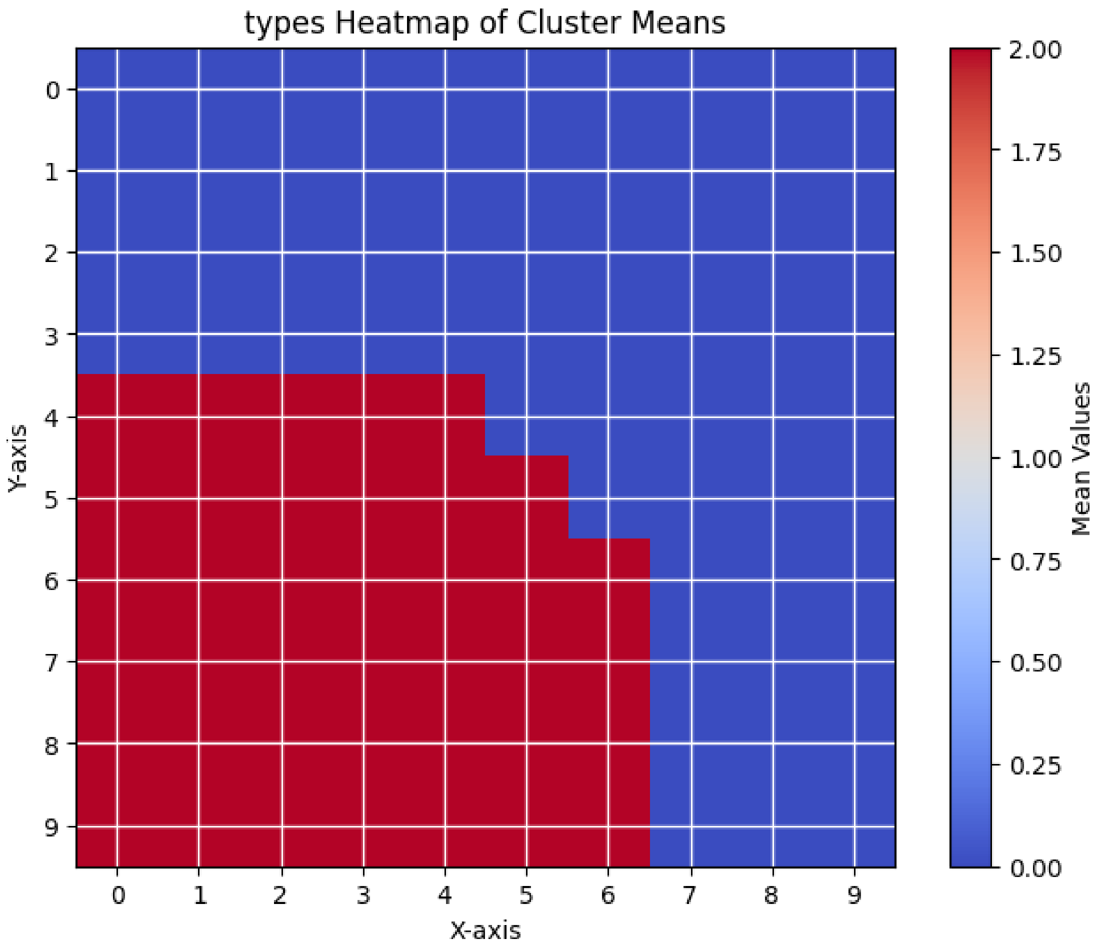

rarity Heatmap of Cluster Means
Y-axis
X-axis
Mean Values
0
1
2
3
4
5
6
7
8
9
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00


setCode Heatmap of Cluster Means
Y-axis
X-axis
Mean Values
0
1
2
3
4
5
6
7
8
9
20
40
60
80
100


supertypes Heatmap of Cluster Means
Y-axis
X-axis
Mean Values
0 1 2 3 4 5 6 7 8 9
0.100
0.075
0.050
0.025
0.000
−0.025
−0.050
−0.075
−0.100

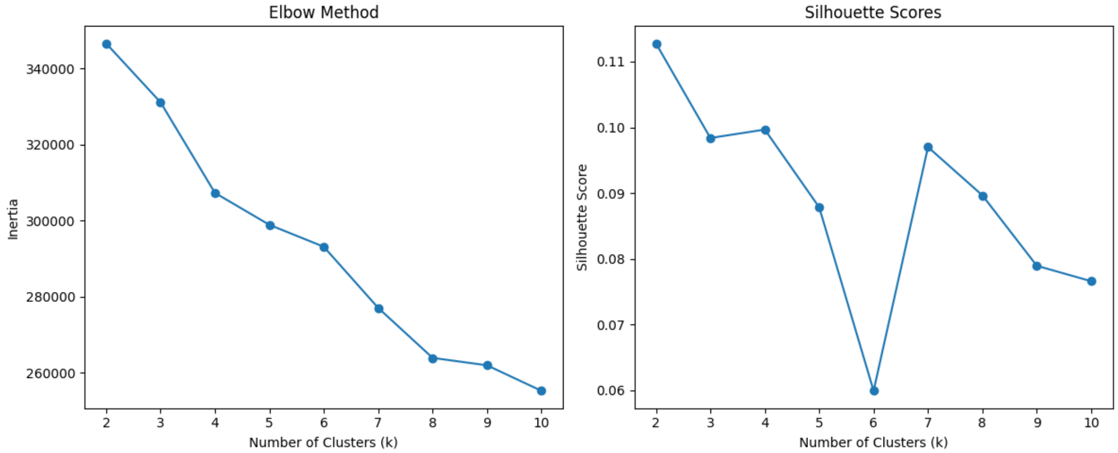

toughness Heatmap of Cluster Means
Y-axis
X-axis
Mean Values
0
1
2
3
4
5
6
7
8
9

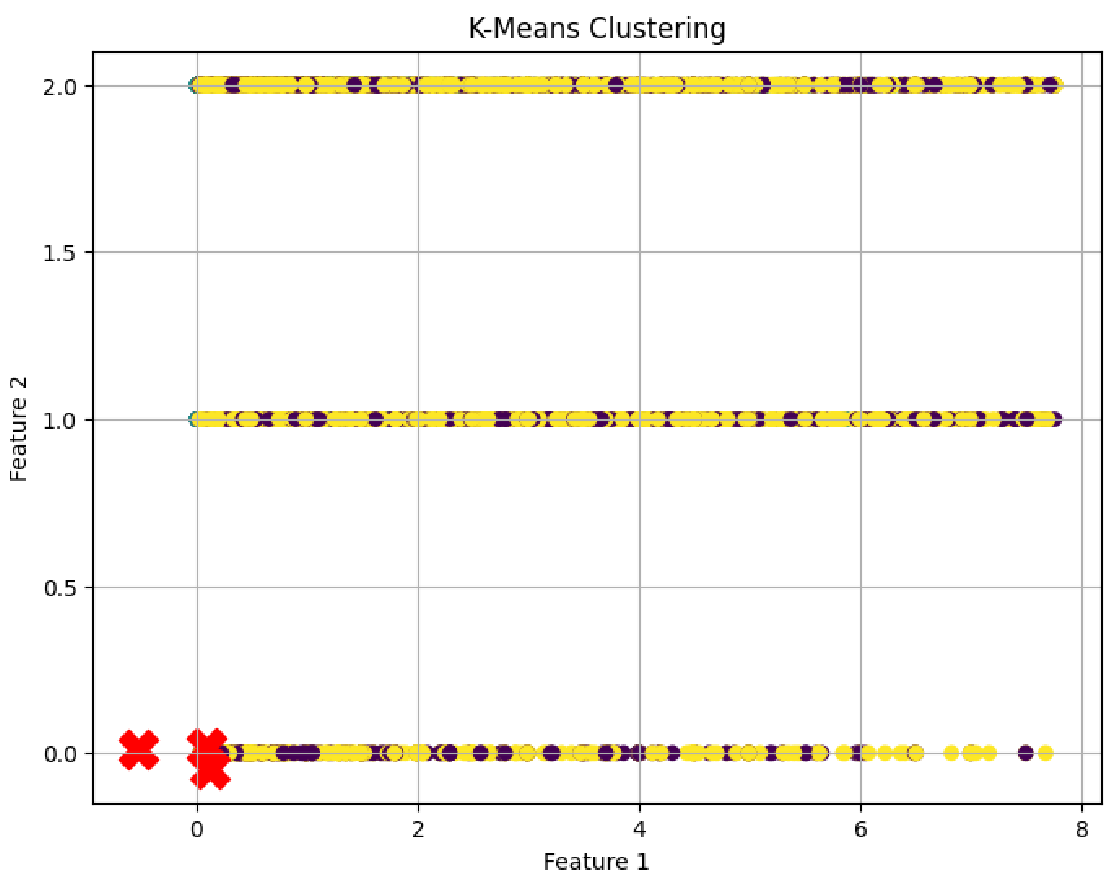

type Heatmap of Cluster Means
Y-axis
X-axis
Mean Values
0
1
2
3
4
5
6
7
8
9
25
50
75
100
125
150
175
200



[10]:
```
scaler = StandardScaler()
scaled_data = scaler.fit_transform(data)

inertia = []
silhouette_scores = []
k_values = range(2,11)

for k in k_values:
    kmeans = KMeans(n_clusters=k, random_state=42)
    kmeans.fit(scaled_data)
    inertia.append(kmeans.inertia_)
    silhouette_scores.append(silhouette_score(scaled_data, kmeans.labels_))

# Step 4: Plot the Elbow Method results
plt.figure(figsize=(12, 5))

# Inertia Plot
```

```
plt.subplot(1, 2, 1)
plt.plot(k_values, inertia, marker='o')
plt.title('Elbow Method')
plt.xlabel('Number of Clusters (k)')
plt.ylabel('Inertia')

# Silhouette Score Plot
plt.subplot(1, 2, 2)
plt.plot(k_values, silhouette_scores, marker='o')
plt.title('Silhouette Scores')
plt.xlabel('Number of Clusters (k)')
plt.ylabel('Silhouette Score')

plt.tight_layout()
plt.show()

# Step 5: Fit the K-Means model with the chosen k (e.g., k=3)
optimal_k = 3  # Choose based on the Elbow method or Silhouette score
kmeans = KMeans(n_clusters=optimal_k, random_state=42)
kmeans.fit(scaled_data)

# Step 6: Add cluster labels to the original DataFrame
data['cluster'] = kmeans.labels_

# Step 7: Visualize the clusters
plt.figure(figsize=(8, 6))
plt.scatter(data['price'], data['cardFinish'], c=data['cluster'], cmap='viridis', marker='o')
plt.scatter(kmeans.cluster_centers_[:, 0], kmeans.cluster_centers_[:, 1], s=300, c='red', marker='X')  # Cluster centers
plt.title('K-Means Clustering')
plt.xlabel('Feature 1')
plt.ylabel('Feature 2')
plt.grid()
plt.show()
```


Elbow Method
Silhouette Scores
Inertia
Silhouette Score
Number of Clusters (k)
Number of Clusters (k)


K-Means Clustering
Feature 1
Feature 2