Practical implementation of k-means clustering

CUSTOMER SEGMENTATION IN PYTHON

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Key steps

- Data pre-processing
- Choosing a number of clusters
- Running k-means clustering on pre-processed data
- Analyzing average RFM values of each cluster

Data pre-processing

We've completed the pre-processing steps and have these two objects:

- `datamart_rfm`
- `datamart_normalized`

```
import numpy as np
datamart_log = np.log(datamart_rfm)

from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
scaler.fit(datamart_log)

datamart_normalized = scaler.transform(datamart_log)
```

Methods to define the number of clusters

- Visual methods - elbow criterion
- Mathematical methods - silhouette coefficient
- Experimentation and interpretation

Running k-means

```
# Import package
from sklearn.cluster import KMeans
kmeans = KMeans(n_clusters=2, random_state=1)
```

```
# Compute k-means clustering on pre-processed data
kmeans.fit(datamart_normalized)
```

```
# Extract cluster labels from labels_ attribute
cluster_labels = kmeans.labels_
```

Analyzing average RFM values of each cluster

```
# Create a cluster label column in the original DataFrame
datamart_rfm_k2 = datamart_rfm.assign(Cluster = cluster_labels)
```

```
# Calculate average RFM values and size for each cluster
datamart_rfm_k2.groupby(['Cluster']).agg({
    'Recency': 'mean',
    'Frequency': 'mean',
    'MonetaryValue': ['mean', 'count'],
}).round(0)
```

Analyzing average RFM values of each cluster

The result of a simple 2-cluster solution:

	Recency	Frequency	MonetaryValue	
	mean	mean	mean	count
cluster				
0	137.0	5.0	92.0	2023
1	32.0	35.0	719.0	1620

Let's practice running k-means clustering!

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Choosing number of clusters

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Methods

- Visual methods - elbow criterion
- Mathematical methods - silhouette coefficient
- Experimentation and interpretation

Elbow criterion method

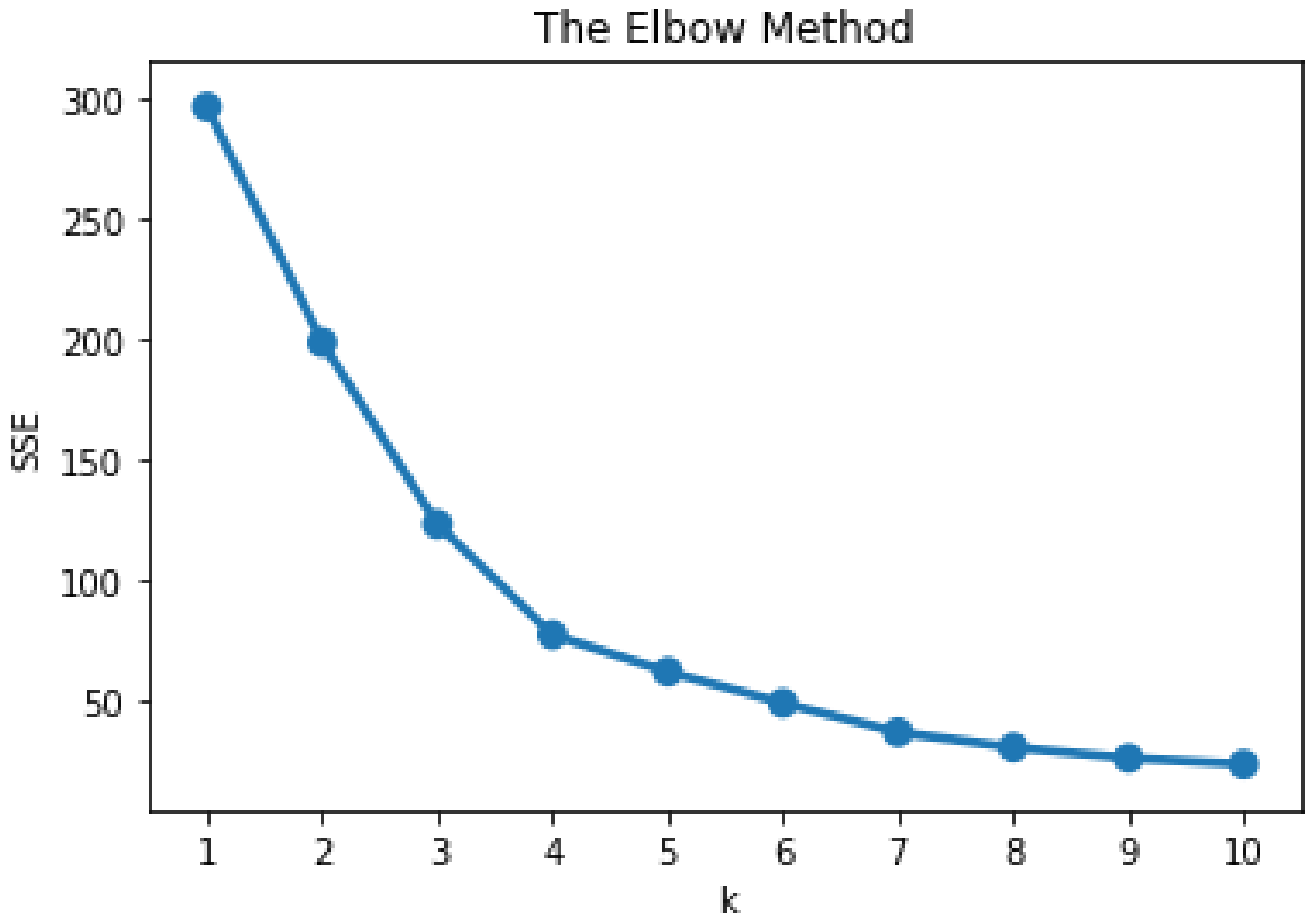
- Plot the number of clusters against within-cluster sum-of-squared-errors (SSE) - *sum of squared distances from every data point to their cluster center*
- Identify an "elbow" in the plot
- Elbow - a point representing an "optimal" number of clusters

Elbow criterion method

```python
# Import key libraries
from sklearn.cluster import KMeans
import seaborn as sns
from matplotlib import pyplot as plt
# Fit KMeans and calculate SSE for each *k*
sse = {}
for k in range(1, 11):
    kmeans = KMeans(n_clusters=k, random_state=1)
    kmeans.fit(data_normalized)
    sse[k] = kmeans.inertia_ # sum of squared distances to closest cluster center
# Plot SSE for each *k*
plt.title('The Elbow Method')
plt.xlabel('k'); plt.ylabel('SSE')
sns.pointplot(x=list(sse.keys()), y=list(sse.values()))
plt.show()
```

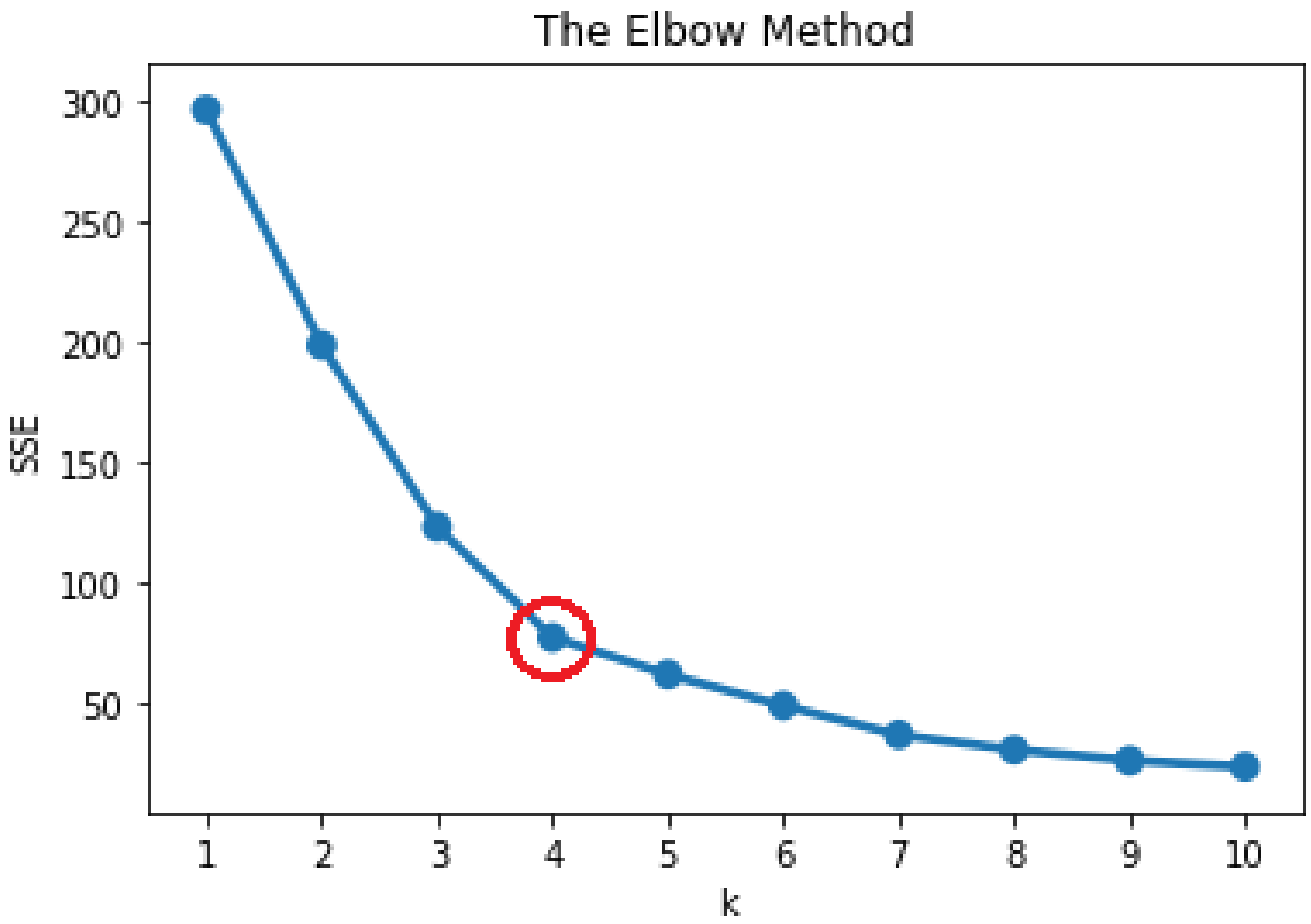
Elbow criterion method

The elbow criterion chart:



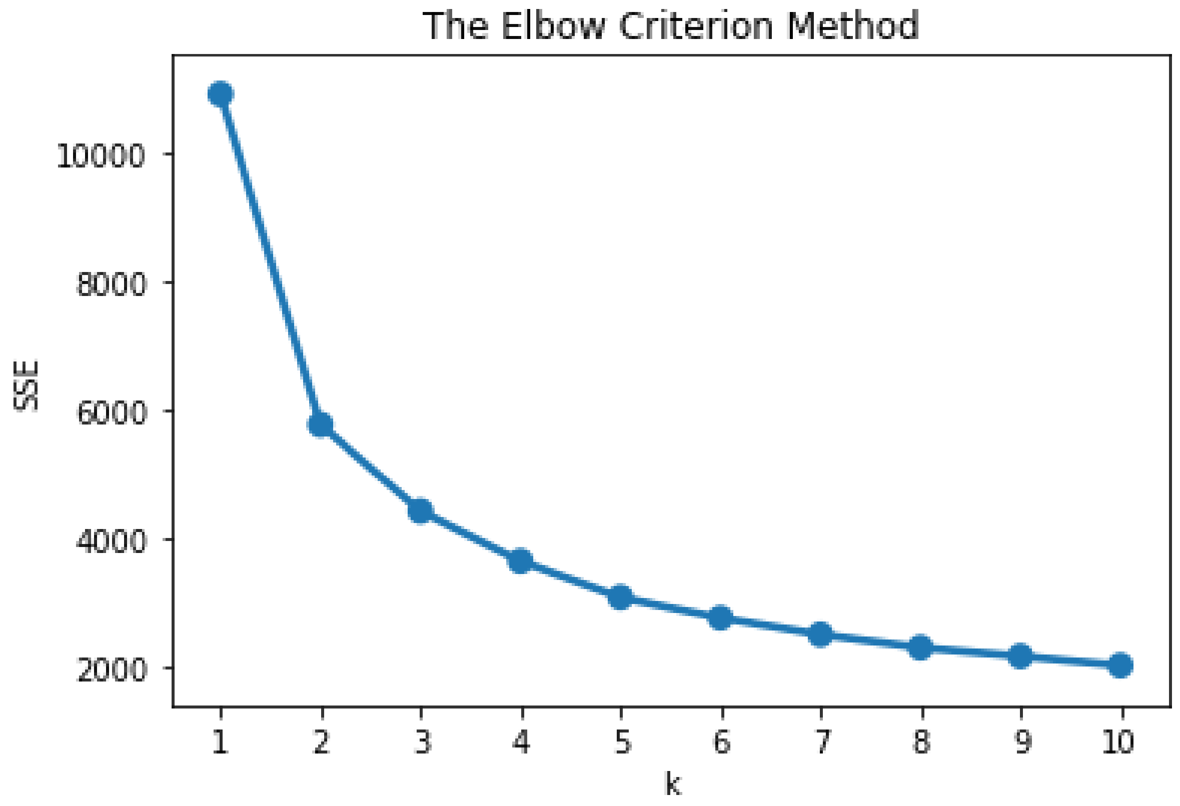
Elbow criterion method

The elbow criterion chart:



Using elbow criterion method

- Best to choose the point on elbow, or the next point
- Use as a guide but test multiple solutions
- Elbow plot built on `datamart_rfm`



Experimental approach - analyze segments

- Build clustering at and around elbow solution
- Analyze their properties - average RFM values
- Compare against each other and choose one which makes most business sense

Experimental approach - analyze segments

- Previous 2-cluster solution

	Recency	Frequency	MonetaryValue	
	mean	mean	mean	count
cluster				
0	137.0	5.0	92.0	2023
1	32.0	35.0	719.0	1620

- 3-cluster solution on the same normalized RFM dataset

	Recency	Frequency	MonetaryValue	
	mean	mean	mean	count
cluster				
0	16.0	50.0	1051.0	901
1	167.0	3.0	53.0	1156
2	77.0	12.0	216.0	1586

Let's practice finding the optimal number of clusters!

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Profile and interpret segments

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Approaches to build customer personas

- Summary statistics for each cluster e.g. average RFM values
- Snake plots (from market research)
- Relative importance of cluster attributes compared to population

Summary statistics of each cluster

- Run k-means segmentation for several **k** values around the recommended value.
- Create a cluster label column in the **original** DataFrame:

```
datamart_rfm_k2 = datamart_rfm.assign(Cluster = cluster_labels)
```

Calculate average RFM values and sizes for each cluster:

```
datamart_rfm_k2.groupby(['Cluster']).agg({
    'Recency': 'mean',
    'Frequency': 'mean',
    'MonetaryValue': ['mean', 'count'],
}).round(0)
```

  - Repeat the same for **k=3**

Summary statistics of each cluster

- Compare average RFM values of each clustering solution

	Recency	Frequency	MonetaryValue	
	mean	mean	mean	count
cluster				
0	137.0	5.0	92.0	2023
1	32.0	35.0	719.0	1620

	Recency	Frequency	MonetaryValue	
	mean	mean	mean	count
cluster				
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Snake plots to understand and compare segments

- Market research technique to compare different segments
- Visual representation of each segment's attributes
- Need to first normalize data (center & scale)
- Plot each cluster's average normalized values of each attribute

Prepare data for a snake plot

Transform `datamart_normalized` as DataFrame and add a `Cluster` column

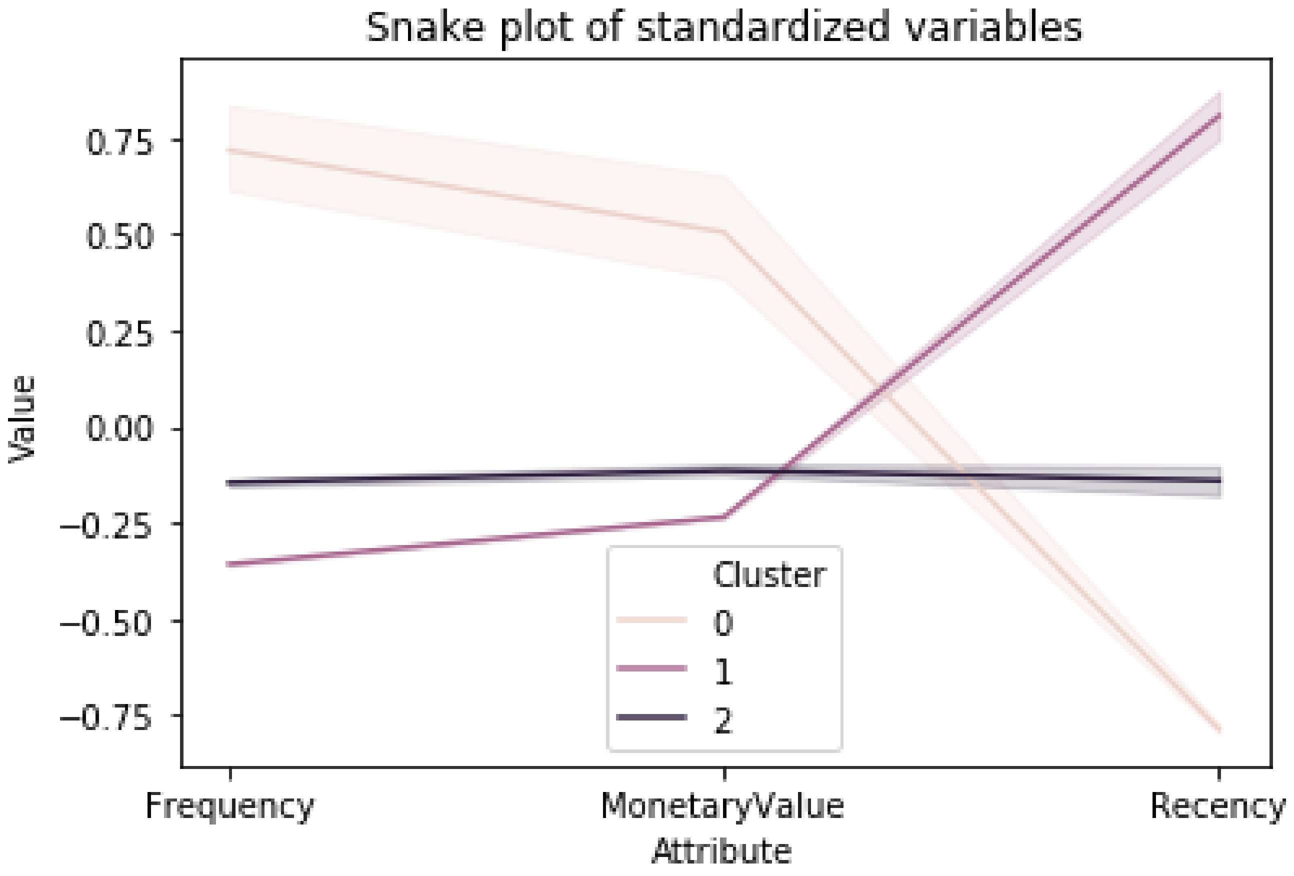
```
datamart_normalized = pd.DataFrame(datamart_normalized,
                                   index=datamart_rfm.index,
                                   columns=datamart_rfm.columns)
datamart_normalized['Cluster'] = datamart_rfm_k3['Cluster']
```

Melt the data into a long format so RFM values and metric names are stored in 1 column each

```
datamart_melt = pd.melt(datamart_normalized.reset_index(),
                    id_vars=['CustomerID', 'Cluster'],
                    value_vars=['Recency', 'Frequency', 'MonetaryValue'],
                    var_name='Attribute',
                    value_name='Value')
```

Visualize a snake plot

```
plt.title('Snake plot of standardized variables')
sns.lineplot(x="Attribute", y="Value", hue='Cluster', data=datamart_melt)
```



Relative importance of segment attributes

- Useful technique to identify relative importance of each segment's attribute
- Calculate average values of each cluster
- Calculate average values of population
- Calculate importance score by dividing them and subtracting 1 (*ensures 0 is returned when cluster average equals population average*)

```
cluster_avg = datamart_rfm_k3.groupby(['Cluster']).mean()
population_avg = datamart_rfm.mean()
relative_imp = cluster_avg / population_avg - 1
```

Analyze and plot relative importance

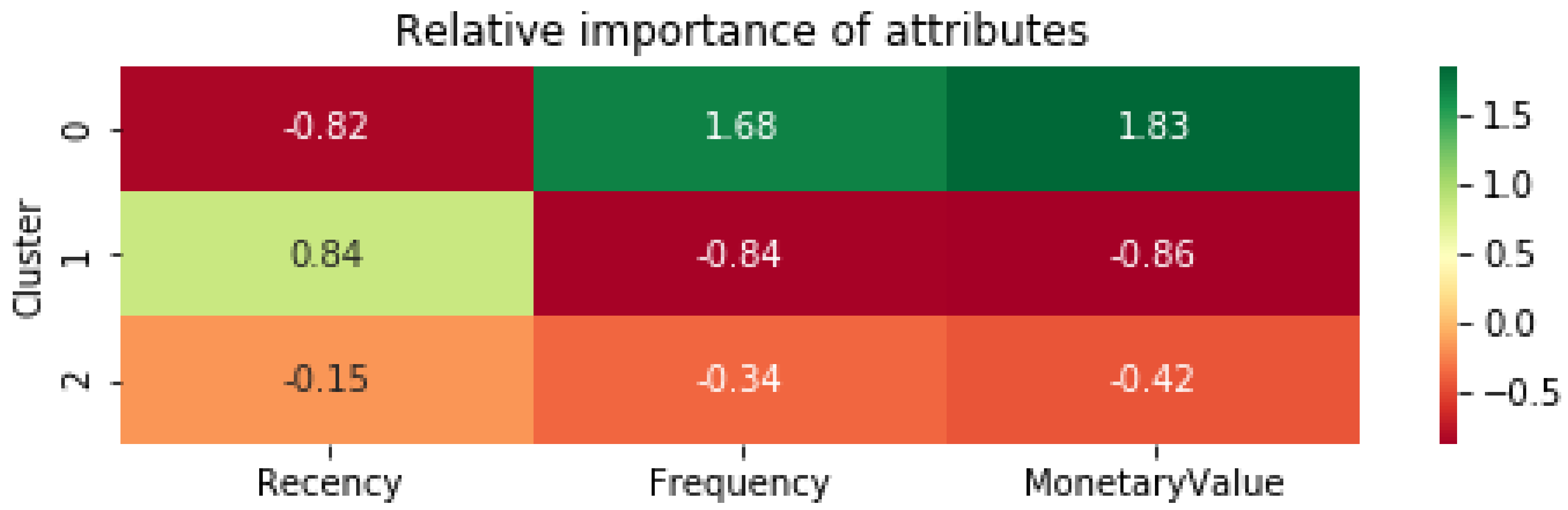
- As a ratio moves away from 0, attribute importance for a segment (relative to total pop.) increases.

```
relative_imp.round(2)
```

```
         Recency  Frequency  MonetaryValue
Cluster
0          -0.82       1.68           1.83
1           0.84      -0.84          -0.86
2          -0.15      -0.34          -0.42
```

```
# Plot heatmap
plt.figure(figsize=(8, 2))
plt.title('Relative importance of attributes')
sns.heatmap(data=relative_imp, annot=True, fmt='.2f', cmap='RdYlGn')
plt.show()
```

Relative importance heatmap



Cluster	Recency	Frequency	MonetaryValue
0	-0.82	1.68	1.83
1	0.84	-0.84	-0.86
2	-0.15	-0.34	-0.42

Your time to experiment with different customer profiling techniques!

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Implement end-to-end segmentation solution

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Key steps of the segmentation project

- Gather data - updated data with an additional variable
- Pre-process the data
- Explore the data and decide on the number of clusters
- Run k-means clustering
- Analyze and visualize results

Updated RFM data

- Same RFM values plus additional `Tenure` variable
- Tenure - time since the first transaction
- Defines how long the customer has been with the company

CustomerID	Recency	Frequency	MonetaryValue	Tenure
12747	3	25	948.70	362
12748	1	888	7046.16	365
12749	4	37	813.45	214
12820	4	17	268.02	327
12822	71	9	146.15	88

Goals for this project

- Remember key pre-processing rules
- Apply data exploration techniques
- Practice running several k-means iterations
- Analyze results quantitatively and visually

Let's dig in!

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Final thoughts

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What you have learned

- Cohort analysis and visualization
- RFM segmentation
- Data pre-processing for k-means
- Customer segmentation with k-means
  - Evaluating number of clusters
  - Reviewing and visualizing segmentation solutions

Congratulations!

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