



Practical implementation of k-means clustering

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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

Code from previous lesson:

```
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 KMeans from sklearn library and initialize it as kmeans

```
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:



Analyzing average RFM values of each cluster

The result of a simple 2-cluster solution:

	Recency	ecency Frequency Monetary\		ryValue
	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!





CUSTOMER SEGMENTATION IN PYTHON

Choosing number of clusters

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Methods

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

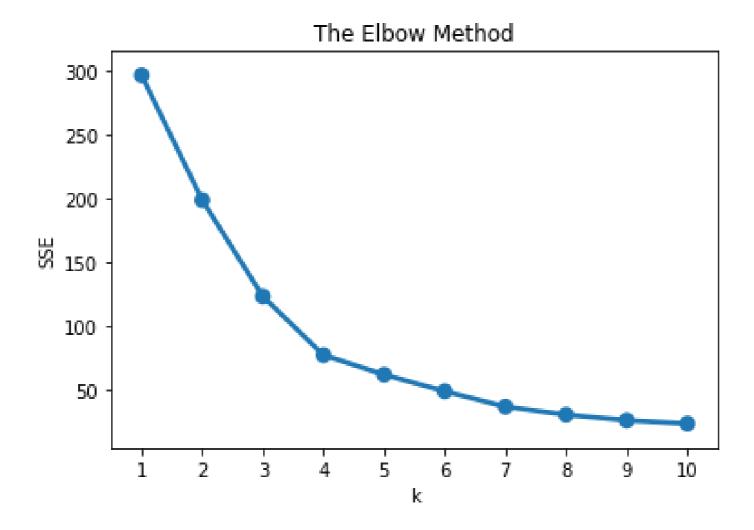


- Plot the number of clusters against within-cluster sum-of-squared-errors (SSE) sum of squared distances from every data point to their cluster center
- Identify an "elbow" in the plot
- Elbow a point representing an "optimal" number of clusters



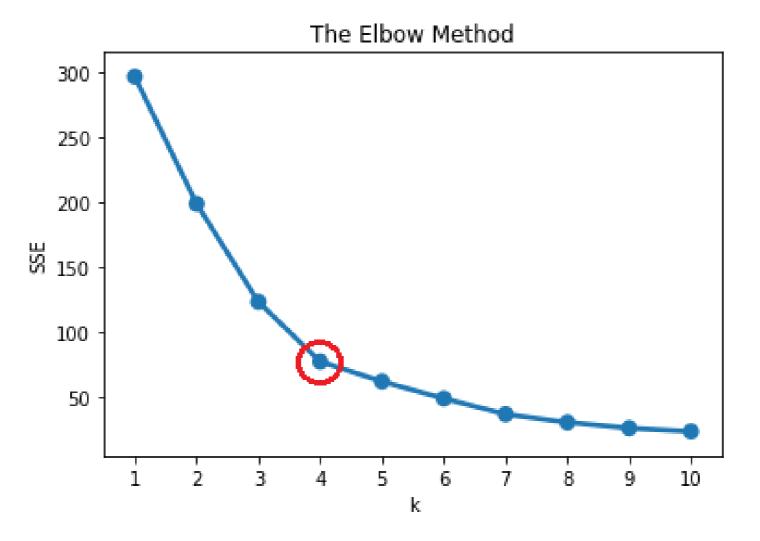
```
# Import key libraries
from sklearn.cluster import KMeans
import seaborn as sns
from matplotlib import pyplot as plt
# Fit KMeans and calculate SSE for each *k*
sse = \{ \}
for k in range (1, 11):
    kmeans = KMeans(n clusters=k, random state=1)
    kmeans.fit(data normalized)
    sse[k] = kmeans.inertia # sum of squared distances to closest cluster cente
# 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()
```

The elbow criterion chart:





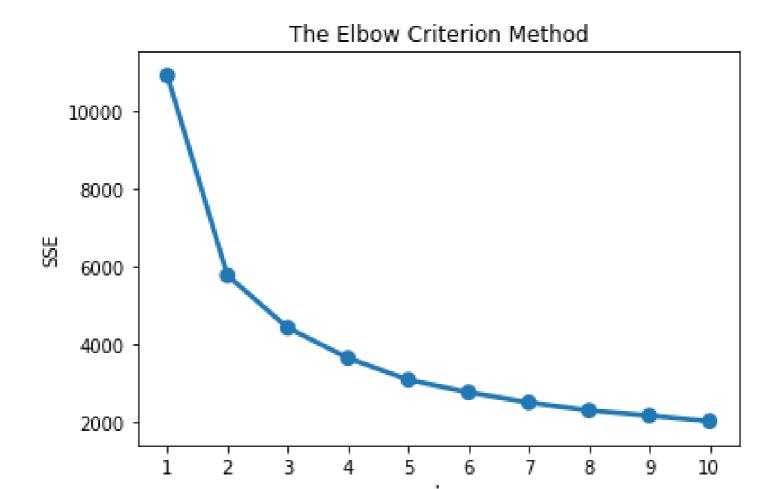
The elbow criterion chart:





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	Recency Frequency Monetary		ıryValue
	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	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!





CUSTOMER SEGMENTATION IN PYTHON

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:

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	Moneta	rvValue
		. roquono,		.,
	mean	mean	mean	count
cluster	_	_		-
cluster 0	_	_		-
	mean	mean	mean	count
0	mean 16.0	mean 50.0	mean 1051.0	count 901



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

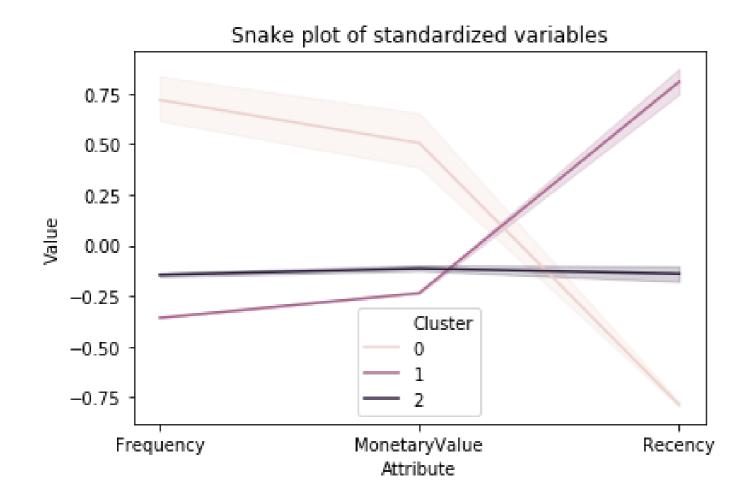
Transform datamart normalized as DataFrame and add a Cluster column

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



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

```
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

• The further a ratio is from 0, the more important that attribute is for a segment relative to the total population.

```
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 a heatmap for easier interpretation:

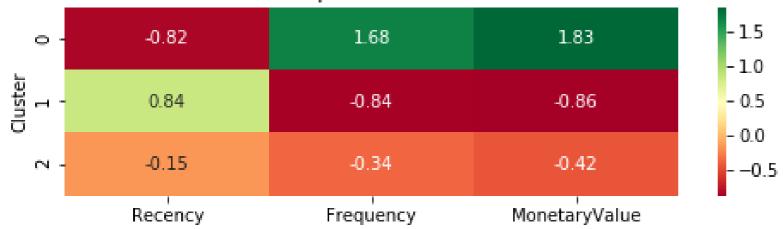
```
plt.figure(figsize=(8, 2))
plt.title('Relative importance of attributes')
sns.heatmap(data=relative_imp, annot=True, fmt='.2f', cmap='RdYlGn')
plt.show()
```



Relative importance heatmap

Heatmap plot:





vs. printed output:

	Recency	Frequency	MonetaryValue
Cluste 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!





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

	Recency	Frequency	MonetaryValue	Tenure
CustomerID				
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!





CUSTOMER SEGMENTATION IN PYTHON

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!