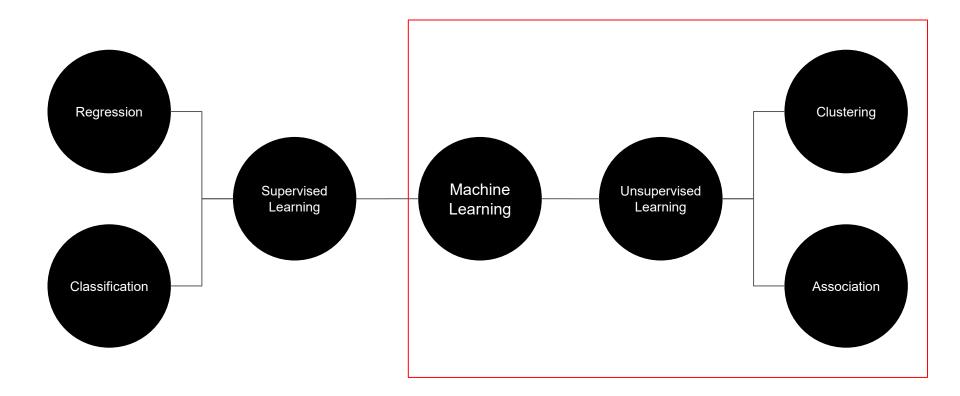
Data Prediction Model and Machine Learning

Online course #9 K-Means Clustering



Unsupervised Learning

When unsupervised learning is useful..

- Unsupervised machine learning finds all kind of unknown patterns in data
- Unsupervised methods help you to find features which can be useful for categorization
- It is easier to get unlabelled data from a computer than labelled data, which needs manual intervention

Unsupervised Learning (Example)

Type 1: Clustering

Clustering is an important concept when it comes to unsupervised learning. It mainly deals with finding a structure or pattern in a collection of uncategorized data. Clustering algorithms will process your data and find natural clusters(groups) if they exist in the data. You can also modify how many clusters your algorithms should identify. It allows you to adjust the granularity of these groups.



sample

Cluster/group

Unsupervised Learning (Example)

Type 2: Association

Association rules allow you to establish associations amongst data objects inside large databases. This unsupervised technique is about discovering interesting relationships between variables in large databases. For example, people that buy a new home most likely to buy new furniture.

Other Examples:

- Groups of shopper based on their browsing and purchasing histories
- Movie group by the rating given by movies viewers

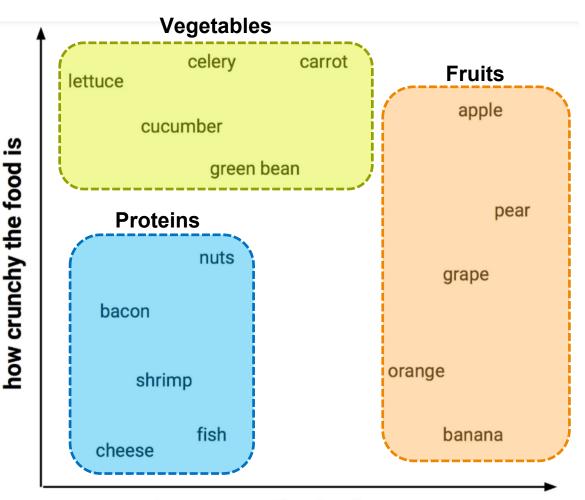
K-NN (Nearest Neighbours) ~ K-means Clustering

"Birds of a feather flock together"

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K-NN (Nearest Neighbours)

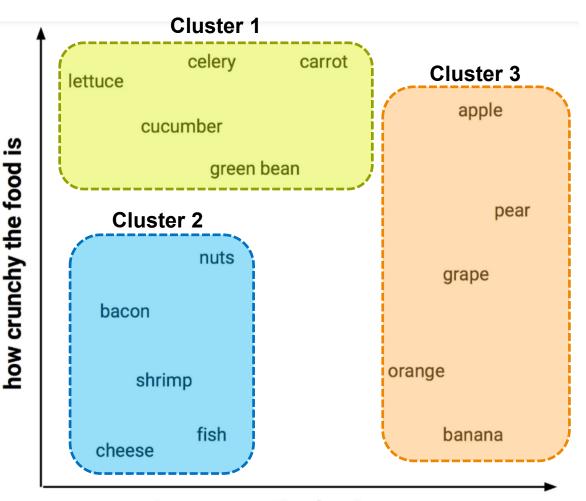
- Vege: Crunchy but not sweat
- Fruit: Mostly sweet
- Protein: not so crunchy and not sweet as well



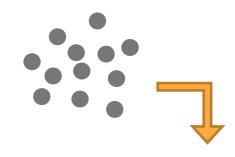
how sweet the food tastes

K-means clustering

- Cluster 1: Crunchy
- Cluster 2: not so crunchy and not sweet as well but not sweat
- Cluster 3: Mostly
 sweet



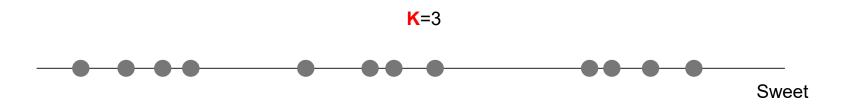
how sweet the food tastes



Sweet

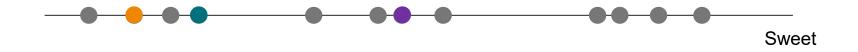
Step 1: Choose the number of clusters you want to identify in your data

K-means clustering

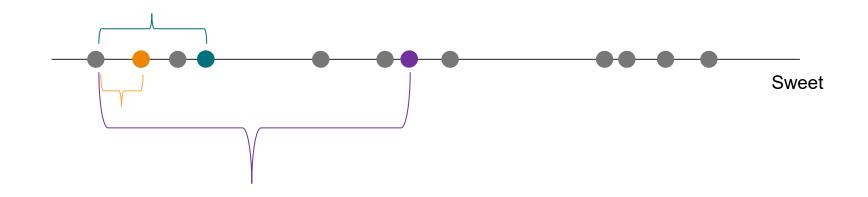


Step 2: Randomly select 3 distinct data points

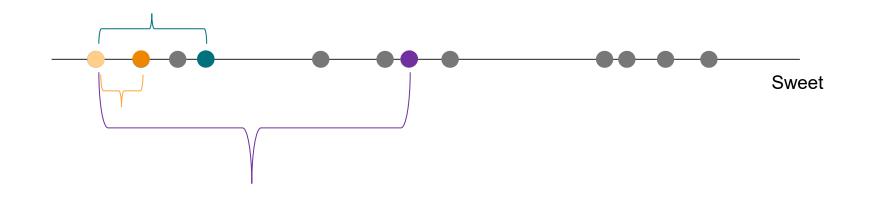
They will be the initial 3 clusters' centroids

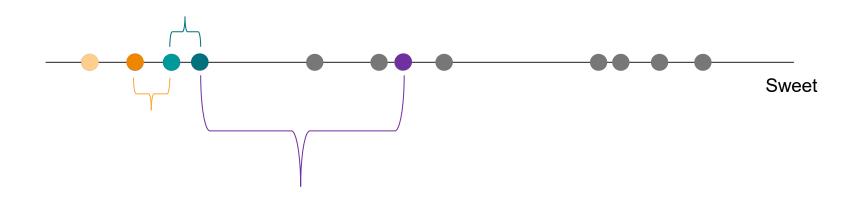


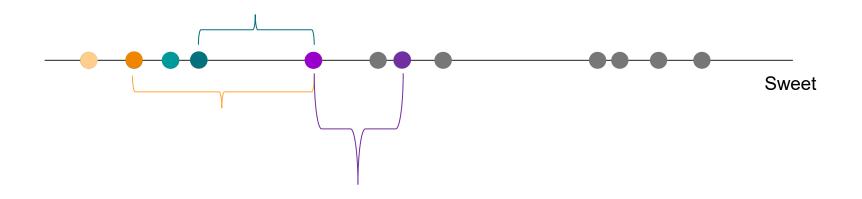
Step 3: Measure the distance btw the 1st point and the three clusters' centroids

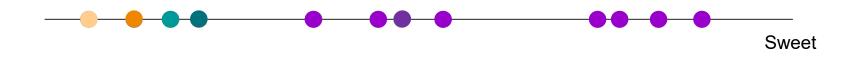


Step 4: Assign the first data point to the nearest cluster

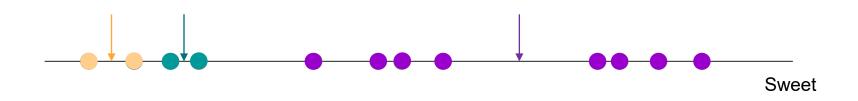


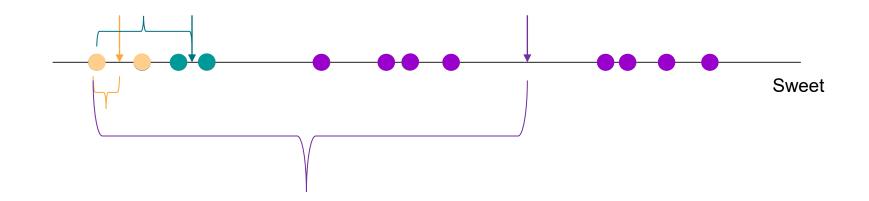


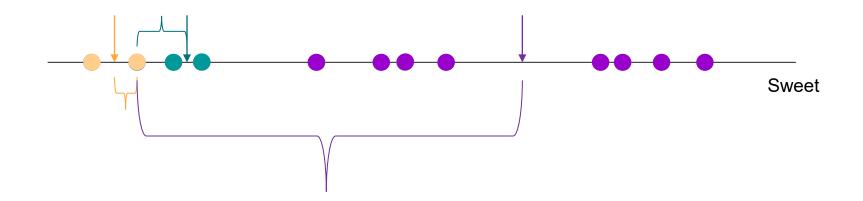


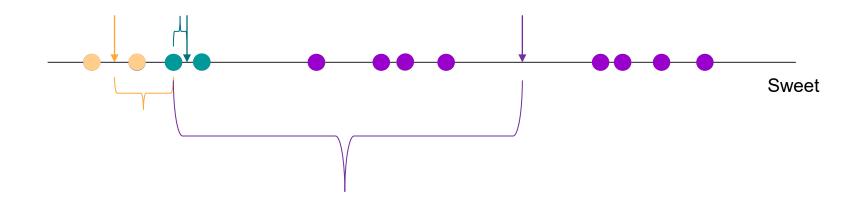


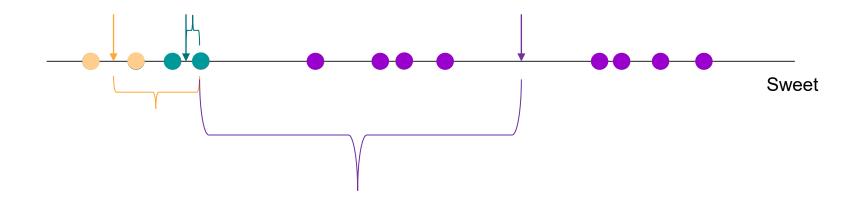
Step 6: Calculate the mean of each cluster = Reassigning each cluster's centroid

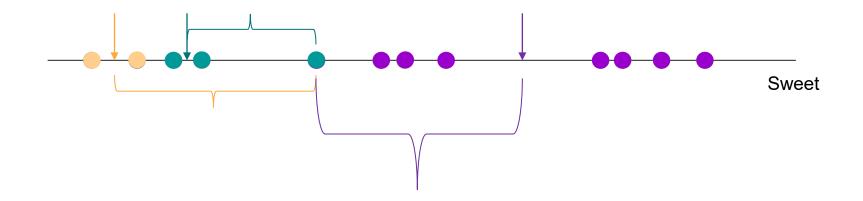


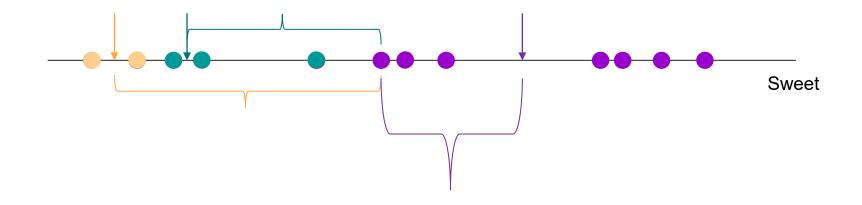


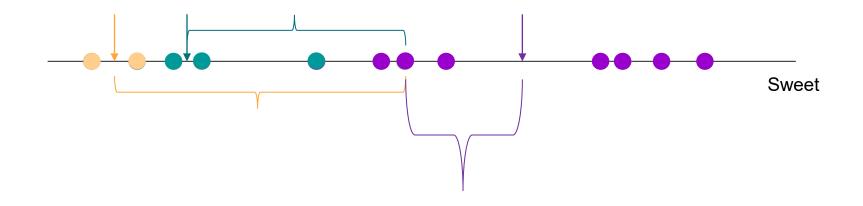






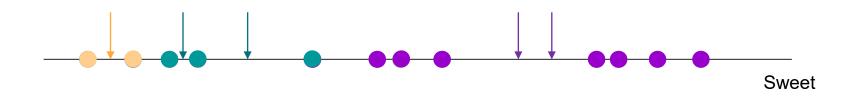




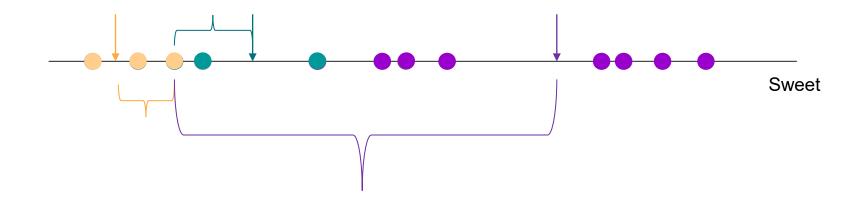


Since the clustering changed we go back to Step 6: Reassigning each cluster's centroid

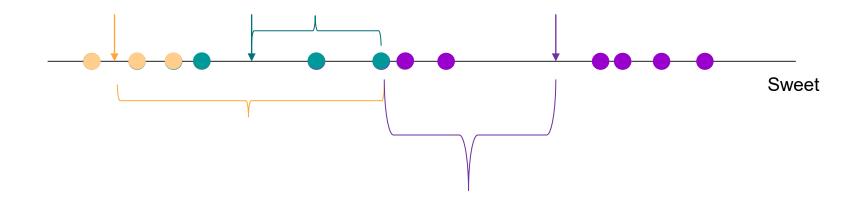
Step 6: Reassigning each cluster's centroid



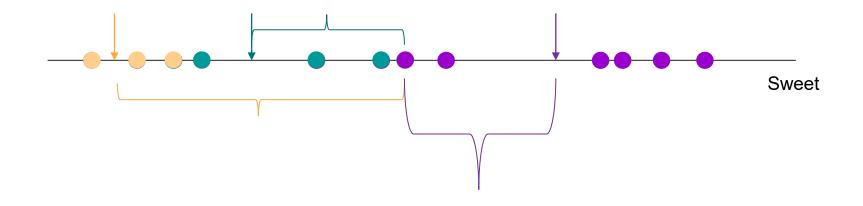
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Since the clustering changed we go back to Step 6: Reassigning each cluster's centroid

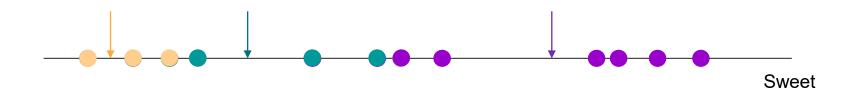


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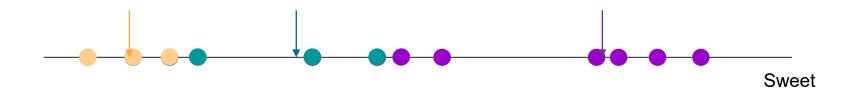
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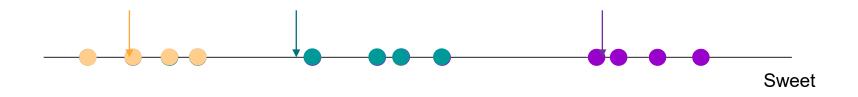


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Step 7: Repeat measuring the distance from each data point to clusters' centroids

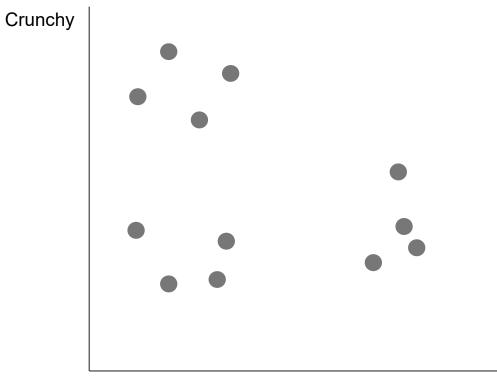


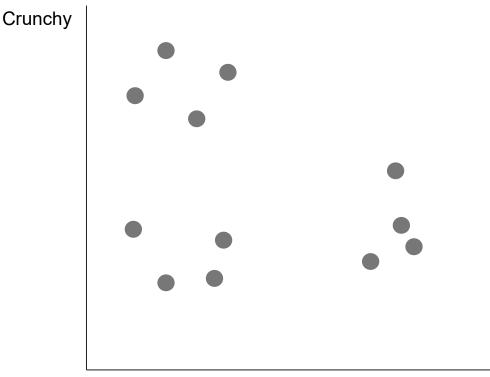
Since the clustering did not change, the algorithm stops

Crunchy

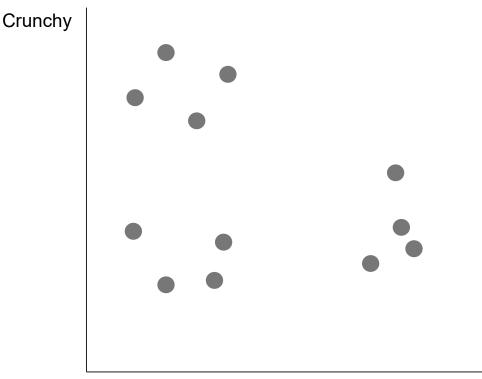




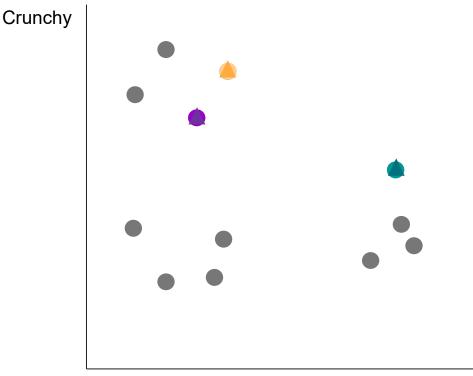




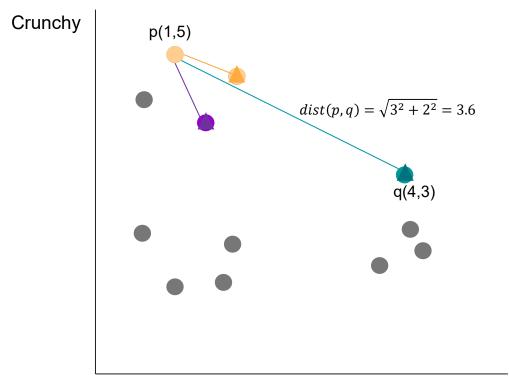
- **Step 1**: Choose the number of clusters you want to identify in your data
- Step 2: Randomly select 'K' distinct data points
- **Step 3**: Measure the distance btw each data point and the three clusters' centroids
- Step 4: Assign each data point to the nearest cluster
- **Step 5**: Calculate the mean of each cluster (Centroid reassign)
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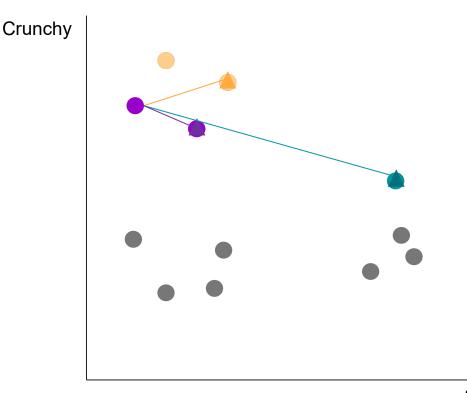
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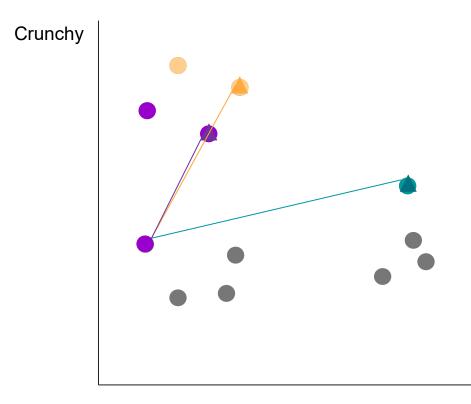
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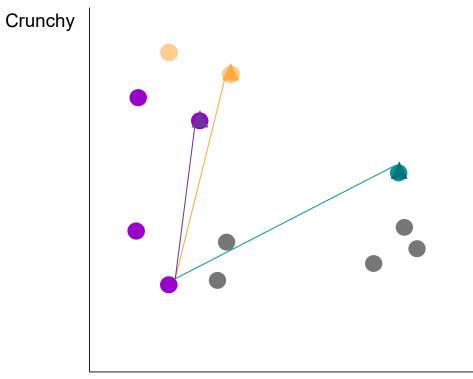
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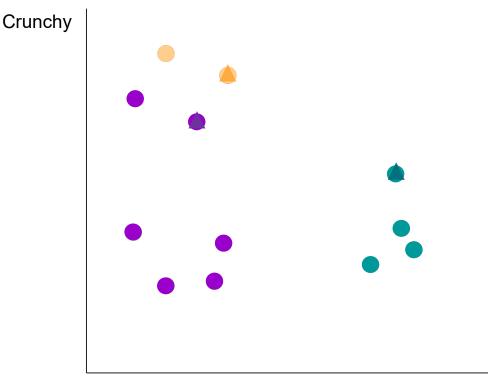
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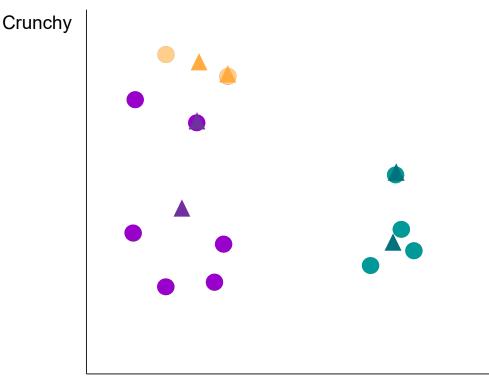
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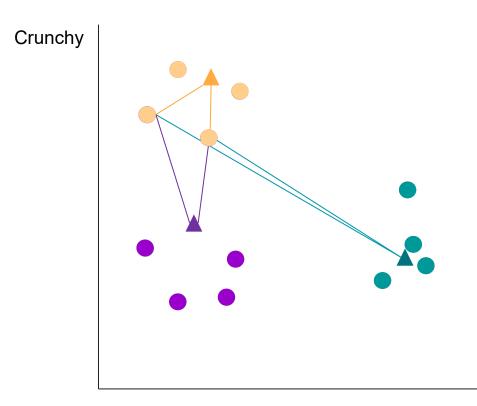
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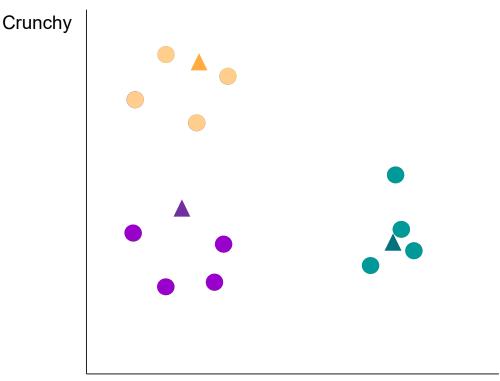
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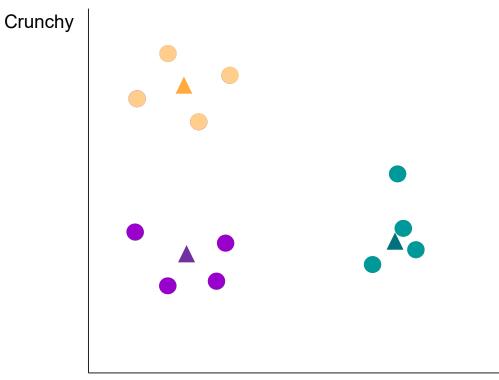
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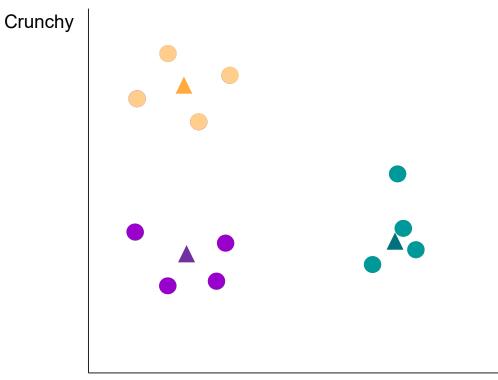
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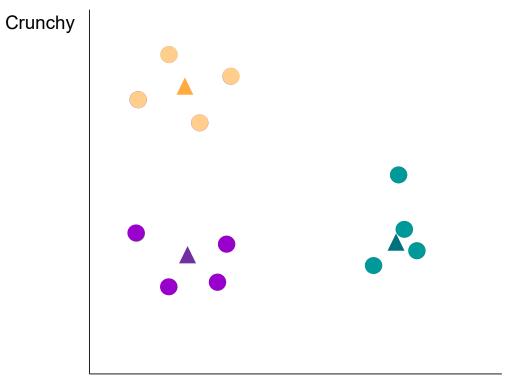
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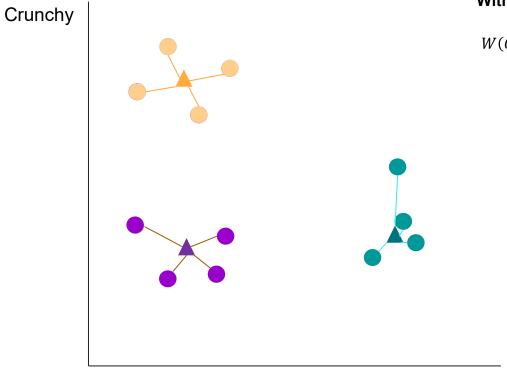
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K number of clusters (We can adjust)



Because we set each cluster's centroid. In other word, we have K means of clusters

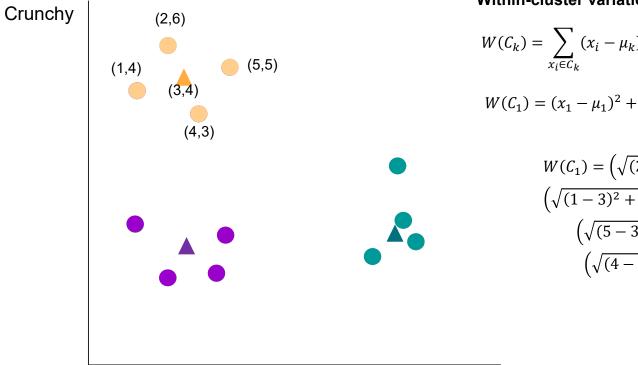
How to choose the number of clusters (k)?



Within-cluster variation (Intra-cluster variation)

$$W(C_k) = \sum_{x_i \in C_k} (x_i - \mu_k)^2$$

Sweet



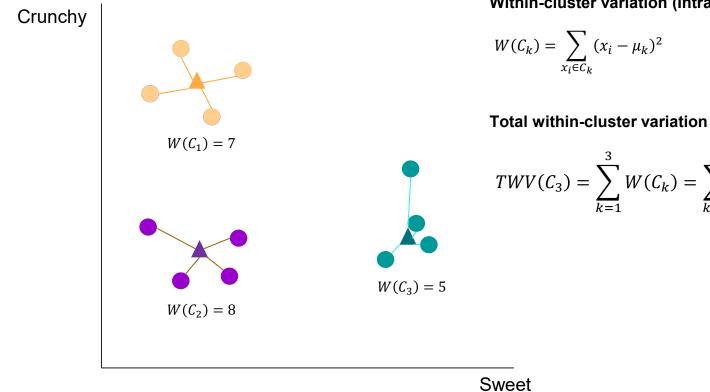
Within-cluster variation (Intra-cluster variation)

$$W(C_k) = \sum_{x_i \in C_k} (x_i - \mu_k)^2$$

$$W(C_1) = (x_1 - \mu_1)^2 + (x_2 - \mu_1)^2 + (x_3 - \mu_1)^2 + (x_4 - \mu_1)^2$$

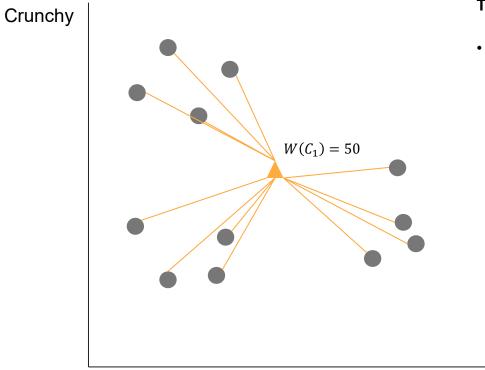
$$W(C_1) = \left(\sqrt{(2-3)^2 + (6-4)^2}\right)^2 + \left(\sqrt{(1-3)^2 + (4-4)^2}\right)^2 + \left(\sqrt{(5-3)^2 + (5-4)^2}\right)^2 + \left(\sqrt{(4-3)^2 + (3-4)^2}\right)^2$$

Sweet



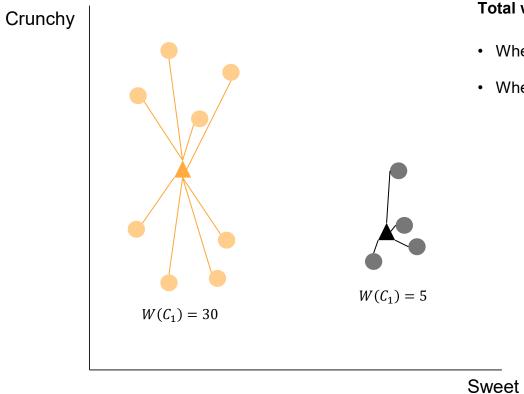
Within-cluster variation (Intra-cluster variation)

$$TWV(C_3) = \sum_{k=1}^3 W(C_k) = \sum_{k=1}^3 \sum_{x_i \in C_k} (x_i - \mu_k)^2 = 20$$

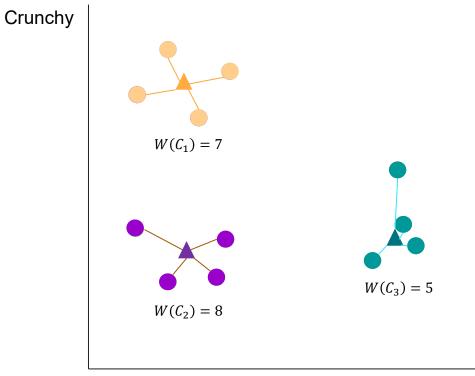


Total within-cluster variation

• When K=1: TWC=50



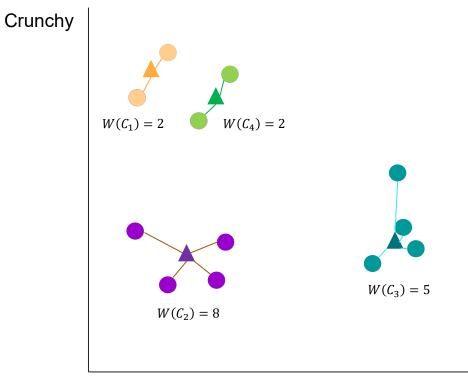
- When K=1: TWC=50
- When K=2: TWC=35



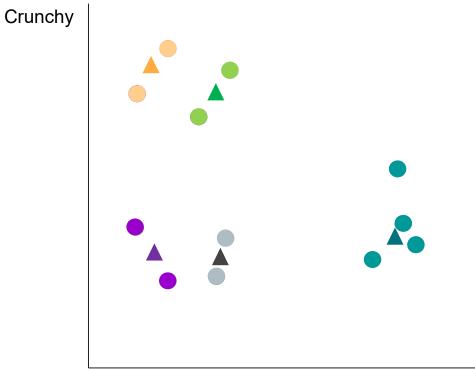
Total within-cluster variation

- When K=1: TWC=50
- When K=2: TWC=35
- When K=3: TWC=20

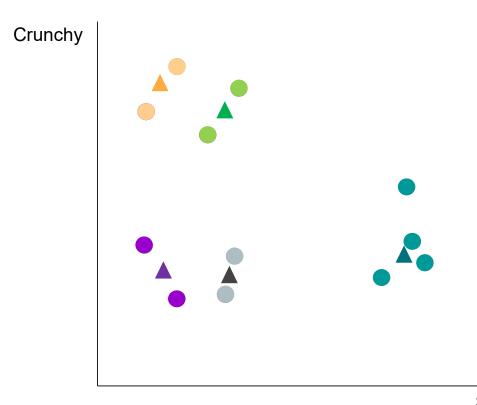
Sweet



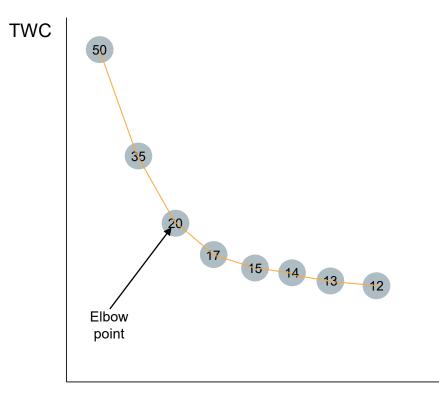
- When K=1: TWC=50
- When K=2: TWC=35
- When K=3: TWC=20
- When K=4: TWC=17



- When K=1: TWC=50
- When K=2: TWC=35
- When K=3: TWC=20
- When K=4: TWC=17
- When K=5: TWC=15



- When K=1: TWC=50
- When K=2: TWC=35
- When K=3: TWC=20
- When K=4: TWC=17
- When K=5: TWC=15
- When K=6: TWC=14
- When K=7: TWC=13.5
- (...)



Total within-cluster variation

- When K=1: TWC=50
- When K=2: TWC=35
- When K=3: TWC=20
- When K=4: TWC=17
- When K=5: TWC=15
- When K=6: TWC=14
- When K=7: TWC=13.5
- (...)

Elbow method is one of the 30 or more methods to find appropriate k in k-means clustering