

## Class 7 Unsupervised Learning and K-Means Clustering

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## Section 1

# Overview of Predictive Analytics

# Roadmap for Predictive Analytics

- The core of any business decision is **profitability analysis** (BEQ, NPV, CLV). To increase firm profitability,
  - ① Increase revenue
  - ② Reduce costs (CAC or variable marketing costs)
  - ③ Reduce customer churn
- In Weeks 4 and 5, we will learn how to utilize **predictive analytics** to improve profitability. Correspondingly,
  - ① Develop customers through ML recommender systems
  - ② **Reduce costs by targeting more responsive customers**
  - ③ Predict customer churn and take preventive actions



# Types of Predictive Analytics

- Unsupervised Learning
  - Only observe  $X \Rightarrow$  Want to uncover unknown subgroups
- Supervised Learning
  - Observe both  $X$  and  $Y \Rightarrow$  Want to predict  $Y$  for new data

In Term 2, you will learn predictive analytics models systematically. By then, think about how those techniques can be applied back to these case studies.

# Types of Predictive Analytics



# Learning Objectives for Today

- Understand the concept of unsupervised learning
- Understand how to apply K-means clustering and find the optimal number of clusters
- How to apply clustering analyses for customer segmentation for M&S

## Section 2

# K-Means Clustering

# K-Means Clustering

- K-means clustering is one of the most commonly used unsupervised machine learning algorithms for partitioning a given data set into a set of  $k$  groups (i.e.  $k$  clusters), where  $k$  represents the number of groups pre-specified by the analyst.
- For data scientists: It can classify customers into multiple segments (i.e., clusters), such that customers within the same cluster are as **similar** as possible, whereas customers from different clusters are as **dissimilar** as possible.
- Input: (1) customer characteristics; (2) the number of clusters
- Output: cluster membership of each customer



## Similarity and Dissimilarity

- The clustering of observations into groups requires computing the (dis)similarity between each pair of observations. The result of this computation is known as a dissimilarity or distance matrix.
- The choice of similarity measures is a critical step in clustering.
- The most common distance measures are the Euclidean distance (the default for K-means) and the Manhattan distance.

# Euclidean Distance

- The most common distance measure is the Euclidean distance.

$$d_{\text{euc}}(x, y) = \sqrt{\sum_{i=1}^n (x_i - y_i)^2}$$

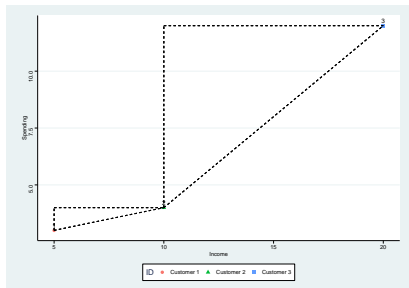
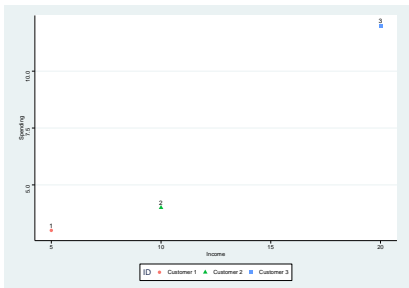
- Example of Income and Spending for 3 customers

- *Income* = (5, 10, 20)
- *Spending* = (3, 4, 12)

- Euclidean distance

- $d_{\text{euc}}(2, 1) = \sqrt{(10 - 5)^2 + (4 - 3)^2} = \sqrt{25 + 1} = \sqrt{26}$
- $d_{\text{euc}}(2, 3) = \sqrt{(10 - 20)^2 + (4 - 12)^2} = \sqrt{100 + 64} = \sqrt{164}$

# Visualization of Euclidean Distance



# Manhattan Distance

- Another common distance measure is the Manhattan distance, which is less commonly used because the absolute value function is not differentiable.

$$d_{\text{man}}(x, y) = \sum_{i=1}^n |x_i - y_i|$$

- Example of Income and Spending for 3 customers
  - $\text{Income} = c(5, 10, 20)$
  - $\text{Spending} = c(3, 4, 12)$
- Distance
  - $d_{\text{man}}(2, 1) = |10 - 5| + |4 - 3| = 5 + 1 = 6$
  - $d_{\text{man}}(2, 3) = |10 - 20| + |4 - 12| = 10 + 8 = 18$

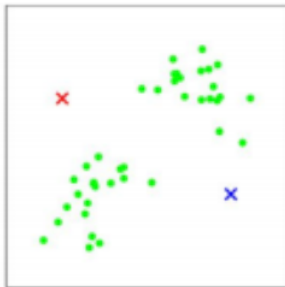
# K-Means Clustering: Step 1



(a)

- Raw data points; each dot is a customer
- X and Y axis are customer characteristics, say, income and spending
- Obviously there should be 2 segments
- Let's see how K-means uses a data-driven way to classify customers into 2 segments

## K-Means Clustering: Step 2



(b)

- We specify 2 segments
- K-means initializes the process by **randomly** selecting 2 centroids

Due to this randomness, different starting points may yield varying results. We need to reinitialize the process repeatedly to ensure **robustness** of results.

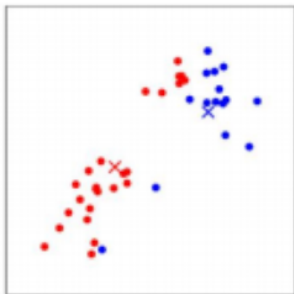
## K-Means Clustering: Step 3



(c)

- K-means computes the distance of each customer to the red and blue centroids
- K-means assigns each customer to red segment or blue segment based on which centroid is closer

## K-Means Clustering: Step 4

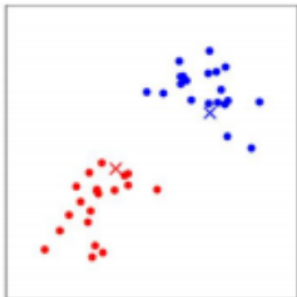


(d)

- K-means updates the new centroids of each segment
- The red cross and blue cross in the picture are the new centroids
- We still see some “outliers”, so the algorithm continues



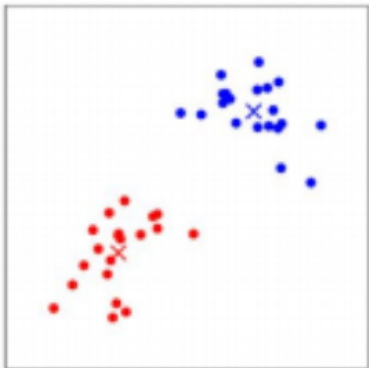
## K-Means Clustering: Step 5



(e)

- K-means computes the distance of each customer to the red and blue centroids
- K-means updates each customer to red segment or blue segment based on which centroid is closer
- Now the outliers are correctly assigned each segment

## K-Means Clustering: Step 6



(f)

- K-means updates the new centroid from the previous clustering
- K-means computes the distance of each customer to the new centroids
- K-means finds that all customers are correctly assigned to their nearest centroids, so the algorithm does not need to continue
- We say, the algorithm **converges**, and the algorithm stops

## After-Class Readings

- More technical details: [K-means Cluster Analysis](#)