Customer Segmentation

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This technical note introduces what is Customer Segmentation and its benefits and limitations.

customer segmentation | clustering | customer analytics | r

The problem

- **Problem**: we don't know if we have different types of customers and how to approach them
- **Goals**:
  - We want to understand better our customers
  - We want to have a clear criteria to segment our customers
- **Why?** To perform specific actions to improve the customer experience

But,... we have many attributes! How we can choose the relevant attributes? How do they combine to explain our customers?

We will use what is called **customer segmentation**.

Definition

We need a formal definition:

> **Customer segmentation** is the practice of dividing a customer base into groups of individuals that are similar in specific ways relevant to marketing, such as age, gender, interests, spending habits among many others.

Types. The most common forms of customer segmentation are:

- **Geographic segmentation**: considered as the first step to international marketing, followed by demographic and psychographic segmentation.
- **Demographic segmentation**: based on variables such as age, sex, generation, religion, occupation and/or education level.
- **Firmographic**: based on features such as company size (either in terms of revenue or number of employees), industry sector and/or location (city, country and/or region).
- **Behavioral segmentation**: based on knowledge of, attitude towards, usage rate, response, loyalty status, and/or readiness stage to a product.
- **Psychographic segmentation**: based on the study of activities, interests, and/or opinions (AIOs) of customers.
- **Occasional segmentation**: based on the analysis of occasions (for instance, being thirsty).
- **Segmentation by benefits**: based on RFM, CLV, etc.
- **Cultural segmentation**: based on cultural origin.
- **Multi-variable segmentation**: based on the combination of several techniques and/or attributes.

Comparing customers

We want to know if two customers are similar. To compare customers, we will use their attributes. These attributes are a vector of values (numeric and/or categorical). Basically, we will translate our purpose (comparing customers) into measure the similarity or dissimilarity between objects (vectors of curstomers attributes) and we will use a distance measure such as Euclidean, Manhattan or Minkowski. A distance function returns a lower value for pairs of objects that are more similar to one another.

In general, we will speak about **clustering** instead of segmentation.

Euclidean Distance.

$$d_2(x,y) = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2}$$

Squared Euclidean Distance.

$$d_2^2(x,y) = \sum_{i=1}^{n}(x_i - y_i)^2$$

Manhattan Distance.

$$d_1(x,y) = \sum_{i=1}^{n}|x_i - y_i|$$

Maximum Distance.

$$d_\infty(x,y) = max_i|x_i - y_i|$$

Minkwoski Distance.

$$d_q(x,y) = \sqrt[q]{\sum_{i=1}^{n}(|x_i - y_i|)^q}$$

Jaccard distance.

$$d(A,B) = 1 - J(A,B) = 1 - \frac{|A \cap B|}{|A \cup B|}$$

Canberra distance.

$$d(p,q) = \sum_{i=1}^{n}\frac{|p_i - q_i|}{|p_i| + |q_i|}$$

Levenshtein distance.

$$\mathrm{lev}_{a,b}(i,j) = \begin{cases} \max(i,j) \text{ if } \min(i,j) = 0, \\ \min \begin{cases} \mathrm{lev}_{a,b}(i-1,j)+1 \\ \mathrm{lev}_{a,b}(i,j-1)+1 \\ \mathrm{lev}_{a,b}(i-1,j-1)+1_{(a_i \neq b_j)} \end{cases} & \text{otherwise.} \end{cases}$$

Note: there are many distance functions (for example, gower, a general coefficient of Similarity).

Techniques

As we already discussed, **clustering** consists of grouping similar or different data into previously unknown groups. Clustering is one of the applications of unsupervised learning.

> In **Unsupervised Learning**, all data is unlabelled and the algorithms learn the inherent structure from the input data.

There are many clustering segmentation techniques. This is a list of some of them:

- **Hierarchical** (or connectivity): data points placed into a set of nested clusters, organized into a hierarchical tree
  - **Agglomerative**: forms a hierarchy of nested clusters based on aggregation
  - **Divisive**: forms a hierarchy of nested clusters based on division
- **Partitioning**: data points divided into finite number of partitions
  - **Centroid (or Partitioning Relocation)**: given a database of n objects, it constructs k partitions of the data, based on interative relocation
  - **Density-based**: clusters are contiguous 'dense' regions in the data space, separated by areas of low point density
  - **Grid-based**: clusters are created by quantizing the object space into finite number of cells
  - **Subspace**: finds clusters within different subspaces (a selection of one or more dimensions)
- **Distribution-based**: there is a model or probability that describes the clusters
  - **Model-based**: based on hypothesizing a model for every cluster to find best fit of the data according to the mathematical model
  - **Fuzzy**: each element has a probability of belonging to each cluster
- **Ensemble (or hybrid)**: combination of clustering techniques working together
  - **Median Partition Based**: find a partition that maximises the similarity between P and all the N partitions in the ensemble
  - **Co-occurrence based**: based on relabeling/voting, co-association matrix or graph based methods

Why do we have some many techniques?

- Type of attributes algorithm can handle
- Scalability to large datasets
- Ability to work with high dimensional data
- Ability to find clusters of irregular shape
- Handling outliers
- Time complexity (or just complexity)
- Data order dependency
- Labelling or assignment (hard or strict vs. soft or fuzzy)
- Reliance on a priori knowledge and user defined parameters
- Interpretability of results

For each type, there are many algorithms:

- Agglomerative: Single Link, Complete Link, Average Link, Ward, BRICH, CURE, ROCK, AGNES
- Divisive: Diana, Mona
- Partitioning Relocation Clustering: EM, SNOB, PAM, CLARA, MCLUST, CLARANS, K-MEANS, AUTOCLASS, FUZZY C-MEANS
- Density-Based Partitioning: DBSCAN, SNN, DENCLUE, DB-CLASO, OPTICS
- Subspace Clustering: ENCLUS, ORCLUS, PROCLUS, OPT-GRID, MAFIA
- Grid-Based Methods: BANG, STING, WAVECLUST, CLIQUE, MAFIA

We just introduce some of them. R supports all types of clustering (hierarchical, partitioning,...). More information here: https://cran.r-project.org/web/views/Cluster.html

We will reivew about several aspects in this document:

- **Clustering tendency**: How to statistically evaluate clustering tendency, i.e. if we can really find clusters in a data set.
- **Dimensionality reduction**: How to reduce the number of attributes in the clustering, ie. do we need all the attributes? In particular using PCA (Principal Component Analysis).
- **Clustering techniques**: (1) What is k-means and (2) What is hiearchical clustering
- **Clustering validation**: How to validate a cluster, i.e. how good is our cluster?
- **Cluster stability**: Does the cluster represent actual structure in the data, or is it an artifact of the clustering algorithm?

Clustering tendency

Clustering tendency assessment determines whether a given dataset contains meaningful clusters (i.e., **non-random structure**).

Hopkins statistic is used to assess the **clustering tendency** of a dataset by measuring the probability that a given dataset is generated by a uniform data distribution. In other words it tests the **spatial randomness** of the data.

Let D be a real dataset. The Hopkins statistic can be calculated as follow:

- Sample uniformly n points $(p_1, \ldots, p_n)$ from D.
- For each point $p_i \in D$, find it's nearest neighbor p_j; then compute the distance between p_i and p_j and denote it as $x_i = dist(p_i, p_j)$
- Generate a simulated dataset ($randomD$) drawn from a random uniform distribution with n points $(q_1, \ldots, q_n)$ and the same variation as the original real dataset D.
- For each point $q_i \in randomD$, find it's nearest neighbor q_j in D; then compute the distance between q_i and q_j and denote it $y_i = dist(q_i, q_j)$
- Calculate the Hopkins statistic (H) as the mean nearest neighbor distance in the random dataset divided by the sum of the mean nearest neighbor distances in the real and across the simulated dataset.

The formula is defined as follow:

$$H = \frac{\sum_{i=1}^{n} y_i}{\sum_{i=1}^{n} x_i + \sum_{i=1}^{n} y_i}$$

A value of H about 0.5 means that $\sum_{i=1}^{n} y_i$ and $\sum_{i=1}^{n} x_i$ are close to each other, and thus the data D is uniformly distributed.

The null and the alternative hypotheses are defined as follow:

- **Null hypothesis**: the dataset D is uniformly distributed (i.e., no meaningful clusters).
- **Alternative hypothesis**: the dataset D is not uniformly distributed (i.e., contains meaningful clusters).

If the value of Hopkins statistic is close to zero, then we can reject the null hypothesis and conclude that the dataset D is significantly a clusterable data set.

Dimensionality Reduction

Principal Component Analysis (PCA). It is a technique used to emphasize variation and bring out strong patterns in a dataset. It's often used to make data easy to explore and visualize.

- It uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components (or sometimes, principal modes of variation).
- The number of principal components is less than or equal to the smaller of the number of original variables or the number of observations.
- This transformation is defined in such a way that the first principal component has the largest possible variance (that is, accounts for as much of the variability in the data as possible), and each succeeding component in turn has the highest variance possible under the constraint that it is orthogonal to the preceding components.
- The resulting vectors are an uncorrelated orthogonal basis set. PCA is sensitive to the relative scaling of the original variables.

PCA is useful for eliminating dimensions.

Clustering techniques

Kmeans. Given a set of observations $(x1, x2, \ldots, xn)$, where each observation is a d-dimensional real vector, k-means clustering aims to partition the n observations into $k (\leq n)$ sets $S = S1, S2, \ldots, Sk$ so as to minimize the within-cluster sum of squares (WCSS) (sum of distance functions of each point in the cluster to the K center). In other words, its objective is to find:

$$\arg\min_{\mathbf{S}} \sum_{i=1}^{k} \sum_{\mathbf{x} \in S_i} \left\| \mathbf{x} - \boldsymbol{\mu}_i \right\|^2$$

where μ_i is the mean of points in S_i.

Hiearchical Clustering. Hierarchical clustering involves creating clusters that have a predetermined ordering from top to bottom (or otherwise). There are two types of hierarchical clustering, Divisive and Agglomerative.

- **Divisive method**: In this method we assign all of the observations to a single cluster and then partition the cluster to two least similar clusters. Finally, we proceed recursively on each cluster until there is one cluster for each observation.
- **Agglomerative method**: In this method we assign each observation to its own cluster. Then, compute the similarity (e.g., distance) between each of the clusters and join the two most similar clusters. Finally, repeat steps 2 and 3 until there is only a single cluster left. The related algorithm is shown below.

Before any clustering is performed, it is required to determine the proximity matrix containing the distance between each point using a distance function. Then, the matrix is updated to display the distance between each cluster. The following three methods differ in how the distance between each cluster is measured.

- **Single Linkage**: In single linkage hierarchical clustering, the distance between two clusters is defined as the shortest distance between two points in each cluster. For example, the distance between clusters "r" and "s" to the left is equal to the length of the arrow between their two closest points.

  $$L(R, S) = min(D(x_{ri}, x_{sj}))$$

  where R and S are clusters and x_{ri} and x_{sj} are points in these clusters.

- **Complete Linkage**: In complete linkage hierarchical clustering, the distance between two clusters is defined as the longest distance between two points in each cluster. For example, the distance between clusters "r" and "s" to the left is equal to the length of the arrow between their two furthest points.

$$L(R, S) = max(D(x_{ri}, x_{sj}))$$

where R and S are clusters and x_{ri} and x_{sj} are points in these clusters.

- **Average Linkage**: In average linkage hierarchical clustering, the distance between two clusters is defined as the average distance between each point in one cluster to every point in the other cluster. For example, the distance between clusters "r" and "s" to the left is equal to the average length each arrow between connecting the points of one cluster to the other.

$$L(R, S) = \frac{1}{n_r n_s} \sum_{i}^{n_r} \sum_{j}^{n_s} (D(x_{ri}, x_{sj}))$$

where R and S are clusters and x_{ri} and x_{sj} are points in these clusters.

Clustering validation

The final step is to validate the quality of the cluster. For example, we can use Average Silhouette Analysis to validate whether the clusters has a good structure or not. ¿How to use the value?:

- **0.71 - 1.0**: A strong structure has been found.
- **0.51 - 0.70**: A reasonable structure has been found.
- **0.26 - 0.50**: The structure is weak and could be artificial.
- **< 0.25**: No substantial structure has been found.

Clustering stability

One way to assess whether a cluster represents true structure is to see if the cluster holds up under plausible variations in the dataset. **Bootstrap resampling** can be used to evaluate how stable a given cluster is (see Christian Henning, "Cluster-wise assessment of cluster stability," Research Report 271, Dept. of Statistical Science, University College London, December 2006). This algorithm uses the Jaccard coefficient, a similarity measure between sets. The Jaccard similarity between two sets A and B is the ratio of the number of elements in the intersection of A and B over the number of elements in the union of A and B. The basic general strategy is as follows:

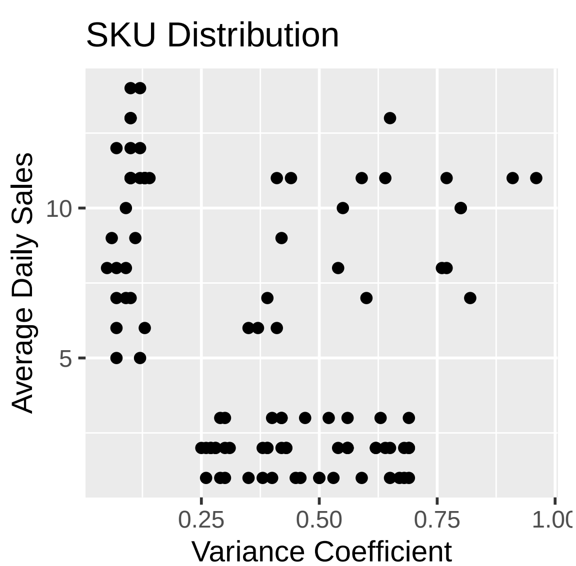
- Cluster the data as usual.
- Draw a new dataset (of the same size as the original) by resampling the original dataset with replacement (meaning that some of the data points may show up more than once, and others not at all). Cluster the new dataset.
- For every cluster in the original clustering, find the most similar cluster in the new clustering (the one that gives the maximum Jaccard coefficient) and record that value. If this maximum Jaccard coefficient is less than 0.5, the original cluster is considered to be dissolved-it didn't show up in the new clustering. A cluster that's dissolved too often is probably not a "real" cluster.
- Repeat steps 2-3 several times.

The cluster stability of each cluster in the original clustering is the mean value of its Jaccard coefficient over all the bootstrap iterations. As a rule of thumb:

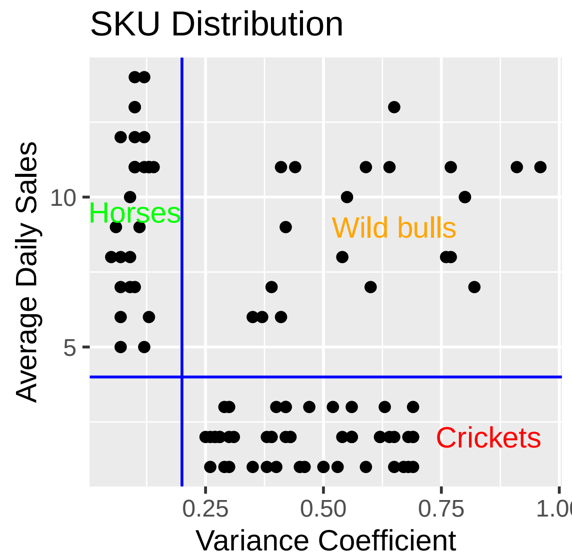
- clusters with a stability value less than 0.6 should be considered unstable.
- Values between 0.6 and 0.75 indicate that the cluster is measuring a pattern in the data, but there isn't high certainty about which points should be clustered together.
- Clusters with stability values above about 0.85 can be considered highly stable (they're likely to be real clusters).

CS is an art

Sometimes data has shape, and shape has meaning,...



We just need to pay attention:



How to apply Custering Techniques

- **[BU]** Determine business needs
- **[DU]** Sourcing, Cleaning & Exploration
- **[DP]** Feature Creation (Extract additional information to enrich the set)
- **[DP]** Feature Selection (Reduce to a smaller dataset to speed up computation)
- **[M]** Select Customer Segmentation Technique (test and compare some of them)
- **[M]** Applied Selected Customer Segmentation Technique
- **[E]** Analyze results and adjust parameters
- **[D]** Present and explain the results

Note: Good clustering method requirements are:

- The ability to discover some or all of the hidden clusters.
- Within-cluster similarity and between-cluster dissimilarity.
- Ability to deal with various types of attributes.
- Can deal with noise and outliers.
- Can handle high dimensionality.
- Scalable, Interpretable and usable.

Benefits

- Customer profiling
- Targeted marketing actions
- Targeted operations

Use Cases

- Reporting
- Commercial actions: Retention offers, Product promotions, Loyalty rewards
- Operations: Optimise stock levels, store layout
- Pricing: price elasticity
- Strategy: M&A, new products,...

Interesting packages

- RSKC: An R Package for a Robust and Sparse K-Means Clustering Algorithm
- Clustering Mixed Data Types in R

- Equi-Rank Hierarchical Clustering Validation
- Rdimtools
- CrossClustering: A Partial Clustering Algorithm with Automatic Estimation of the Number of Clusters and Identification of Outliers
- CEC: Cross-Entropy Clustering
- klaR: Classification and Visualization and a introduction
- clustMixType: k-Prototypes Clustering for Mixed Variable-Type Data
- clues: Clustering Method Based on Local
- mclust: Gaussian Mixture Modelling for Model-Based Clustering, Classification, and Density Estimation
- QuClu: Quantile-Based Clustering Algorithms
- clusterlab: Flexible Gaussian Cluster Simulator
- spherical k-Means
- Affinity Propagation clustering
- hierarchical clustering
- hybrid hierarchical clustering
- [Latent Class Analysis (LCA): random LCA
- polytomous variable LCA
- Bayesian LCA
- Mixtools
- PCA
- Topological Data Analysis

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