Data Analysis Course

Cluster Analysis and Decision Trees(version-1)

Venkat Reddy

Data Analysis Course

- Data analysis design document
- Introduction to statistical data analysis
- Descriptive statistics
- Data exploration, validation & sanitization
- Probability distributions examples and applications
- Simple correlation and regression analysis
- Multiple liner regression analysis
- Logistic regression analysis
- Testing of hypothesis
- Clustering and Decision trees
- Time series analysis and forecasting
- Credit Risk Model building-1
- Credit Risk Model building-2

Note

- This presentation is just class notes. The course notes for Data Analysis Training is by written by me, as an aid for myself.
- The best way to treat this is as a high-level summary; the actual session went more in depth and contained other information.
- Most of this material was written as informal notes, not intended for publication
- Please send questions/comments/corrections to venkat@trenwiseanalytics.com or 21.venkat@gmail.com
- Please check my website for latest version of this document

-Venkat Reddy

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- What is the need of Segmentation
- Introduction to Segmentation & Cluster analysis
- Applications of Cluster Analysis
- Types of Clusters
- Building Partitional Clusters
- K means Clustering & Analysis
- Building Decision Trees
- CHAID Segmentation & Analysis

What is the need of segmentation?

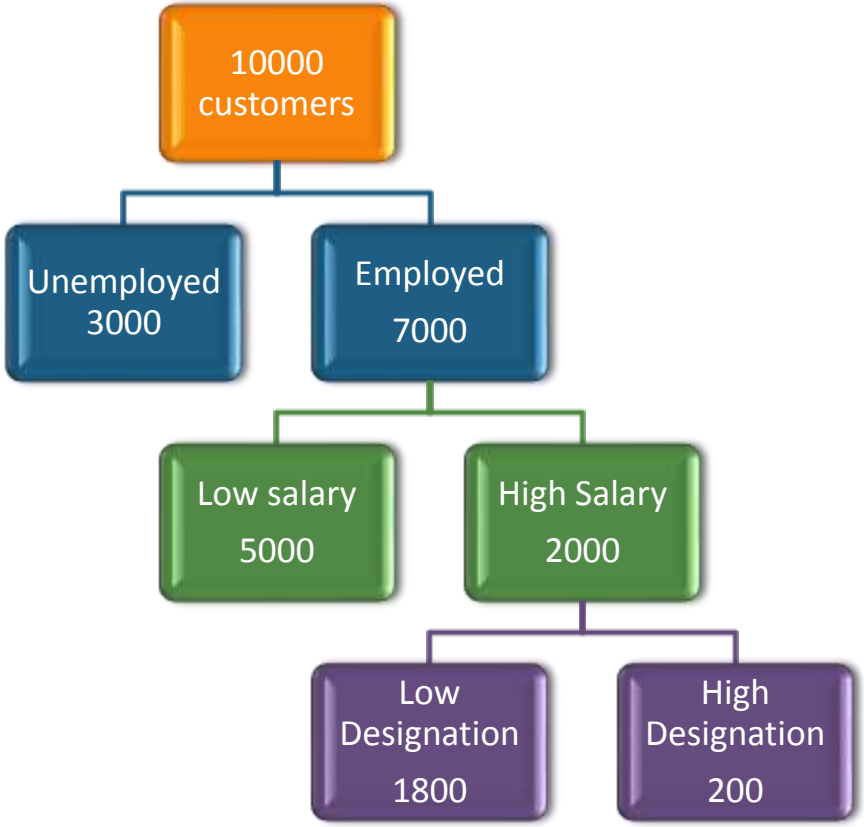
Problem:

- 10,000 Customers - we know their age, city name, income, employment status, designation
- You have to sell 100 Blackberry phones(each costs $1000) to the people in this group. You have maximum of 7 days
- If you start giving demos to each individual, 10,000 demos will take more than one year. How will you sell maximum number of phones by giving minimum number of demos?

What is the need of segmentation?

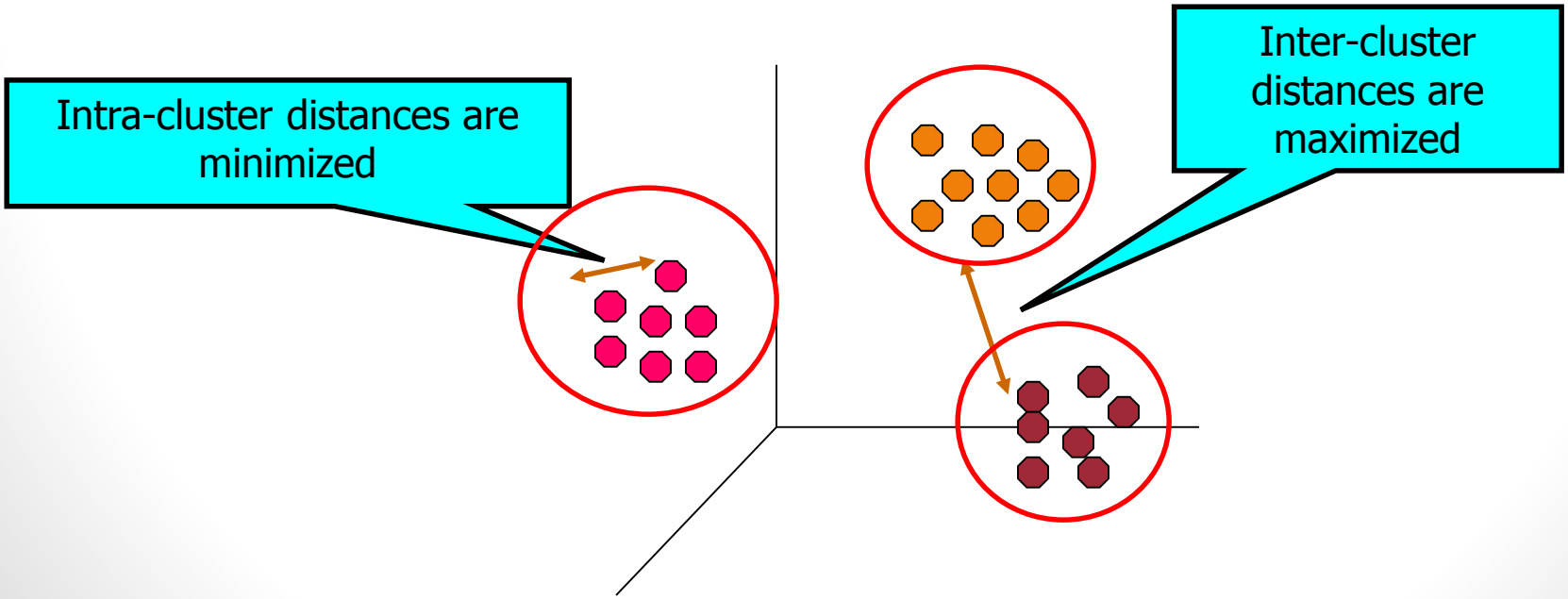
Solution

- Divide the whole population into two groups employed / unemployed
- Further divide the employed population into two groups high/low salary
- Further divide that group into high /low designation



Segmentation and Cluster Analysis

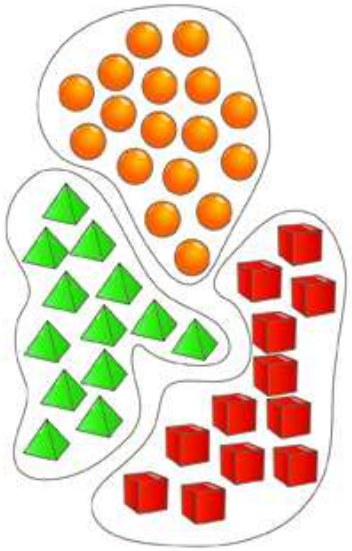
- Cluster is a group of similar objects (cases, points, observations, examples, members, customers, patients, locations, etc)
- Finding the groups of cases/observations/ objects in the population such that the objects are
  - Homogeneous within the group (high intra-class similarity)
  - Heterogeneous between the groups(low inter-class similarity)



Applications of Cluster Analysis

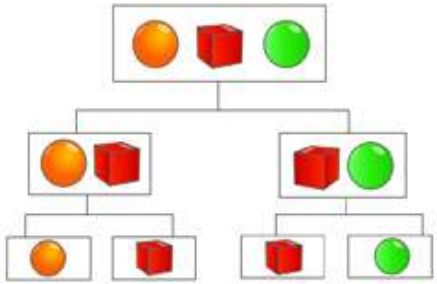
- **Market Segmentation:** Grouping people (with the willingness, purchasing power, and the authority to buy) according to their similarity in several dimensions related to a product under consideration.
- **Sales Segmentation**: Clustering can tell you what types of customers buy what products
- **Credit Risk**: Segmentation of customers based on their credit history
- **Operations**: High performer segmentation & promotions based on person's performance
- **Insurance**: Identifying groups of motor insurance policy holders with a high average claim cost.
- **City-planning:** Identifying groups of houses according to their house type, value, and geographical location
- **Geographical**: Identification of areas of similar land use in an earth observation database.

Types of Clusters



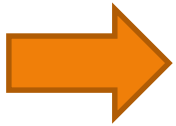
- ***Partitional* clustering or non-hierarchical :** A division of objects into non-overlapping subsets (clusters) such that each object is in exactly one cluster
- The non-hierarchical methods divide a dataset of N objects into M clusters.
- **K-means clustering**, a non-hierarchical technique, is the most commonly used one in business analytics

- ***Hierarchical* clustering:** A set of nested clusters organized as a hierarchical tree
- The hierarchical methods produce a set of nested clusters in which each pair of objects or clusters is progressively nested in a larger cluster until only one cluster remains
- **CHAID tree** is most widely used in business analytics



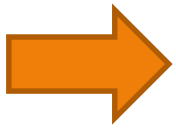
Cluster Analysis -Example

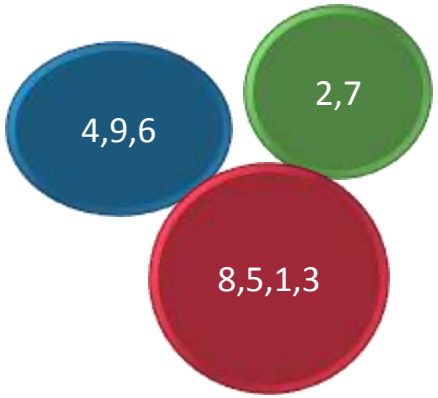
	Maths	Science	Gk	Apt
Student-1	94	82	87	89
Student-2	46	67	33	72
Student-3	98	97	93	100
Student-4	14	5	7	24
Student-5	86	97	95	95
Student-6	34	32	75	66
Student-7	69	44	59	55
Student-8	85	90	96	89
Student-9	24	26	15	22



	Maths	Science	Gk	Apt
Student-1	✓ 94	✓ 82	✓ 87	✓ 89
Student-2	! 46	! 67	✗ 33	✓ 72
Student-3	✓ 98	✓ 97	✓ 93	✓ 100
Student-4	✗ 14	✗ 5	✗ 7	✗ 24
Student-5	✓ 86	✓ 97	✓ 95	✓ 95
Student-6	✗ 34	✗ 32	✓ 75	! 66
Student-7	✓ 69	! 44	! 59	! 55
Student-8	✓ 85	✓ 90	✓ 96	✓ 89
Student-9	✗ 24	✗ 26	✗ 15	✗ 22

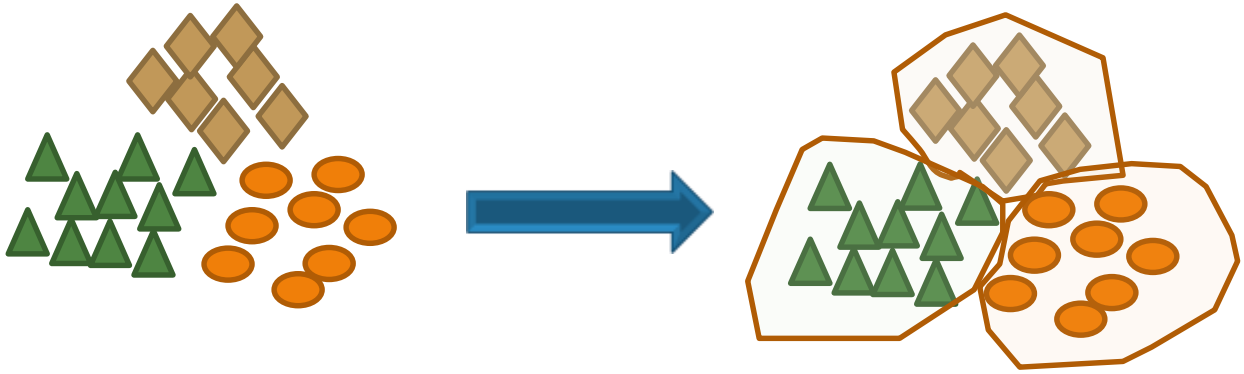
	Maths	Science	Gk	Apt
Student-4	✗ 14	✗ 5	✗ 7	✗ 24
Student-9	✗ 24	✗ 26	✗ 15	✗ 22
Student-6	✗ 34	✗ 32	✓ 75	! 66
Student-2	! 46	! 67	✗ 33	✓ 72
Student-7	✓ 69	! 44	! 59	! 55
Student-8	✓ 85	✓ 90	✓ 96	✓ 89
Student-5	✓ 86	✓ 97	✓ 95	✓ 95
Student-1	✓ 94	✓ 82	✓ 87	✓ 89
Student-3	✓ 98	✓ 97	✓ 93	✓ 100





Building Clusters

1. Select a **distance measure**
2. Select a **clustering algorithm**
3. Define the **distance between two clusters**
4. Determine the **number of clusters**
5. **Validate** the analysis



- The aim is to build clusters i.e divide the whole population into group of similar objects
- What is similarity/dis-similarity?
- How do you define distance between two clusters

Distance measures

- To measure similarity between two observations a distance measure is needed. With a single variable, similarity is straightforward
  - Example: income – two individuals are similar if their income level is similar and the level of dissimilarity increases as the income gap increases
- Multiple variables require an **aggregate distance measure**
  - Many characteristics (e.g. income, age, consumption habits, family composition, owning a car, education level, job…), it becomes more difficult to define similarity with a single value
- The most known measure of distance is the Euclidean distance, which is the concept we use in everyday life for spatial coordinates.

Examples of distances

$$D_{ij} = \sqrt{\sum_{k=1}^{n} \left(x_{ki} - x_{kj} \right)^2}$$ ***Euclidean distance***

$$D_{ij} = \sum_{k=1}^{n} \left| x_{ki} - x_{kj} \right|$$ ***City-block (Manhattan) distance***

D_{ij} distance between cases *i* and *j* x_{kj} - value of variable x_k for case *j*

Other distance measures: Chebychev, Minkowski, Mahalanobis, maximum distance, cosine similarity, simple correlation between observations etc.,

Data matrix

$$\begin{bmatrix} x_{11} & \cdots & x_{1f} & \cdots & x_{1p} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ x_{i1} & \cdots & x_{if} & \cdots & x_{ip} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ x_{n1} & \cdots & x_{nf} & \cdots & x_{np} \end{bmatrix}$$

Dissimilarity matrix

$$\begin{bmatrix} 0 & & & & \\ d(2,1) & 0 & & & \\ d(3,1) & d(3,2) & 0 & & \\ \vdots & \vdots & \vdots & & \\ d(n,1) & d(n,2) & \cdots & \cdots & 0 \end{bmatrix}$$

K -Means Clustering – Algorithm

1. The number *k* of clusters is fixed
2. An initial set of *k "seeds" (aggregation centres)* is provided
    1. First *k* elements
    2. Other seeds (randomly selected or explicitly defined)
3. Given a certain fixed threshold, all units are assigned to the nearest cluster seed
4. New seeds are computed
5. Go back to step 3 until no reclassification is necessary

Or simply

Initialize k cluster centers

Do

Assignment step: Assign each data point to its closest cluster center

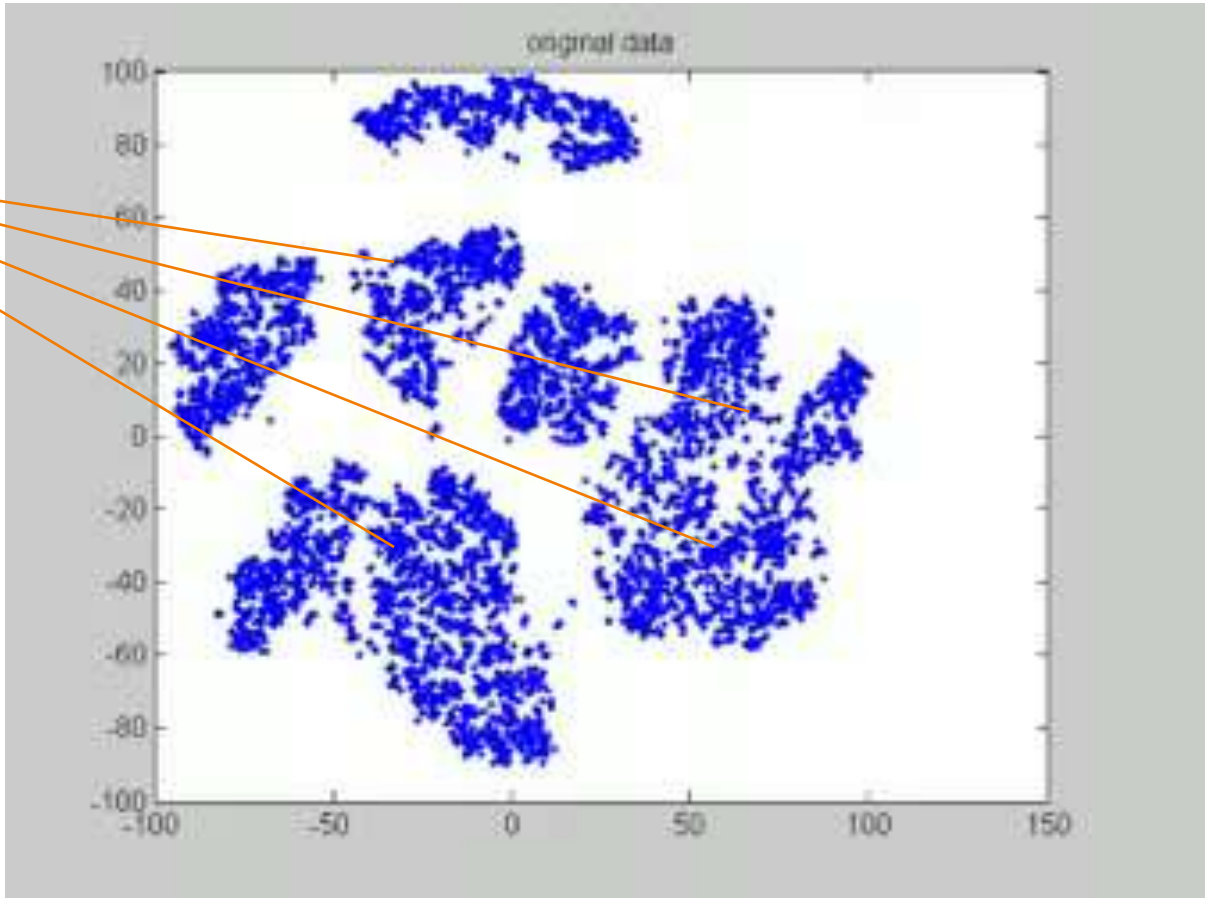
Re-estimation step: Re-compute cluster centers

While (there are still changes in the cluster centers)

K Means clustering in action

- Dividing the data into 10 clusters using K-Means

Distance metric will decide cluster for these points



SAS Code & Options

```
proc fastclus  data= mylib.super_market_data
radius=0 replace=full maxclusters=3 maxiter =20 list distance;
id cust_id;
var age income spend family_size visit_Other_shops;
run;
```

Options

- The **RADIUS**= option establishes the minimum distance criterion for selecting new seeds. No observation is considered as a new seed unless its minimum distance to previous seeds exceeds the value given by the RADIUS= option. The default value is 0.
- The **MAXCLUSTERS**= option specifies the maximum number of clusters allowed. If you omit the MAXCLUSTERS= option, a value of 100 is assumed.
- The REPLACE= option specifies how seed replacement is performed.
  - FULL :requests default seed replacement.
  - PART :requests seed replacement only when the distance between the observation and the closest seed is greater than the minimum distance between seeds.
  - NONE : suppresses seed replacement.
  - RANDOM :Selects a simple pseudo-random sample of complete observations as initial cluster seeds.

SAS Code & Options

- The **MAXITER**= option specifies the maximum number of iterations for re computing cluster seeds. When the value of the MAXITER= option is greater than 0, each observation is assigned to the nearest seed, and the seeds are recomputed as the means of the clusters.
- The **LIST** option lists all observations, giving the value of the ID variable (if any), the number of the cluster to which the observation is assigned, and the distance between the observation and the final cluster seed.
- The **DISTANCE** option computes distances between the cluster means.
- The **ID** variable, which can be character or numeric, identifies observations on the output when you specify the LIST option.
- The **VAR** statement lists the numeric variables to be used in the cluster analysis. If you omit the VAR statement, all numeric variables not listed in other statements are used.

Lab- Clustering

- **Retail Analytics problem:** Supermarket data. A super market want to give a special discount to few selected customers. The aim to increase the sales by studying the buying capacity of the customers
- Find the customer segments using cluster analysis code(do not mention maxclusters)
- How many clusters have been created?
- What are the properties of customers in each cluster?
- Analyze the output and identify the customer group with good income, high spend, large family size.
- How much time does it take to create the clusters?
- Now create 5 clusters using K means clustering techniques
- Find the target customer group
- Further clustering in cluster 3?

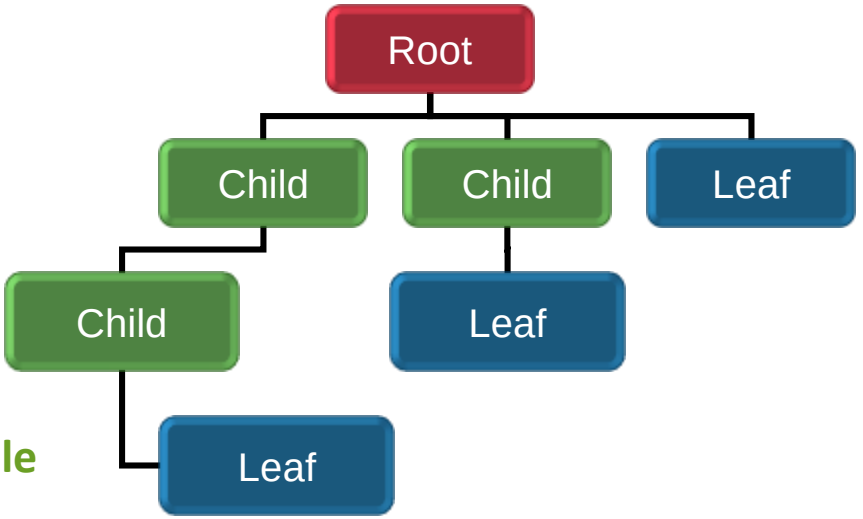
SAS output interpretation

- **RMSSTD** - Pooled standard deviation of all the variables forming the cluster. Since the objective of cluster analysis is to form homogeneous groups, the
  - RMSSTD of a cluster should be as small as possible
- **SPRSQ** -Semipartial R-squared is a measure of the homogeneity of merged clusters, so SPRSQ is the loss of homogeneity due to combining two groups or clusters to form a new group or cluster.
  - Thus, the SPRSQ value should be small to imply that we are merging two homogeneous groups
- **RSQ** (R-squared) measures the extent to which groups or clusters are different from each other
  - So, when you have just one cluster RSQ value is, intuitively, zero). Thus, the RSQ value should be high.
- **Centroid Distanc**e is simply the Euclidian distance between the centroid of the two clusters that are to be joined or merged.
  - So, Centroid Distance is a measure of the homogeneity of merged clusters and the value should be small.

Hierarchical Clustering -Decision Trees

Decision Tree Vocabulary

- Drawn top-to-bottom or left-to-right
- Top (or left-most) node = **Root Node**
- Descendent node(s) = **Child Node(s)**
- Bottom (or right-most) node(s) = **Leaf Node(s)**
- Unique path from root to each leaf = **Rule**



Decision Tree Types

- **Binary trees** – only two choices in each split. Can be non-uniform (uneven) in depth
- **N-way trees** or ternary trees – three or more choices in at least one of its splits (3-way, 4-way, etc.)

Decision Tree-Example

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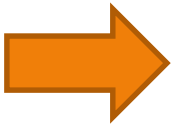

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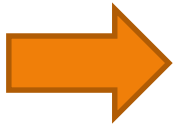
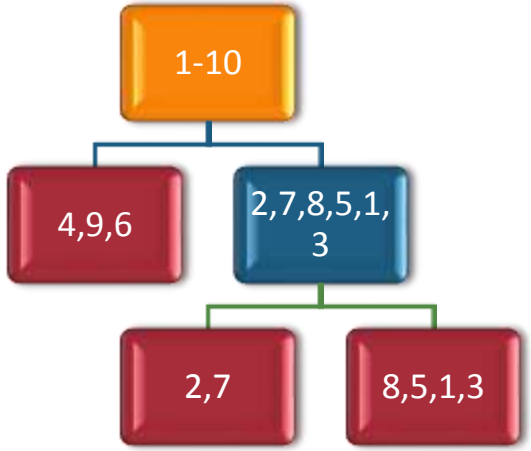
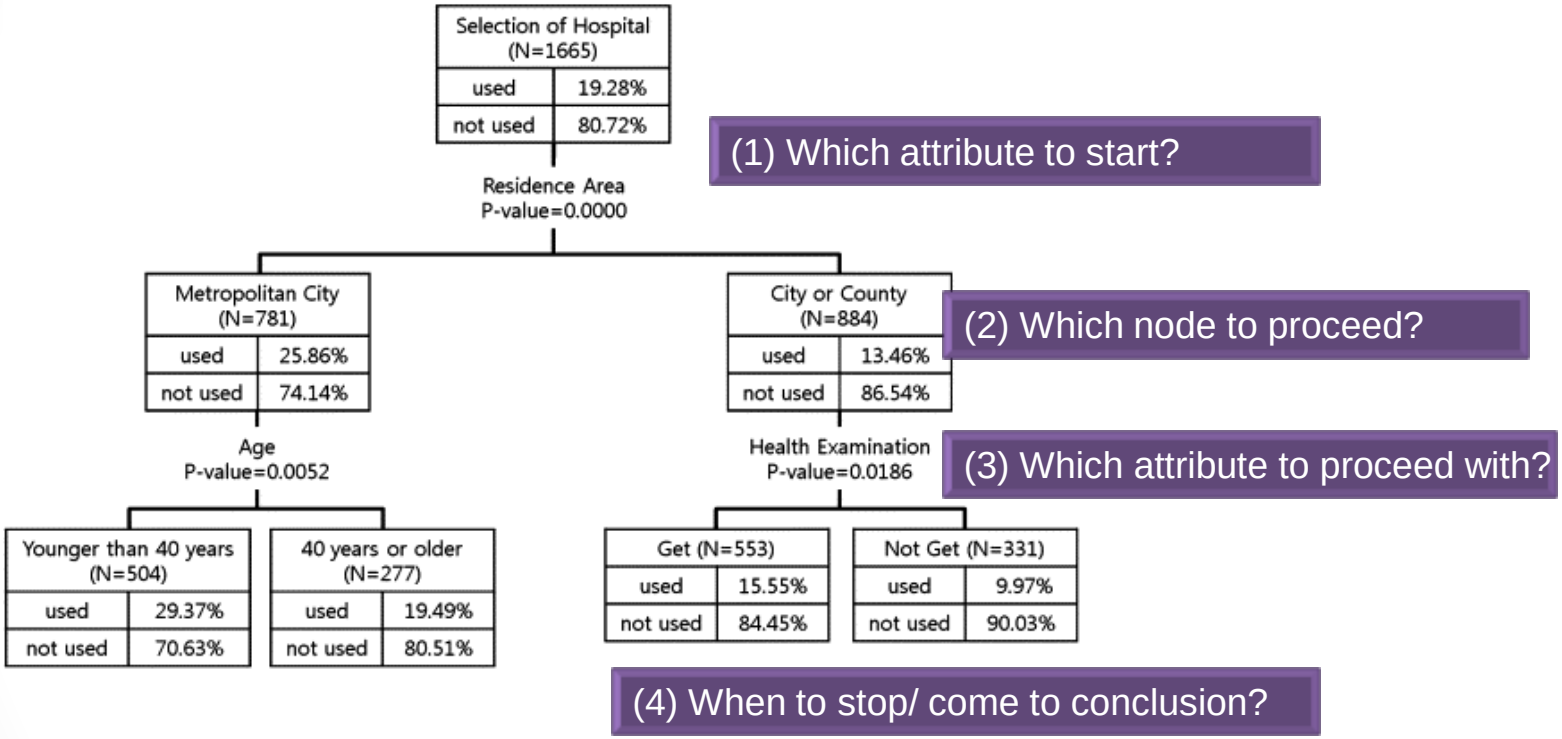




Decision Trees Algorithm



1. Start with best split attribute at root
2. Split the population into heterogeneous groups
3. Go to each group and repeat step 1 and 2 until there is no further best split

Best Splitting attribute

- The best split at root(or child) nodes is defined as one that does the best job of separating the data into groups where a single class predominates in each group
  - Example: Population data input variables/attributes include: Height, Gender, Age
  - Split the above according to the above "best split" rule
- Measure used to evaluate a potential split is **purity**
- The best split is one that increases purity of the sub-sets by the greatest amount
- Purity (Diversity) Measures:
  - Gini (population diversity)
  - Entropy (information gain)
  - Information Gain Ratio
  - **Chi-square Test**

Clustering SAS Code & Options

```
proc cluster data= mylib.cluster_data
simple noeigen method=centroid rmsstd rsquare nonorm out=tree;
id cust_id;
var age income spend family_size Other_shops;
run;
```

Options

- SIMPLE: The `simple` option displays simple, descriptive statistics.
- NOEIGEN: The `noeigen` option suppresses computation of eigenvalues. Specifying the `noeigen` option saves time if the number of variables is large
- The METHOD= specification determines the clustering method used by the procedure. Here, we are using CENTROID method.
- The RMSSTD option displays the root-mean-square standard deviation of each cluster.
- The RSQUARE option displays the R^2 and semipartial R^2 to evaluate cluster solution.
- The NONORM option prevents the distances from being normalized to unit mean or unit root mean square with most methods.

Lab: Hierarchical clustering

- Build hierarchical clusters for the supermarket data
- Draw the tree diagram
- What are the properties of customers in each cluster?
- Analyze the output and identify the customer group with good income, high spend, large family size.

SAS output interpretation

- **RMSSTD** - Pooled standard deviation of all the variables forming the cluster. Since the objective of cluster analysis is to form homogeneous groups, the
  - RMSSTD of a cluster should be as small as possible
- **SPRSQ** -Semipartial R-squared is a measure of the homogeneity of merged clusters, so SPRSQ is the loss of homogeneity due to combining two groups or clusters to form a new group or cluster.
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- **Centroid Distanc**e is simply the Euclidian distance between the centroid of the two clusters that are to be joined or merged.
  - So, Centroid Distance is a measure of the homogeneity of merged clusters and the value should be small.

CHAID Segmentation

- CHAID- Chi-Squared Automatic Interaction Detector
- CHAID is a non-binary decision tree.
- The decision or split made at each node is still based on a single variable, but can result in multiple branches.
- The split search algorithm is designed for categorical variables.
- Continuous variables must be grouped into a finite number of bins to create categories.
  - A reasonable number of “equal population bins” can be created for use with CHAID.
  - ex. If there are 1000 samples, creating 10 equal population bins would result in 10 bins, each containing 100 samples.

- A Chi-square value is computed for each variable and used to determine the best variable to split on.

CHAID Algorithm

1. Select significant independent variable
2. Identify category groupings or interval breaks to create groups most different with respect to the dependent variable
3. Select as the primary independent variable the one identifying groups with the most different values of the dependent variable based on chi-square
4. Select additional variables to extend each branch if there are further significant differences

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