"Drowning in Data, Starving for Knowledge"

Data Exploration and Pattern Detection via Partitioning

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Contents

I

What is clustering? Why do we cluster?

How does one cluster?

Partitional Clustering: K-means

Hierarchical (agglomerative) Clustering

Clustering: What Is It and Why?

Example Questions From Data?

- Types of **pages** are there on the **Web**?
- Types of **customers** are there in my **market**?
- Types of **people** are there on a Social **network**?
- Types of **e-mails** in my **Inbox**?

Example Questions From Data?

Types of **genes** the **human genome** has?

Types of stars/planets/galaxies are in the universe?

Types of **songs/movies** in my **audio library**?

Types of **animals/plants** are there on **Earth**?

Nature Is "Naturally" Organized



Hydrogen 3 Li Litium 11 Na Sodlum	Be Beryllium 12 Mod Magnesium			STABLE half life more than one trillion years half life in range of billion years half life in range of million years half life in range of thousands of years half life in range of years half life in range of days half life in range of hours half life in range of minutes half life in range of milliseconds half life in range of milliseconds half life undetermined								B Boron	6 Carbon	7 Nitrogen 15 P	8 Oxygen 16 Sulfur	Fluorine	He Helium 10 Ne Neon 18 Ar
19 K Potassium	Calcium	SC Scandium	22 Ti Titanium	23 V	24 Cr	25 Mn Manganese	Fe Iron	Co Cobalt	28 Ni Nickel	Cu Copper	$ \overset{30}{Z_{\text{Inc}}} $	Gallium	Germanium	33 AS Arsenic	Se Selenium	35 Br Bromine	36 Kr Krypton
Rb Rubidium	Sr Strontium	39 Y	Zr Zirconium	Nb Niobium	MO Molybdenium	TC Technetium	Rutenium	Rh Rhodium	Palladium	A7 Ag Silver	48 Cd	49 In	Sn _™	Sb Antimony	Tellurium	53 L	Xe Xenon
55 CS Caesium	Ba _{Barium}	57 La Lanthanum	72 Hf	73 Ta Tantalum	74 W Tungsten	75 Re	76 OS Osmium	77 r	78 Pt Platinum	79 Au Gold	80 Hg Mercury	81 Tl	Pb Lead	83 Bi	PO Polonium	85 At Astatine	Rn Radon
87 Fr Francium	Radium 88	Actinium	104 Rf Rutherfordium	Db Db Dubnium	106 Sg Seaborgium	Bh Bohrium	108 HS Hassium	109 Mt Meitnerium	110 DS Darmstadtium	Roentgenium	112 UUb Ununbium	113 UUt Ununtrium	114 UUq _{Ununquadium}	115 UUp Ununpentium	116 UUh _{Ununhexium}	117 UUS Ununseptium	118 UU0 Ununoctium

Cerium	59 Pr Praseodymium	60 Nd Neodymium	61 Pm	62 Sm Samarium	63 Europium	64 Gd	65 Tb	66 Dy Dysprosium	67 Ho	68 Er	Tm	70 Yb Ytterbium	71 Lu Lutetium
Th Thorium	Pa Protactinium	92 Uranium	93 Np Neptunium	94 Pu	95 Am Americium	Cm	97 Bk Berkelium	98 Cf Californium	99 ES Einsteinium	100 Fm Fermium	101 Md Mendelevium	Nobelium	103 Lr Lawrencium

Hierarchy of Organization



http://vlib.org/

The WWW Virtual Library

Quick se

Agriculture

Irrigation, Livestock, Poultry Science, ...

The Arts

Art History, Classical Music, Theatre and Drama, ...

Business and Economics

Finance, Marketing, Transportation, ...

Communications and Media

Broadcasters, Publishers, Telecommunications, ...

Computing and Computer Science

Artificial Intelligence, Cryptography, Logic Programming, ...

Education

Primary, Secondary, Tertiary, ...

Engineering

Architecture, Electrical, Mechanical, ...

Humanities and Humanistic Studies

History, Languages and Linguistics, Museums, ...

Information and Libraries

Information Quality, Knowledge Management, Libraries, ...

International Affairs

International Relations and Security, Sustainable Development, \dots

Law

Arbitration, Forensic Toxicology, Legal History, ...

Natural Sciences and Mathematics

Biosciences, Earth Science, Medicine and Health, Physics, ...

Recreation

Gardening, Recreation and Games, Sport, ...

Regional Studies

African, Asian, Latin American, European, ...

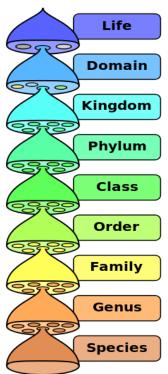
Social and Behavioural Sciences

Anthropology, Archaeology, Population and Development Studies, ...

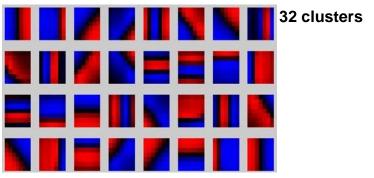
Society

Peoples, Religion, Gender Studies, ...

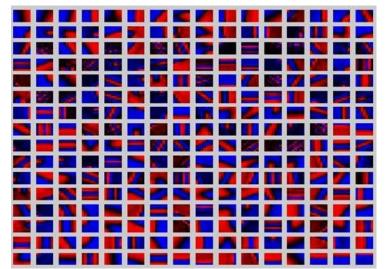
Biological Classification



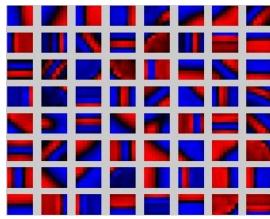
Cluster to Create Features



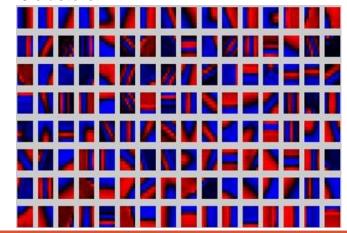






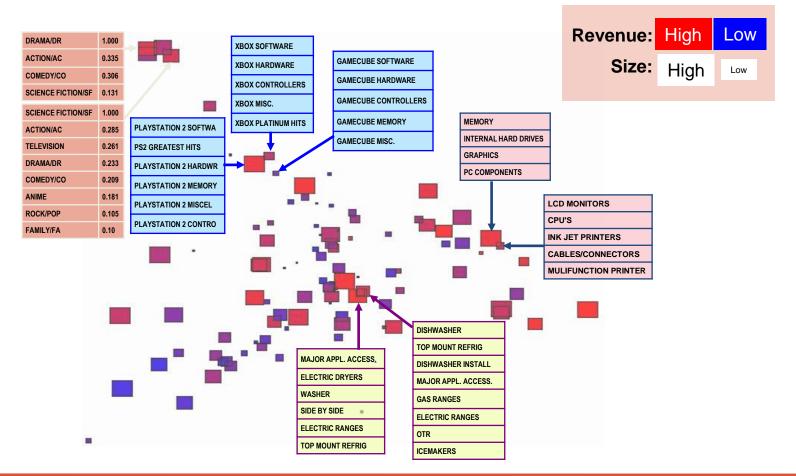


128 clusters



Customer Clustering by Purchase





Applications

Forecasting

Pricing

Strange patterns of residuals might imply a cluster

Missing data might mean a cluster!

So Why Clustering?

Clustering = Grouping "Similar" things together!

Understand/discover structure in data

Summarize data points by their "cluster center"

Compress data variability into "representative vectors"

So Why Clustering?

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Clustering = Grouping "Similar" things together!

Extract features from data for Supervised Learning
Generate class labels when not known
Business rules can be uncovered

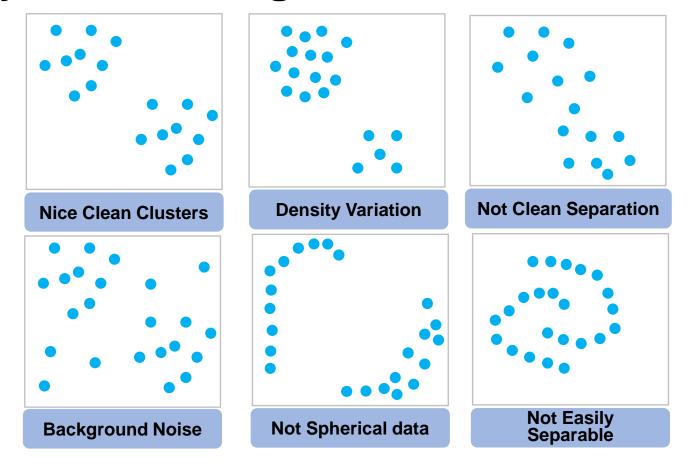
How Does One Cluster?

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It depends!

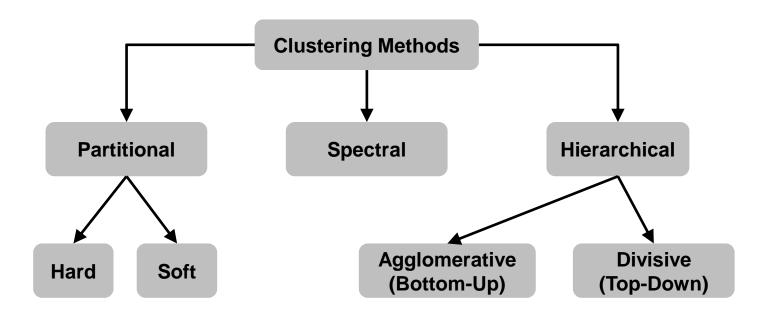
Why is Clustering Non-trivial?





Clustering Methods





Key to Clustering is how we define "**Distance**" or "**Similarity**" between two data points

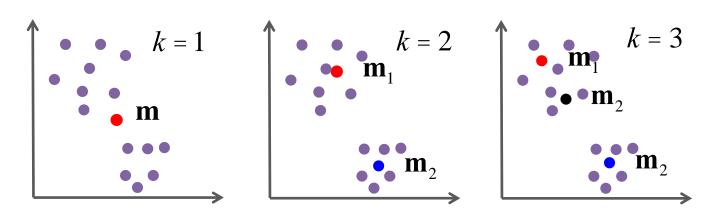
Partitional Clustering

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K-Means Clustering

K-Means - Objective Function





What are the **Parameters**?

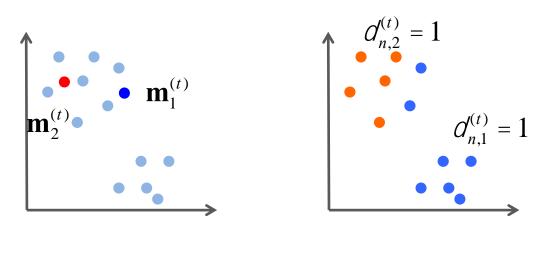
What is the **Objective Function**?

What is the **Model Complexity**?

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K-Means: 1. Expectation

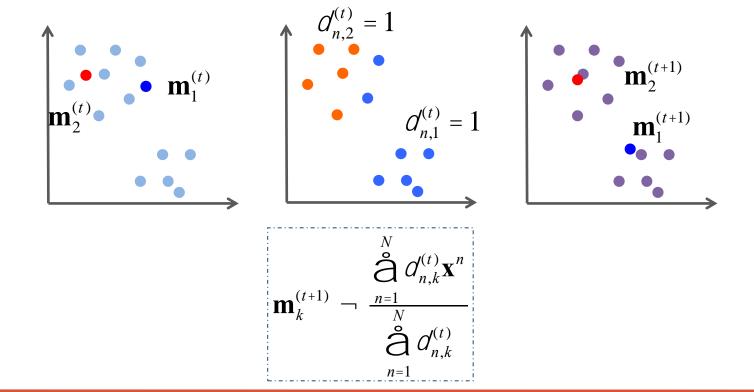
cluster *centers* → cluster *assignments*



$$O_{n,k}^{(t+1)} = \left(k = \arg\min_{j=1...K} \left\{ D\left(\mathbf{x}^{(n)}, \mathbf{m}_{j}^{(t)}\right) \right\} \right)$$

K-Means: 2. Maximization

cluster *assignments* → cluster *centers*



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Technical considerations

Distance measures

Initialization

Number of clusters

Rattle

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Build a model

Improve a model

Data- BestFit's Body_Measure

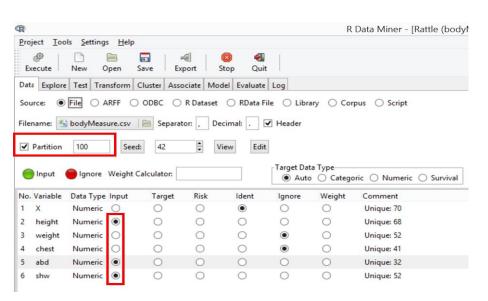


Objective – Find a few groups(clusters) on the basis of the given attributes

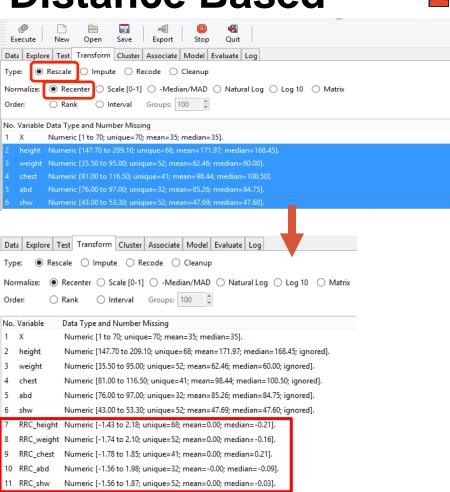
Variable	Description
Height	The height measured in (cm)
Weight	The weight measured in (kg)
Chest	The circumference of chest measured in (cm)
abd	The circumference of abdomen measured in (cm)
shw	The shoulder width measured in (cm)

First five rows of data											
height	weight	chest	abd	shw							
168	61.5	98.5	85	47.5							
149.3	53	90	78	44.9							
148.4	44.5	89.5	77	43.9							
195.5	91.5	111	94.5	52.7							
159.1	52.5	84	79.5	44.7							

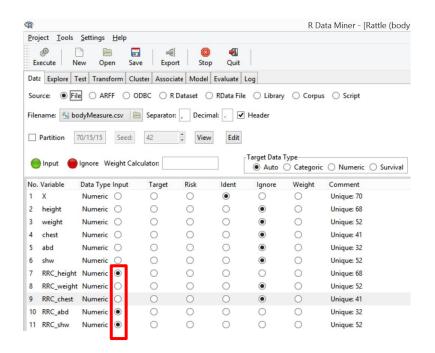
Rescale the Data for Distance Based Algorithms (KNN) Date Explore Test Transform Cluster Associate Model Evaluate Log Date Explore Test Transform Cluster Associate Model Evaluate Log



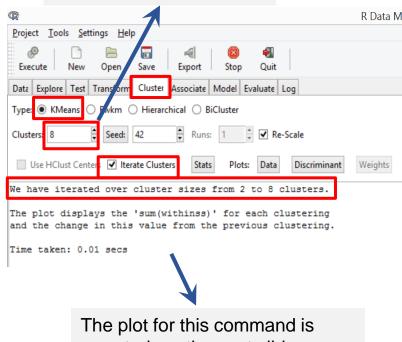
Large scale should not affect distances. We transform the data.



Select the Input Variables and Select the Best K





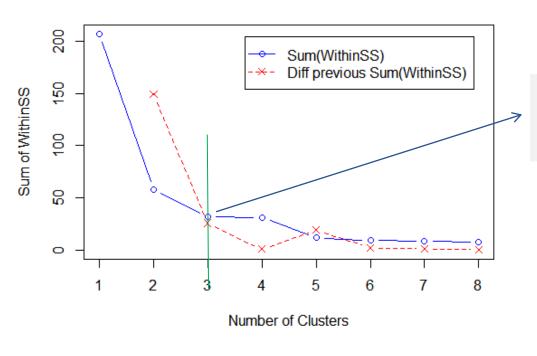


The plot for this command is reported on the next slide. Plot is in R!

Selecting the Best K



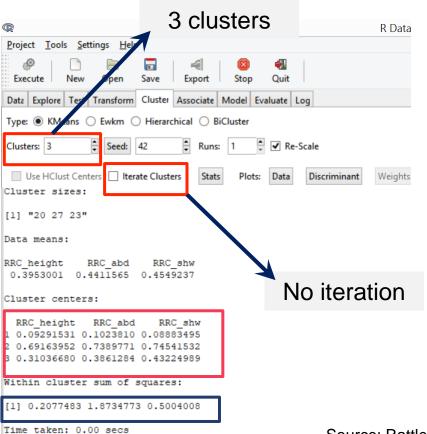
Sum of WithinSS Over Number of Clusters



At K=3, the red line cuts the blue line from above, thus we select K=3. This is a heuristic rule!

Running K Means for K=3

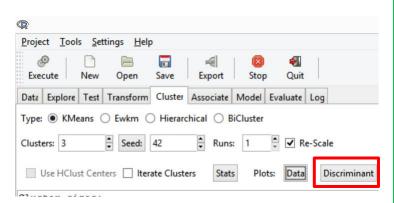


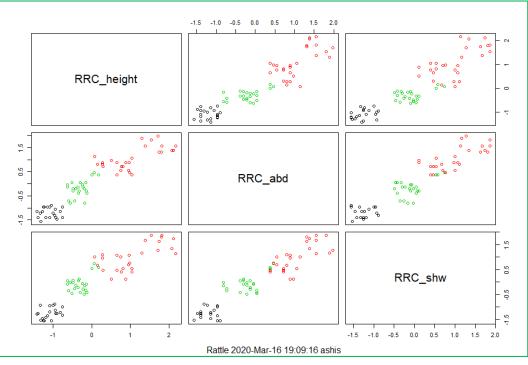


Once a model has been built, the Stats, Data Plot, and Discriminant Plot buttons become available

Kmeans – Plot

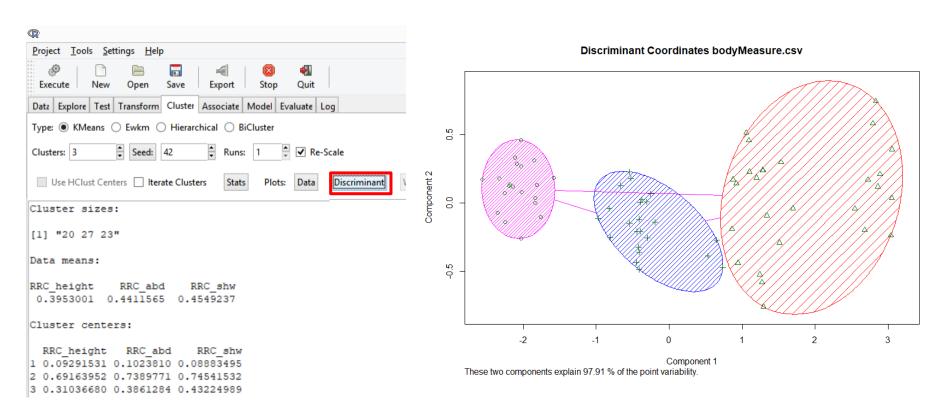






Kmeans - Discriminant Plot





Limitations

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High dimensional data

Knowledge of how many clusters

Hierarchical (Agglomerative) Clustering

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A B2B firm wants to work on pricing policy for their set of customer based on their purchasing pattern. The analyst in the company selected top 10 representative accounts and analyzed their monthly purchasing (in \$ 000's) and wants to group (cluster) them in some meaningful way.

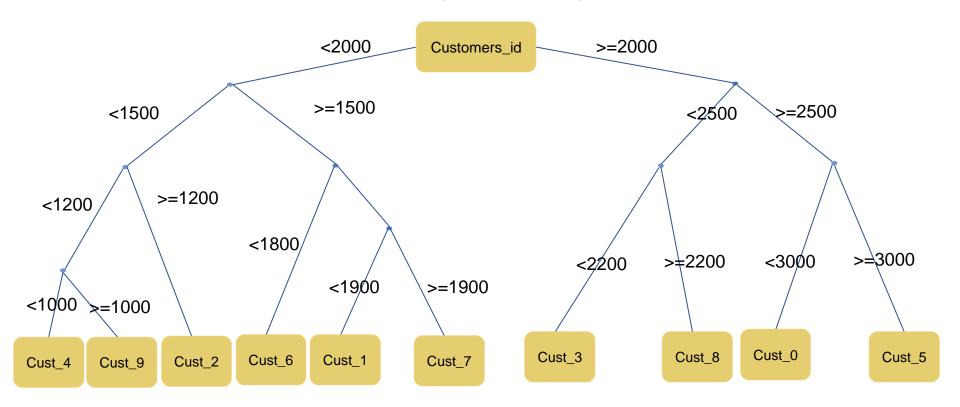
Clustering Example

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The task also involves deciding in how many groups should they be divided?

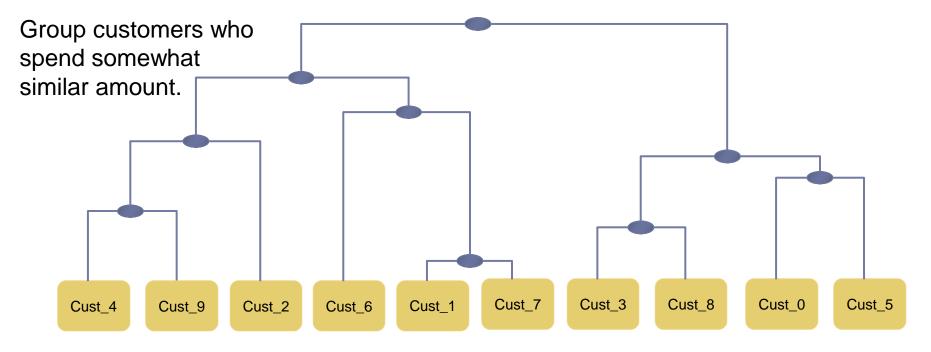
Classification of Key Accounts on Purchase Amount (\$ 000s)





Bottom-Up (Agglomerative)

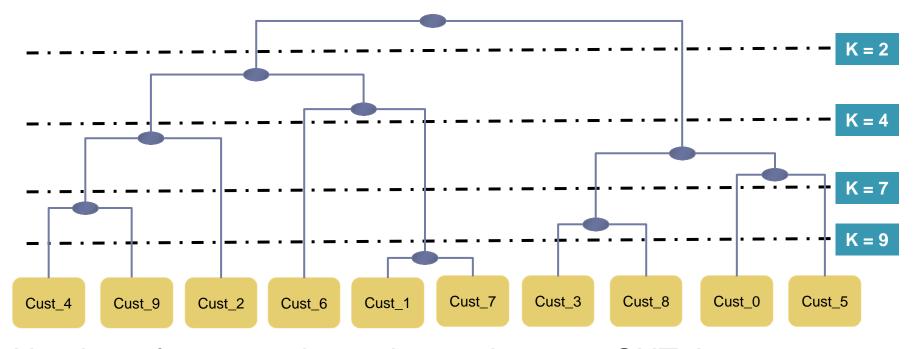




SIMILARITY between two DATA POINTS? Sim(0, 5) SIMILARITY between CLUSTERS? Sim({3, 8}, {0, 5})

How Many Clusters? Depends!

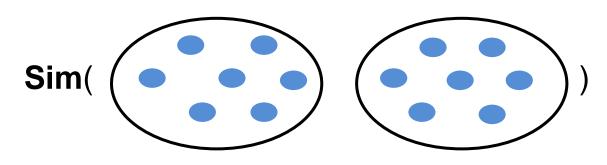




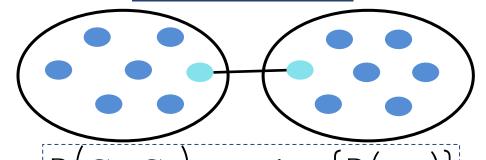
Number of clusters depends on where we CUT the dendrogram.

Similarity Between Clusters





Single Linkage Nearest Neighbor **Complete Linkage Farthest Neighbor**

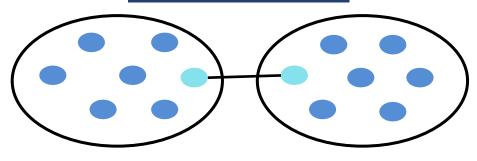


$$D(\mathbf{C}_{a}, \mathbf{C}_{b}) = \max_{\mathbf{x} \in \mathbf{C}_{a}, \mathbf{y} \in \mathbf{C}_{b}} \{D$$

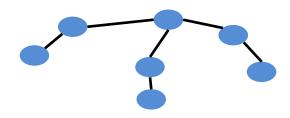
Single Link Examples



Single Linkage Nearest Neighbor



$$D(\mathbf{C}_{a}, \mathbf{C}_{b}) = \min_{\mathbf{x} \in \mathbf{C}_{a}, \mathbf{y} \in \mathbf{C}_{b}} \{D(\mathbf{x}, \mathbf{y})\}$$

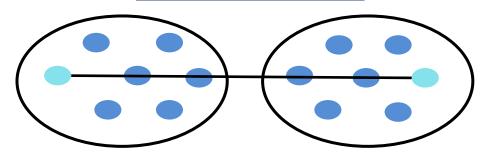


- Elongated Clusters
- Minimum Spanning Trees

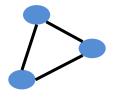
Complete Linkage Example

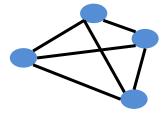


Complete Linkage Farthest Neighbor



$$D(\mathbf{C}_{\partial}, \mathbf{C}_{b}) = \max_{\mathbf{x} \in \mathbf{C}_{\partial}, \mathbf{y} \in \mathbf{C}_{b}} \{D(\mathbf{x}, \mathbf{y})\}$$

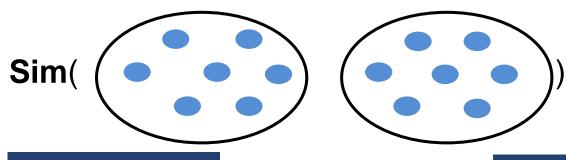




Compact Clusters

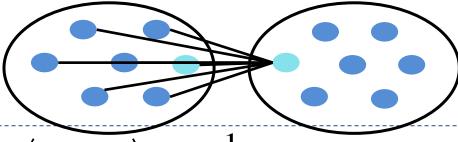
Similarity between Clusters





Average Linkage All Neighbors

Mean Linkage Mean Neighbor



$$D(\mathbf{C}_a, \mathbf{C}_b) = \frac{1}{|\mathbf{C}_a||\mathbf{C}_b|} \sum_{\mathbf{x} \in \mathbf{C}_a} \sum_{\mathbf{y} \in \mathbf{C}_b} D(\mathbf{x}, \mathbf{y})$$

$$D(\mathbf{C}_{\mathcal{A}},\mathbf{C}_{\mathcal{B}}) = ||\mathbf{m}_{\mathcal{A}} - \mathbf{m}_{\mathcal{B}}||$$

Now It All Boils Down To...

 $D(\mathbf{x}, \mathbf{y})$

Distance or **Similarity** between two points

Foundation of all Machine Learning algorithms

"Similar things have similar properties (e.g. class/cluster labels)"



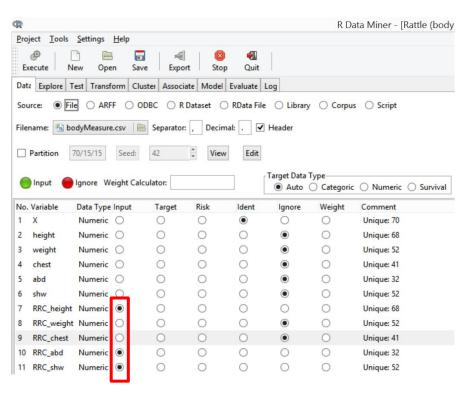
 $D(\mathbf{x}, \mathbf{y})$

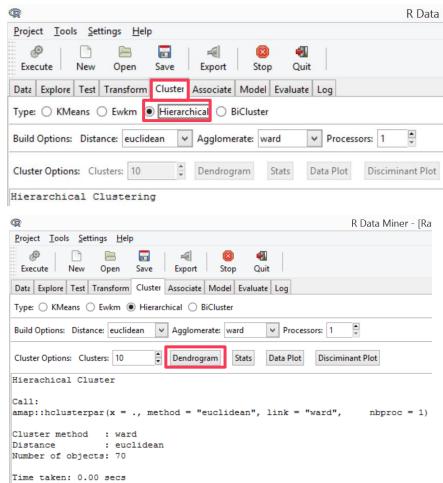
Depends on the domain

Multi-variate numeric, categorical, Text, Bag, Basket, Image,...

Can be static (constant) or dynamic (learnt)

Data: bodyMeasure

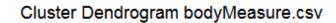




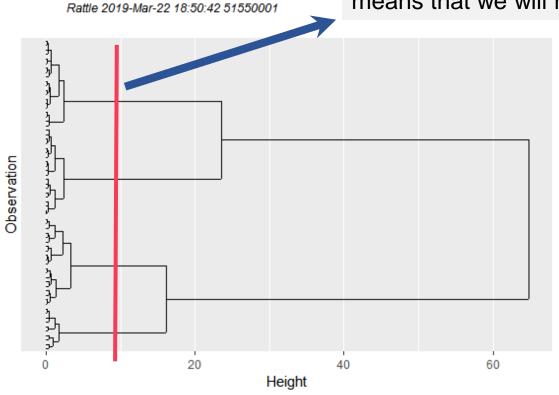
Source: Rattle GUI / Togaware

Dendogram



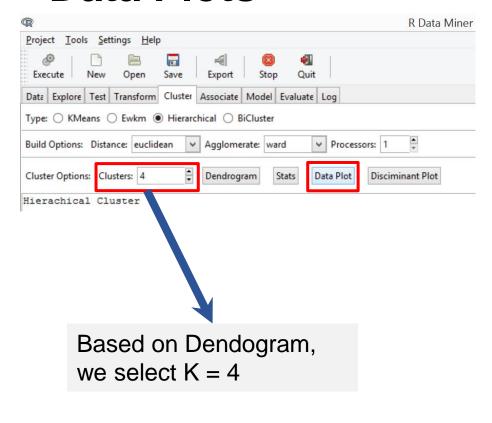


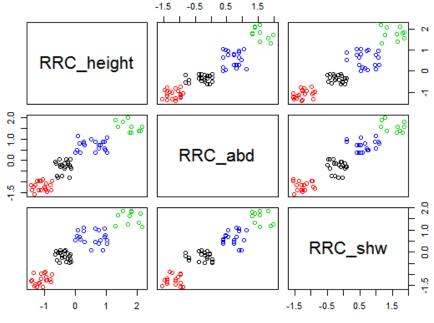
We cut the dendogram here. That means that we will have four clusters.



Data Plots





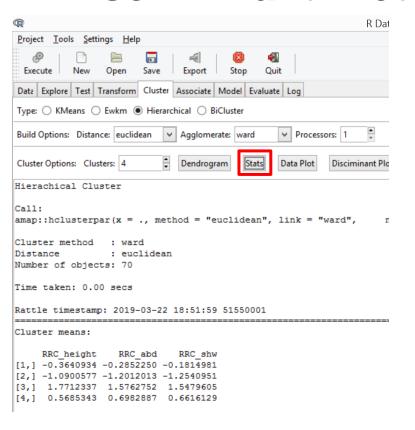


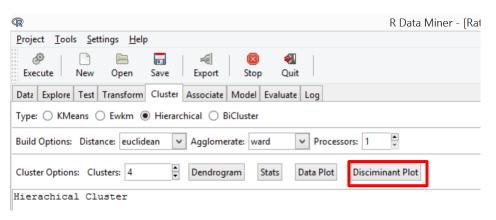
Rattle 2019-Mar-22 18:51:49 51550001

Source: Rattle GUI / Togaware

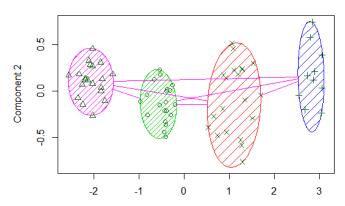
Discriminant Plot







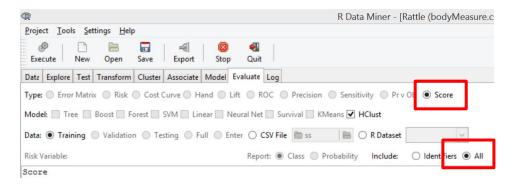
Discriminant Coordinates bodyMeasure.csv

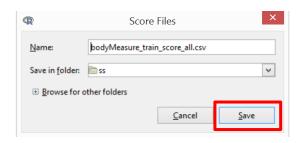


Component 1
These two components explain 97.91 % of the point variability.

Cluster Membership







Χ	height	weight	chest	abd	shw	RRC_heigh	RRC_weigl	RRC_chest	RRC_abd	RRC_shw	kmeans	hclust
1	168	61.5	98.5	85	47.5	-0.23317	-0.06162	0.006581	-0.04462	-0.06177	1	1
2	149.3	53	90	78	44.9	-1.33107	-0.60885	-0.86355	-1.22653	-0.9265	1	2
3	148.4	44.5	89.5	77	43.9	-1.38391	-1.15608	-0.91473	-1.39537	-1.25908	1	2
4	195.5	91.5	111	94.5	52.7	1.381391	1.869782	1.286181	1.559391	1.667692	2	3
5	159.1	52.5	84	79.5	44.7	-0.7557	-0.64104	-1.47776	-0.97326	-0.99301	1	2
6	172	74	106	87.5	49.3	0.001677	0.74313	0.774341	0.377486	0.536892	3	4

Source: Rattle GUI / Togaware

Exercise - Clustering



Perform Kmeans clustering on Universities data (use all rows and these variables: GradRate, SAT, TOP10, Accept, SFRatio and Expenses. Find the optimum number of clusters through iterative clustering. (Download from

http://users.stat.umn.edu/~kb/classes/8401/files/data/JWD ata5.txt)

For the chosen "K" above, run Kmeans clustering

Report the first two within cluster sum of squares (check your answer: 1.275 and 0.442 for K = 3)

You will see small difference due to random start of algorithm.

Exercise - Clustering

Perform Hierarchical clustering on Universities data (use all rows and these variables: GradRate, SAT, TOP10, Accept, SFRatio and Expenses). Find the optimum number of clusters based on the Dendrogram. Do you see a pattern in data identified by this method?

Universities data from http://users.stat.umn.edu/~kb/classes/8401/files/data/JWData5.txt

Summary

From data to clusters

K means and hierarchical clustering

Both problematic with high dimensional data

Hierarchical clustering cannot handle big data well but K Means clustering can due to run time being linear versus quadratic in number of points.

K Means clustering requires prior knowledge of number of clusters --in hierarchical clustering can stop by interpreting the dendrogram

Further Readings

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PRACTICAL GUIDE TO CLUSTER ANALYSIS IN R

https://www.datanovia.com/en/product/practical-guide-to-cluster-analysis-in-r/

Clustering algorithms: A comparative approach (using R)

https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0210236

Nuclear Norm Clustering: a promising alternative method for clustering tasks https://www.nature.com/articles/s41598-018-29246-4

Supervised clustering with Support Vector Machines

https://www.cs.cornell.edu/people/tj/publications/finley_joachims_05a.pdf

K-Means Complexity

E-Step: cluster **centers** → cluster **assignments**

$$O_{n,k}^{(t+1)} = \left(k == \arg\min_{j=1...K} \left\{ D\left(\mathbf{x}^{(n)}, \mathbf{m}_{j}^{(t)}\right) \right\} \right) \quad O(NKD)$$

M-Step: cluster **assignments** → cluster **centers**

$$\mathbf{m}_{k}^{(t+1)} - \frac{\overset{N}{\overset{n}{\bigcirc}} \mathcal{O}_{n,k}^{(t)} \mathbf{x}^{n}}{\overset{n}{\overset{n}{\bigcirc}} \mathcal{O}_{n,k}^{(t)}}$$

$$O(DN) = O\left(D\sum_{k=1}^{K} N_{k}\right)$$

$$n=1$$

$$O(DN) = O\left(D\sum_{k=1}^{K} N_k\right)$$

References

Biological Classification. (n.d.). In *Wikipedia*. Retrieved May 22, 2019, from https://commons.wikimedia.org/wiki/File:Biological_classification_L_Pengo_vflip.svg

Johnson, R.A., & Wichern, D.W. (2002). Applied Mulivariate Statistical Analysis (5th ed.)
Prentice Hall.

Rattle GUI / Togaware (https://rattle.togaware.com/)