

# Clustering of Mixed and Continuous Data

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# Methods used

- K-prototypes
- Agglomerative Clustering
- Partitioning around medoids
- DBSCAN
- Mixture of skew-t distributions
- Gaussian mixture model
- Mixture of t distributions
- Mixture of skew-Gaussian distribution
- K-means

# K- Prototypes

Cost function is:

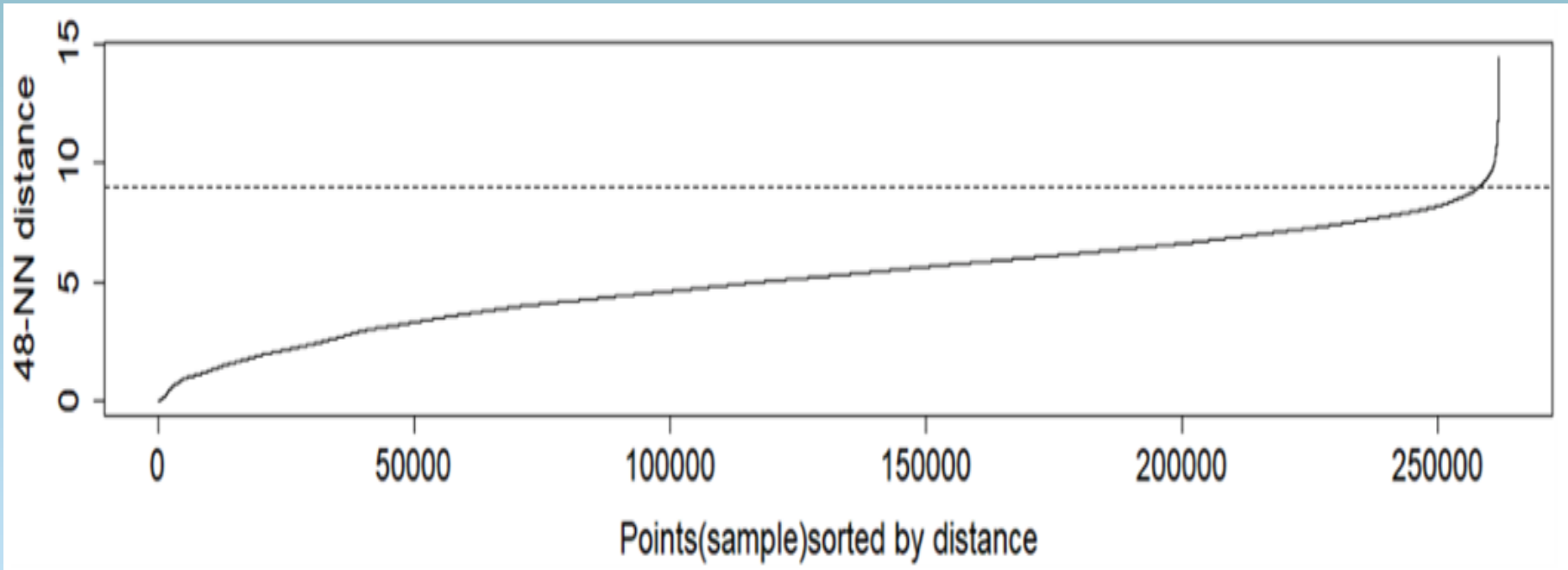
$$E_l = \sum_{i=1}^n y_{il} \sum_{j=1}^{m_r} \lambda_j (x_{ij}^r - q_{lj}^r)^2 + \sum_{j=m_r+1}^m \lambda_j n_l (1 - p(q_{ij}^c \in C_j | l)) = E_l^r + E_l^c$$

- $m_r$  is the number of numeric variables,  $m$  is the total number of variables, so  $m - m_r$  is number of categorical variables
- $r$  represents the numerical data and  $c$  represents the categorical data
- $n$  is the number of observations
- $y_{il}$  is the membership of  $X_i$  to the cluster  $l$ :  $y_{il} = 1$ , if  $X_i$  belongs to the cluster  $l$  and  $y_{il} = 0$  otherwise
- $n_l$  is the number of members in cluster  $l$
- $\lambda_j$  is the weight parameter which determines the degree of the variable's influence on the cost
  - We will use the lambda vector as it takes the inverse variability of each variable

# DBSCAN

- Detects dense and sparse regions of data
- Two parameters required are:
  - $\epsilon$ , is the degree of density
  - Minimum sample size
- Core points are observations with number of neighbors within  $\epsilon$  greater than the minimum sample size
- Border points are observations within  $\epsilon$  of a core point
- Outliers are neither core nor border points

# Selecting the DBSCAN epsilon



- Find epsilon at the point where the points sharply increase

# Simulation study

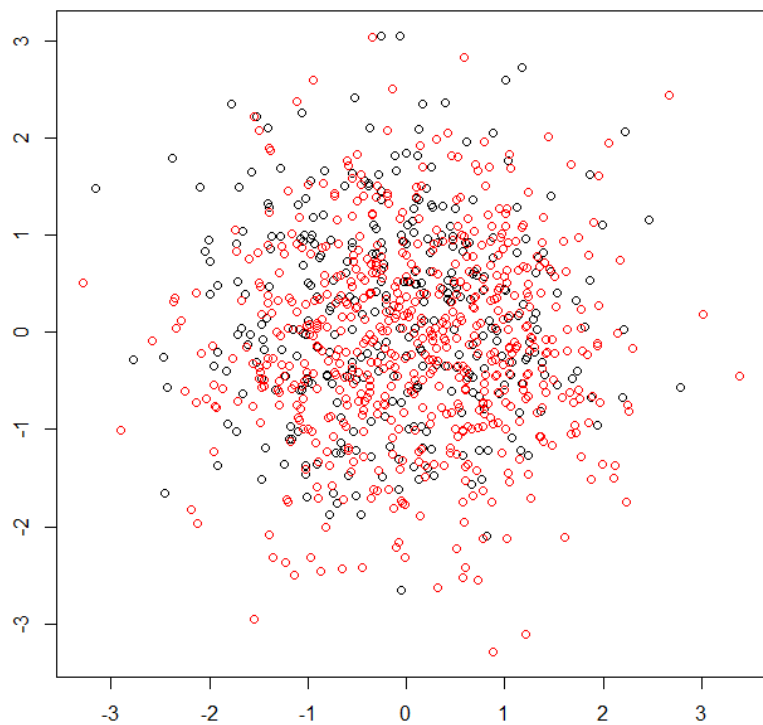
K-means, PAM, DBSCAN, and Skew-t mixture model

Considered

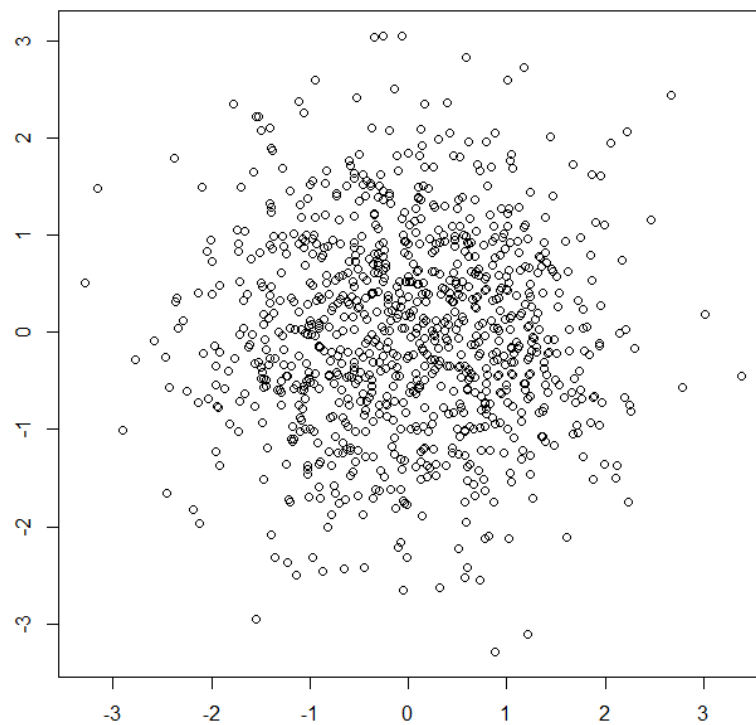
- Overlappedness
- 2 vs. 4 clusters
- No correlation vs. moderate correlation
- Types of distributions(Gaussian, skew-Gaussian, t, skew-t)

	Separation	Distribution	Correlation	k-means	PAM	DBS CAN	Ske w-t
1	Clear	(G, G)	(X, X)	1.00	1.00	0.98	1.00
2	Clear	(G, G, G, t)	(X, X, X, X)	0.98	0.99	0.95	0.99
3	Clear	(G, G)	(X, mod-pos)	1.00	1.00	0.98	1.00
4	Clear	(G, G, G, t)	(X, mod-pos, mod-pos, mod-pos)	0.99	0.99	0.96	0.99
5	Clear	(G, skew-G)	(X, mod-pos)	0.63	0.64	0.93	1.00
6	Clear	(G, skew-G, G, t)	(X, mod-pos, mod-pos, mod-pos)	0.85	0.84	0.95	0.99
7	Over	(G, G)	(X, X)	0.01	0.01	0.00	0.00
8	Over	(G, G, G, skew-t)	(X, X, X, X)	0.02	0.12	0.01	0.33
9	Over	(G, G)	(X, mod-pos)	0.01	0.01	0.00	0.61
10	Over	(G, G, G, skew-t)	(X, mod-pos, mod-pos, mod-pos)	0.02	0.12	0.00	0.86
11	Over	(G, skew-G)	(X, mod-pos)	0.08	0.17	-0.02	0.79
12	Over	(G, skew-G, G, skew-t)	(X, mod-pos, mod-pos, mod-pos)	0.08	0.18	0.00	0.91

**True**



**Skew-t**





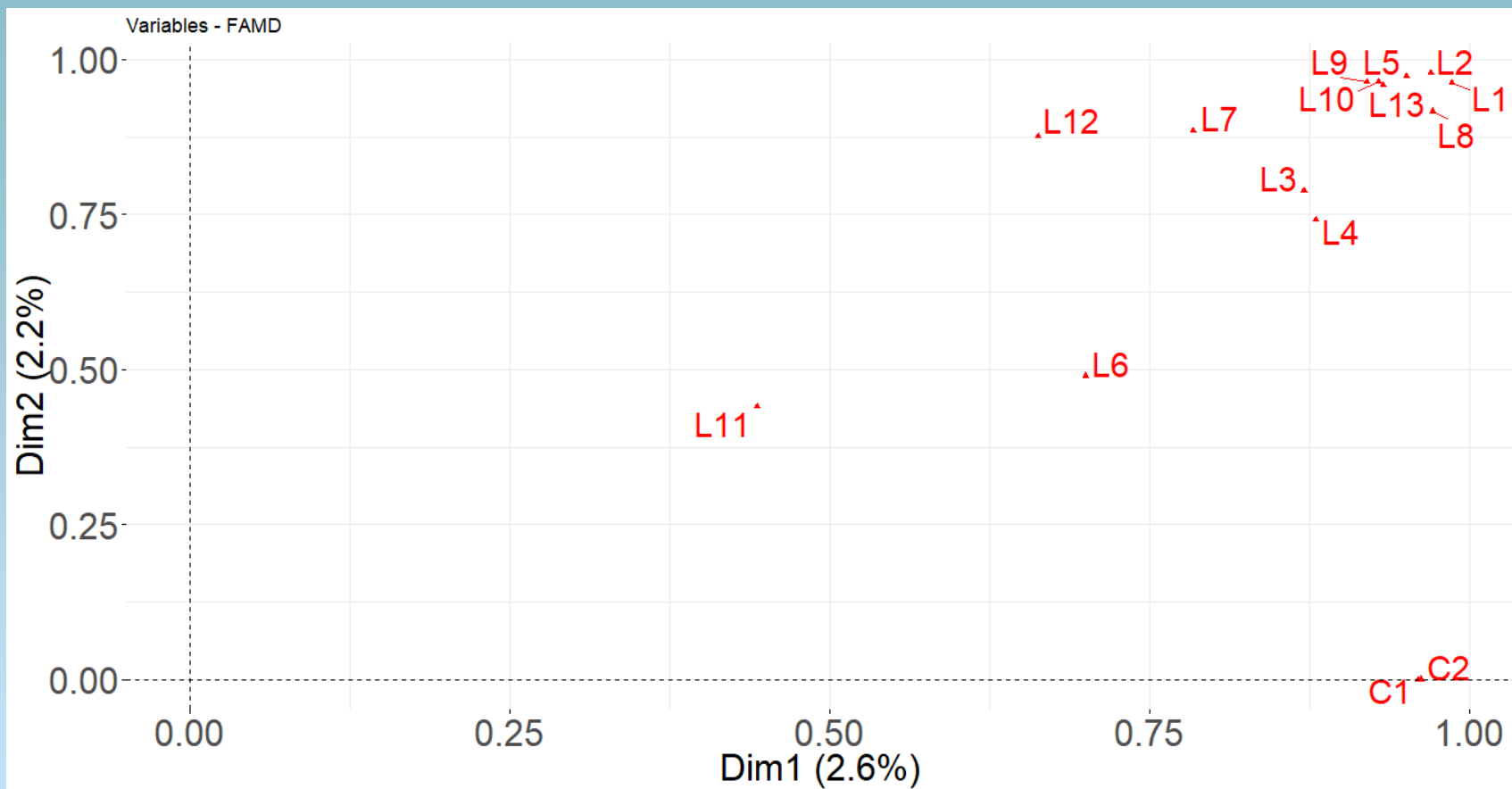
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## Tetragonula Bee Species

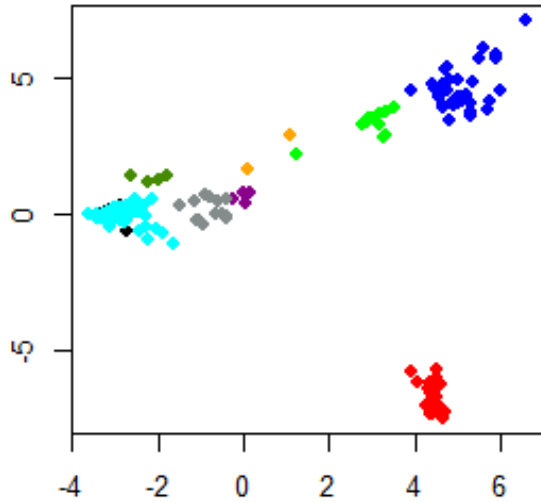
- Genetic data for 236 Tetragonula bees from Australia and Southeast Asia
- 13 categorical variables: L1 – L13 are strings of six digits which encode a pair of alleles with no numeric information.
- 2 numerical variables: C1 and C2 are coordinates of locations of individual bees. C1 is latitude (negative values are South). C2 is longitude (negative values are West).
- Species represent the species out of 9 categories labeled from 1 to 9.

## Bee Species: 2 numeric & 13 categorical

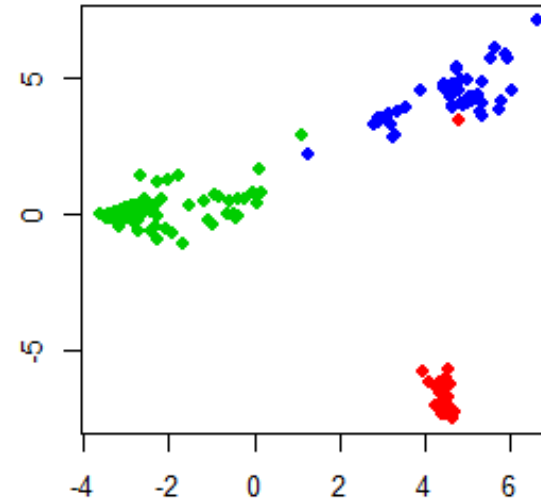


Bee Species: 2 numeric & 13 categorical

**9 Species**

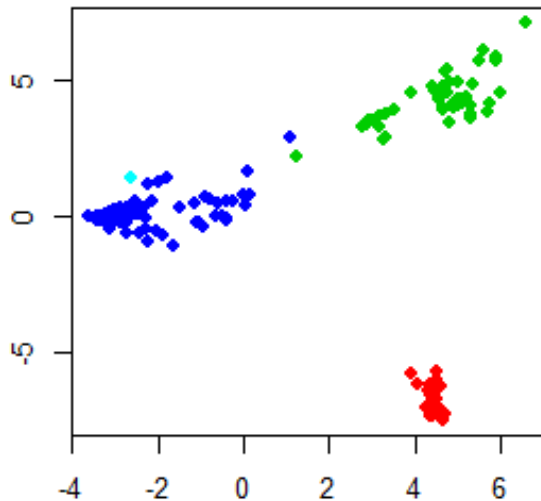


**KPROTO-3cls**



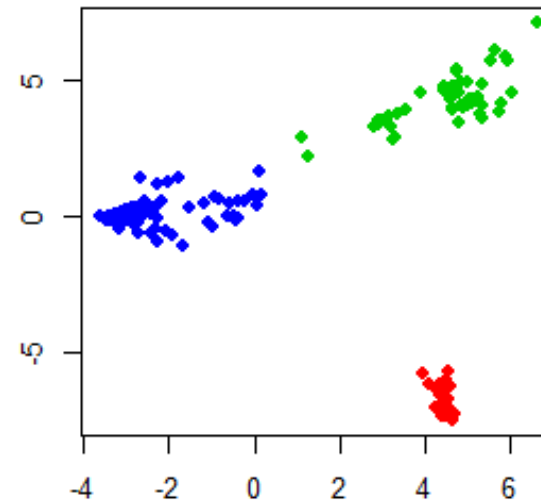
ARI: 43%  
AvgSil: 0.35

**AVGAGGM-3cls, 1outlr**



ARI: 48%  
AvgSil: 0.32

**PAM-3cls**

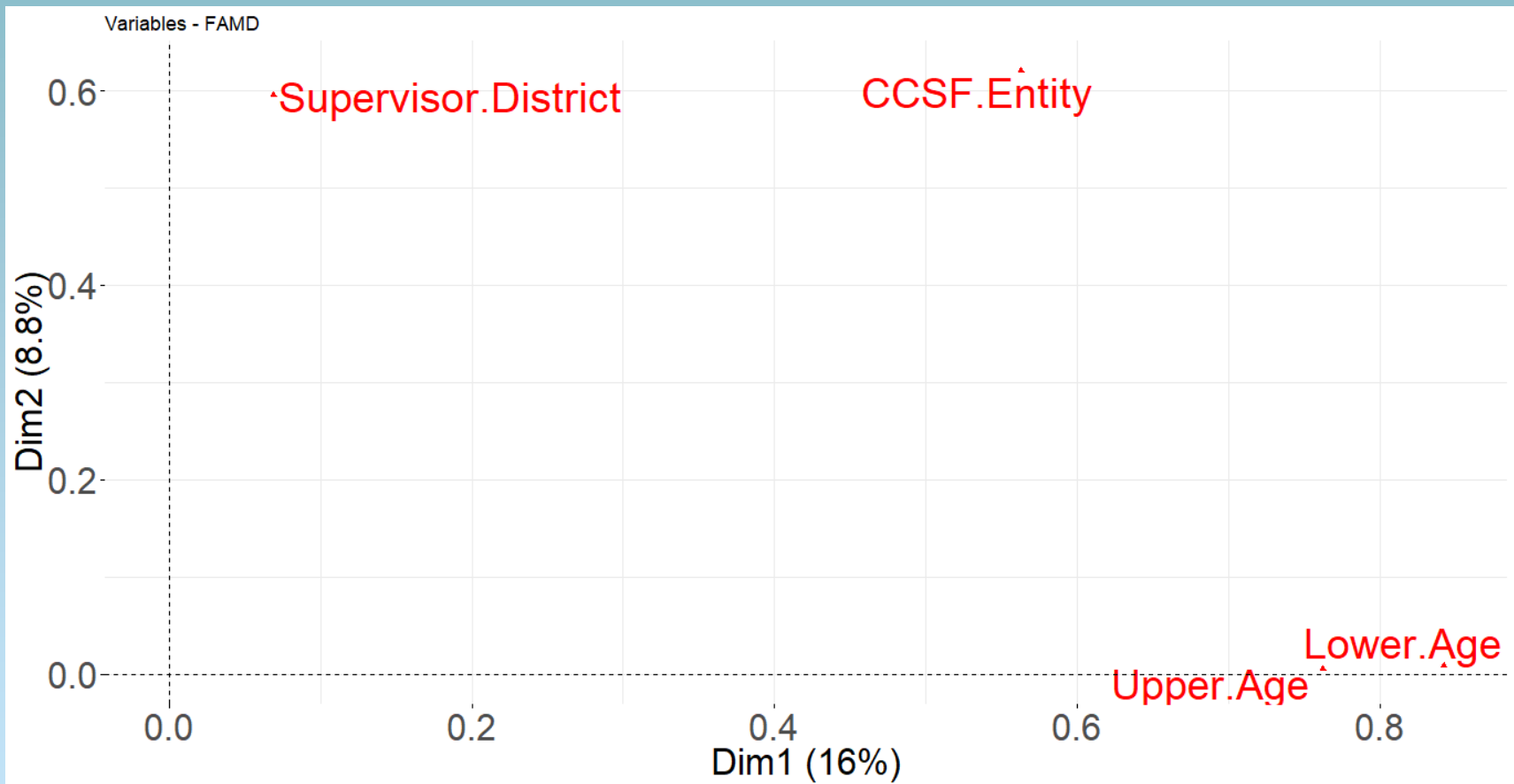


ARI: 44%  
AvgSil: 0.35

# Schools

- Features of 445 public and private schools for infant, Pre-K, and K-14 students in San Francisco, California
- 4 variables were selected out of 16 variables.
- 2 categorical variables:
  - o CCSF Entity: City College of San Francisco entities
    - ⊗ Private
    - ⊗ SFCCD = San Francisco Community College District
    - ⊗ SFUSD = San Francisco Unified School District
  - o Supervisor District: City and County Supervisor District number
    - ⊗ 1-9 (9 levels)
- 2 numerical variables:
  - o Lower Age: Lower bound of generic age of the education program
  - o Upper Age: Upper bound of generic age of the education program
- General Type: Broad category of schools
  - ⊗ CC = Community College
  - ⊗ CDC = Child Development Center
  - ⊗ IND = Independent / Private
  - ⊗ PS = Public School

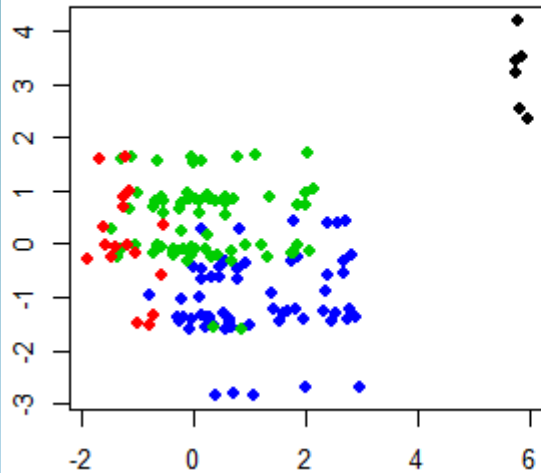
School: CCSF Entity, Supervisor District, Lower Age, Upper Age



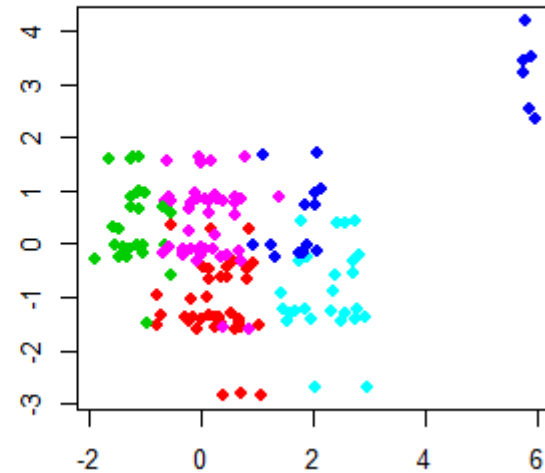
School: CCSF Entity, Supervisor District, Lower Age, Upper Age

Black =CC  
Red=CDC  
Green=IND  
Blue=PS

**General 4 Types**

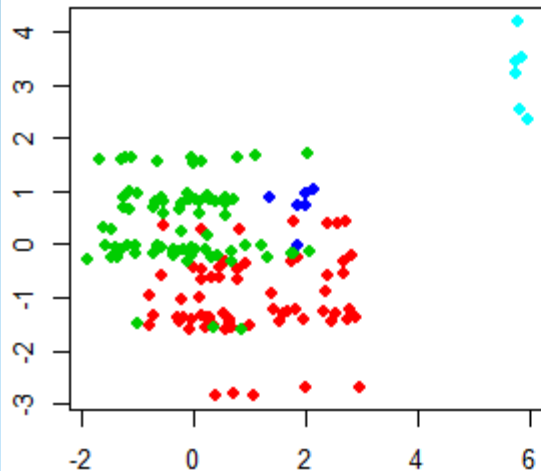


**KPROTO-5cls**



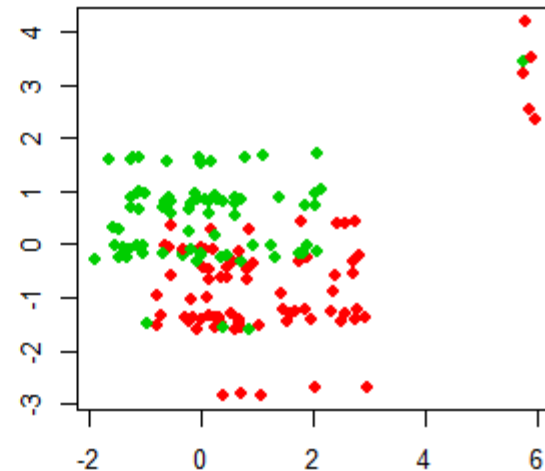
ARI: 71%  
AvgSil: 0.43

**AVGAGGM-4cls**



ARI: 53%  
AvgSil: 0.37

**PAM-2cls**



ARI: 48%  
AvgSil: 0.41



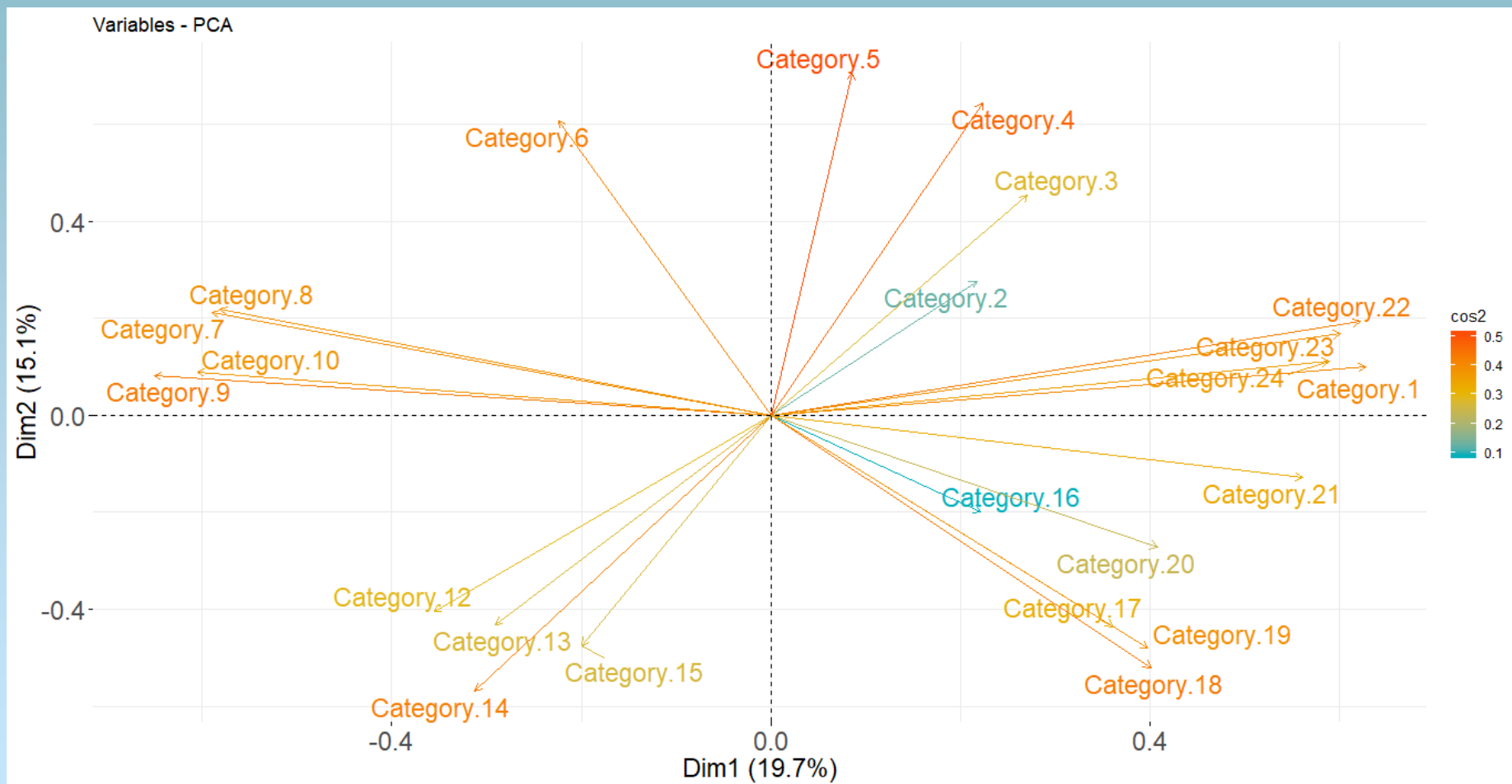
# Travel Review Ratings

- 5454 Google ratings on attractions from 23 categories across Europe.

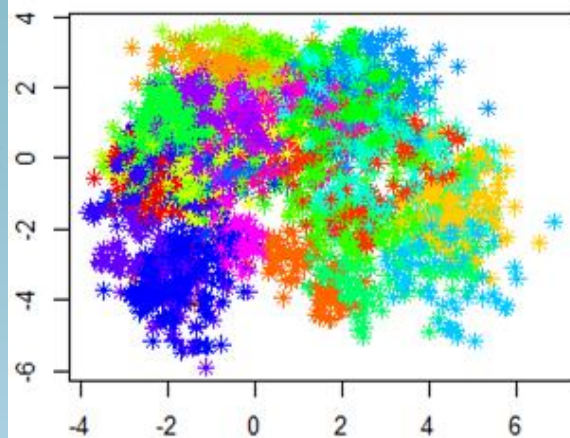
The rating ranges from 1 to 5.

- 23 numerical variables: Average user rating per category

## Travel: 23 numeric variables

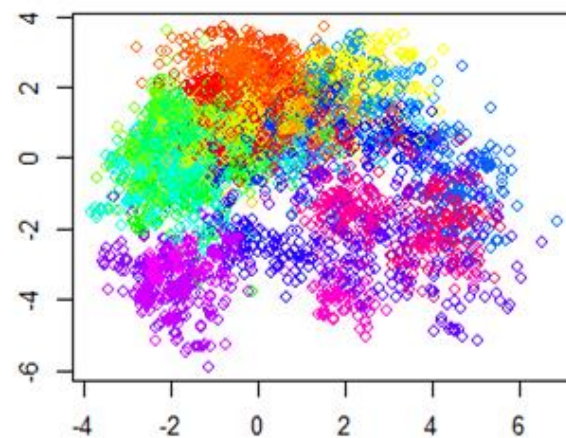


**K-MEANS-28cls**



AvgSil:  
0.18

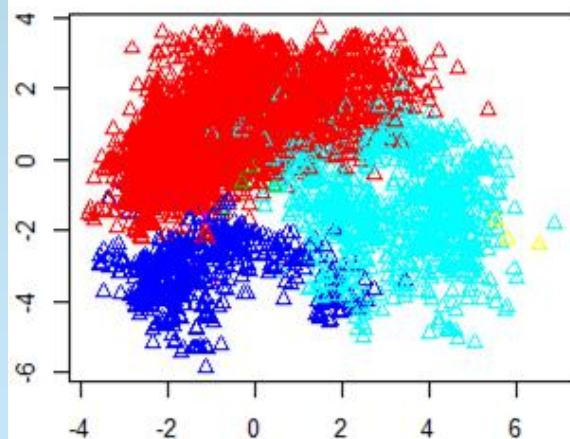
**PAM-30cls**



AvgSil:  
0.15

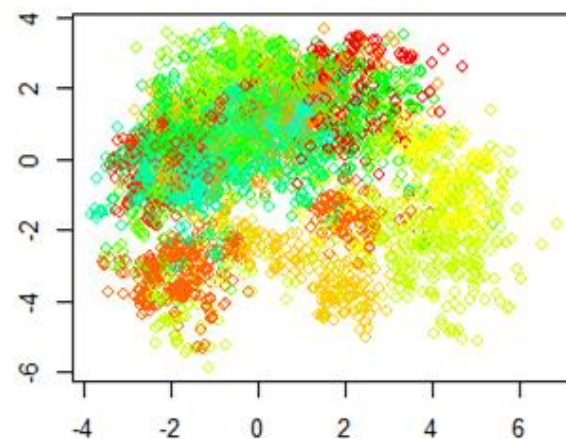
↔  
50% agreed

**AVGAGGM-6cls**



AvgSil:  
0.12

**MST-15cls**

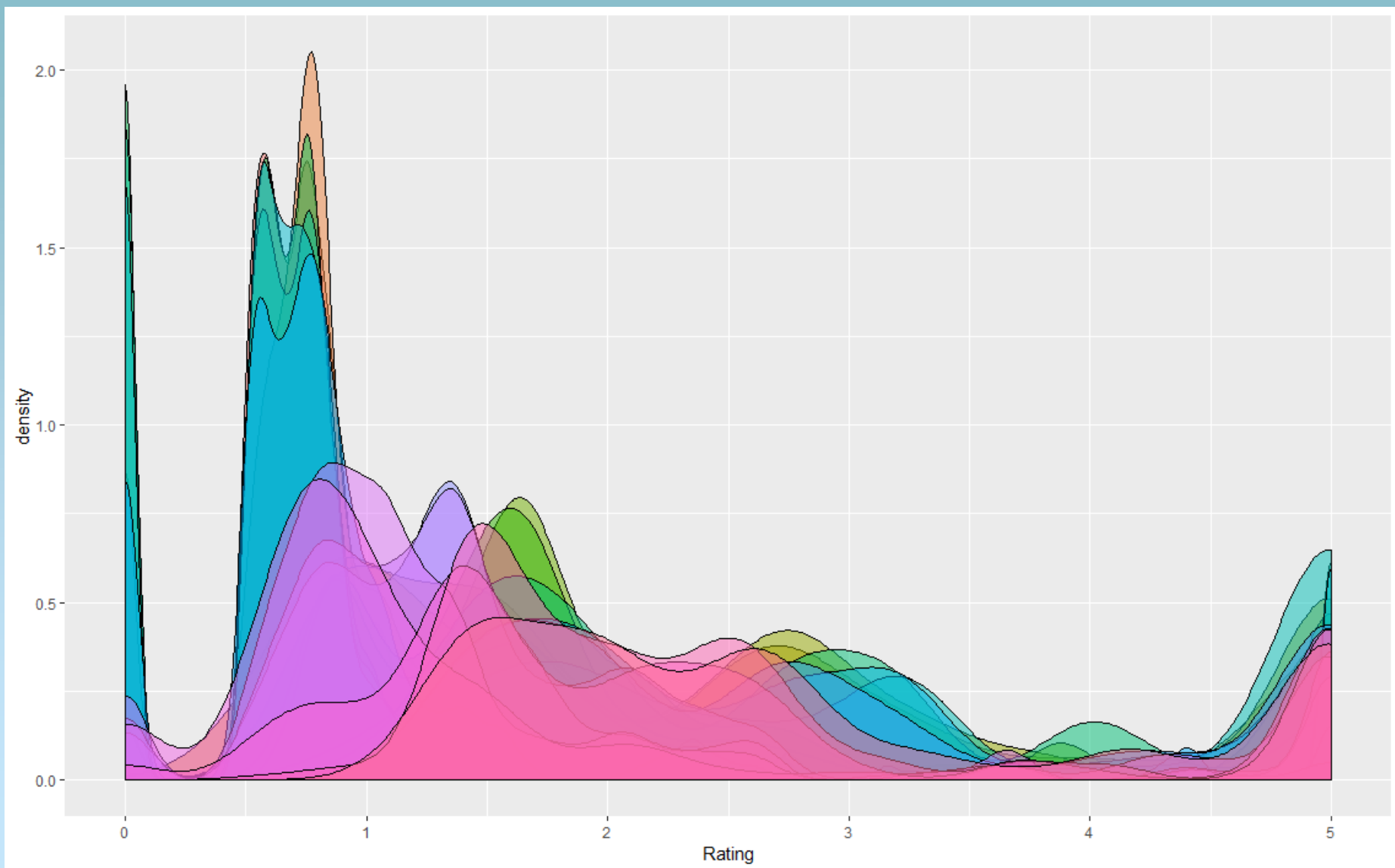


AvgSil:  
0.02

↘  
20% agreed

↕  
18% agreed

## 23 Distributions



## Conclusion

- Mixture model is robust in overlapping clusters with different shapes
- DBSCAN detects non-spherical shapes with skewness
  - Sensitive to parameter settings
- K-prototypes more robust than PAM and Agglomerative clustering using  $\lambda$ 
  - Assumes spherical shapes and sensitive to initial prototypes
- Future: Mixture model for mixed data, proper parameter setting for DBSCAN, proper weights for K-prototypes

Thank you! Questions?