# Clustering Astronomical Data

## 5 Clustering Methods Compared


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April 24, 2015

# Outline

- Brief Introduction
- Questions of Interest
- Clustering Methods
- Conclusion and Final Thoughts

# Introduction

- We have about 1500 training observations and 50,000 test observations of variable star data.
- The task is to cluster the data accurately.
- We focus on the training data because it allows us to compare the known clusters to the clusters the algorithms assign to the observations.

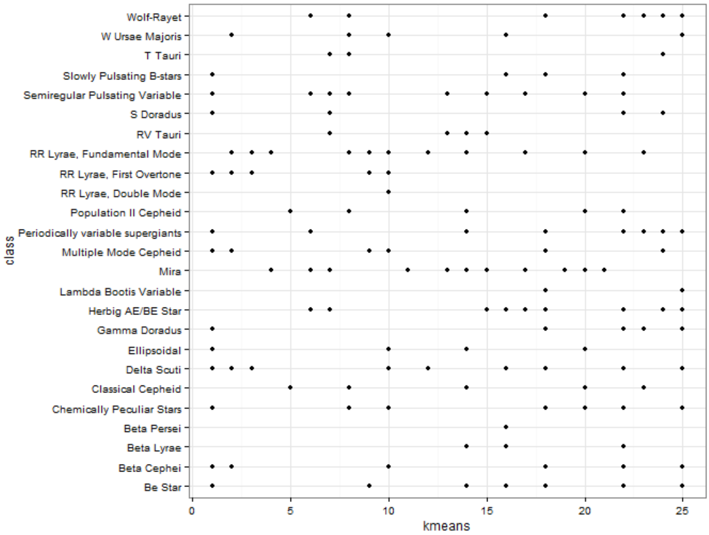
# Questions of Interest

- What clustering algorithms perform the best?
- Does subsetting the data help (i.e. Does clustering in stages improve performance)?

# K-Means Clustering

- Advantages:
  - Easy to implement.
  - Built in function in R is relatively quick.
- Disadvantages:
  - Poor performance when data has overlapping variable values.
  - NP-Hard problem.

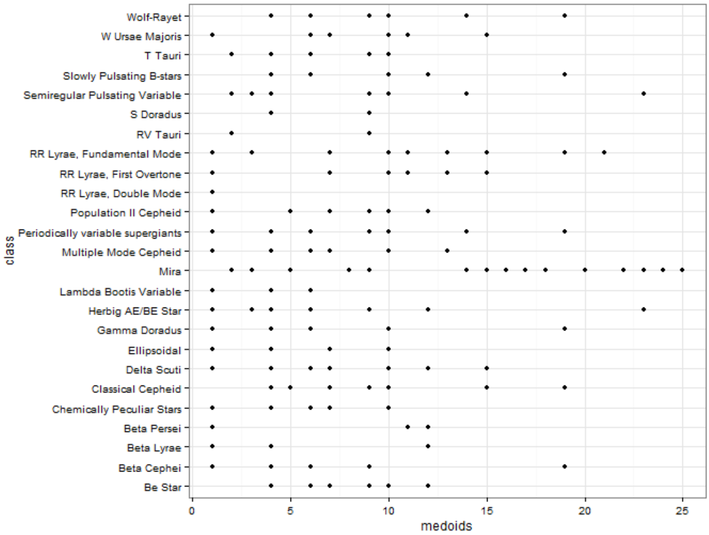
# K-Means Clustering Results



# K-Medoids Clustering

- Advantages:
  - Improved performance over K-means.
  - Freedom to choose distance metric (typically any $\ell_p$ metric) although R only allows $\ell_1$ or $\ell_2$.
- Disadvantages:
  - Performance still suffers when data has overlapping variable values.
  - Another NP-Hard problem.

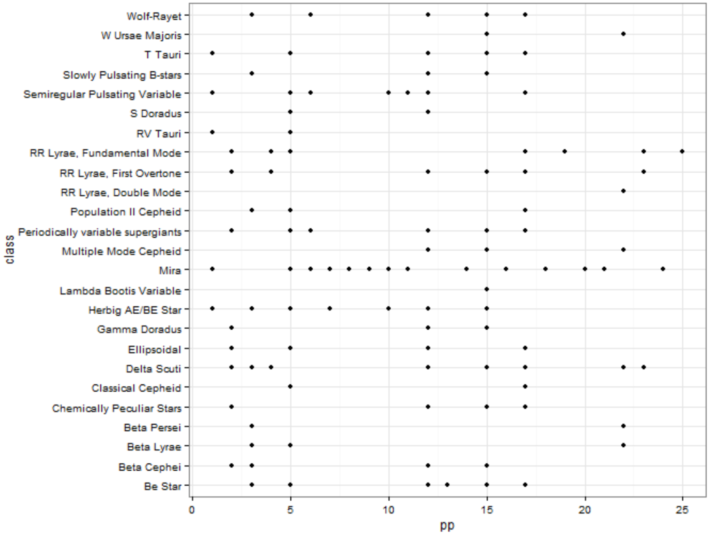
# K-Medoids Clustering Results



# K-Means ++

- Advantages:
    - Iterative process yields improved performance over K-medoids.
    - Algorithm checks multiple possible cluster centers and returns best cluster assignments.
- Disadvantages:
    - Iterative process takes time.
    - Algorithm may miss ideal solution since there are so many possible starting configurations.

# K-Means++ Clustering Results



## Hierarchical Clustering Methods

- Chose the complete linkage over the single or average linkages
- All 85 explanatory variables were used for hierarchical clustering
- Each column variable was normalized to the interval $[0, 1]$ via

$$x_i^* = \frac{x_i - x_{min}}{x_{max} - x_{min}}$$

- Advantages:
  - Adjusts column variables to a notionally common scale
  - "Better" spread in observation assignment to different clusters
  - Quick run time
- Disadvantages
  - Algorithm still wants to push many observations into a small number of clusters
  - Artificial scaling of units may or may not be a good thing

# Tables

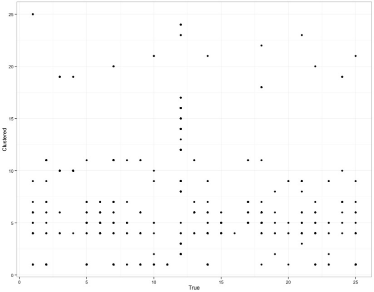
| C. ID | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Obs. | 196 | 38 | 11 | 171 | 298 | 102 | 39 | 9 | 38 | 39 | 55 | 21 |
| C. ID | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 | 24 |
| Obs. | 1 | 13 | 11 | 17 | 3 | 6 | 11 | 4 | 4 | 1 | 3 | 6 |

Table: Farthest-Neighbor on Non-subsetted Training Data: Normalized (3)

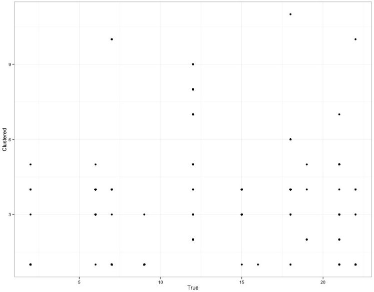
| C. ID | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Obs. | 856 | 22 | 7 | 4 | 37 | 81 | 4 | 11 | 45 | 1 | 2 | 1 |
| C. ID | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 | 24 |
| Obs. | 6 | 2 | 12 | 7 | 2 | 1 | 1 | 1 | 1 | 1 | 1 | 3 |

Table: Farthest-Neighbor on Non-subsetted Training Data: Standardized (1)

# Hierarchical Clustering Results

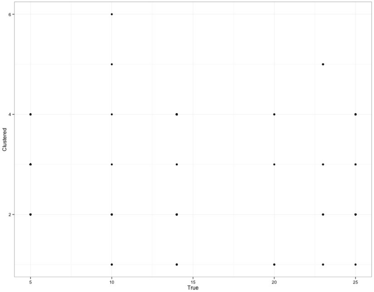



(a) All Star types

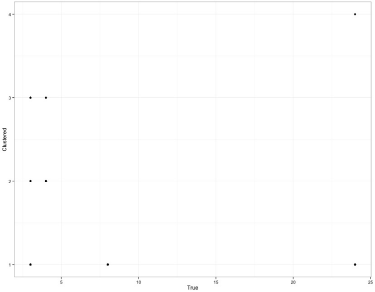



(b) Pulsating Star types only

# Hierarchical Clustering Results




(c) Eruptive Star types only

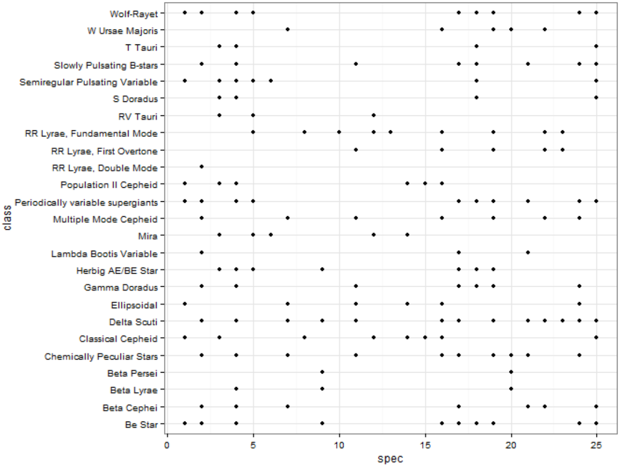



(d) Multi-Star types only

# Spectral Clustering

- Advantages:
  - Compared to k-means, spectral clustering is better at identifying find clusters that have non-convex boundaries (i.e., a circle within a circle).
- Disadvantages:
  - When computing the similarity matrix for a large number of observations it can become ill-conditioned.
  - Choosing the correct kernel to measure the connectivity between points.

# Spectral Clustering Results



# Conclusions and Final Thoughts

- Our results were not informative.
- All these methods quickly become computationally expensive and we could consider other resources to use besides our puny laptops (and Dane's 4 year old desktop).
- Possibly explore different data manipulations and metrics for the different clustering algorithms.