

Centroid Algorithm

- ▶ Find a centroid, a tree minimizing the sum of squared distances, for a set of trees
- ▶ Start at a tree and check if any neighbour has a better objective function
- ▶ Repeat until a local optimum is reached

Conjecture:

- ▶ We tested for up to 7 taxa treespace and a variation of different tree set sizes
- ▶ This algorithm always returned a global optimal solution

Variation for application

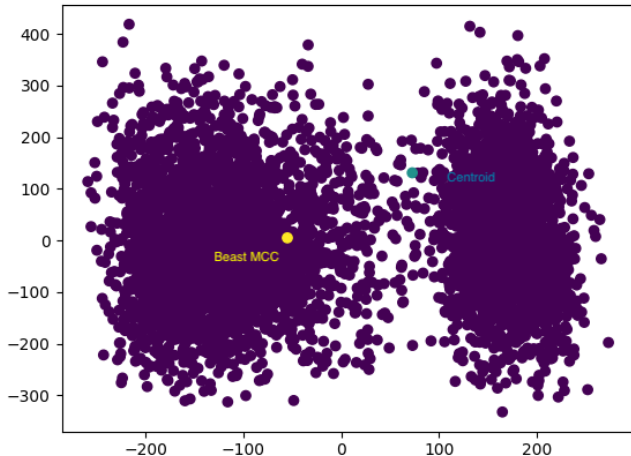
Problems :

- ▶ Number of trees
- ▶ Unknown number of local and global optimal solution to the problem
- ▶ Hard to prove that it finds a global optimal solution

Variation:

- ▶ Greedy choice, only following the path with the most improvement in each step
- ▶ Start with a sample of the tree set and add more trees until the tree set is found
- ▶ Choice of the starting tree is important
- ▶ Return value will be a local optimum

MDS plot for binary_single_cell_K047_gamma_beta.667 using R isoMDS



Colors correspond to the cluster file 1clustering_binary_single_cell_K047_gamma_beta.667.csv

Figure: Comparing the MCC(yellow) vs Centroid tree (blueish), visual result is also present in the tree distances!

MDS plot for binary_K047_error_including_burnin using R isoMDS

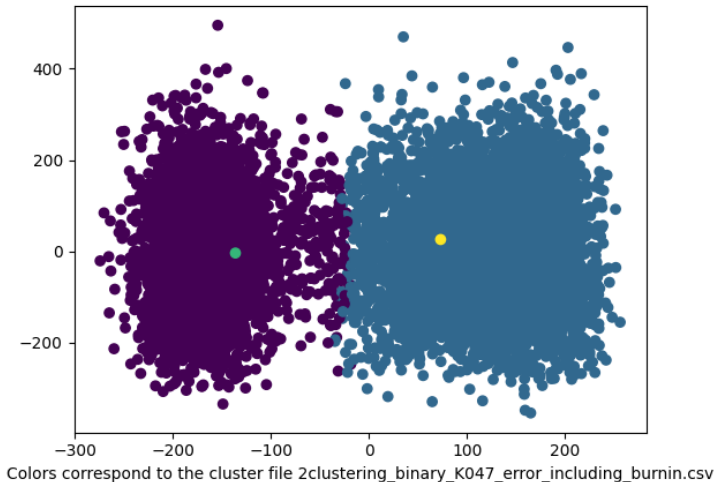


Figure: Summarize identified clusters separately

MDS plot for conv_beast.trees using R isoMDS

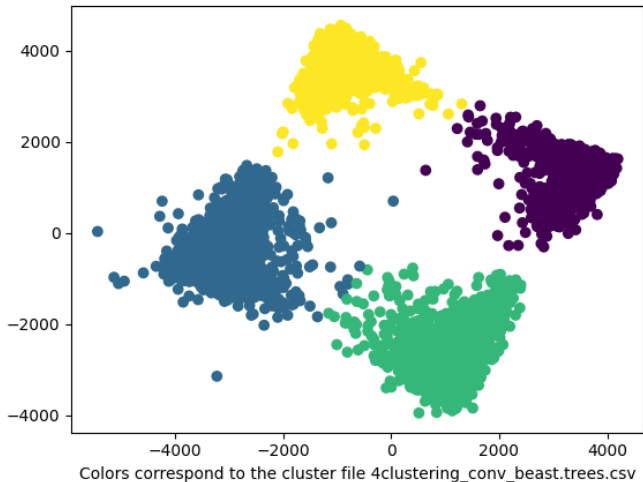


Figure: Able to identify clusters via the true tree-distance Matrix

Choosing the number of clusters

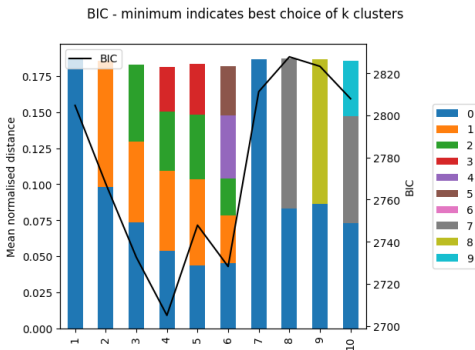


Figure: Choosing the number of clusters with Bayesian inference criterion

- ▶ Clustering is not using the MDS, only for visualization
- ▶ MDS is not a perfect visualisation

Bayesian inference criterion

set of trees \mathcal{T} , clustering σ , \mathcal{R} set of summary trees
 $m = |\mathcal{T}|$, k clusters

$$\tilde{d}(\mathcal{T}, \mathcal{R}, \sigma) = \frac{\sum_{i=1}^m d(\mathcal{T}_i, \mathcal{R}_{\sigma(i)})}{m * \frac{(n-1)(n-2)}{2}}$$

$$h(\mathcal{T}, \mathcal{R}, \sigma) = 1 - \tilde{d}(\mathcal{T}, \mathcal{R}, \sigma)$$

$$BIC = \frac{k}{2} * \ln(m) - 2 * \ln(h((\mathcal{T}, \mathcal{R}, \sigma))^m)$$

- ▶ Defining a likelihood for data \mathcal{T} given the model \mathcal{R}, k
- ▶ Depending highly on the clustering **and** the summary method

MDS Distortion

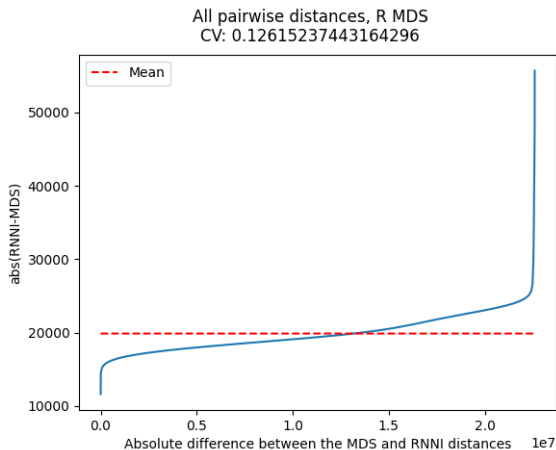


Figure: A constant distortion of the distances would be ideal

- ▶ Distortion = $|D_{MDS} - D_{RNNI}|$ for all trees
- ▶ $CV = \frac{\sigma}{\mu}$, coefficient of variation for distortion

Another Application of the SoS

- ▶ Given a summary tree and a treeset
- ▶ compute the relative sum of squared distance for the summary
- ▶ relative meaning to divide by the number of trees
- ▶ Do this for different burnin percentages
- ▶ Indication for the quality of the summary tree
- ▶ Also indicates whether the posterior set has converged

Converged data

Convergence indicates the best choice of burnin-%

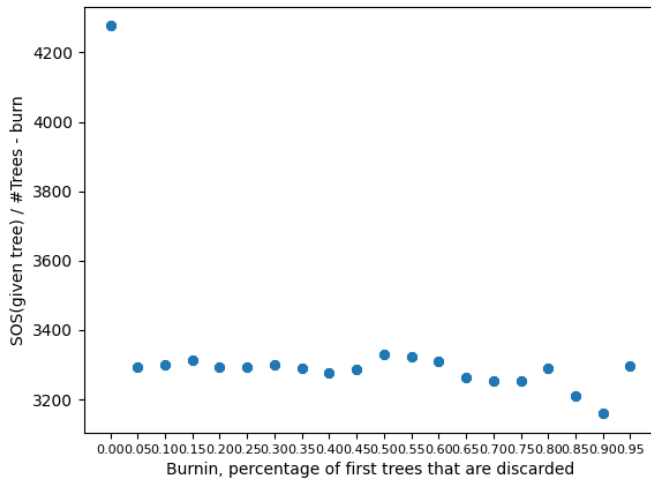


Figure: Good summary tree for a converged chain

Not so converged data

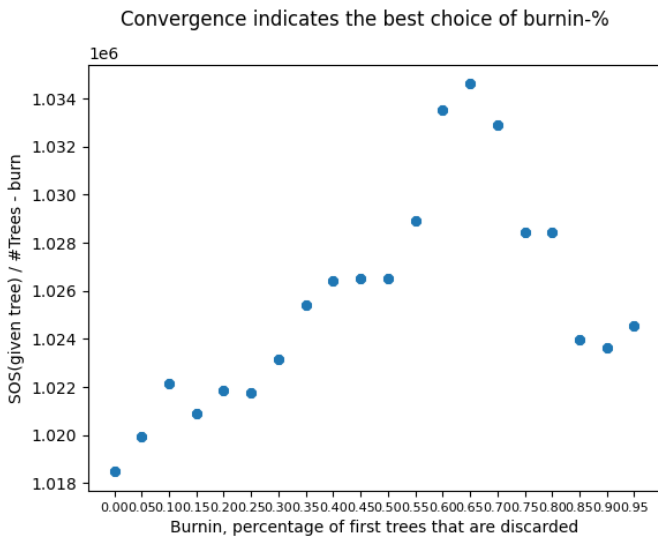


Figure: Increasing the rel. SoS value indicates that the chain has not converged