

1 Introduction

k -means is a clustering algorithm that partitions a set of data points into k classes.

Suppose we have a set of data points $\{\mathbf{x}_i\}_{i=1}^n$ where each data point is a vector of generally continuous values $\mathbf{x}_i = [x_i, \dots, x_p]$. Note that k -means works best with continuous data because it updates clusters with Euclidean distance.

An approximate approach is given by:

- (i) Randomly assigning cluster centers $\hat{\mu}_1, \dots, \hat{\mu}_M$. Generally, we these to be points in the training data.
- (ii) Determine which of the clusters R_1, \dots, R_M each data point \mathbf{x}_i belongs to by computing the closest cluster center $\hat{\mu}$.
- (iii) Update the cluster centers $\hat{\mu}_m$ as the average of all $\mathbf{x}_i \in R_m$.

This process is iterated until we reach some max number of iterations or a convergence threshold where the change in cluster centers is deemed negligible.

2 Algorithm

Algorithm 1 k -Means Clustering

Input: Data set $\mathcal{T} = \{\mathbf{x}_i\}_{i=1}^n$, max iterations s , stopping threshold ϵ (optional)

Output: Set of k clusters

```
1: function  $k$ -MEANS( $\mathcal{T}, s, \epsilon$ )
2:    $\hat{\mu}_i \leftarrow$  random  $\mathbf{x}_p \in \mathcal{T}$  for  $p = 1, \dots, k$ 
3:    $t \leftarrow 1$ 
4:   repeat
5:      $R_j \leftarrow \emptyset$  for  $j = 1, \dots, k$ 
6:     for  $\mathbf{x}_i \in \mathcal{T}$  do
7:        $j^* \leftarrow \arg \min_i ||x_j - \hat{\mu}_i||^2$  (assign  $\mathbf{x}_j$  to the closest cluster center)
8:        $R_{j^*} \leftarrow R_{j^*} \cup \mathbf{x}_j$ 
9:     end for
10:    for  $i = 1, \dots, k$  do
11:       $\hat{\mu}_i \leftarrow \frac{1}{|R_i|} \sum_{\mathbf{x}_j \in R_i} \mathbf{x}_j$  (update cluster centers to average of points in cluster)
12:    end for
13:  until  $t = s$  or largest change in cluster center less than  $\epsilon$ 
14: end function
```
