# The $k$-means clustering 

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## 1 Introduction

Given a set of vectors $X=\left\{x_{1}, \ldots, x_{n}\right\}$, the $k$-means clustering algorithm finds vectors $\mu_{1}, \ldots, \mu_{k}(k<n)$ such that the mean square distance between $X$ and $\mu_{1}, \ldots, \mu_{k}$ is minimal. Informally, $k$-means algorithm finds $k$ vectors, which well approximate the given dataset, i.e. such vectors, to which the euclidean distance of the given vectors is minimal.


Figure 1: One dimensional (left) and two dimensional (right) example of found vectors $\mu_{1}, \ldots, \mu_{k}$.

## 2 The $k$-means algorithm

The $k$-means algorithm is simple. The input consists of a set of vectors $X=\left\{x_{1}, \ldots, x_{n}\right\}$ and of the number $k$ of sought vectors $\mu_{j}$.

1. Initialisation: Initialise $\mu_{j}, j=1, \ldots, k$ to random values. Alternatively, heuristics, based on apriori knowledge about a specific task, can be used.
2. Classification: Vectors $x_{i}, i=1, \ldots, n$ are classified to classes represented by vectors $\mu_{j}, j=1, \ldots, k$. Each $x_{i}$ is assigned to the class, which mean vector is the closest (nearest-neighbour classification). I.e. $x_{i}$ is assigned to class

$$
y_{i}=\underset{j=1, \ldots, k}{\operatorname{argmin}}\left\|x_{i}-\mu_{j}\right\| .
$$

3. Learning: Update vectors $\mu_{j} . \mu_{j}$ is the mean value of all vectors $x_{i}$, which were assigned to $j$-th class. I.e.

$$
\mu_{j}=\frac{1}{n_{j}} \sum_{i \in\left\{i: y_{i}=j\right\}} x_{i},
$$

where $n_{j}$ is the number of $x_{i}$ s classified to $j$-th class.
Steps 2 and 3 are iterated as long as the class assignement changes for any $x_{i}$.

## 3 Notes

Look closely at the last step of the algorithm. Observe, that what we compute there is, in fact, the maximum-likelihood estimate of the mean value of each class. The algorithm can therefore be visualised as


We can therefore imagine the data to be drawn from a mixture of several gaussian distributions. Would we assume that all the gaussians have unit variances, the only free parameters that remain are the mean values. The $k$-means algorithm estimates the means, as well as the 'weights' signifying how much does each of the gaussians contribute to the mixture $\left(\frac{n_{j}}{n}\right)$.

