

Quick and Dirty Machine Learning

K-Means Algorithm

Konstantin Itskov

The Plan!

- Setup the development environment.
- Theory behind K-means
- K-means implementation

Theory

Definition

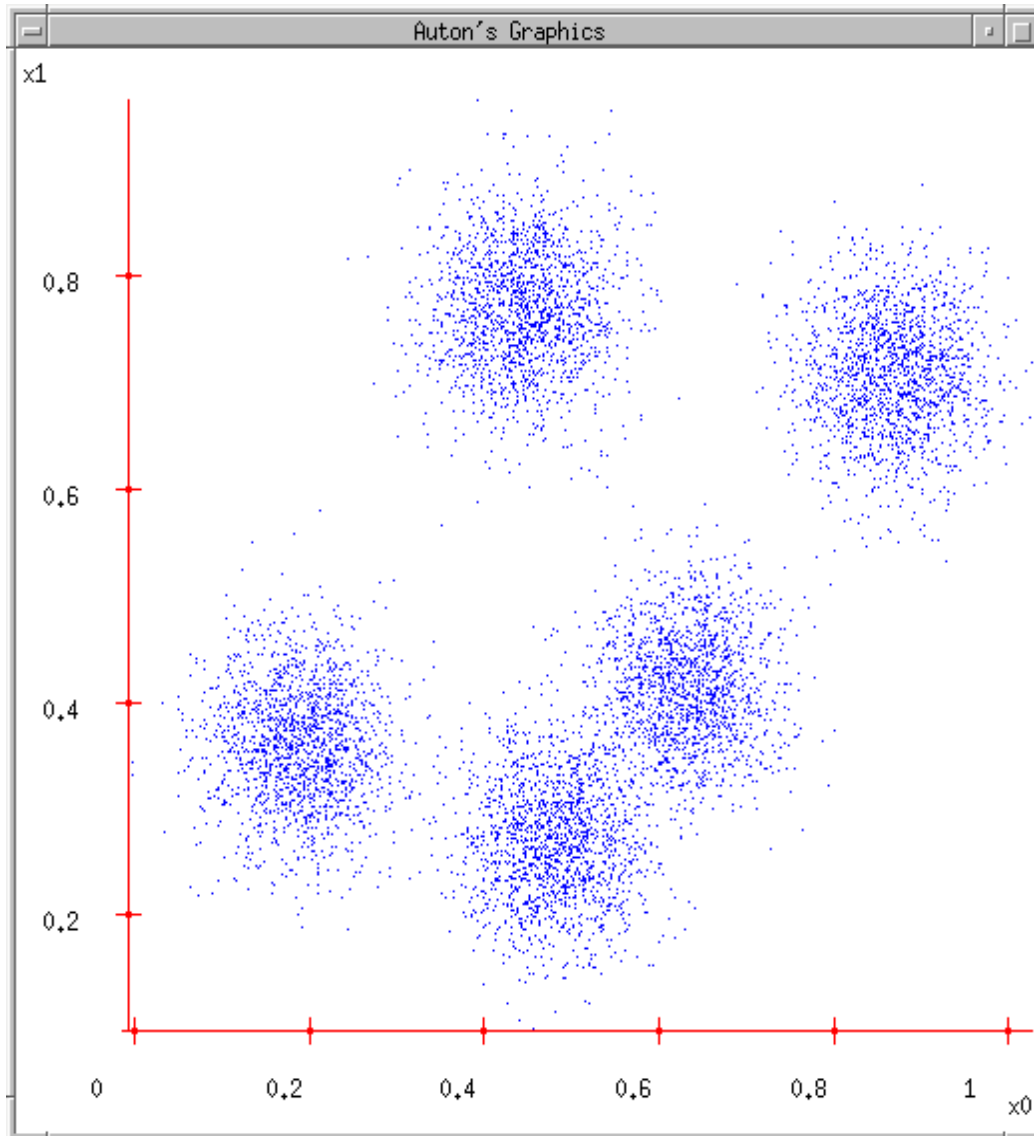
Given a set of observations (x_1, x_2, \dots, x_m) where each observation is a d -dimensional real vector $x_i \in \mathbb{R}^d$, k -means clustering aims to partition the m observations into k clusters by minimizing the sum of square distance within each cluster.

Algorithm

1. Initialize cluster centroids $\mu_1, \mu_2, \dots, \mu_k$ for $\mu_i \in \mathbb{R}^d$ randomly.
2. Repeat until convergence:

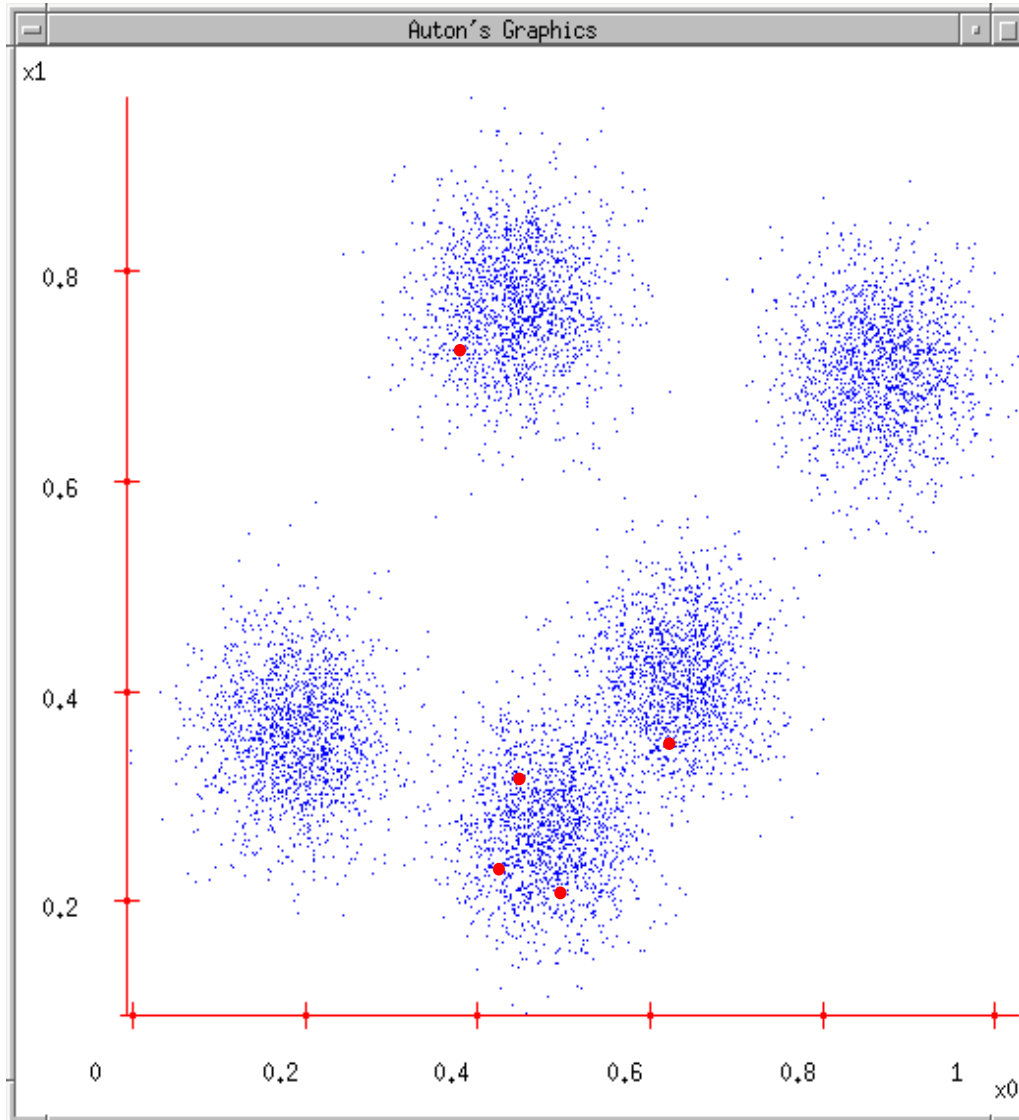
$$\text{label}_i := \arg \min_j \|x_i - \mu_j\|^2$$
$$\mu_j := \frac{\sum_{i=1}^m 1(\text{label}_i = j) x_i}{\sum_{i=1}^m 1(\text{label}_i = j)}$$

K-means Demo



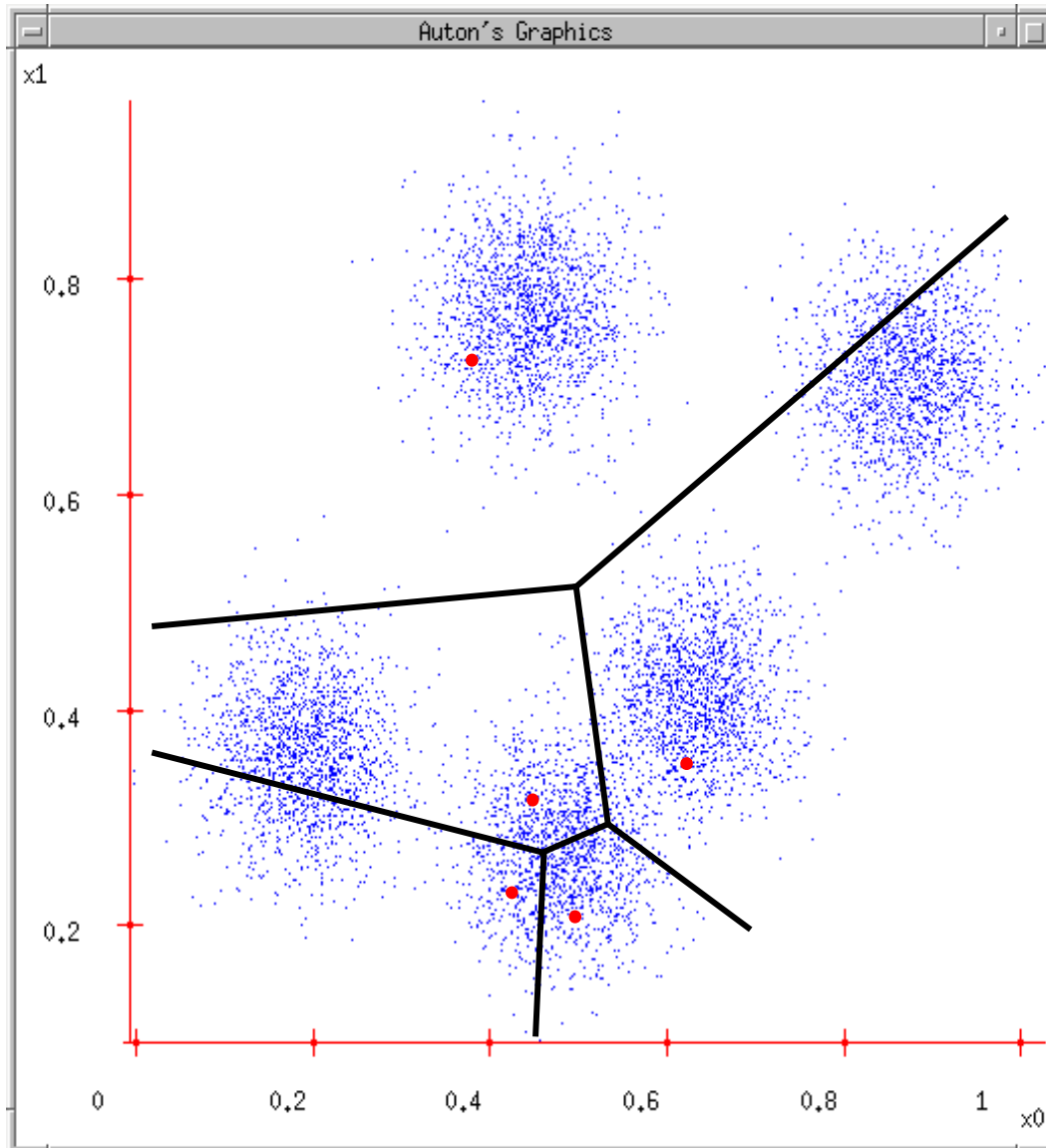
1. User set up the number of clusters they'd like. (*e.g.* $k=5$)

K-means Demo



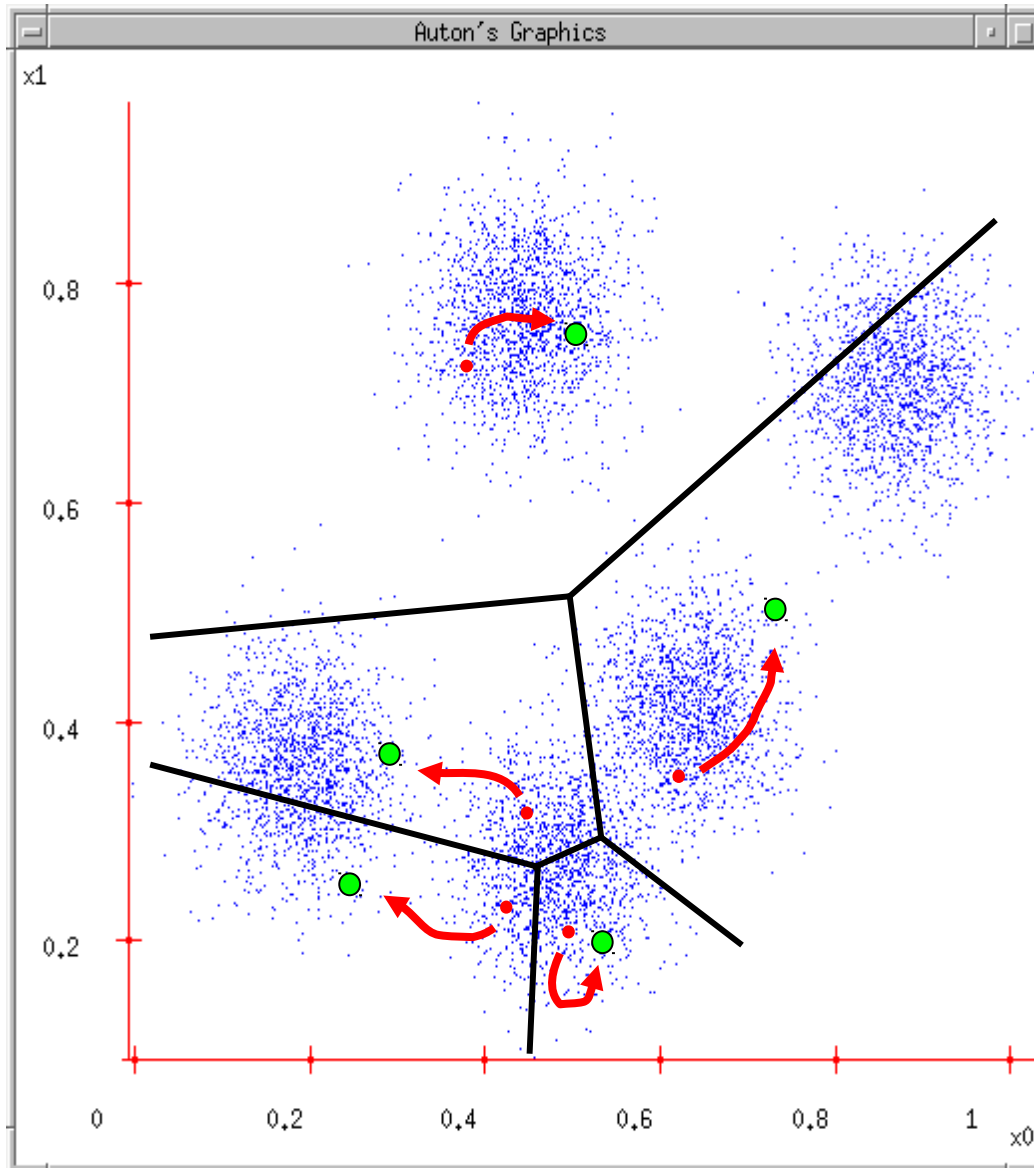
1. User set up the number of clusters they'd like. (*e.g.* $K=5$)
2. Randomly guess K cluster Center locations

K-means Demo



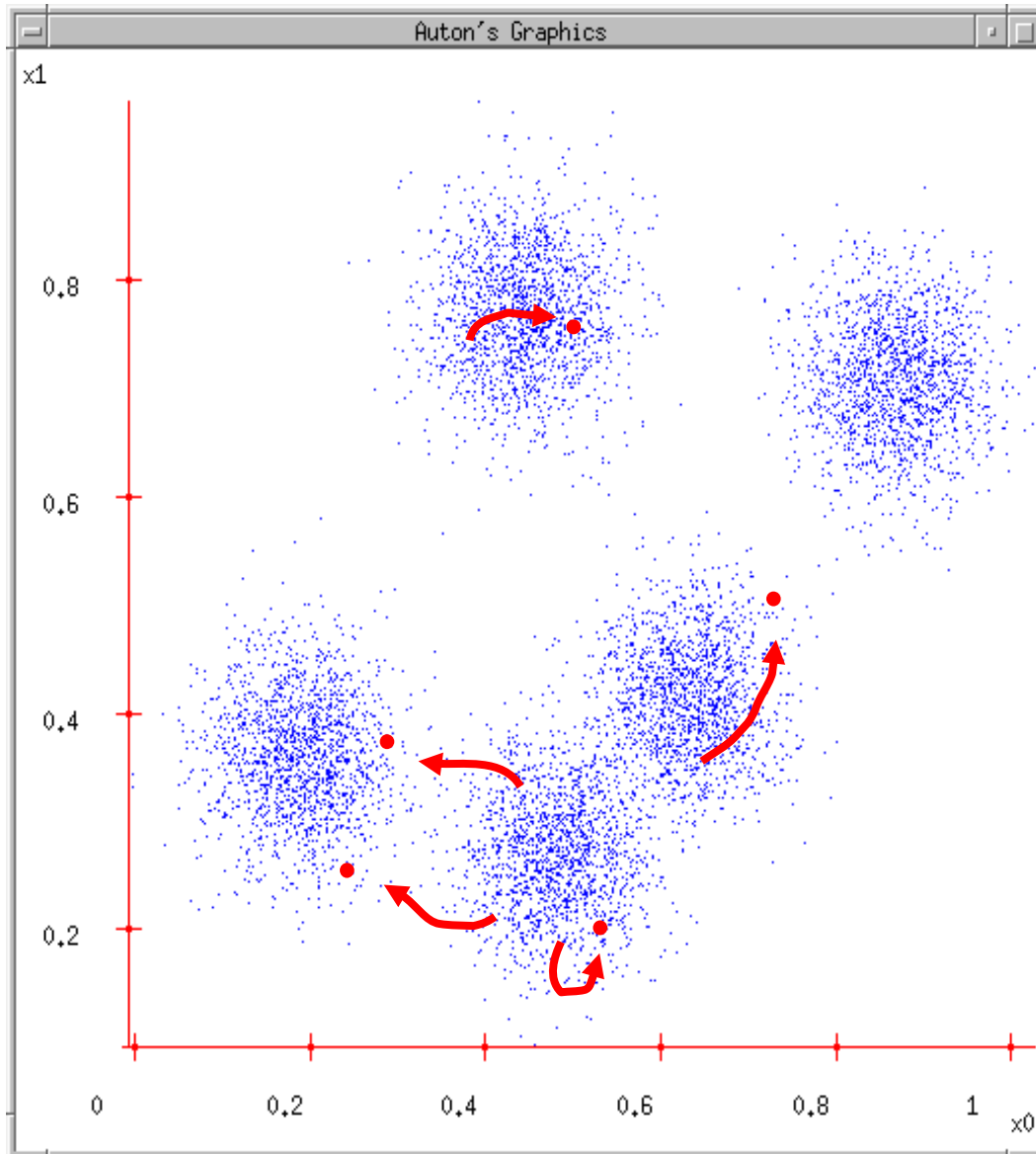
1. User set up the number of clusters they'd like. (*e.g.* $K=5$)
2. Randomly guess K cluster Center locations
3. Each data point finds out which Center it's closest to. (Thus each Center "owns" a set of data points)

K-means Demo



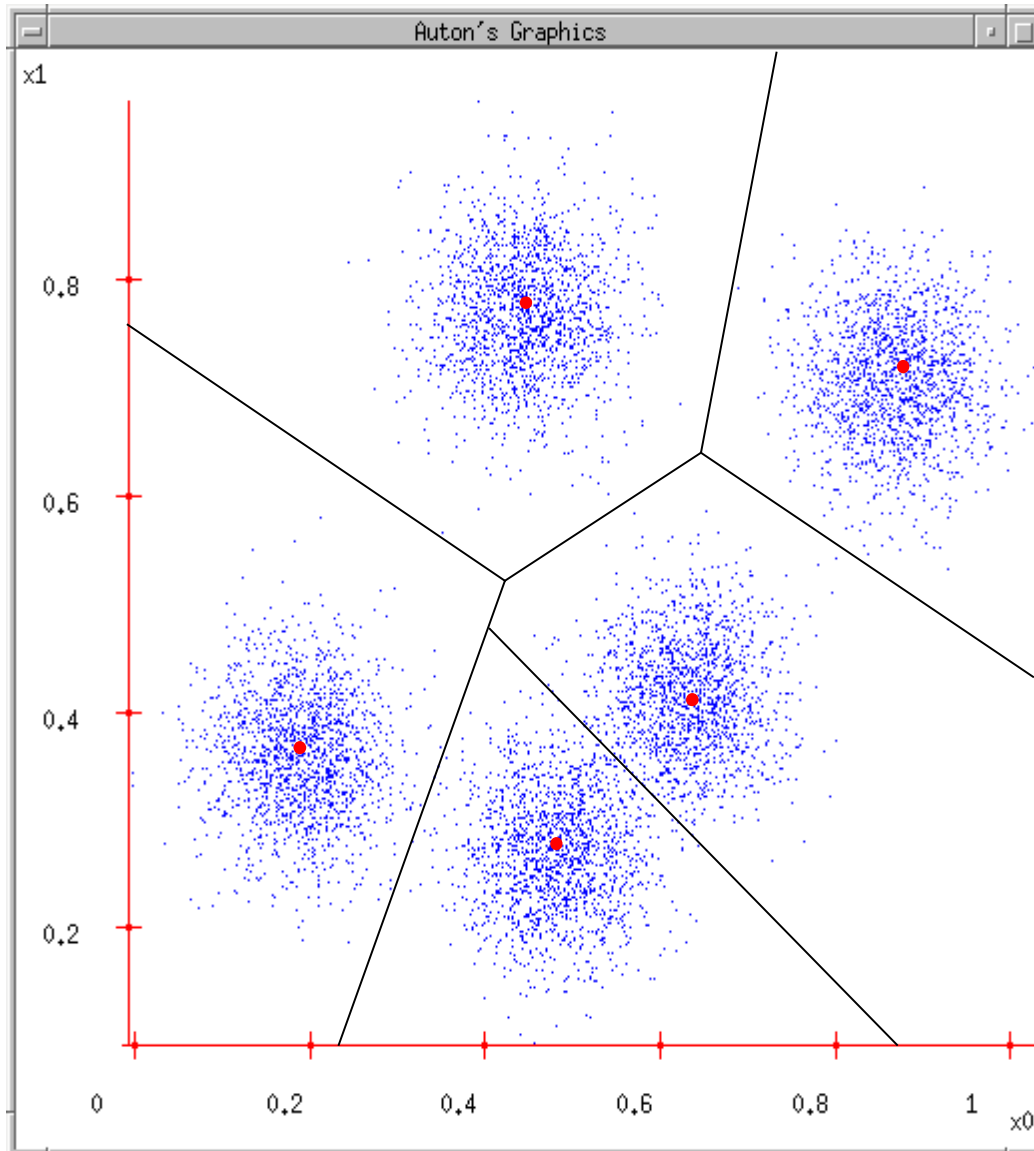
1. User set up the number of clusters they'd like. (*e.g.* $K=5$)
2. Randomly guess K cluster centre locations
3. Each data point finds out which centre it's closest to. (Thus each Center "owns" a set of data points)
4. Each centre finds the centroid of the points it owns

K-means Demo



1. User set up the number of clusters they'd like. (e.g. $K=5$)
2. Randomly guess K cluster centre locations
3. Each data point finds out which centre it's closest to. (Thus each centre "owns" a set of data points)
4. Each centre finds the centroid of the points it owns
5. ...and jumps there

K-means Demo



1. User set up the number of clusters they'd like. (e.g. $K=5$)
2. Randomly guess K cluster centre locations
3. Each data point finds out which centre it's closest to. (Thus each centre "owns" a set of data points)
4. Each centre finds the centroid of the points it owns
5. ...and jumps there
6. ...Repeat until terminated!