

A Bit of History

[J. B. MacQueen, 1967]

- [\[http://img1.wikia.nocookie.net/_cb20110723073418/pixar/images/b/b2/Lightning_mcqueen_cars_2.png\]](http://img1.wikia.nocookie.net/_cb20110723073418/pixar/images/b/b2/Lightning_mcqueen_cars_2.png)



- [H. Steinhaus 57], [S. Lloyd 57], [E. W. Forgy 65]
- **Vector Quantisation/Clustering/Bunching/Grouping**
- **Old, but often still the first choice!**
- **Learning: Supervised, Unsupervised, Reinforcement, Semi-supervised**
- Two flavours of K -Means: K as a parameter, & the distance threshold as a parameter
- **Crisp boundaries: grading, states on a linguistic basis(hmm...), f'print image ROI. Fuzzy: signal-noise separation, concept of well-built (h, w)**

Types of Algorithms

[https://images-na.ssl-images-amazon.com/images/M/MV5BOTU5NDkzNTM5MV5BMi5BanBnXkFtZTgwMDU4ODE5MDE@._V1 QL50_.jpg]

SERGIO LEONE



**THE
BAD** **THE
GOOD** **AND THE
UGLY**

- **The Good:** Polynomial Time Complexity, $\mathcal{O}(n^k)$
Sorting, DFT, FFT
- **The Bad:** Exponential Time Complexity, $\mathcal{O}(k^n)$

NP-Hard

NP-Complete

Boolean functions of n variables: minterms, combinations of minterms; TSP

- **The Ugly:** Opt converge with prob 1, but infinite time



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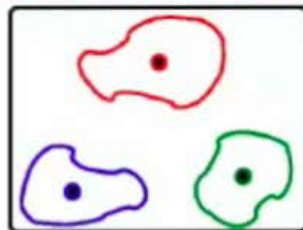
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The Goal

- N points $\{\mathbf{x}_1 \dots \mathbf{x}_N\}$ to be grouped into K clusters
- μ_j : prototype of the j th cluster (e.g., centre)
- such that the sum of squared distances of each data point to its closest vector μ_j is a minimum
- Vector Quantisation: μ_j : codebook vectors
- Objective Function (Distortion Measure):



$$J \triangleq \sum_{i=1}^N \sum_{j=1}^K r_{ij} \|\mathbf{x}_i - \mu_j\|^2$$

- Binary Indicator variable $r_{ij} \triangleq 1$: i th data point assigned to j th cluster, & $\triangleq 0$, otherwise
- Find $\{r_{ij}\}$ & $\{\mu_j\}$ such that J is minimised

One way to solve this: two phases, EM-framework

Choose K initial cluster centres $\{\mu_j\}$

1. Fixed $\{\mu_j\}$, find assignment $\{r_{ij}\}$: Expectation
2. Keep $\{r_{ij}\}$ fixed, find $\{\mu_j\}$: Maximisation

REPEAT till convergence/fixed max# of iterations

Convergence: each step provably convergent!

- Expectation Step: $\{\mu_j\}$ fixed, minimise J wrt $\{r_{ij}\}$

$J \triangleq \sum_{i=1}^N \sum_{j=1}^K r_{ij} \|\mathbf{x}_i - \mu_j\|^2$ This is linear in $\{r_{ij}\}$.
For \mathbf{x}_i , assign it to the closest cluster centre.

- **Minimisation Step:** $\{r_{ij}\}$ fixed, minimise J wrt $\{\mu_j\}$

$J \triangleq \sum_{i=1}^N \sum_{j=1}^K r_{ij} \|\mathbf{x}_i - \mu_j\|^2$ This is quadratic in $\{\mu_j\}$.

$$\frac{\partial J}{\partial \{\mu_j\}} = 0 \implies \sum_{i=1}^N 0 + 0 + \dots + 2r_{ij}(\mathbf{x}_i - \{\mu_j\}) + \dots = 0$$

$$\implies \sum_{i=1}^N r_{ij}(\mathbf{x}_i - \{\mu_j\}) = 0 \implies$$

$$\sum_{i=1}^N r_{ij} \mathbf{x}_i = (\sum_{i=1}^N r_{ij}) \mu_j \implies \mu_j = \frac{\sum_{i=1}^N r_{ij} \mathbf{x}_i}{\sum_{i=1}^N r_{ij}}$$

Sum of points in cluster j / # of points in cluster j
 = Mean of all points in cluster j !

ALGORITHM K -Means

INITIALISATION: Fix μ_j

1. [E-Step] $\{\mu_j\}$ (centres) fixed, find $\{r_{ij}\}$ (assignment)
 Assign points to closest cluster prototype ($J \downarrow$)

1. [M-Step] $\{r_{ij}\}$ (assignment) fixed, find $\{\mu_j\}$ (centres)
 Recompute cluster centres ($J \downarrow$)

REPEAT till no change in assign't/max iterations

***K*-Means: Some Points**

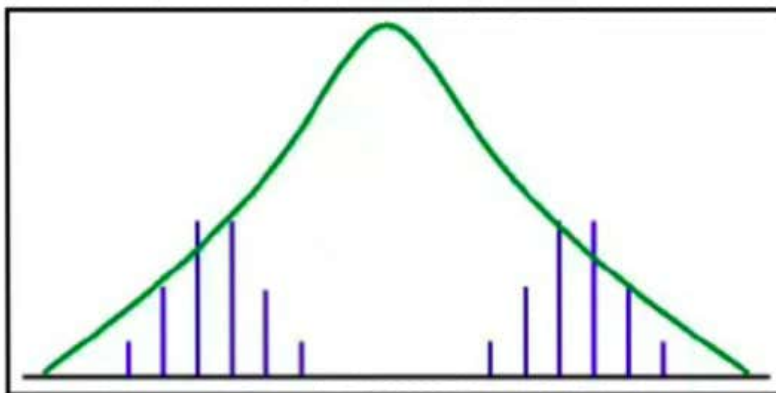
- Could converge to a local min
- Initialisation: random subset of size K of the data points as the cluster prototypes
- E-Step: distance computations b/w every data point & every prototype vector $\mathcal{O}(KN)$
- E-step: $\mathcal{O}(KN)$; M-Step: $\mathcal{O}(N)$ Can run for each $\binom{N}{K}$ start seeds, or a max. Run for few K
- Alternate formulation with distance threshold: on-line algo, works as data comes in
- Limitations: e.g., data in concentric circles

***K*-Means: Some Points**

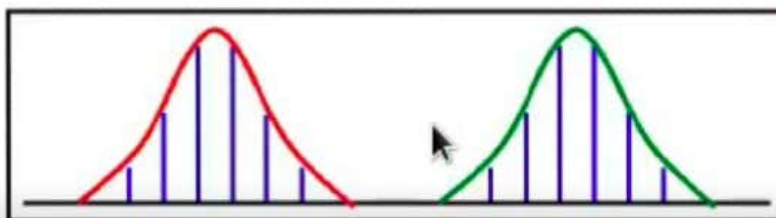
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- Alternate formulation with distance threshold: on-line algo, works as data comes in
- Limitations: e.g., data in concentric circles
- Generalisation: prob/fuzzy assignment of $\{r_{ij}\}$

M-of-Gs: Curve-Fitting

- Almost any parameterised curve can be fitted to a bunch of points with an associated error cost
- Gaussian: computationally nice: 2 moments
 - any hump/bump: one Gaussian
 - const region: many closely-spaced Gaussians



1-G: bad fit as most prob region doesn't have many samples



2-G: better fit