CLUSTERING / GAUSSIAN MIXTURE MODEL

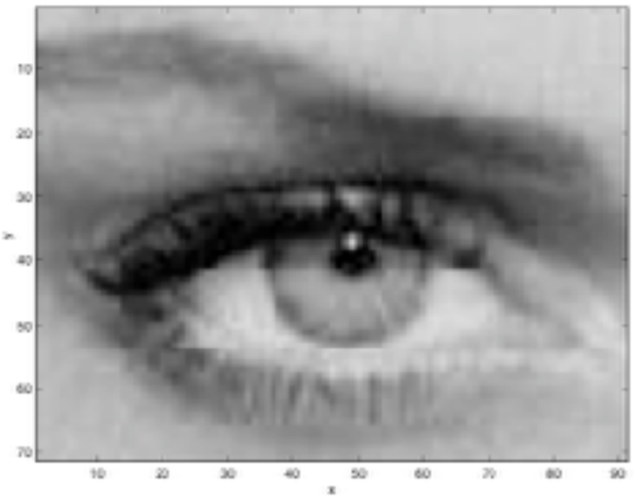
What is an image?

- We can think of an **image** as a function, f, from R^2 to R:
  - $f(x, y)$ gives the **intensity** at position (x, y)

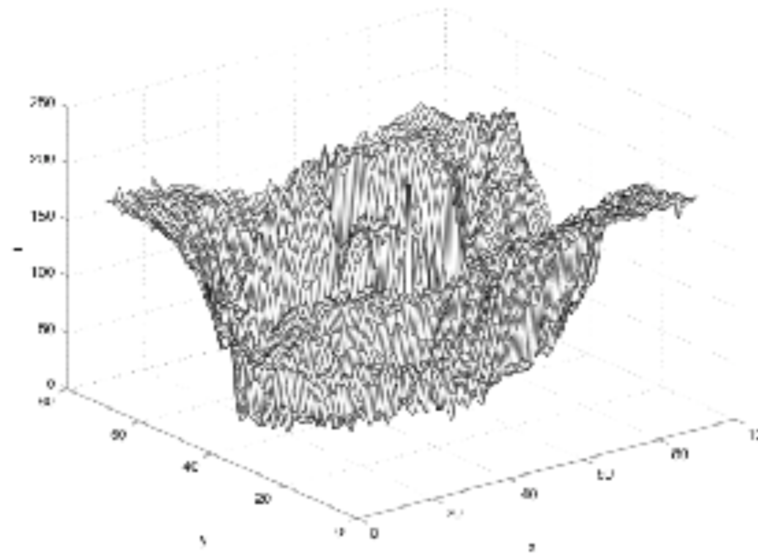
- A color image is just three functions pasted together. We can write this as a "vector-valued" function:

$$f(x, y) = \begin{bmatrix} r(x, y) \\ g(x, y) \\ b(x, y) \end{bmatrix}$$

Image



Brightness values



I(x,y)

What is a digital image?

- In computer vision we usually operate on **digital** (**discrete**) images:
  - **Sample** the 2D space on a regular grid
  - **Quantize** each sample (round to nearest integer)
- If our samples are Δ apart, we can write this as:
- $f[i\ ,j]$ = Quantize{ $f(i\,\Delta,\ j\,\Delta)$ }
- The image can now be represented as a matrix of integer values

62	79	23	119	120	105	4	0
10	10	9	62	12	78	34	0
10	58	197	46	46	0	0	48
176	135	5	188	191	68	0	49
2	1	1	29	26	37	0	77
0	89	144	147	187	102	62	208
255	252	0	166	123	62	0	31
166	63	127	17	1	0	99	30

CLUSTERING

- Group a collection of points into clusters

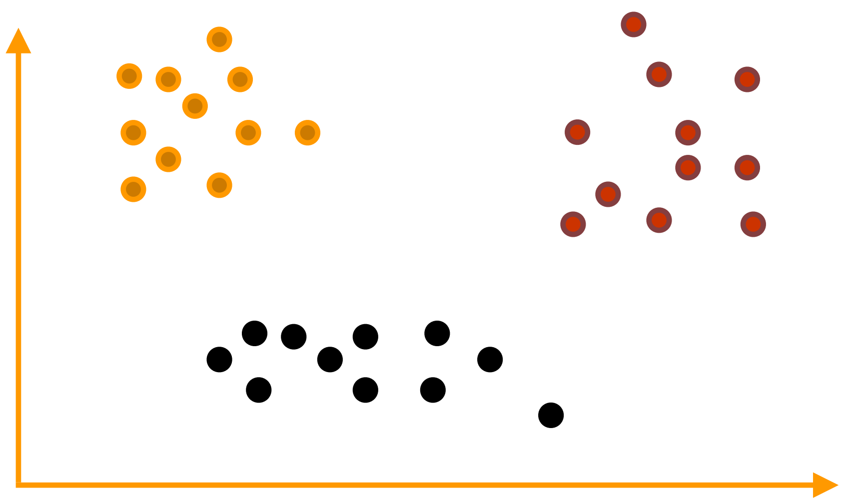
- We have seen “supervised methods”, where the outcome (or response) is based on various predictors.

- In clustering, we want to extract patterns on variables without analyzing a specific response variable.

- This is a form of “unsupervised learning”

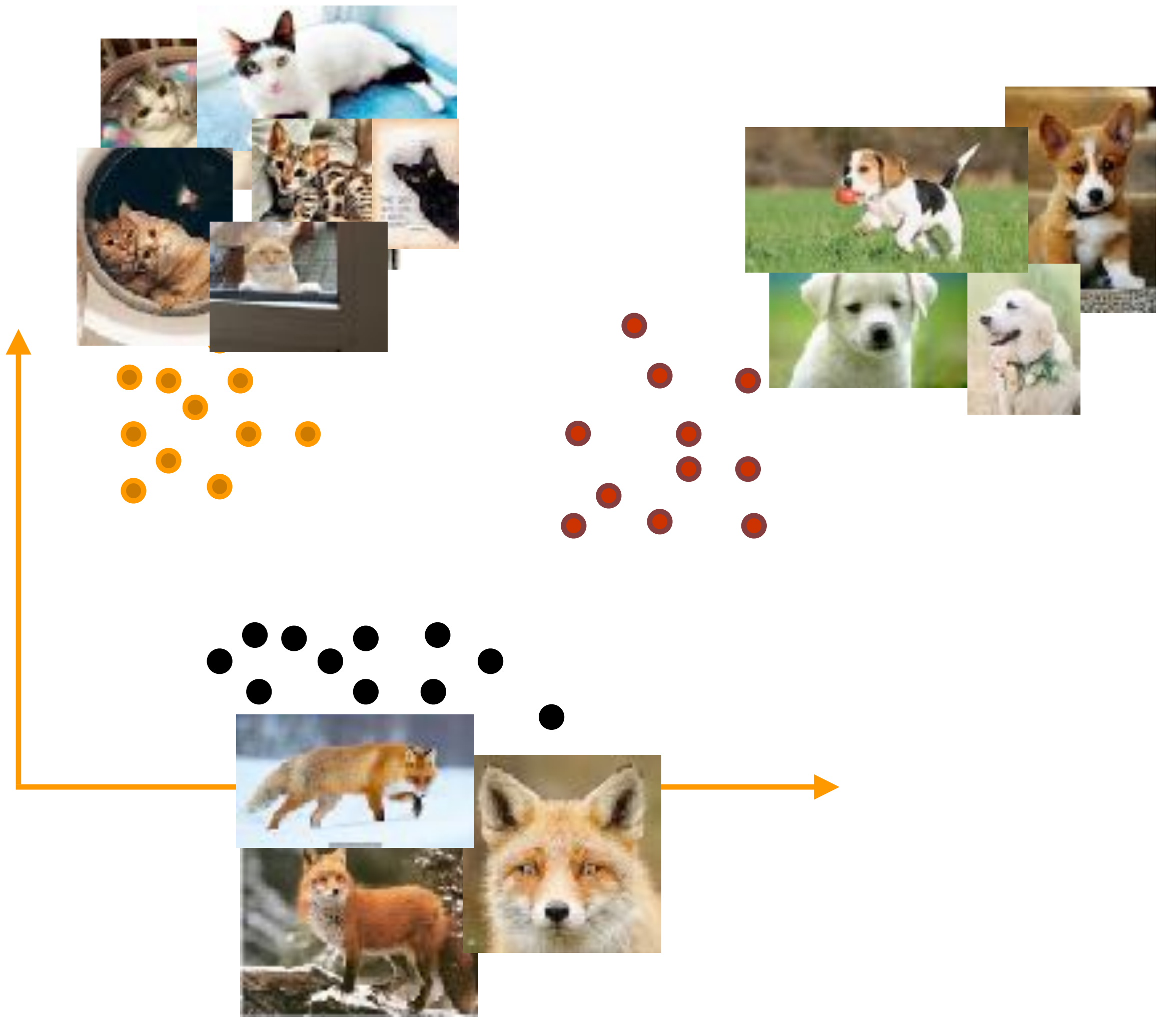
CLUSTERING

- **The points in each cluster are closer to one another and far from the points in other clusters.**



DATA POINTS

- Each of the data points belong to some n-dimensional space.



DISSIMILARITY MEASUREMENTS

Given measurements x_{ij} for $i = 1,\ldots,N$ observations over $j = 1,\ldots,p$ predictors.

Define dissimilarity, $d_j(x_{ij}, x_{i'j})$

- **We can define dissimilarity between objects as**

$$d(x_i, x_{i'}) = \sum_{j=1}^{p} d_j(x_{ij}, x_{i'j})$$

- **The most common distance measure is squared distance**

$$d_j(x_{ij}, x_{i'j}) = (x_{ij} - x_{i'j})^2$$

DISSIMILARITY MEASUREMENTS

- **Absolute difference**

$$d_j(x_{ij}, x_{i'j}) = |x_{ij} - x_{i'j}|$$

- **For categorical variables, we could set**

$$d_j(x_{ij}, x_{i'j}) = 0 \text{ if } x_{ij} = x_{i'j}$$

$$1 \text{ otherwise}$$

K-MEANS CLUSTERING

- A commonly used algorithm to perform clustering

- Assumptions:
    - Euclidean distance,

$$d(x_i, x_{i'}) = \sum_{j=1}^{p} (x_{ij} - x_{i'j})^2 = ||x_i - x_{i'}||^2$$

- K-means partitions observations into K clusters, with K provided as a parameter.

K-MEANS CLUSTERING

- **Given some clustering or partition, C, the cluster assignment of observation, x_i to cluster $k \in \{1, \ldots, K\}$ is denoted as $C(i) = k$.**

- **K-means seeks to minimize a clustering criterion measuring dissimilarity of observations assigned to each cluster**

K-MEANS OBJECTIVE FUNCTION

- **We want to minimize within-cluster dissimilarity.**

$$W = \sum_{k=1}^{K} \sum_{i=1}^{N} ||x_{ik} - \bar{x}_k||^2$$

where $\bar{x}_k$ **is the centroid of the cluster k**

- **The criteria to minimize is the total distance given by each observation to the mean(centroid) of the cluster to which the observation is assigned.**

K-MEANS - ITERATIVE ALGORITHM

1. Initialize by choosing K observations as centroids.

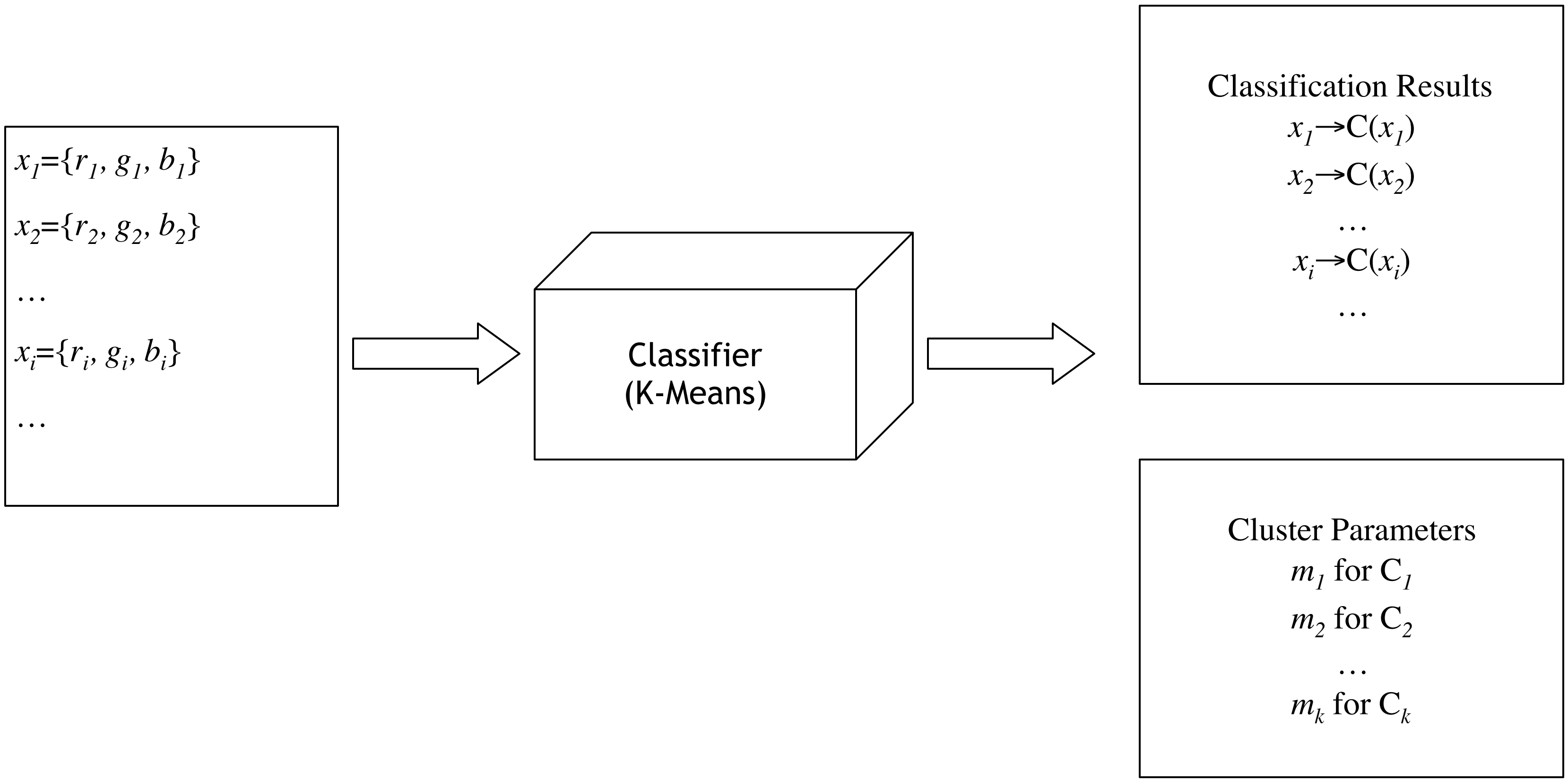
$$m_1, m_2, \ldots, m_k$$

2. Assign each observation i to the cluster with the nearest centroid, i.e,

$$\min_{1 \le k \le K} ||x_i - m_k||^2$$

3. Update centroids $m_k = \bar{x}_k$
4. Iterate steps 2 and 3 until convergence.

K-MEANS - CLASSIFIER



Example

Application of k-means algorithm for color-based image segmentation [Bishop book[1] and its web site]
K-means clustering applied to the color vectors of pixels in RGB color-space

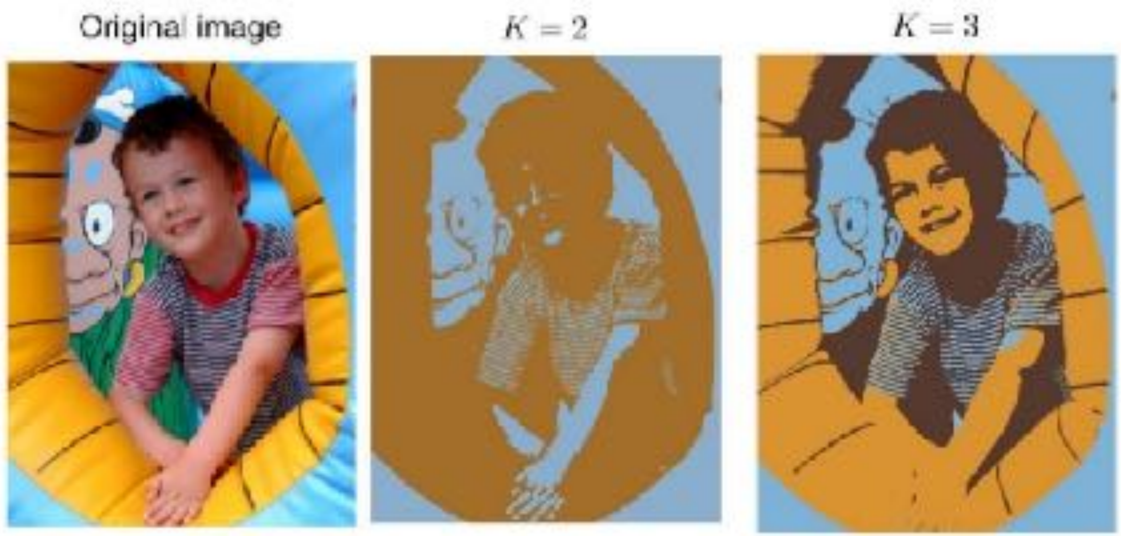


Fig. 3 [1]

Image Segmentation by K-Means

- Select a value of K
- Select a feature vector for every pixel (color, texture, position, or combination of these etc.)
- Define a similarity measure between feature vectors (Usually Euclidean Distance).
- Apply K-Means Algorithm.
- Apply Connected Components Algorithm.
- Merge any components of size less than some threshold to an adjacent component that is most similar to it.

* From Marc Pollefeys COMP 256 2003

Results of K-Means Clustering:

Image

Clusters on intensity

Clusters on color

K-means clustering using intensity alone and color alone

* From Marc Pollefeys COMP 256 2003

K means: Challenges

- Will converge
- But not to the global minimum of objective function
- Variations: search for appropriate number of clusters by applying k-means with different k and comparing the results

K-means Variants

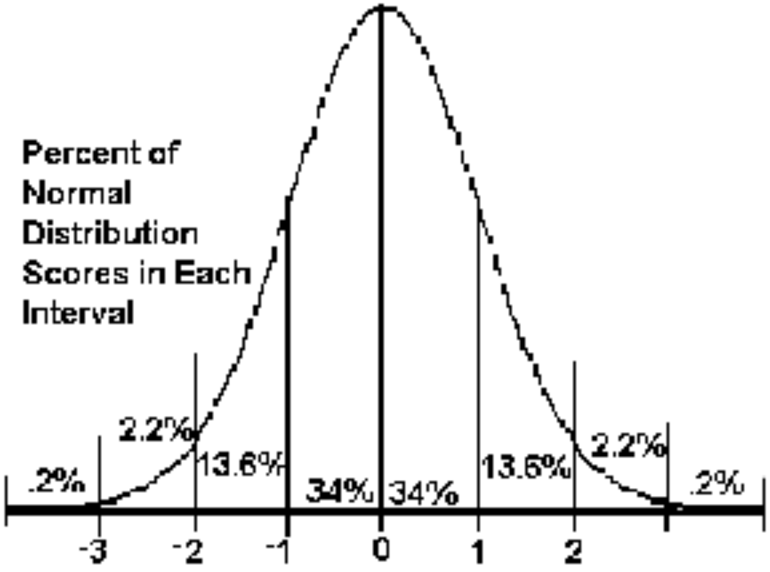
- Different ways to initialize the means
- Different stopping criteria
- Dynamic methods for determining the right number of clusters (K) for a given image

- The EM Algorithm: a probabilistic formulation of K-means

GAUSSIAN MIXTURE MODEL

Notation: Normal distribution 1D case

N(μ , σ) is a 1D normal (Gaussian) distribution with mean μ and standard deviation σ (so the variance is σ^2.



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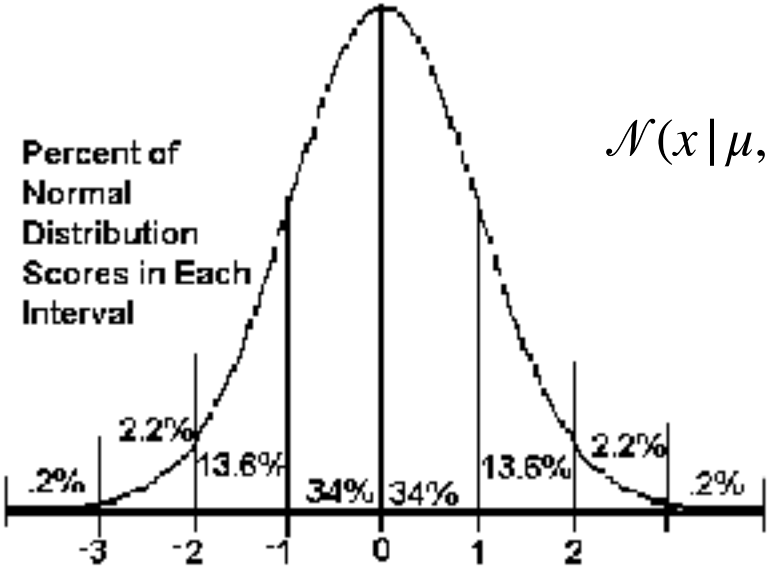


$$\mathcal{N}(x \mid \mu, \sigma^2) = \frac{1}{(2\pi\sigma^2)^{\frac{1}{2}}} exp\left\{ -\frac{1}{2\sigma^2}(x-\mu)^2 \right\}$$

Multivariate Normal distribution

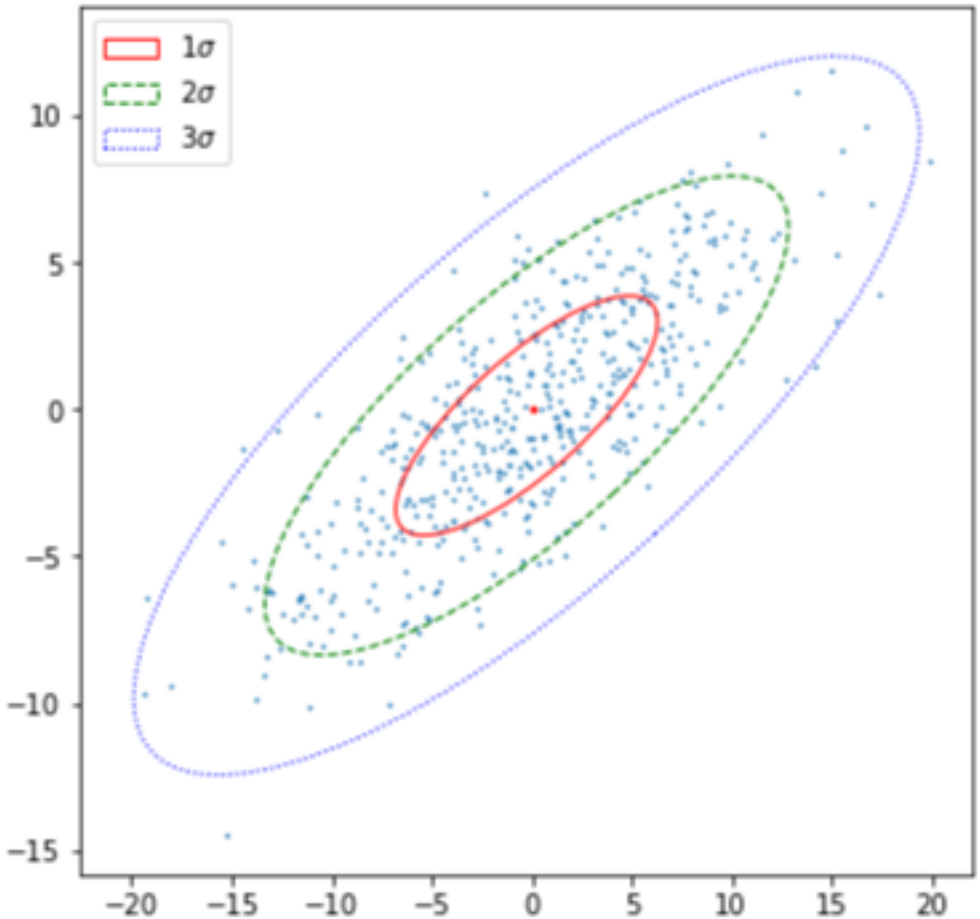
$$\mathcal{N}(x|\mu,\Sigma) = \frac{1}{(2\pi)^{\frac{D}{2}}}\frac{1}{|\Sigma|^{\frac{1}{2}}}exp\left\{-\frac{1}{2}(x-\mu)^T\Sigma^{-1}(x-\mu)\right\}$$

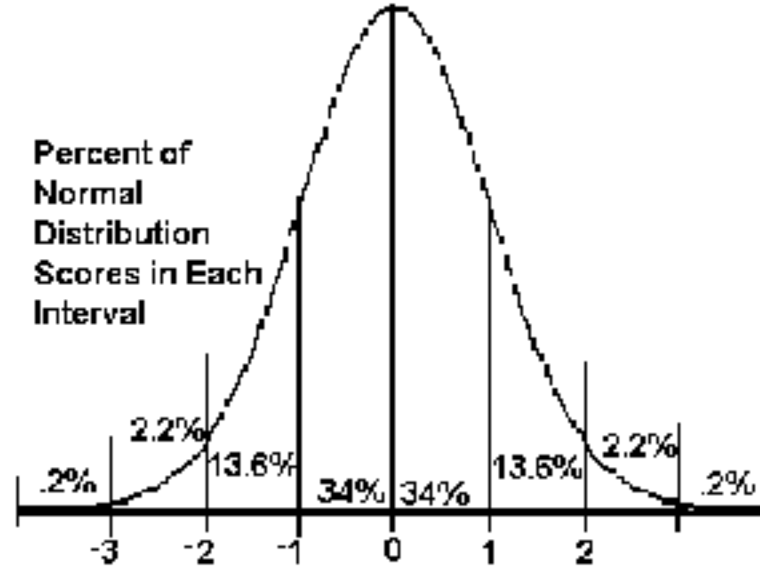
x is a D dimensional vector

μ is a D-dimensinal mean vector

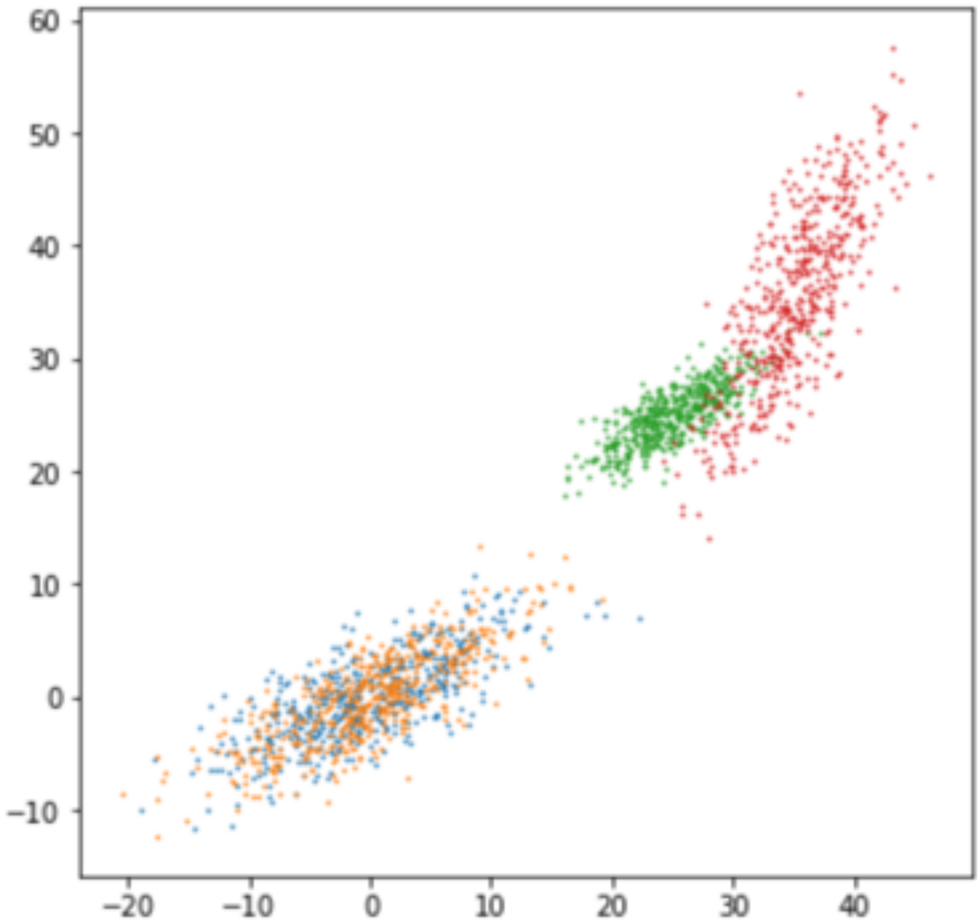
Σ is a D x D covariance matrix

Uni-modal dataset





Multi-modal dataset



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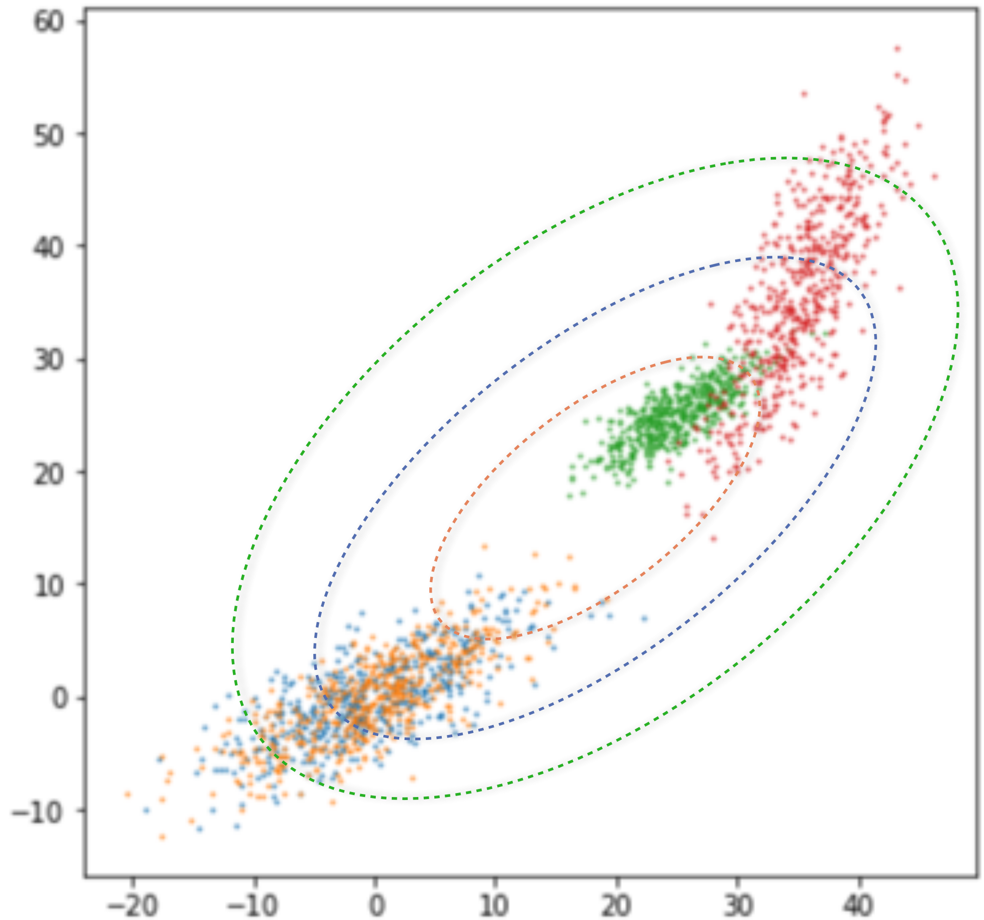

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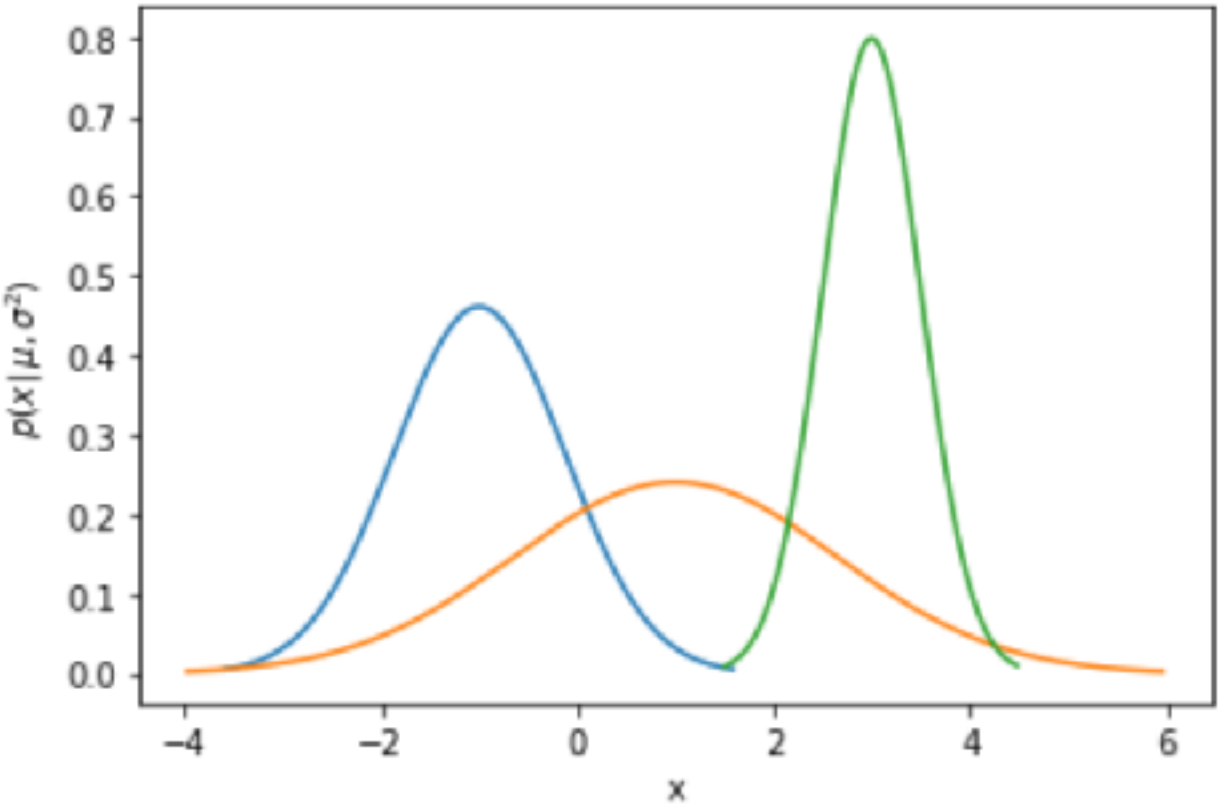
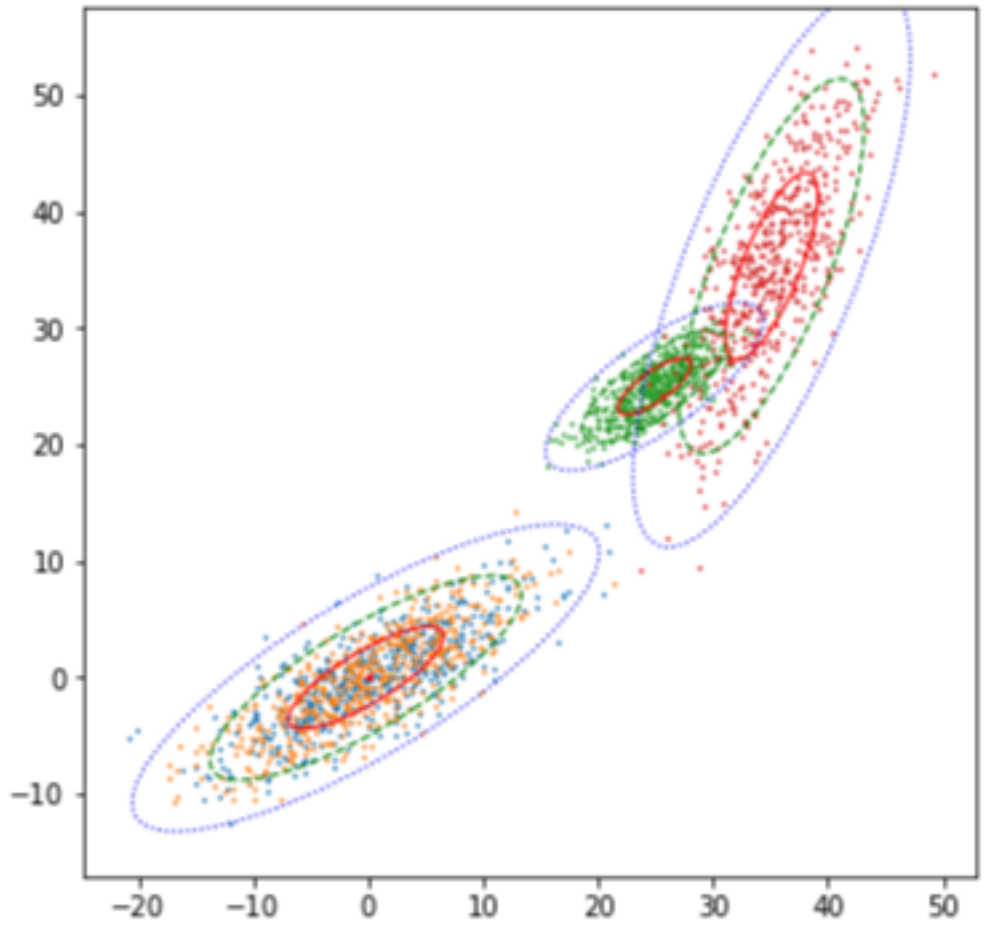


$$\mathcal{N}(x\,|\,\mu,\sigma^2) = \frac{1}{(2\pi\sigma^2)^{\frac{1}{2}}} exp\left\{ -\frac{1}{2\sigma^2}(x-\mu)^2 \right\}$$

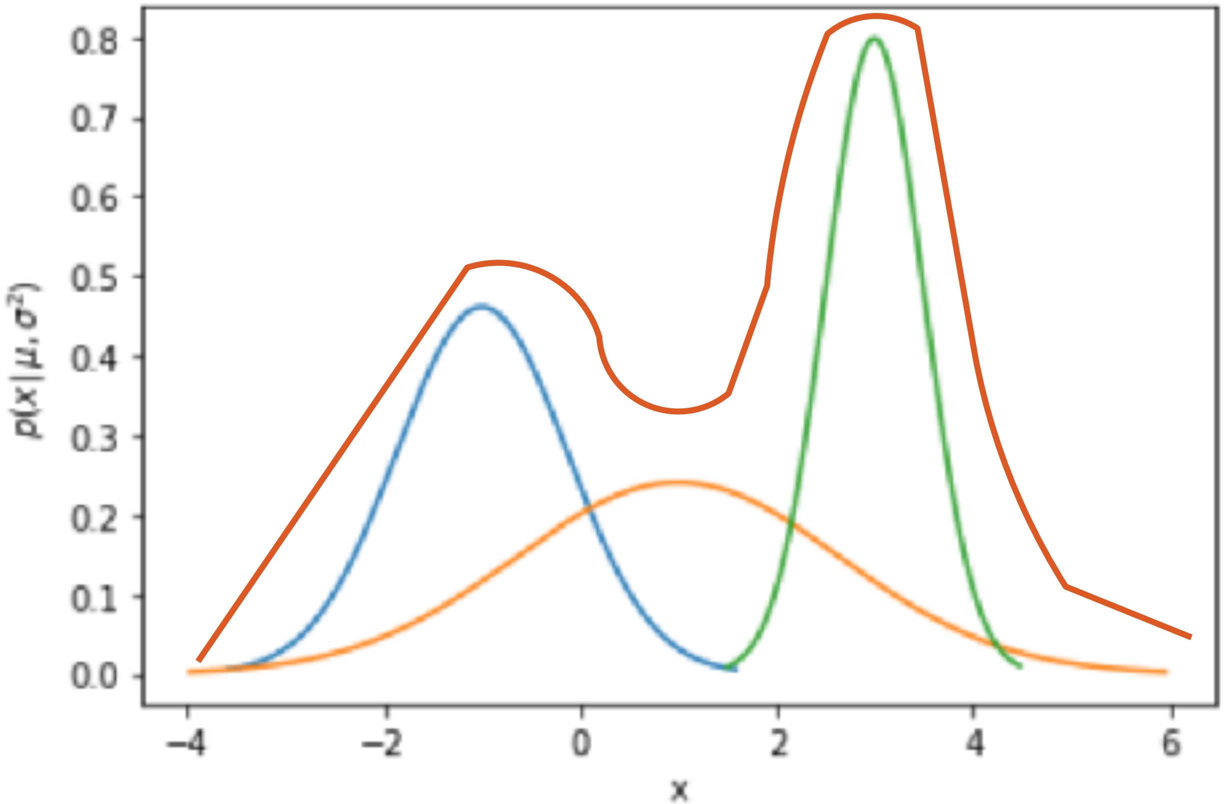
Multi-modal dataset



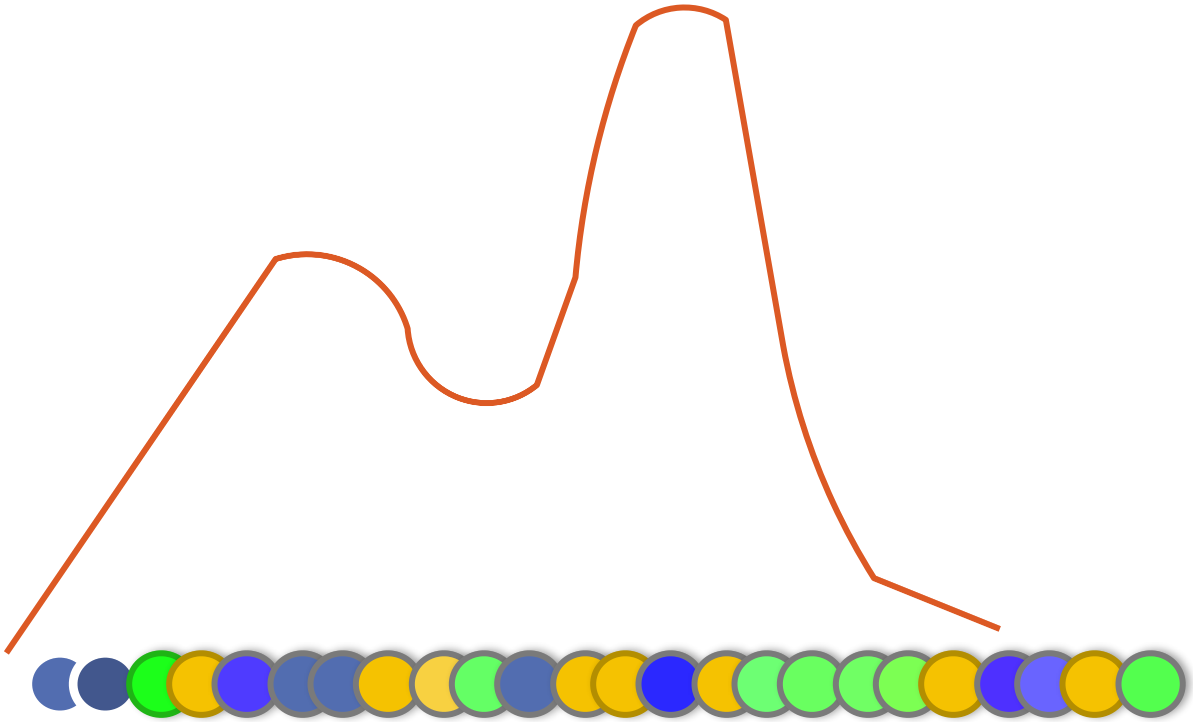
Gaussian Mixtures Model

A linear combination of Gaussian distributions forms a superposition

Formulated as a probabilistic model known as mixture distribution

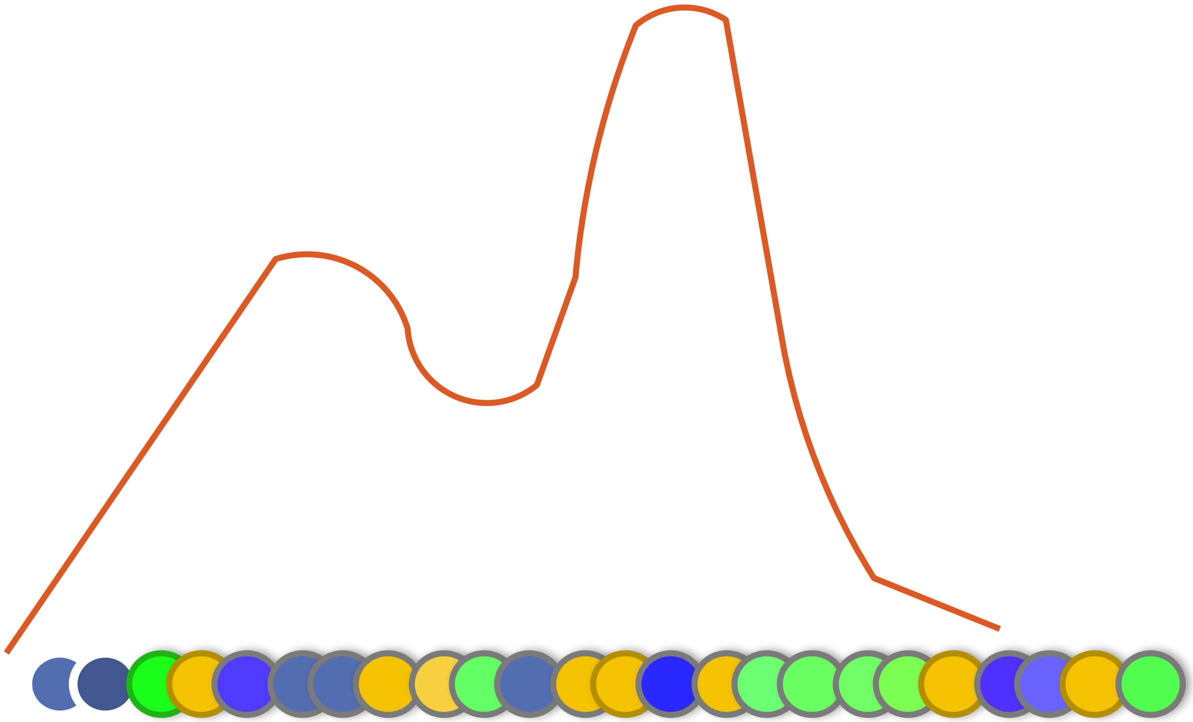


Gaussian Mixtures Model

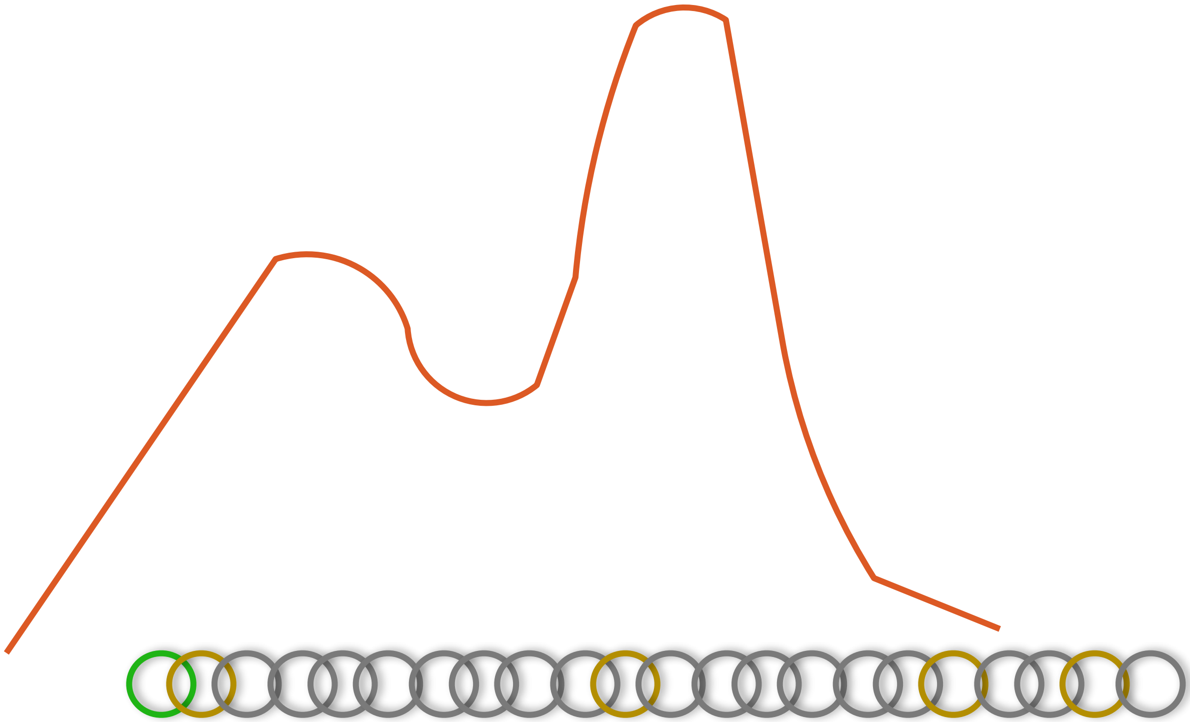


Gaussian Mixtures Model

$$p(x) = \sum_{k=1}^{K} \pi_k \mathcal{N}(x \mid \mu_k, \Sigma_k)$$



Gaussian Mixtures Model



Gaussian Mixtures Model

- We have a linear combination of several Gaussians

- Each Gaussian is a cluster, one of K clusters

- Each cluster has a mean and covariance

- Mixing probability,

Gaussian Mixtures Model

Parameters - μ, Σ, π

$$\sum_{k=1}^{K} \pi_k = 1 \quad ; \quad 0 \leq \pi_k \leq 1$$

$$p(x) = \sum_{k=1}^{K} \pi_k \mathcal{N}(x \,|\, \mu_k, \Sigma_k)$$

$$\mathcal{N}(x \,|\, \mu, \Sigma) = \frac{1}{(2\pi)^{\frac{D}{2}}} \frac{1}{|\Sigma|^{\frac{1}{2}}} exp\left\{ -\frac{1}{2}(x-\mu)^T \Sigma^{-1}(x-\mu) \right\}$$

x is a D dimensional vector

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Maximum Likelihood Estimate

$$\mathcal{N}(x|\mu,\Sigma) = \frac{1}{(2\pi)^{\frac{D}{2}}}\frac{1}{|\Sigma|^{\frac{1}{2}}}exp\left\{-\frac{1}{2}(x-\mu)^T\Sigma^{-1}(x-\mu)\right\}$$

$$ln\mathcal{N}(x|\mu,\Sigma) = -\frac{D}{2}ln\,2\pi - \frac{1}{2}ln\,\Sigma - \frac{1}{2}(x-\mu)^T\Sigma^{-1}(x-\mu)$$

Once Optimal values of the parameters are found,

the solution will correspond to the Maximum Likelihood Estimate (MLE)