

COMS 4030A/7047A

Adaptive Computation and Machine Learning

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Last class:
Unsupervised Learning – K Means

Today:
Unsupervised Learning - GMM

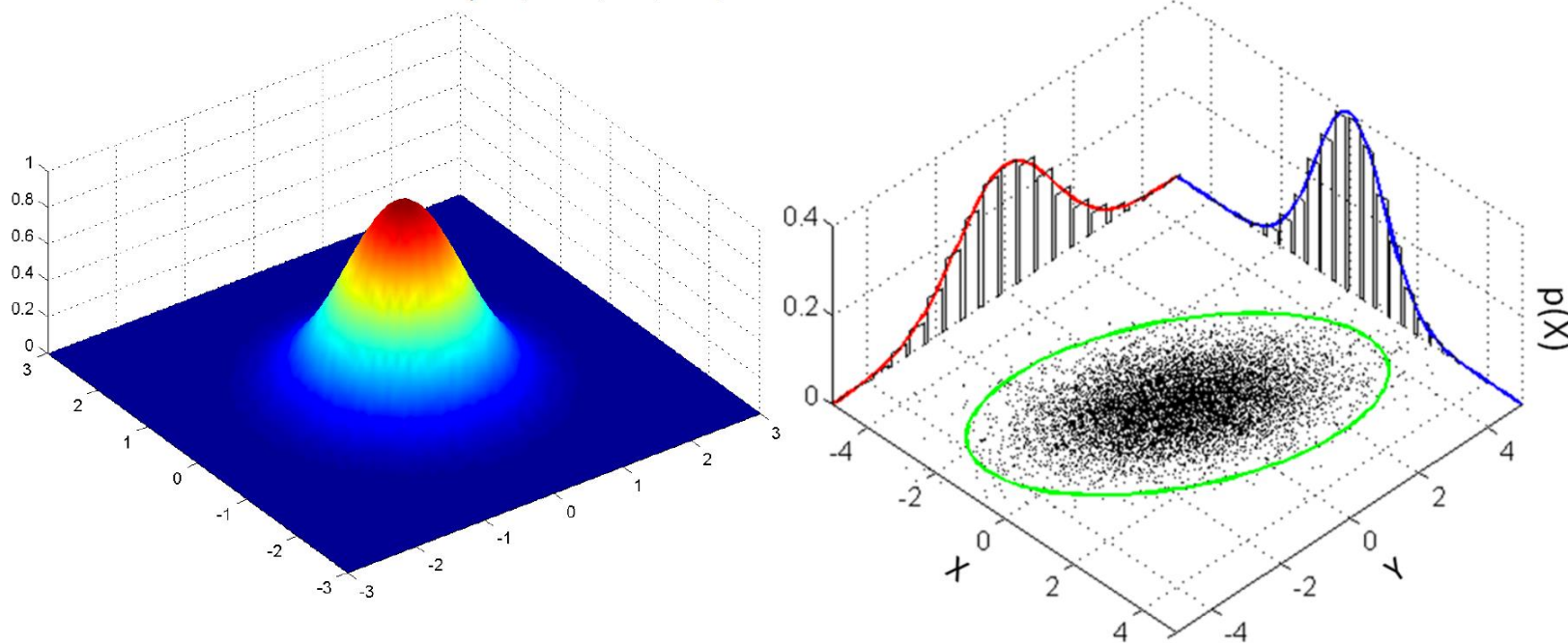
Clustering Methods

- Hard Clustering : Clusters do not overlap
 - Element either belongs to cluster or it does not
- Soft Clustering : Clusters may overlap
 - Strength of association between clusters and instances
- Mixture models
 - Probabilistically - grounded way of performing soft clustering
 - Each cluster is a generative model (Gaussian or multinomial)
 - Parameters (mean/covariance are unknown)
- Expectation – Maximization (EM) algorithm
 - Allows us to estimate all parameters for the mixture of distributions

Gaussian Mixture Models

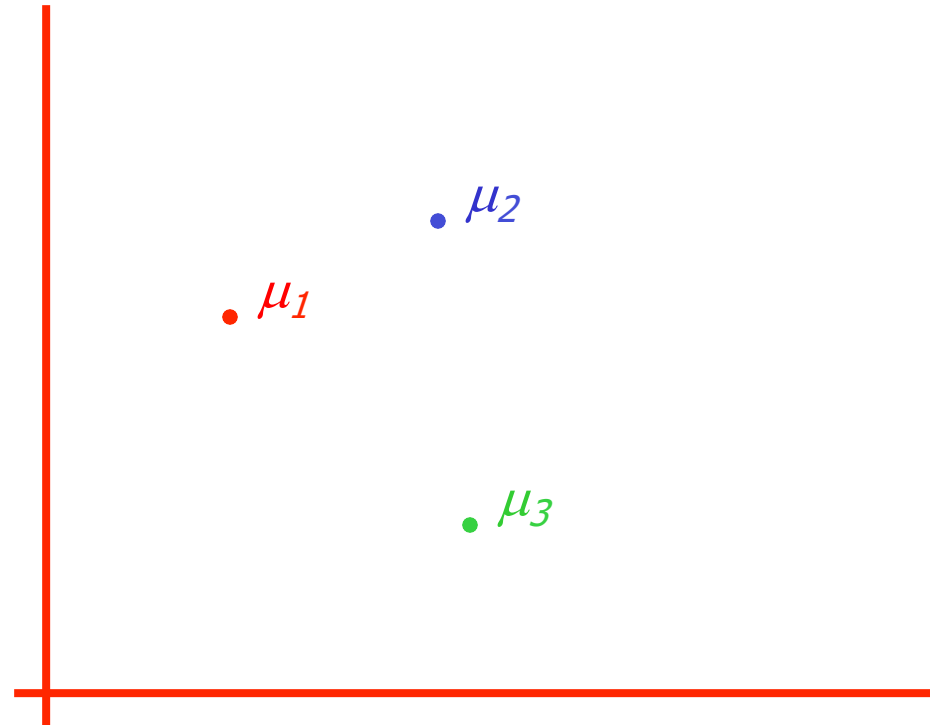
- Recall the Gaussian distribution:

$$P(\mathbf{x} \mid \boldsymbol{\mu}, \boldsymbol{\Sigma}) = \frac{1}{\sqrt{(2\pi)^d |\boldsymbol{\Sigma}|}} \exp \left(-\frac{1}{2} (\mathbf{x} - \boldsymbol{\mu})^\top \boldsymbol{\Sigma}^{-1} (\mathbf{x} - \boldsymbol{\mu}) \right)$$



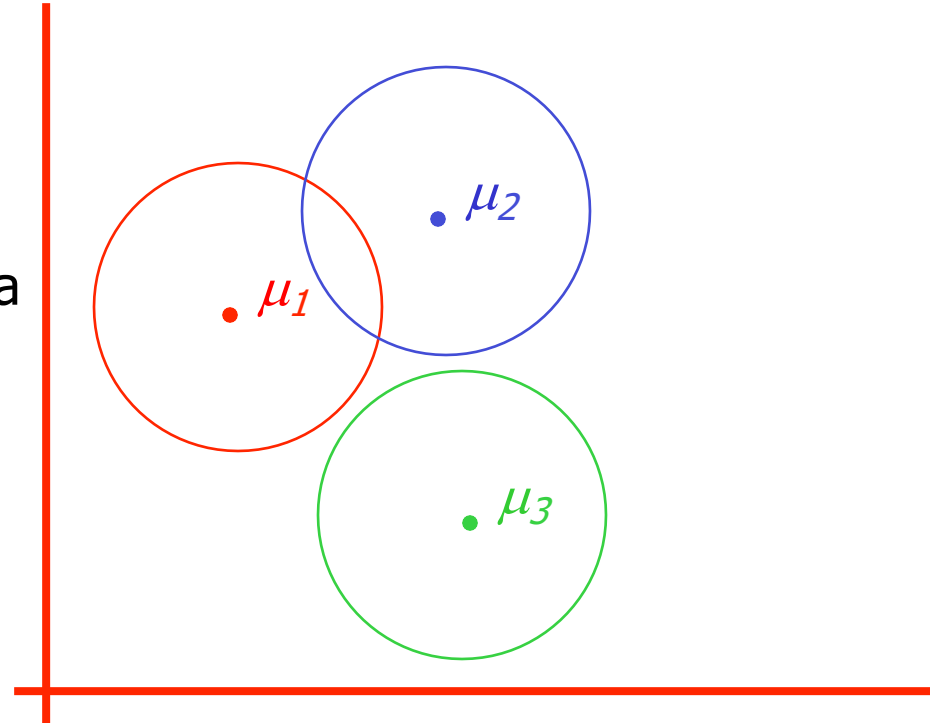
The GMM assumption

- There are k components. The i 'th component is called ω_i
- Component ω_i has an associated mean vector μ_i



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- Each component generates data from a Gaussian with mean μ_i and covariance matrix $\sigma^2 \mathbf{I}$

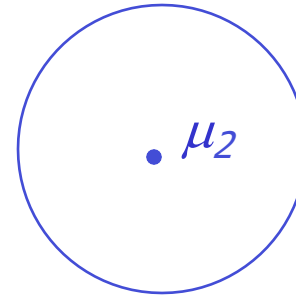


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Assume that each datapoint is generated according to the following recipe:

1. Pick a component at random. Choose component i with probability $P(\omega_i)$.

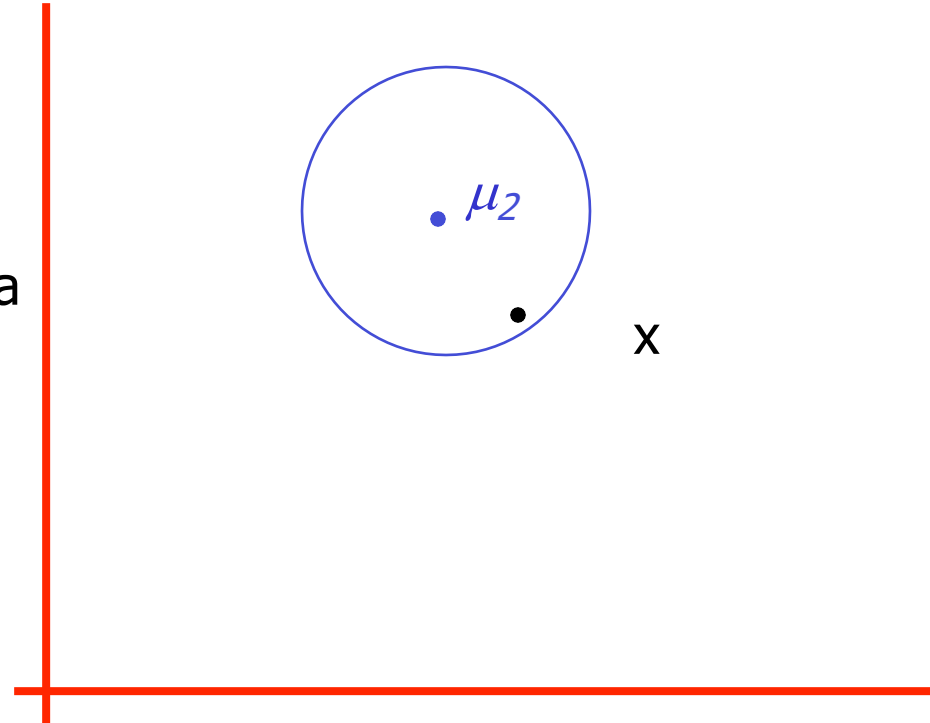


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1. Pick a component at random. Choose component i with probability $P(\omega_i)$.
2. Datapoint $\sim N(\mu_i, \sigma^2 \mathbf{I})$

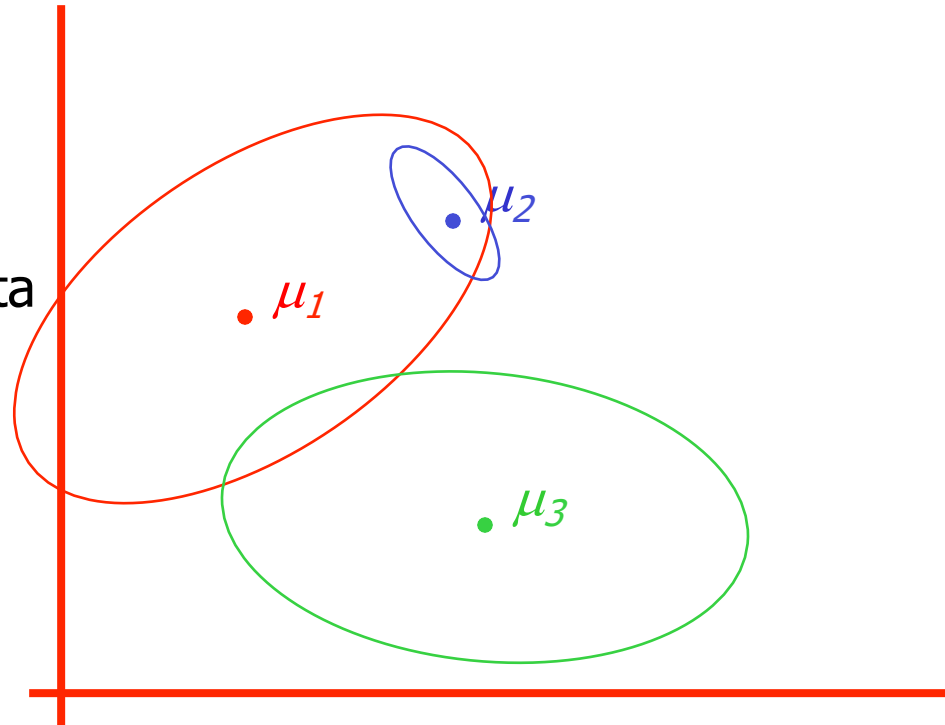


The **General** GMM assumption

- There are k components. The i 'th component is called ω_i
- Component ω_i has an associated mean vector μ_i
- Each component generates data from a Gaussian with mean μ_i and covariance matrix Σ_i

Assume that each datapoint is generated according to the following recipe:

1. Pick a component at random. Choose component i with probability $P(\omega_i)$.
2. Datapoint $\sim N(\mu_i, \Sigma_i)$



E.M. for **General** GMMs

$p_i(t)$ is shorthand
for estimate of
 $P(\omega_i)$ on t 'th
iteration

Iterate. On the t 'th iteration let our estimates be

$$\lambda_t = \{ \mu_1(t), \mu_2(t) \dots \mu_c(t), \Sigma_1(t), \Sigma_2(t) \dots \Sigma_c(t), p_1(t), p_2(t) \dots p_c(t) \}$$

E-step: Compute “expected” clusters of all datapoints

Just evaluate a
Gaussian at x_k

$$P(w_i | x_k, \lambda_t) = \frac{p(x_k | w_i, \lambda_t) P(w_i | \lambda_t)}{p(x_k | \lambda_t)} = \frac{p(x_k | w_i, \mu_i(t), \Sigma_i(t)) p_i(t)}{\sum_{j=1}^c p(x_k | w_j, \mu_j(t), \Sigma_j(t)) p_j(t)}$$

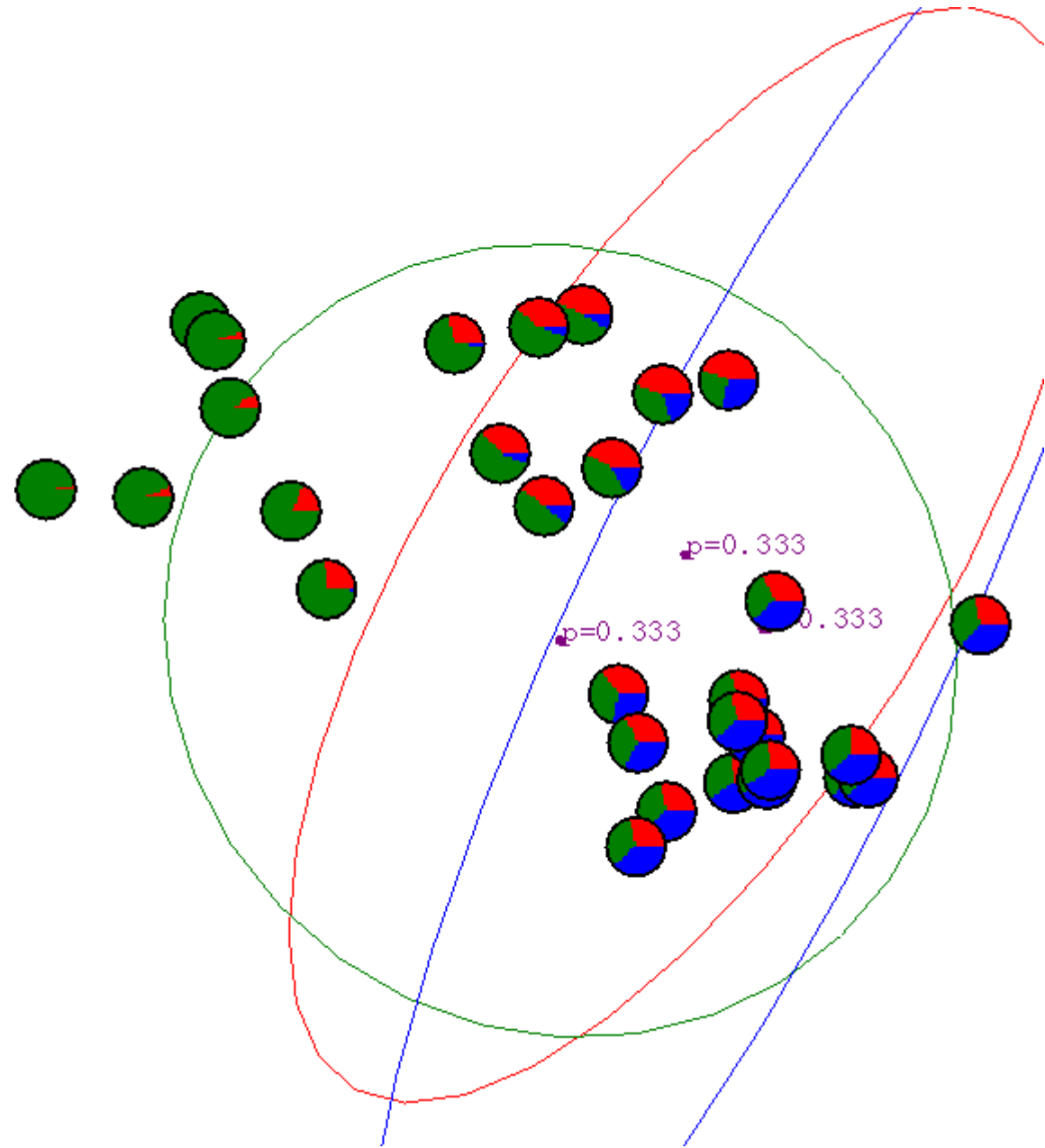
M-step: Estimate μ, Σ given our data's class membership distributions

$$\mu_i(t+1) = \frac{\sum_k P(w_i | x_k, \lambda_t) x_k}{\sum_k P(w_i | x_k, \lambda_t)} \quad \Sigma_i(t+1) = \frac{\sum_k P(w_i | x_k, \lambda_t) [x_k - \mu_i(t+1)][x_k - \mu_i(t+1)]^T}{\sum_k P(w_i | x_k, \lambda_t)}$$

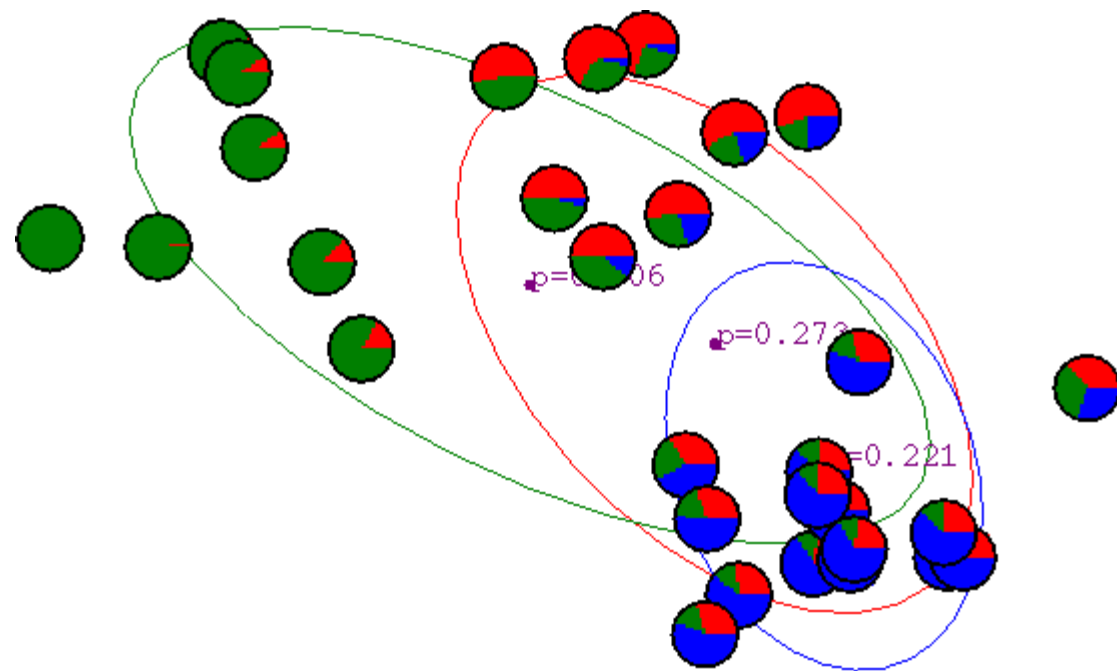
$$p_i(t+1) = \frac{\sum_k P(w_i | x_k, \lambda_t)}{R}$$

$R = \text{\#records}$

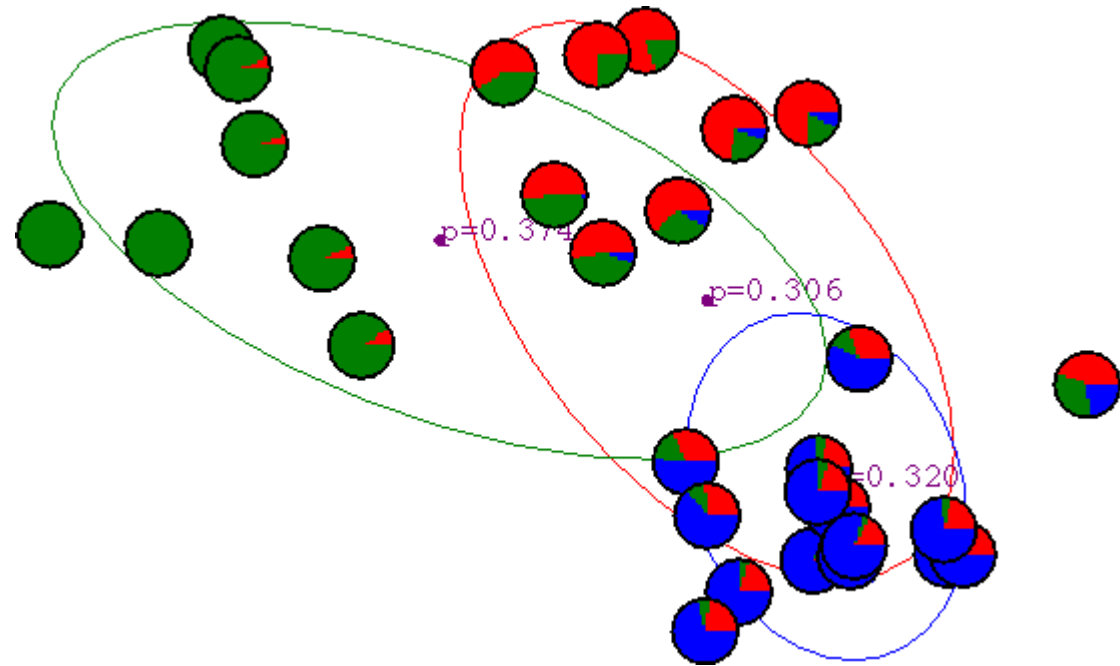
Gaussian Mixture Example: Start



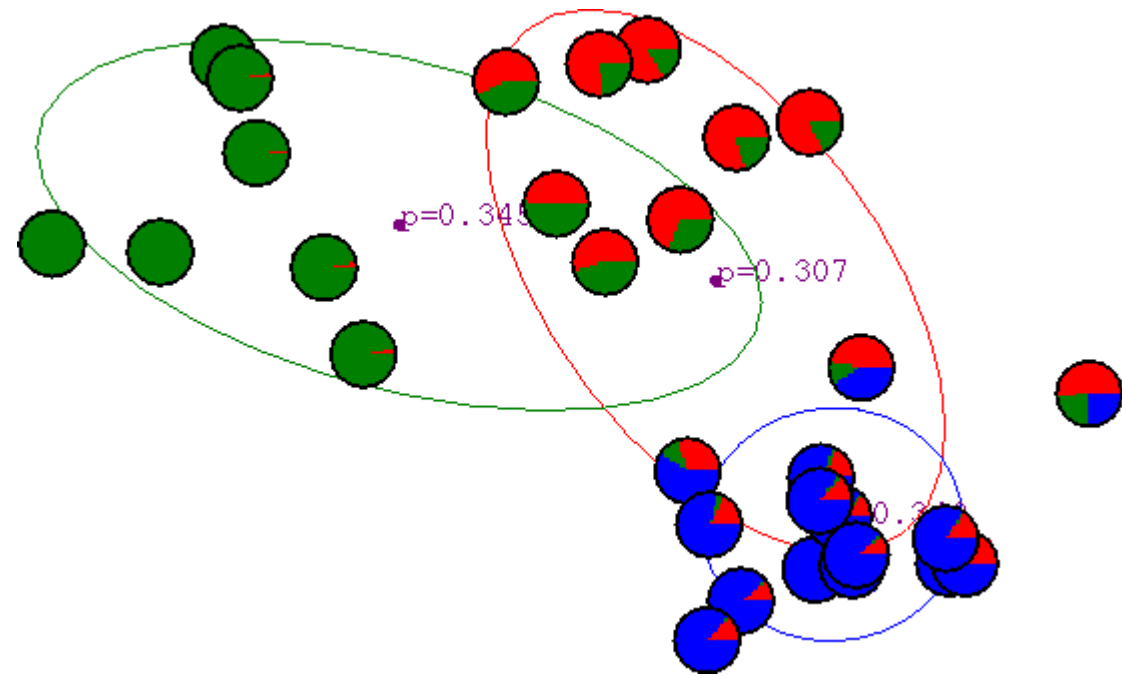
After first
iteration



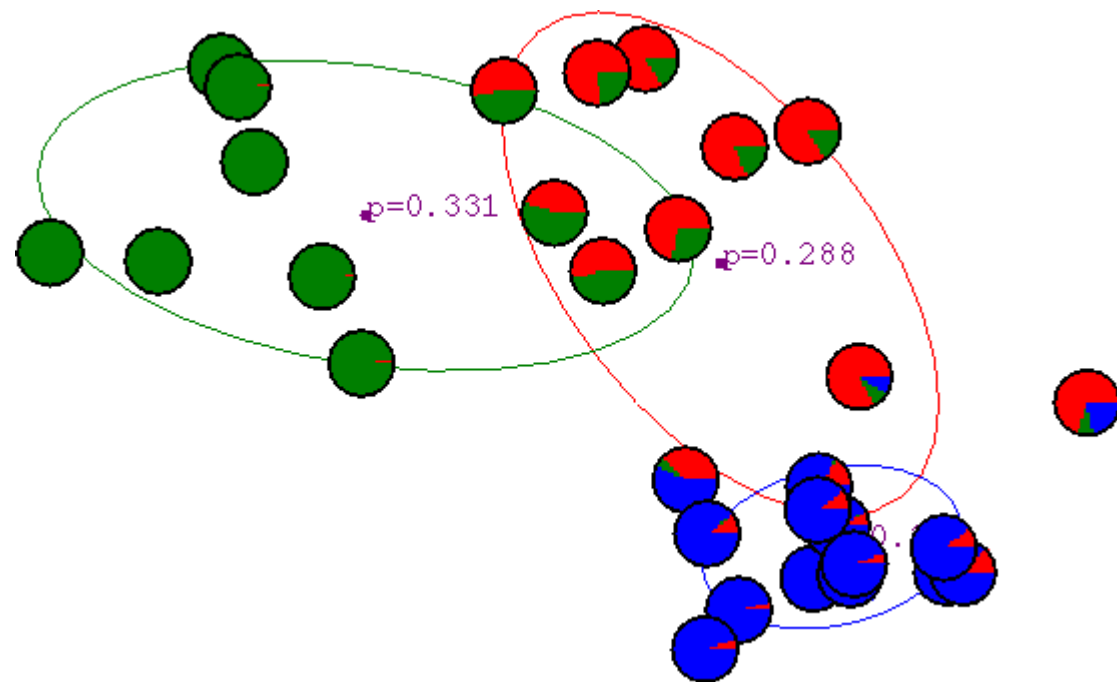
After 2nd
iteration



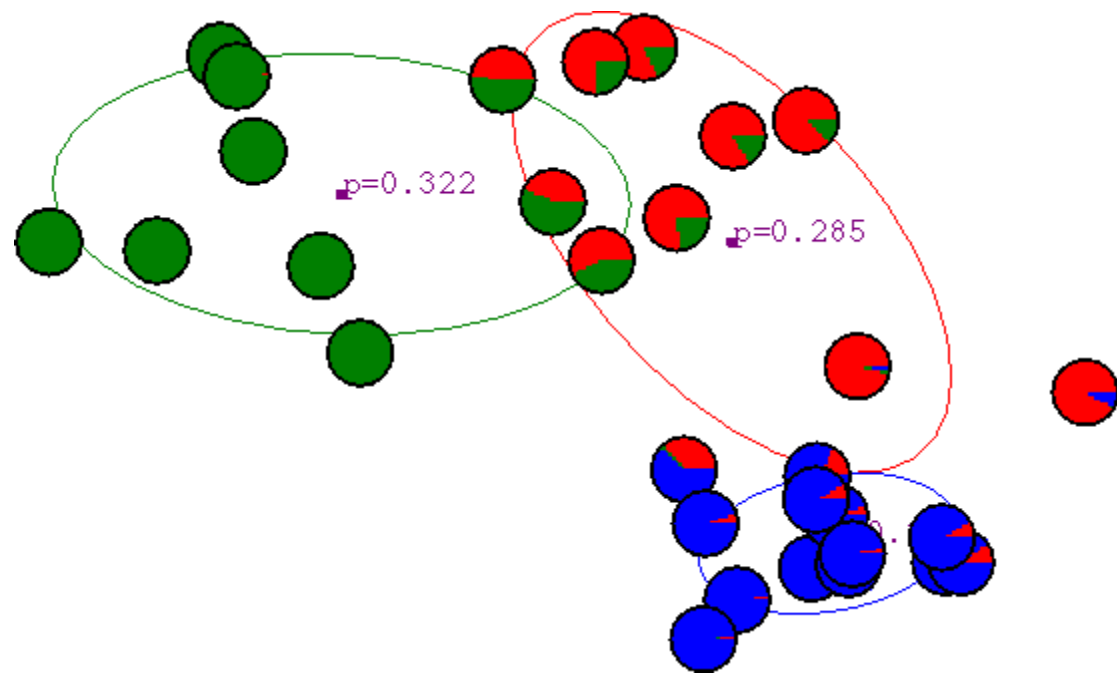
After 3rd
iteration



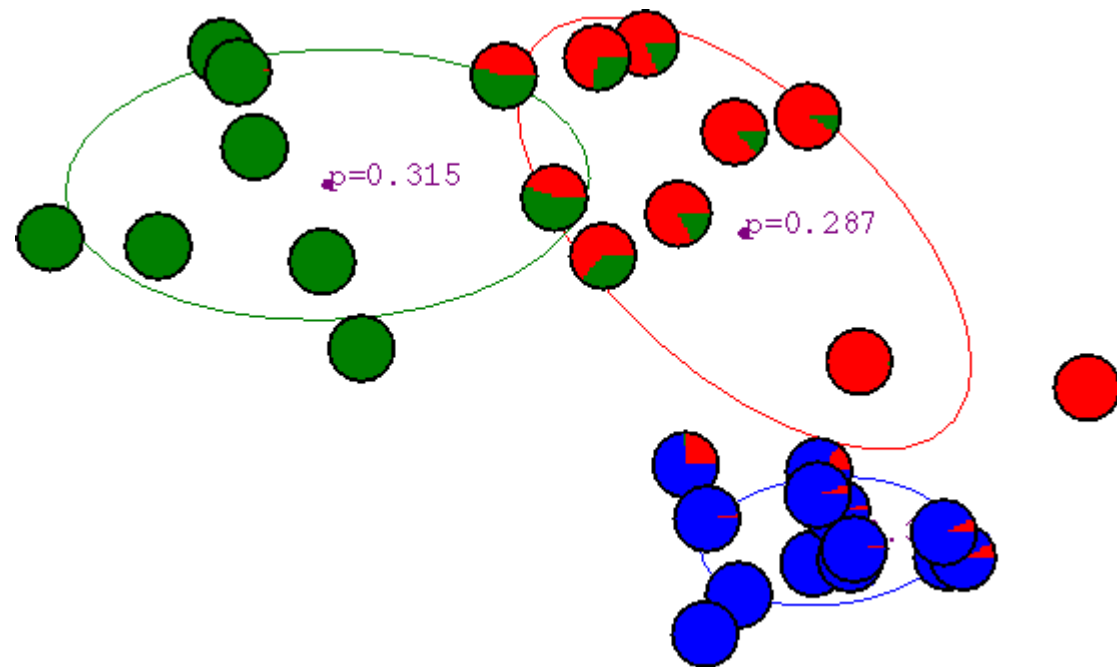
After 4th
iteration



After 5th
iteration



After 6th
iteration



After 20th
iteration

