

MACHINE LEARNING FOR SIGNAL PROCESSING

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<http://leap.ee.iisc.ac.in/sriram/teaching/MLSP25/>



Gaussian Distribution Summary

- ✓ The Gaussian model - parametric distributions
- ✓ **Simple and useful** properties.
- ✓ Can model unimodal (single peak distributions)
- ✓ **MLE** gives intuitive results
- ✓ Issues with Gaussian model
 - Multi-modal data
 - Not useful for complex data distributions

Need for **mixture models**

Gaussian Mixture Models

A Gaussian Mixture Model (GMM) is defined as

$$p(\mathbf{x}|\Theta) = \sum_{k=1}^K \alpha_k p(\mathbf{x}|\theta_k)$$
$$p(\mathbf{x}|\theta_k) = \frac{1}{\sqrt{(2\pi)^D |\Sigma_k|}} \exp\left\{ -\frac{1}{2}(\mathbf{x} - \boldsymbol{\mu}_k)^* \boldsymbol{\Sigma}_k^{-1} (\mathbf{x} - \boldsymbol{\mu}_k) \right\}$$

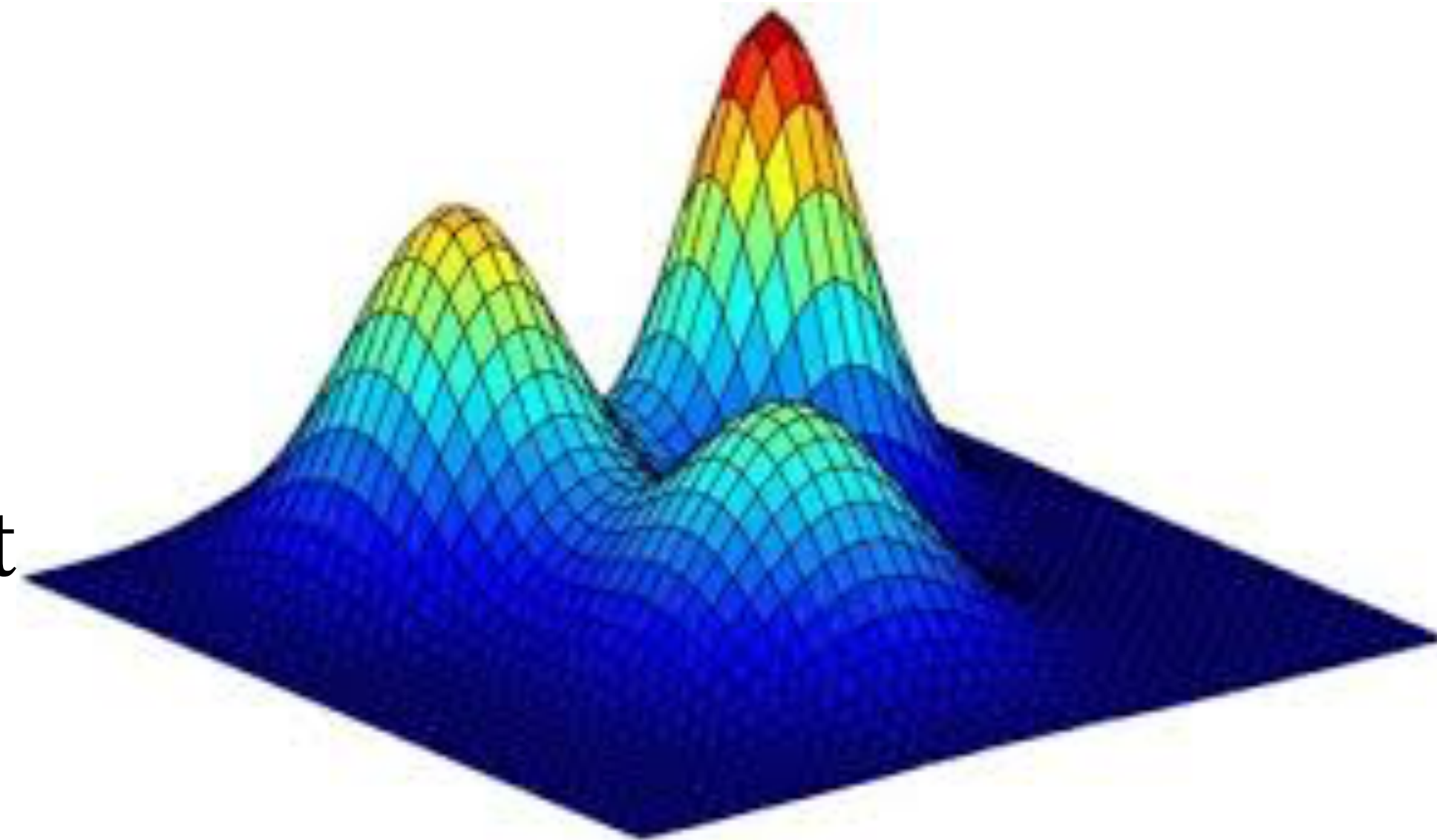
The weighting coefficients have the property

$$\sum_{k=1}^K \alpha_k = 1$$

Gaussian Mixture Models

❖ Properties of GMM

- ✓ Can model multi-modal data.
- ✓ Identify data clusters.
- ✓ Can model arbitrarily complex data dist



The set of parameters for the model are

$$\Theta_k = \{\alpha_k, \theta_k\}_{k=1}^K \quad \theta_k = \{\mu_k, \Sigma_k\}$$

The number of parameters is $KD^2 + KD + K$

MLE for GMM

- ❖ The log-likelihood function over the entire data in this case will have a **logarithm of a summation**

$$\log L(\Theta) = \sum_{i=1}^N \log \left(\sum_{k=1}^K \alpha_k p(\mathbf{x}_i | \theta_k) \right)$$

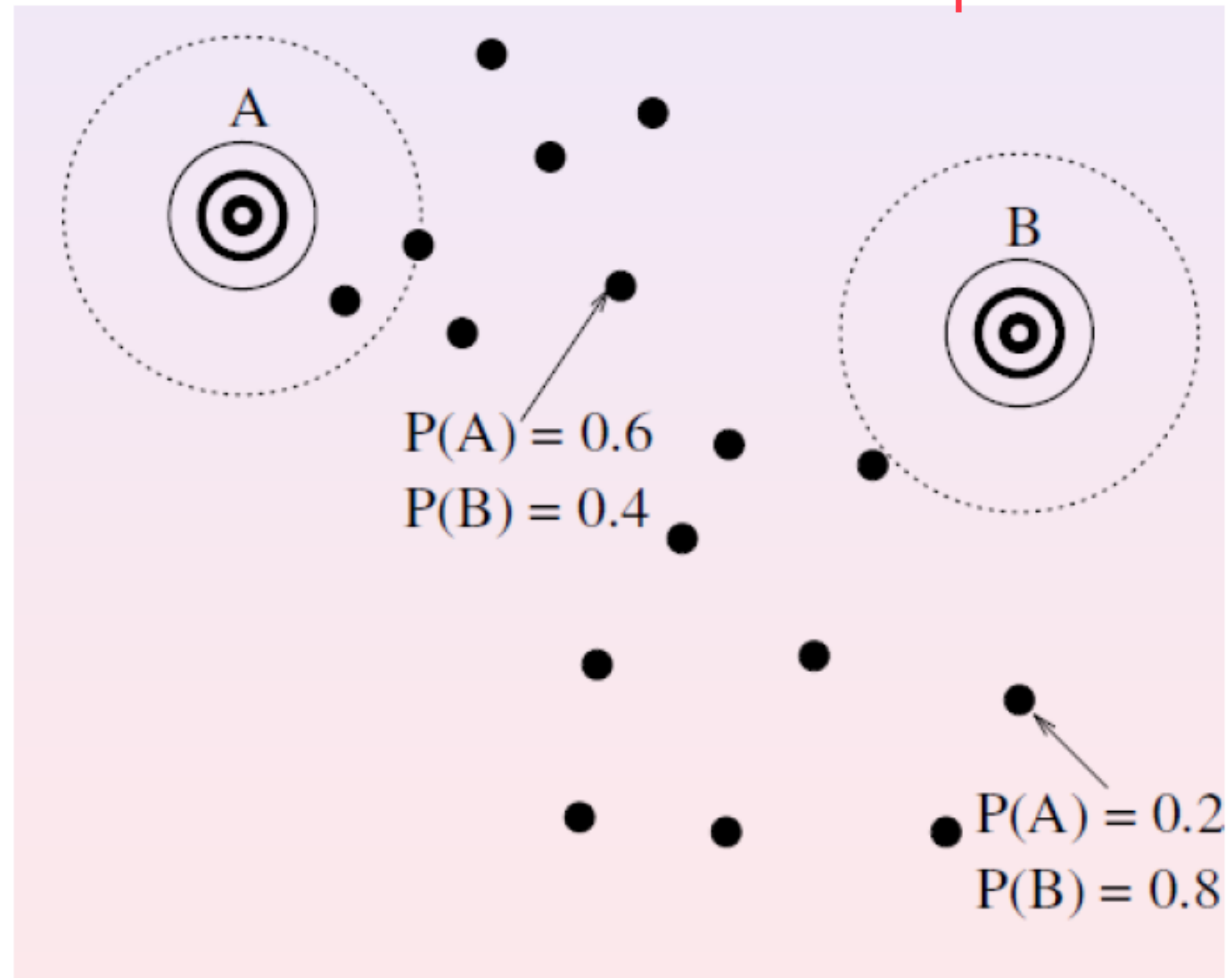
- ❖ Solving for the optimal parameters using MLE for GMM is not straight forward.
- ❖ Resort to the **Expectation Maximization (EM)** algorithm

EM Algorithm For GMMs

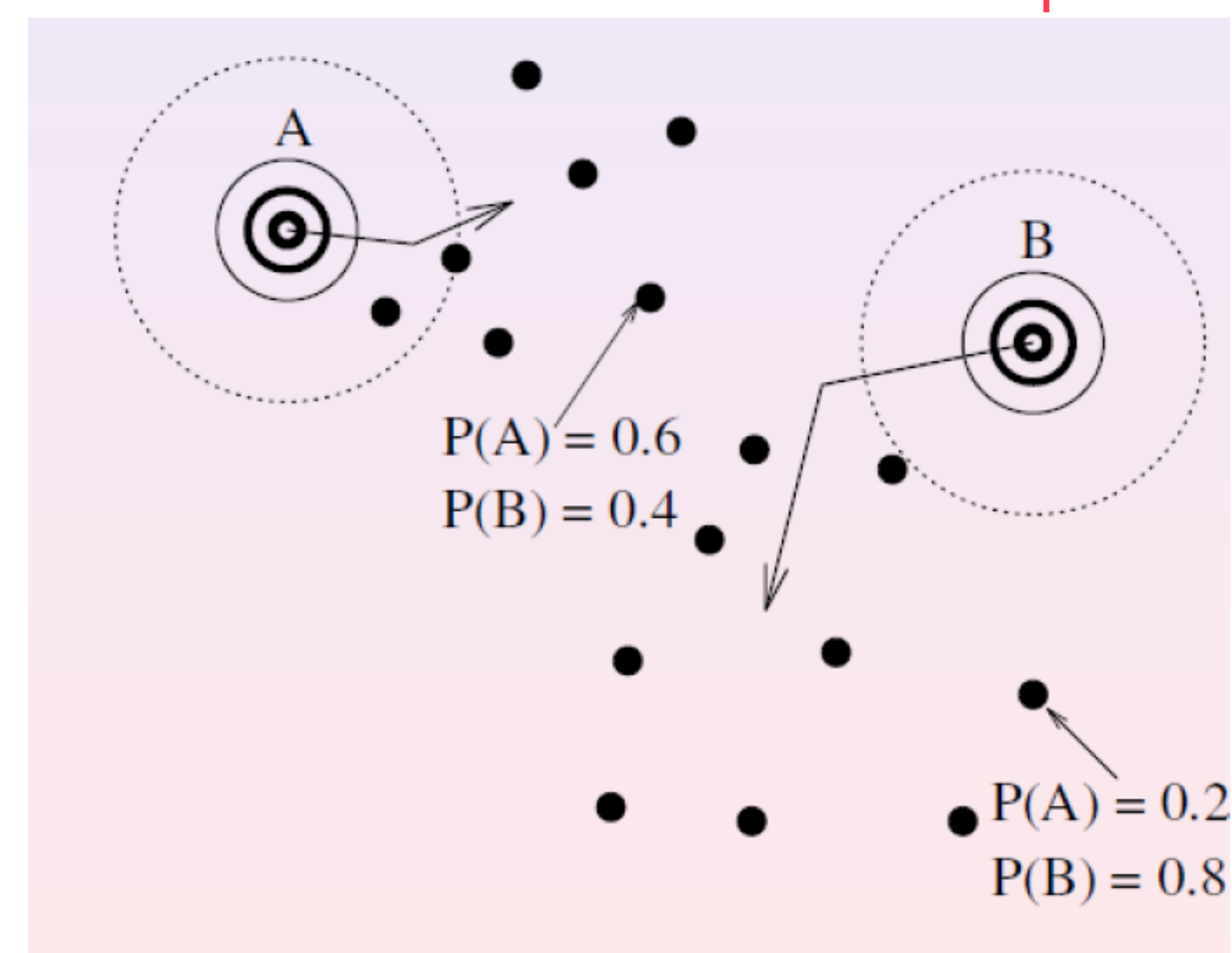
EM Algorithm for GMM

- ✓ The hidden variables will be the index of the mixture component which generated
- ✓ Re-estimation formulae

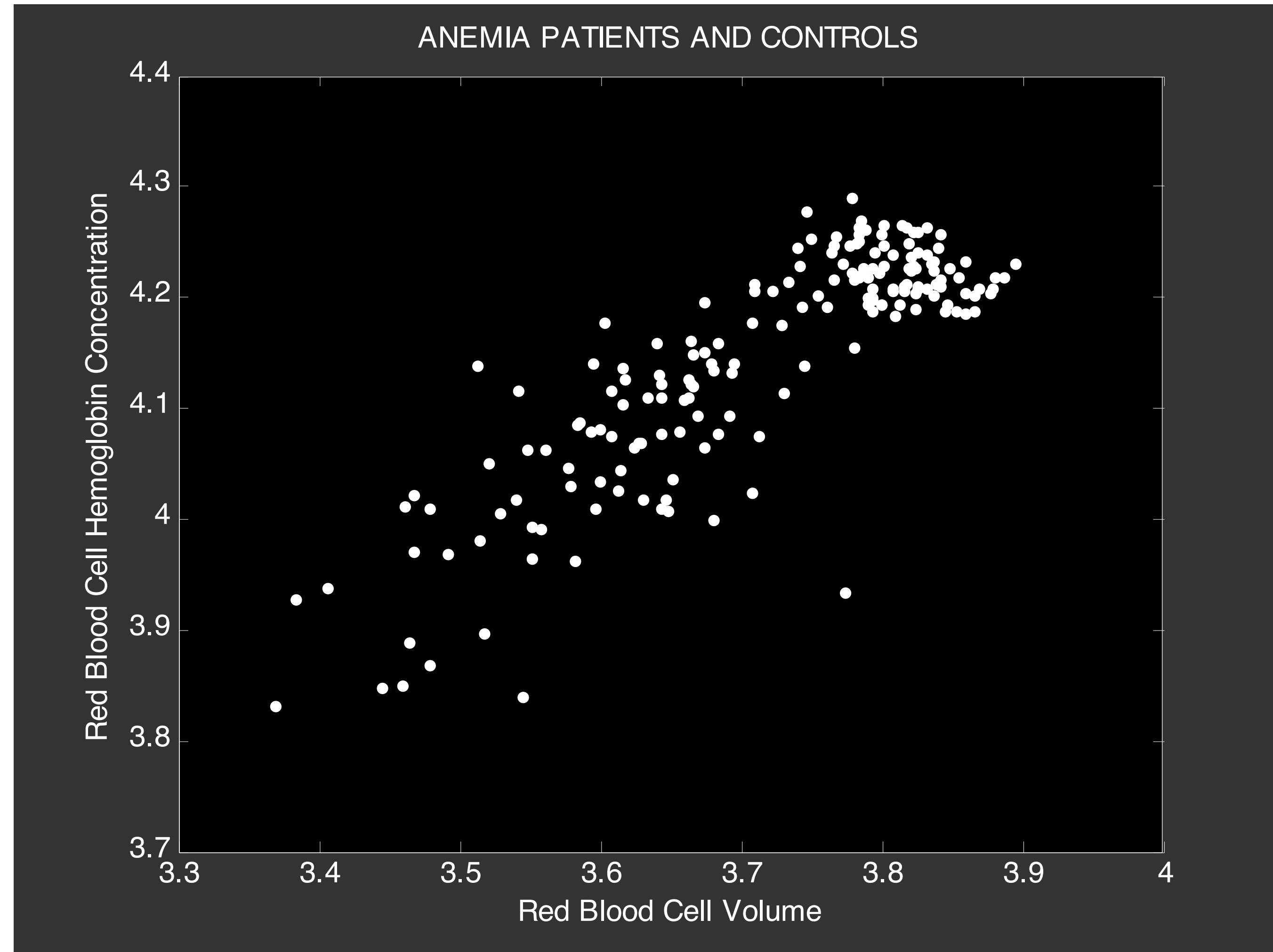
E-step



M-step

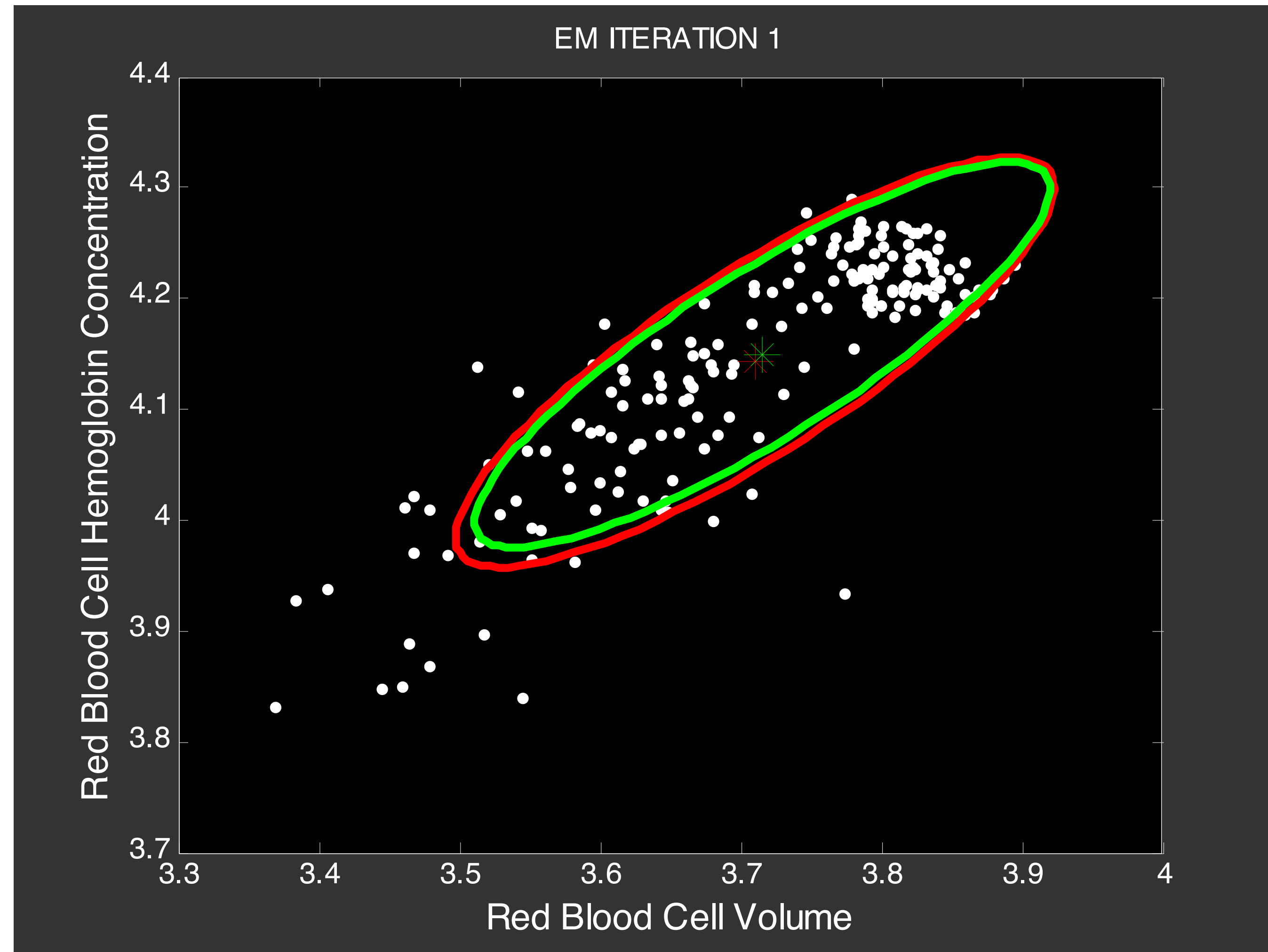


EM Algorithm for GMM



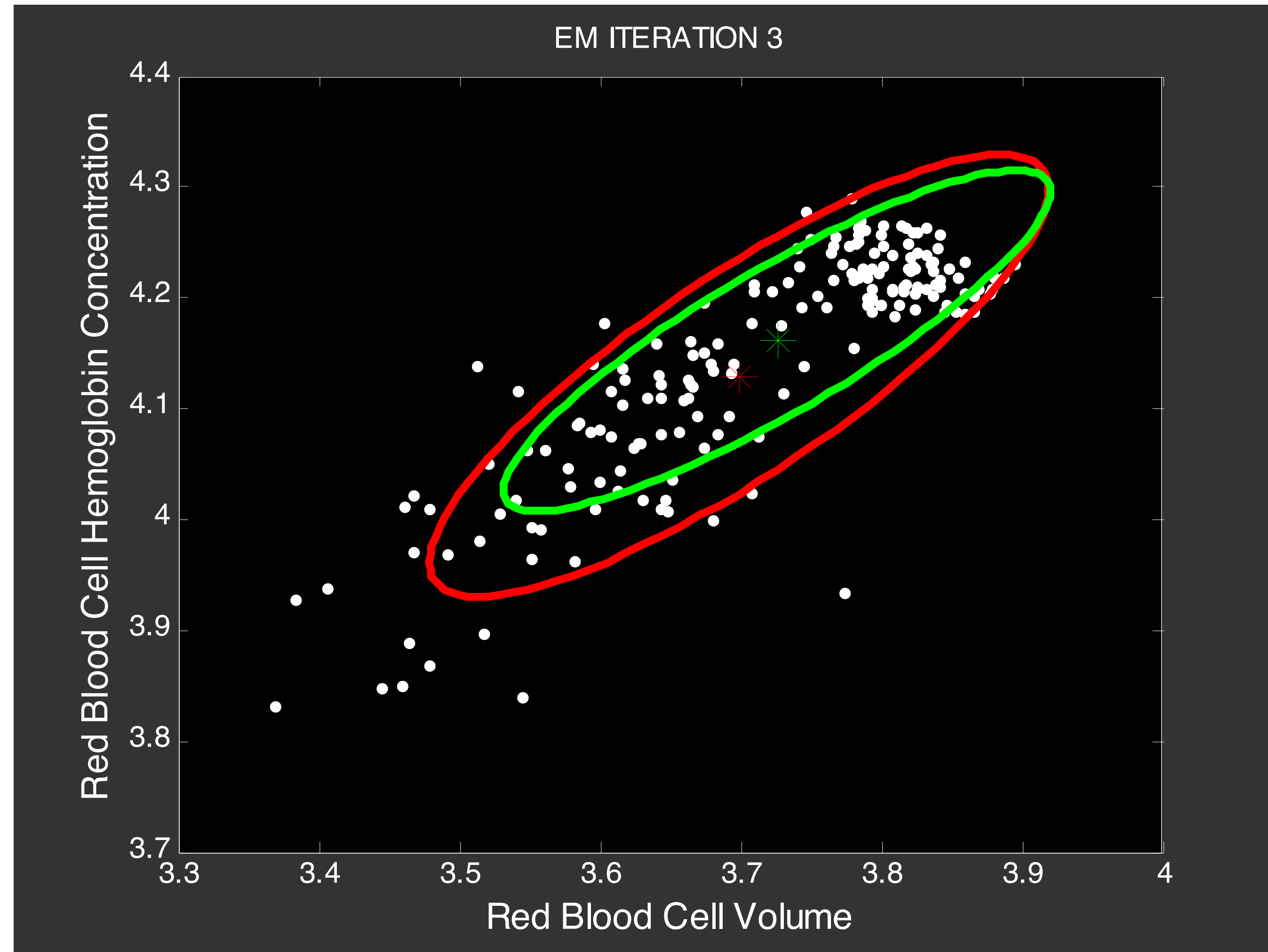
Cadez, Igor V., et al. "Hierarchical models for screening of iron deficiency anemia." *ICML*. 1999.

EM Algorithm for GMM



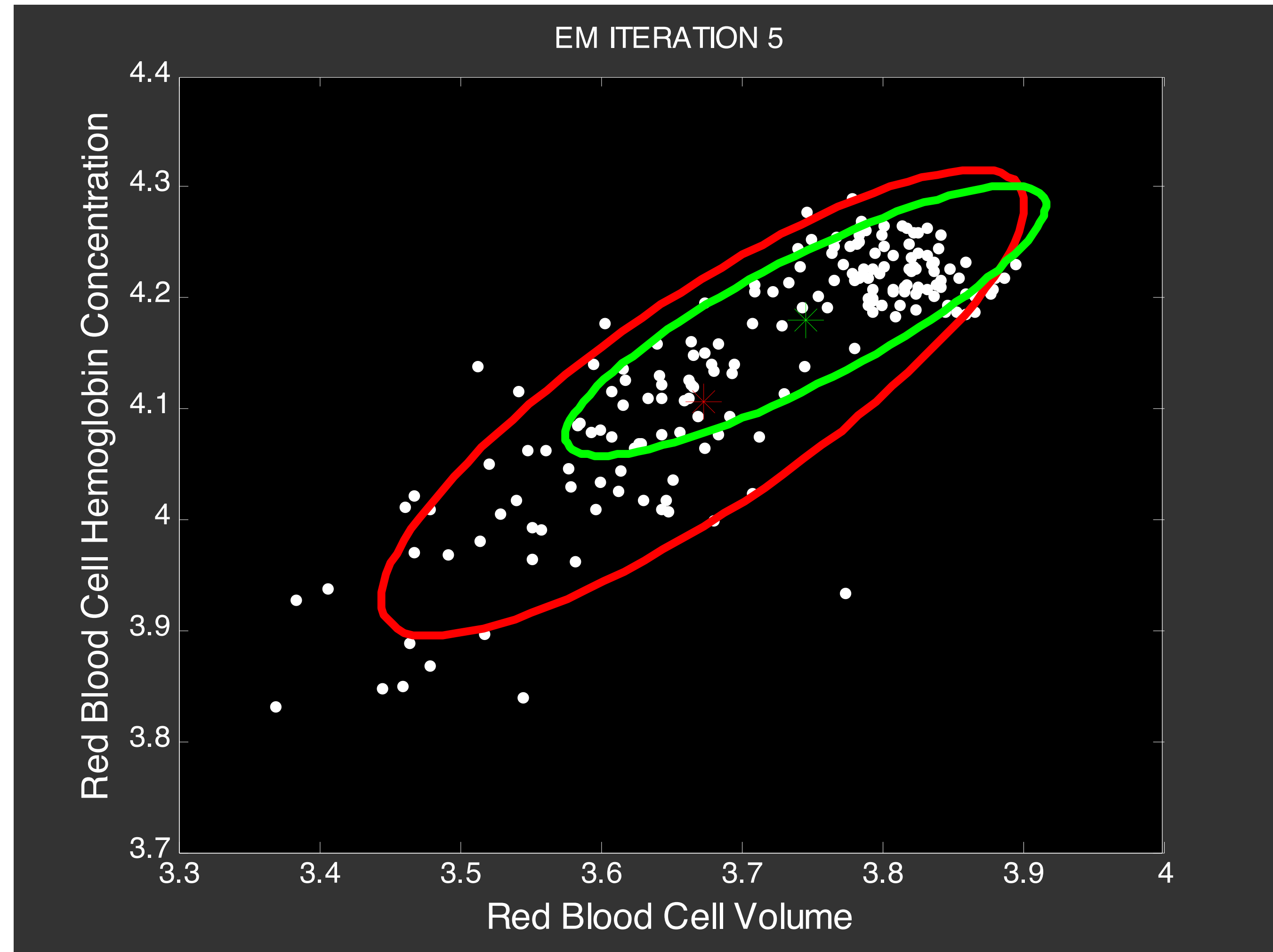
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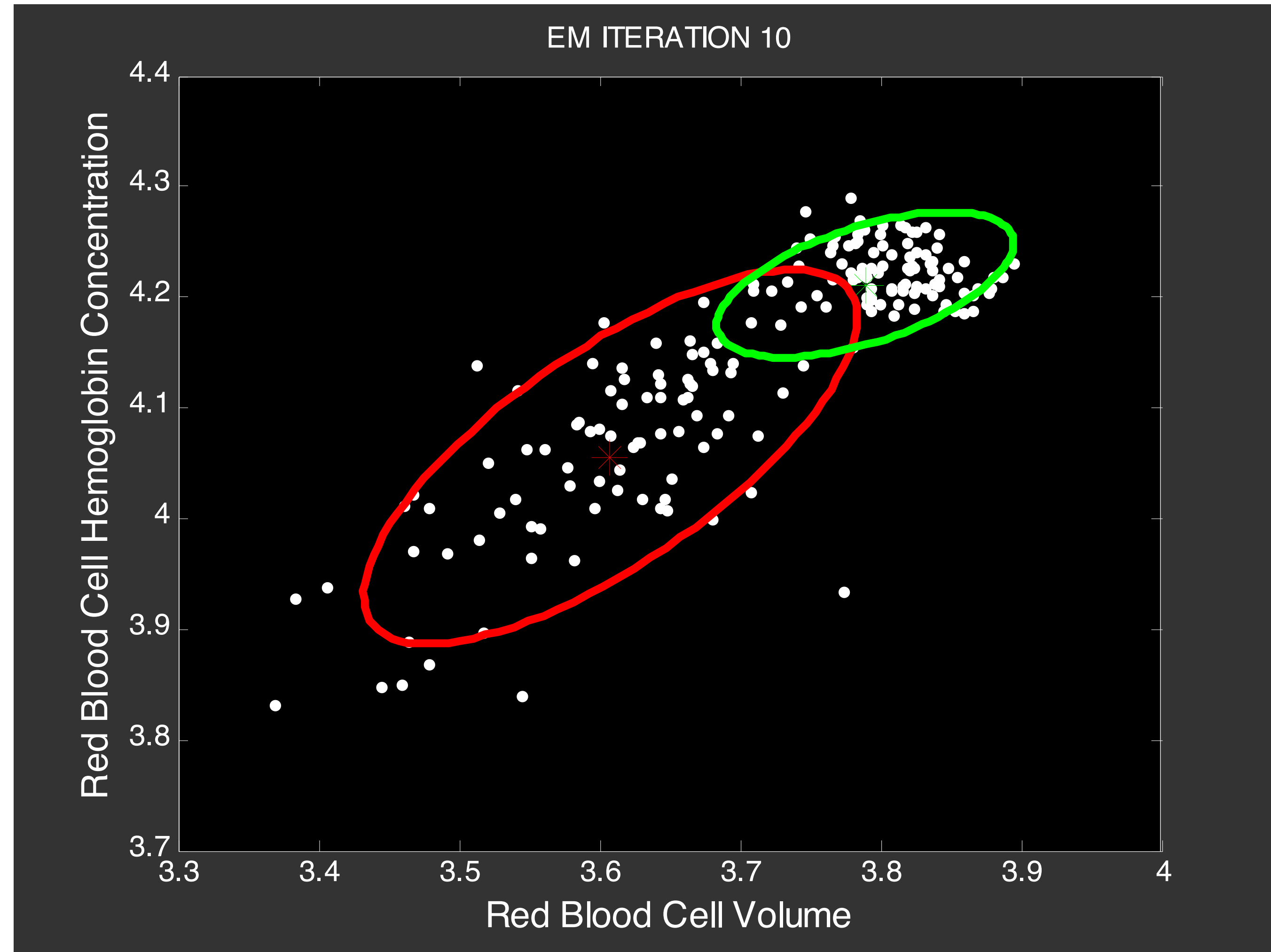
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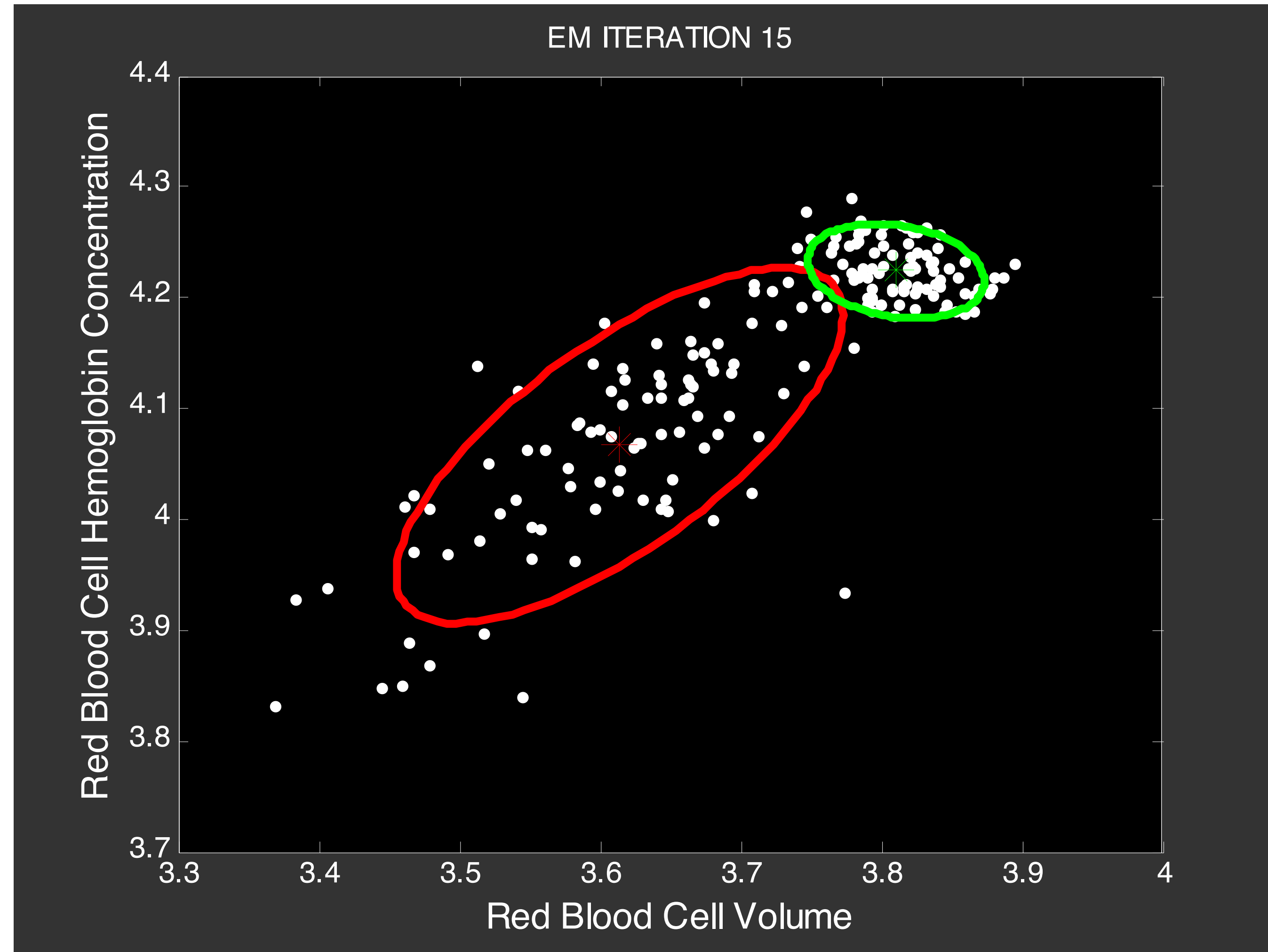
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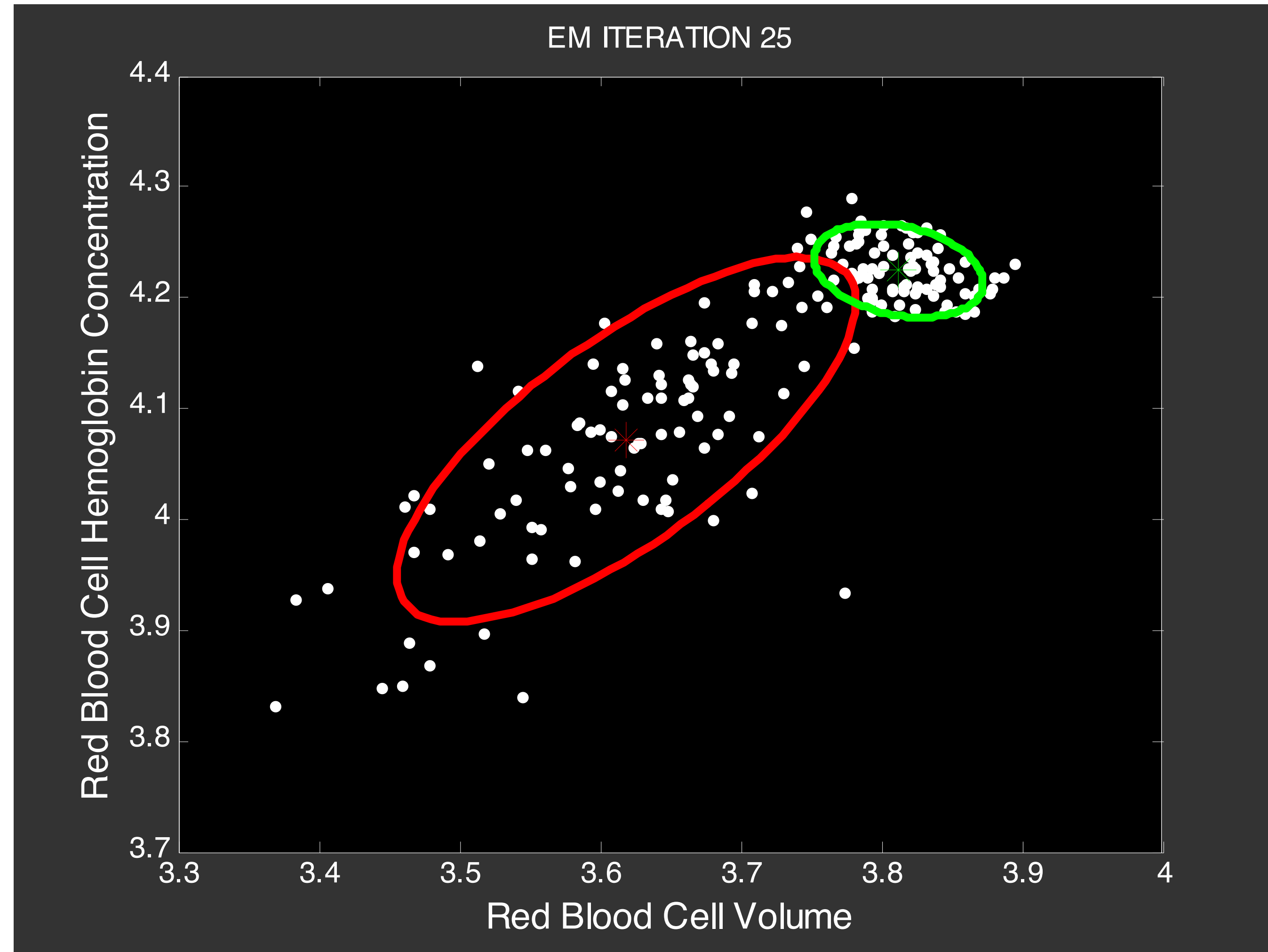
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EM Algorithm for GMM



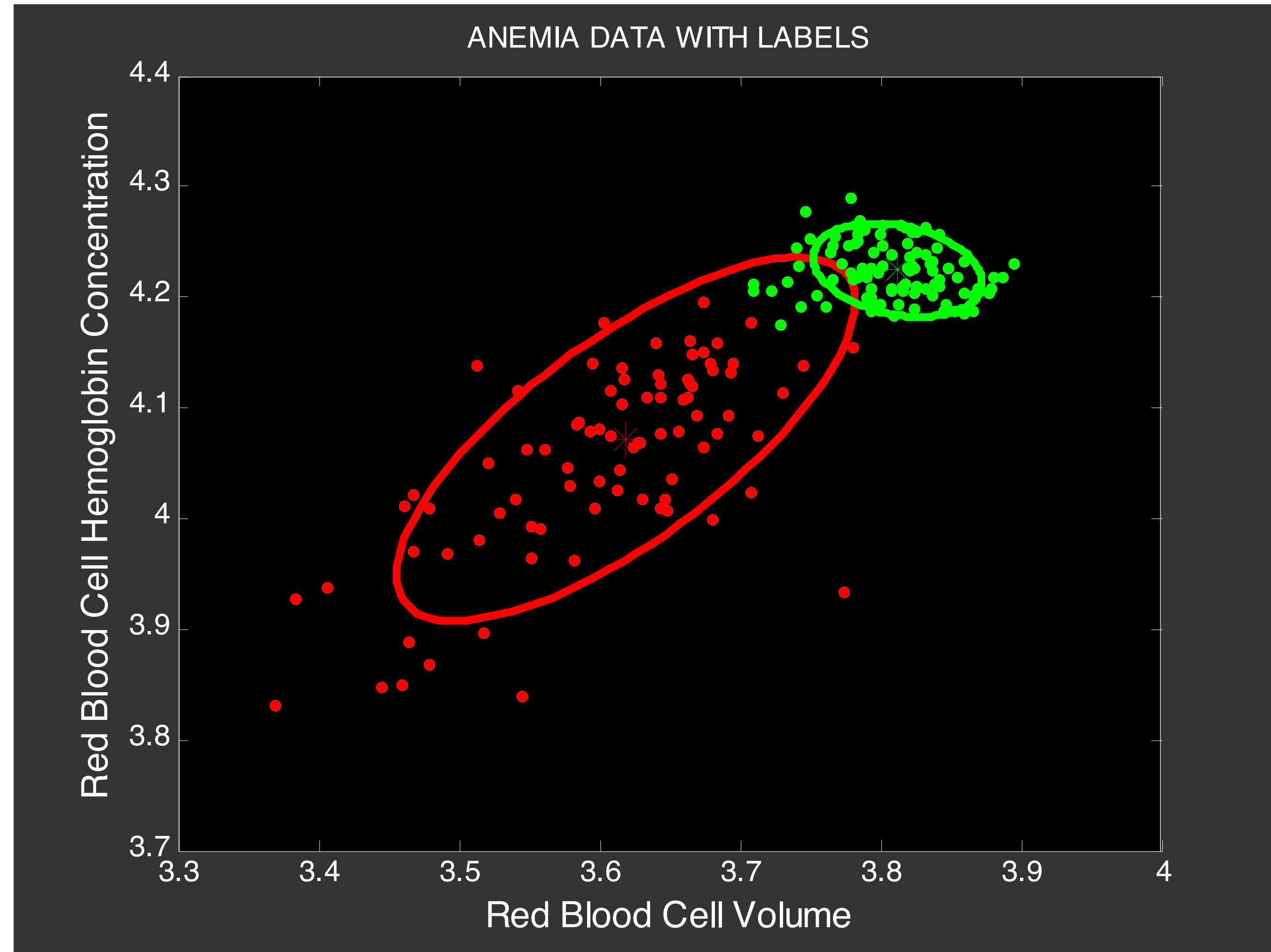
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EM Algorithm for GMM



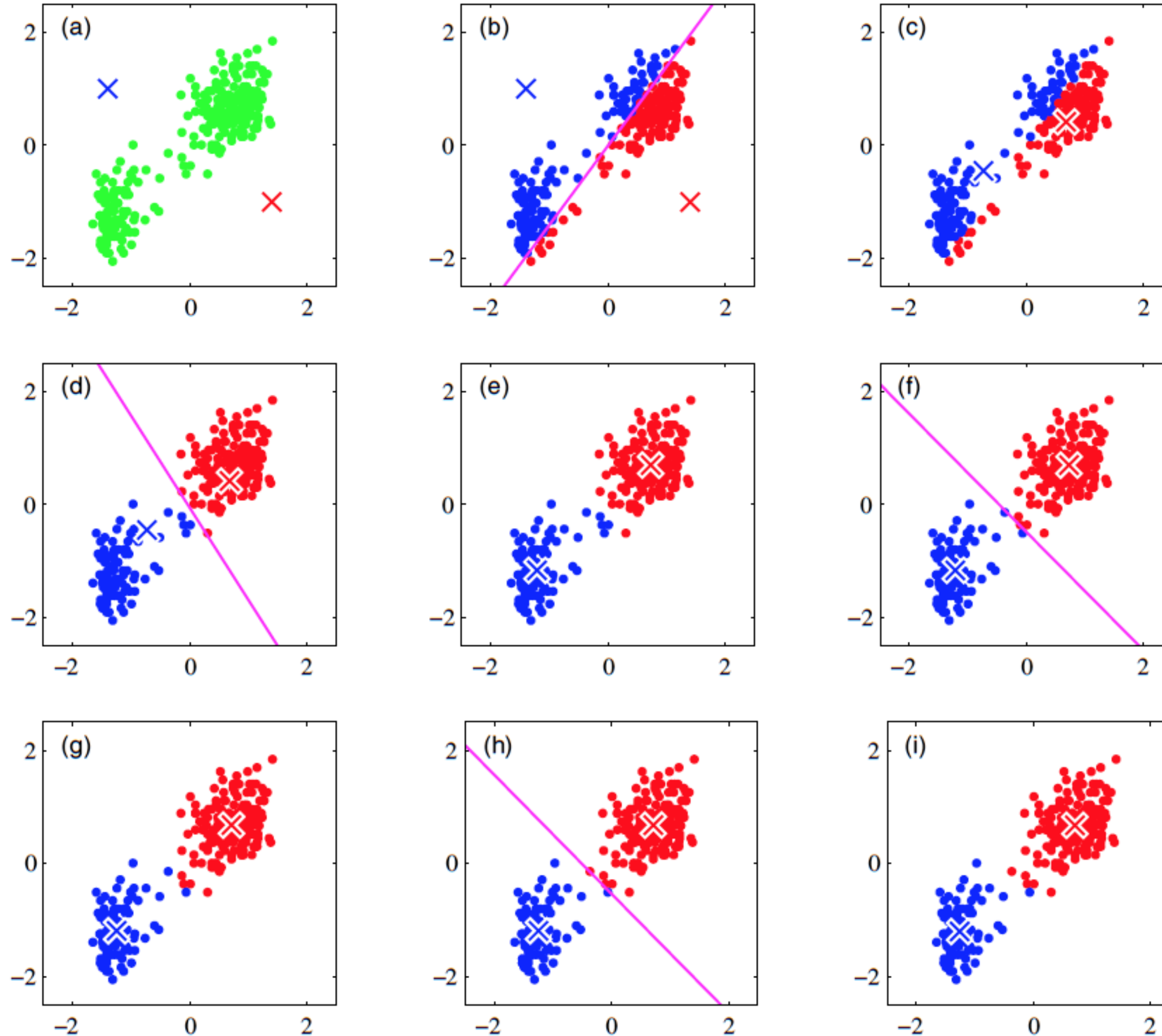
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EM Algorithm for GMM



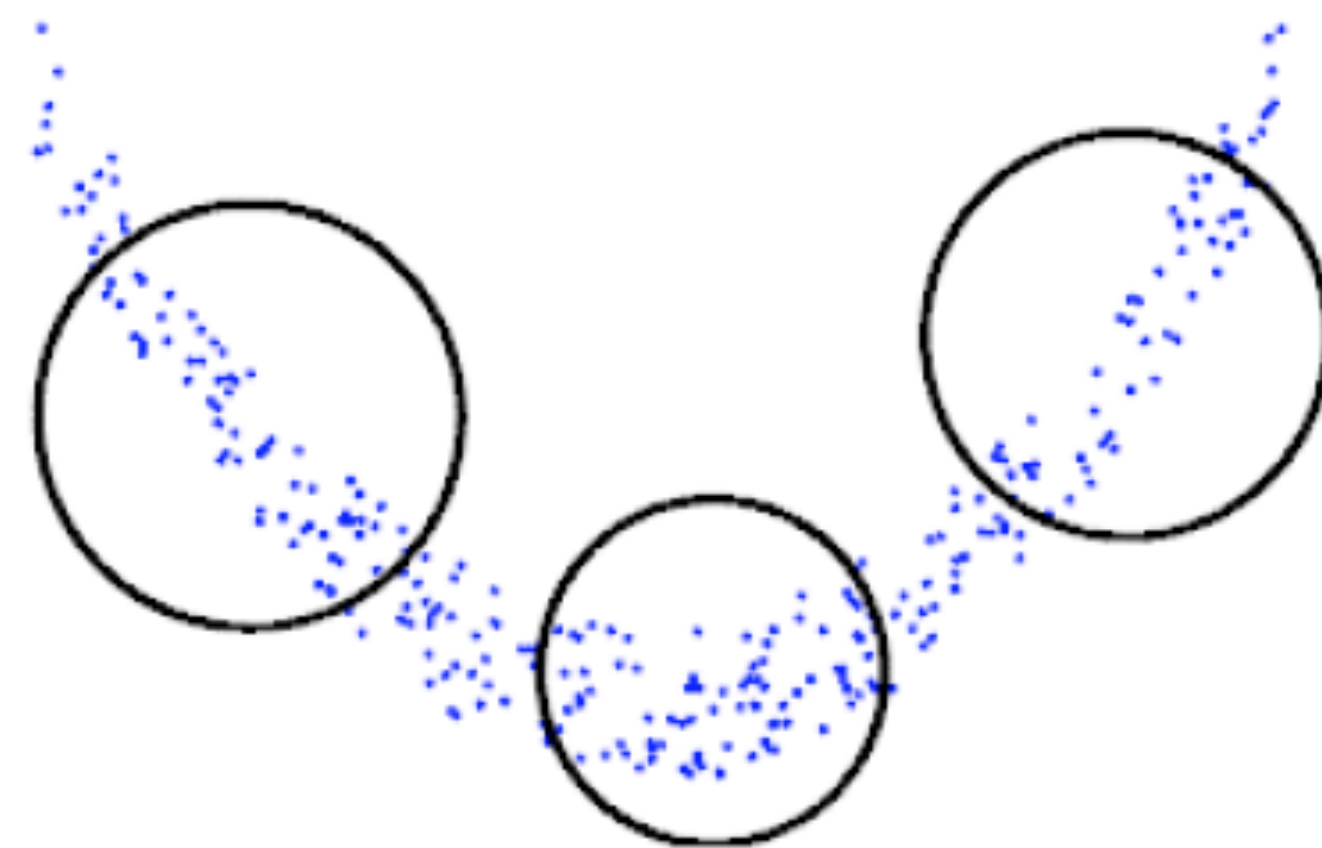
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K-means Algorithm for Initialization



Other Considerations

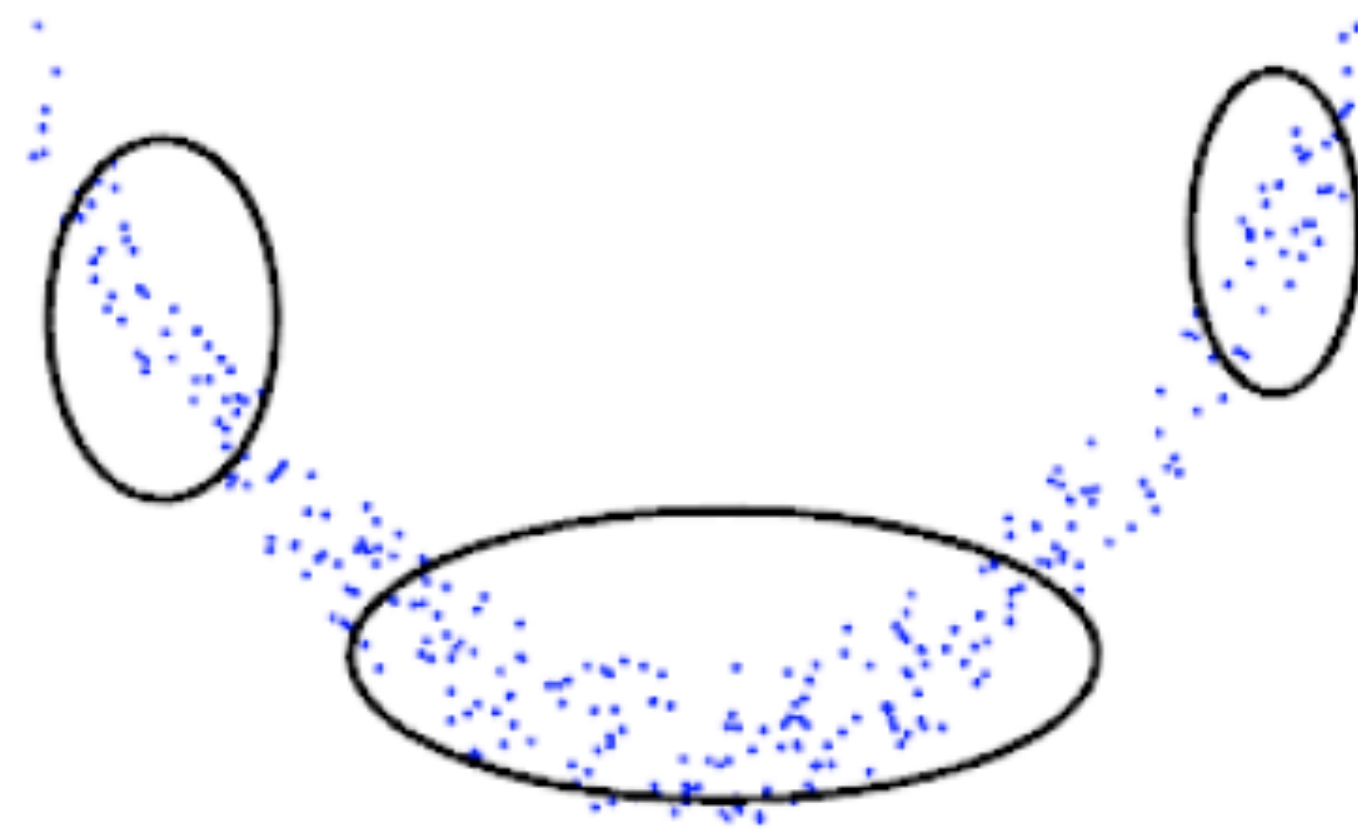
- Initialization - random or k-means
- Number of Gaussians
- Type of Covariance matrix
- Spherical covariance



- Less precise.
- Very efficient to compute.

Other Considerations

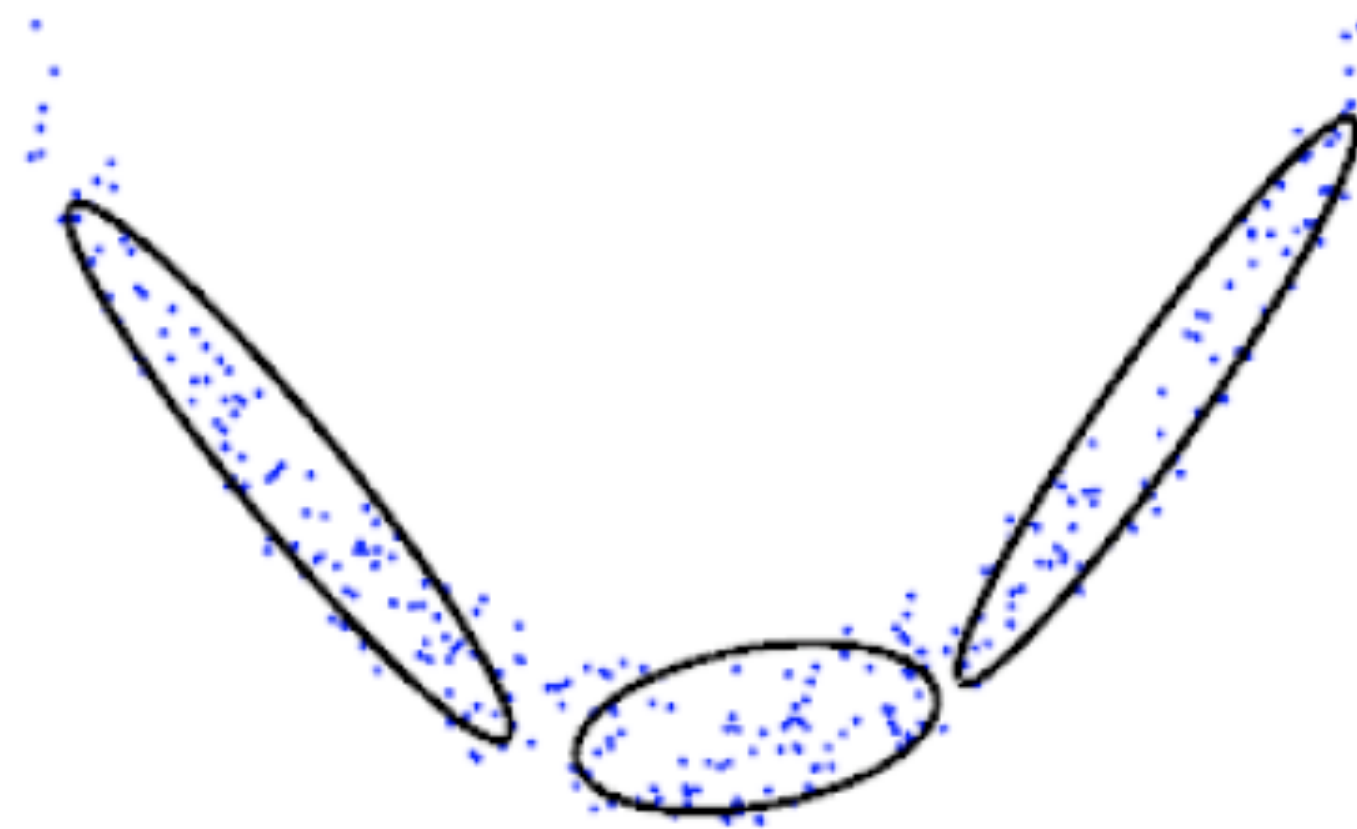
- Initialization - random or k-means
- Number of Gaussians
- Type of Covariance matrix
- Diagonal covariance



**-More precise.
-Efficient to compute.**

Other Considerations

- Initialization - random or k-means
- Number of Gaussians
- Type of Covariance matrix
- Full covariance



- Very precise.
- Less efficient to compute.

THANK YOU

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