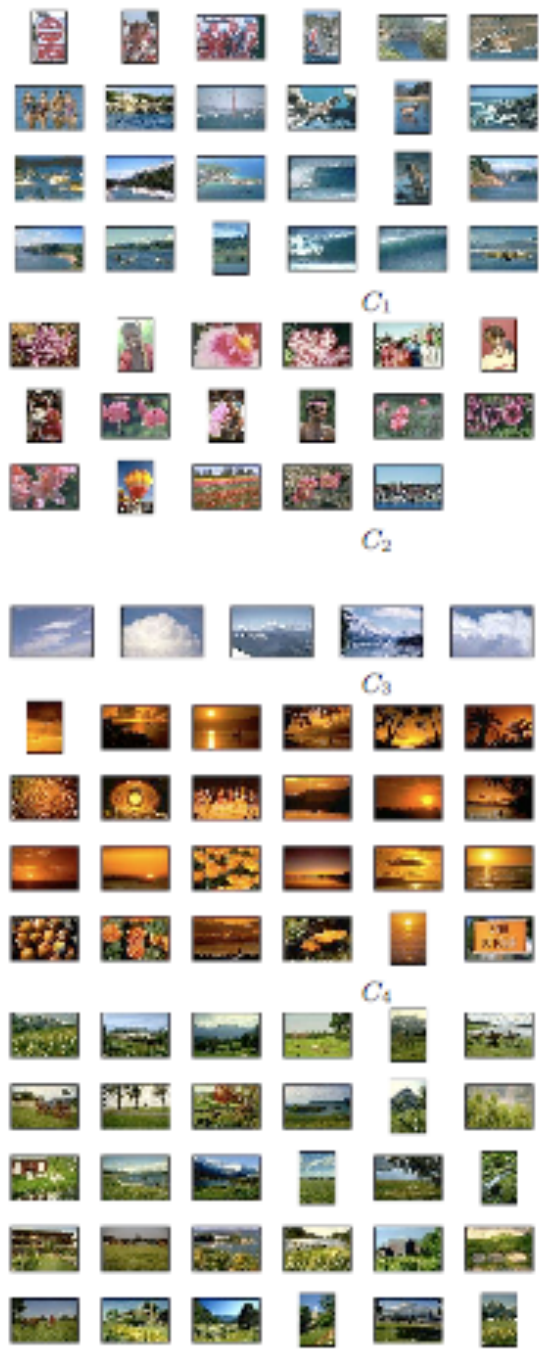
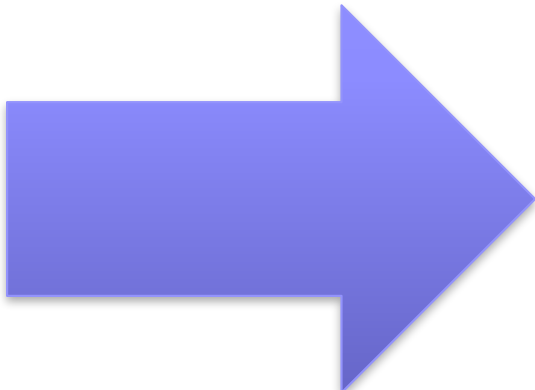


Clustering K-means



Clustering images



[Goldberger et al.]

Clustering web search results

web news images wikipedia blogs jobs more »

Clusty

race Search advanced preferences

clusters sources sites remix

All Results (238)




- Car (28)
- Race cars (7)
- Photos, Races Scheduled (5)
- Game (4)
- Track (3)
- Nascar (2)
- Equipment And Safety (2)
- Other Topics (7)
- Photos (22)
- Game (14)
- Definition (13)
- Team (18)
- Human (8)
 - Classification Of Human (2)
 - Statement, Evolved (2)
 - Other Topics (4)
- Weekend (8)
- Ethnicity And Race (7)
- Race for the Cure (8)
- Race Information (8)




[more](#) | [all clusters](#)




find in clusters: Find




Cluster **Human** contains **8** documents.




Search Results




- [Race \(classification of human beings\) - Wikipedia, the free ...](#)   




The term **race** or racial group usually refers to the concept of dividing **humans** into populations or groups on the basis of various sets of characteristics. The most widely used **human** racial categories are based on visible traits (especially skin color, cranial or facial features and hair texture), and self-identification. Conceptions of **race**, as well as specific ways of grouping **rac**es, vary by culture and over time, and are often controversial for scientific as well as social and political reasons. History · Modern debates · Political and ...
[en.wikipedia.org/wiki/Race_\(classification_of_human_beings\)](http://en.wikipedia.org/wiki/Race_(classification_of_human_beings)) - [cache] - Live, Ask
- [Race - Wikipedia, the free encyclopedia](#)   

General. **Racing** competitions The **Race** (yachting **race**), or La course du millénaire, a no-rules round-the-world sailing event; **Race** (biology), classification of flora and fauna; **Race** (classification of human beings) **Race** and ethnicity in the United States Census, official definitions of "**race**" used by the US Census Bureau; **Race** and genetics, notion of racial classifications based on genetics. Historical definitions of **race**; **Race** (bearing), the inner and outer rings of a rolling-element bearing. **RACE** in molecular biology "Rapid ... General · Surnames · Television · Music · Literature · Video games
en.wikipedia.org/wiki/Race - [cache] - Live, Ask
- [Publications | Human Rights Watch](#)   

The use of torture, unlawful rendition, secret prisons, unfair trials, ... Risks to Migrants, Refugees, and Asylum Seekers in Egypt and Israel ... In the run-up to the Beijing Olympics in August 2008, ...
www.hrw.org/background/usa/race - [cache] - Ask
- [Amazon.com: Race: The Reality Of Human Differences: Vincent Sarich ...](#)   

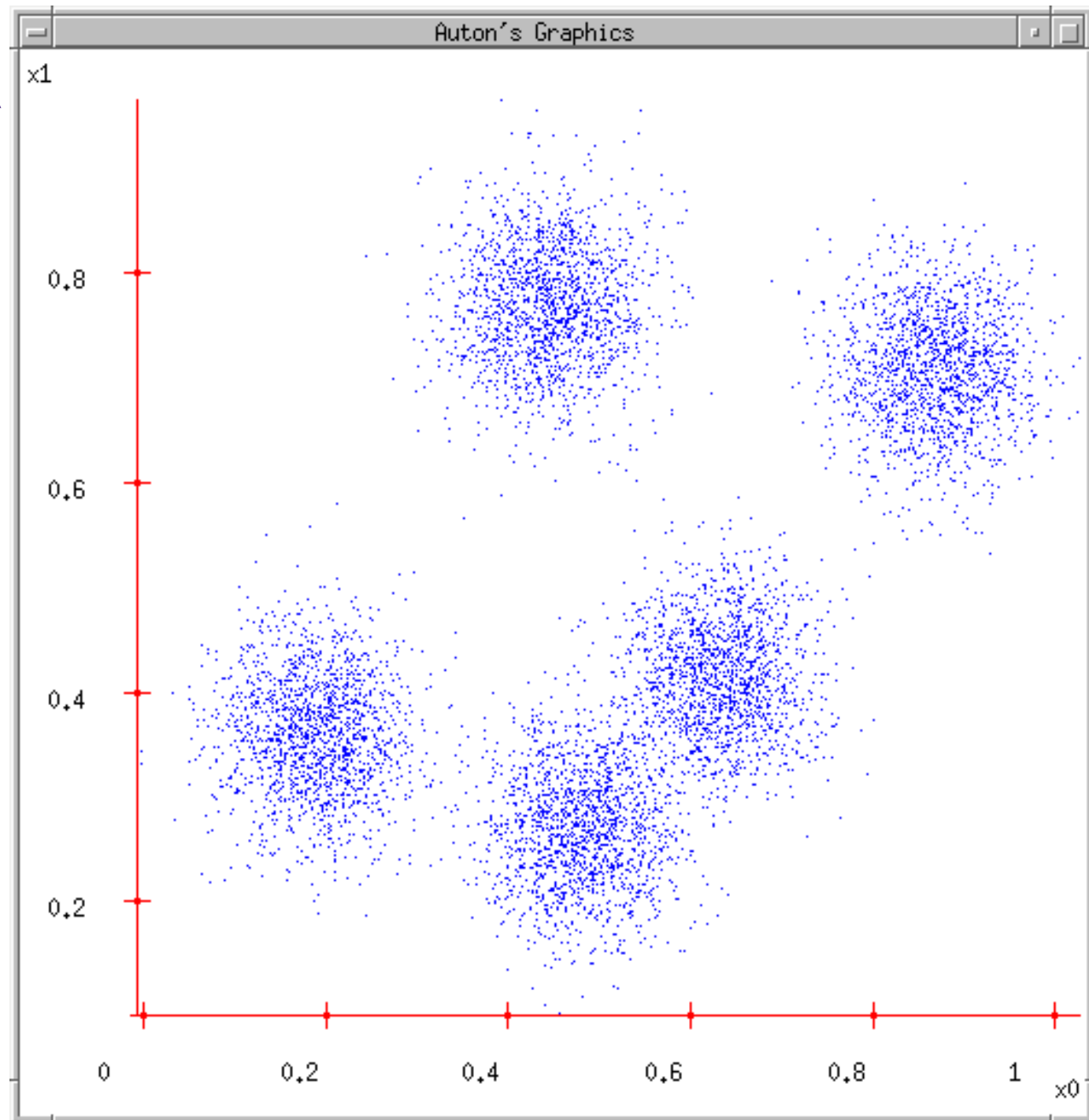
Amazon.com: **Race: The Reality Of Human Differences: Vincent Sarich, Frank Miele: Books ...** From Publishers Weekly Sarich, a Berkeley emeritus anthropologist, and Miele, an editor ...
www.amazon.com/Race-Reality-Differences-Vincent-Sarich/dp/0813340861 - [cache] - Live
- [AAPA Statement on Biological Aspects of Race](#)   

AAPA Statement on Biological Aspects of **Race** ... Published in the American Journal of Physical Anthropology, vol. 101, pp 569-570, 1996 ... PREAMBLE As scientists who study **human** evolution and variation, ...
www.physanth.org/positions/race.html - [cache] - Ask
- [race: Definition from Answers.com](#)   

race n. A local geographic or global **human** population distinguished as a more or less distinct group by genetically transmitted physical
www.answers.com/topic/race-1 - [cache] - Live
- [Dopefish.com](#)   

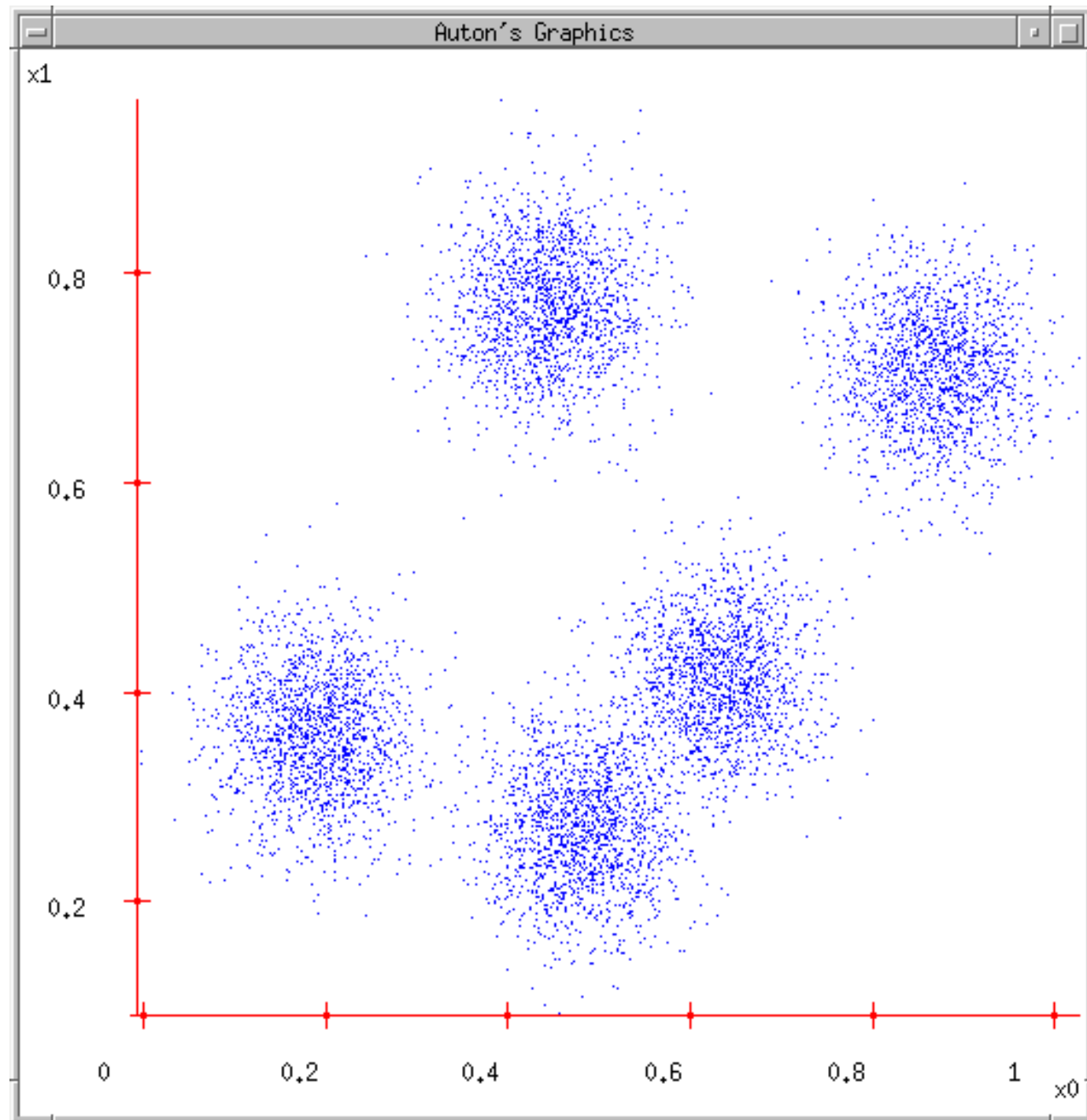
Site for newbies as well as experienced Dopefish followers, chronicling the birth of the Dopefish, its numerous appearances in several computer games, and its eventual take-over of the **human race**. Maintained by Mr. Dopefish himself, Joe Siegler of Apogee Software.
www.dopefish.com - [cache] - Open Directory

Some Data



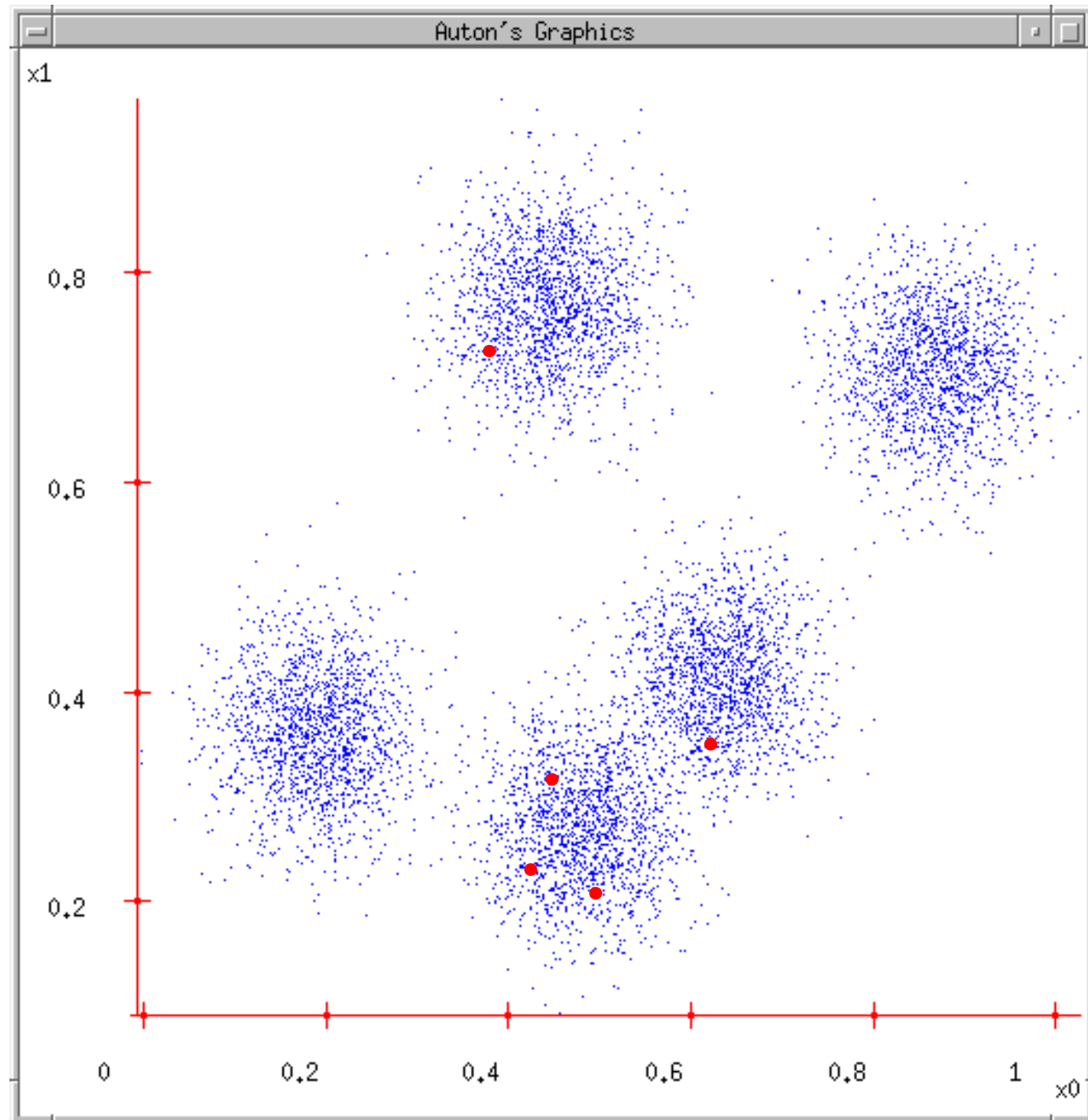
K-means

1. Ask user how many clusters they'd like.
(e.g. $k=5$)



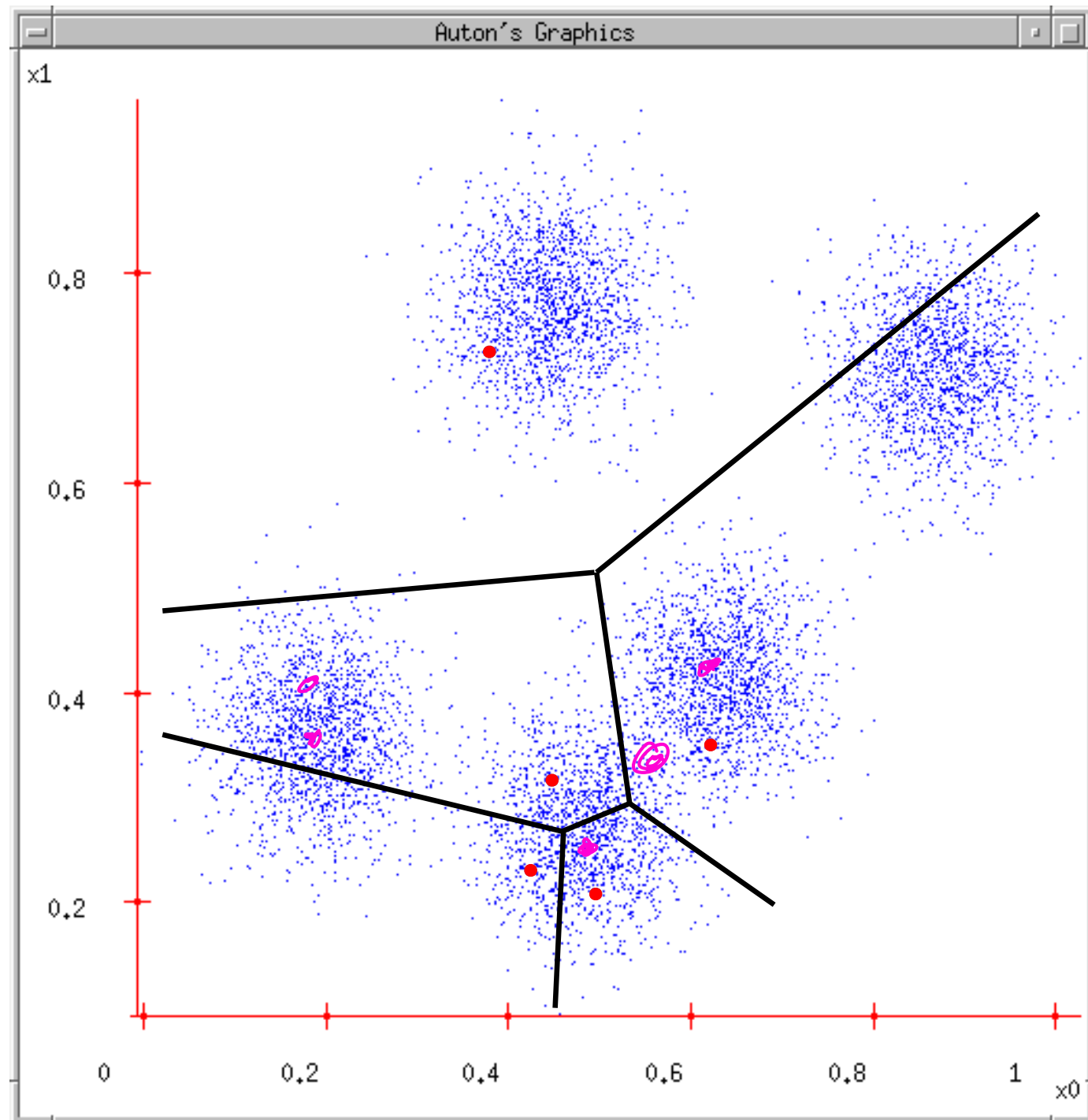
K-means

1. Ask user how many clusters they'd like.
(e.g. $k=5$)
2. Randomly guess k cluster Center locations



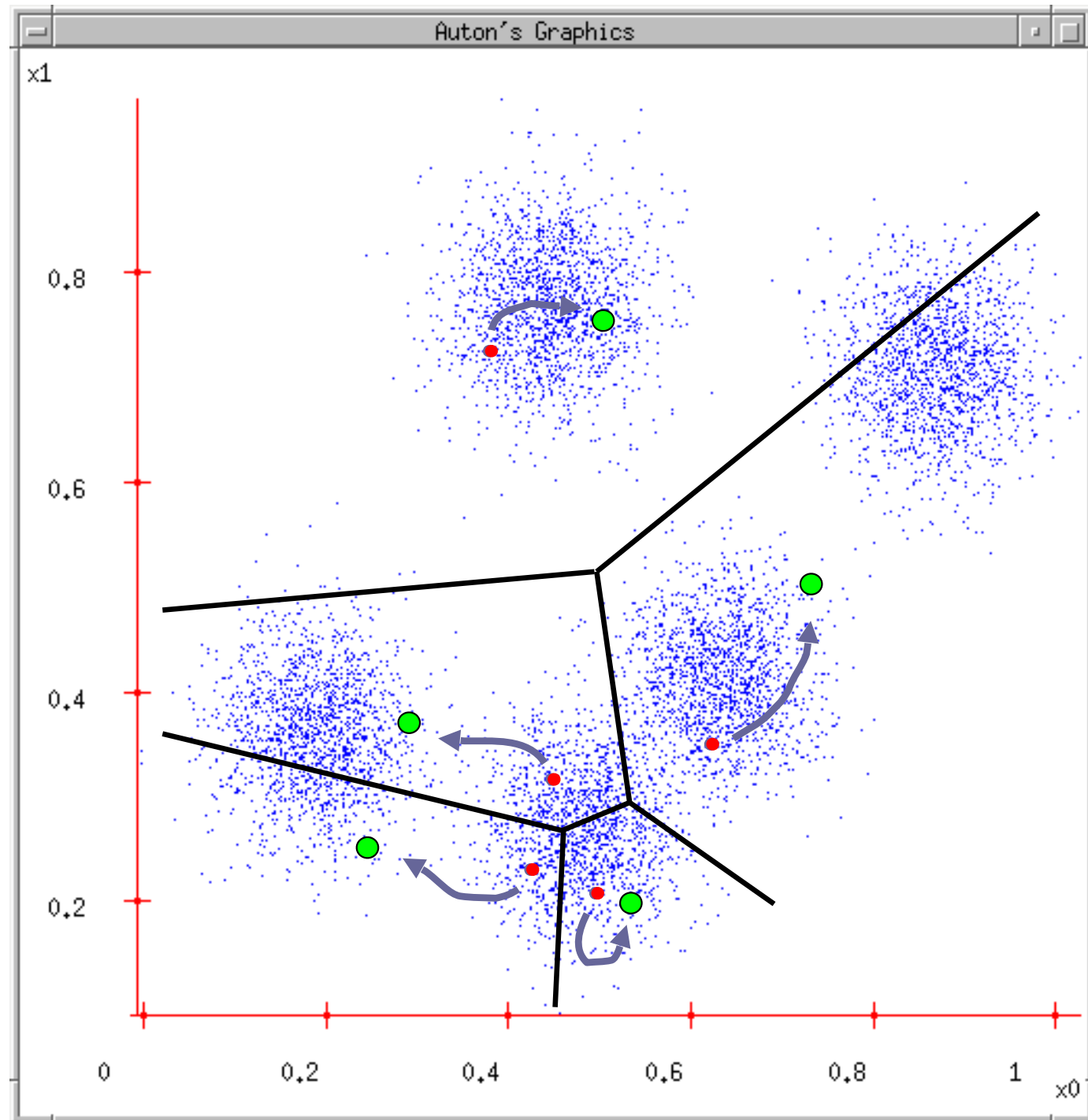
K-means

1. Ask user how many clusters they'd like.
(e.g. $k=5$)
2. Randomly guess k cluster Center locations
3. Each datapoint finds out which Center it's closest to. (Thus each Center "owns" a set of datapoints)



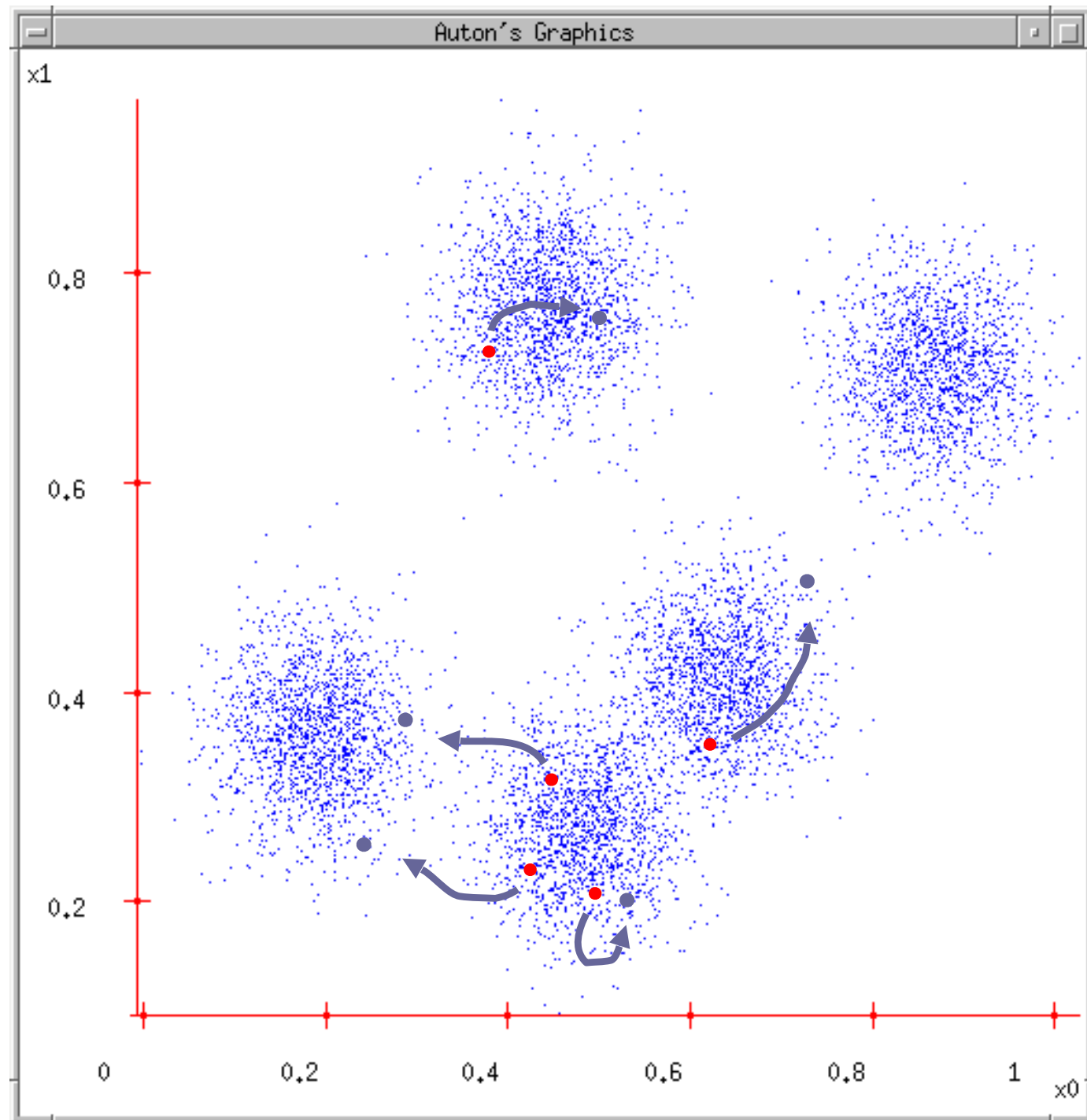
K-means

1. Ask user how many clusters they'd like.
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4. Each Center finds the centroid of the points it owns



K-means

1. Ask user how many clusters they'd like.
(e.g. $k=5$)
2. Randomly guess k cluster Center locations
3. Each datapoint finds out which Center it's closest to.
4. Each Center finds the centroid of the points it owns...
5. ...and jumps there
6. ...Repeat until terminated!



K-means

- Randomly initialize k centers

- $\mu^{(0)} = \mu_1^{(0)}, \dots, \mu_k^{(0)}$

k-means ++

- Classify: Assign each point $j \in \{1, \dots, N\}$ to nearest center:

- $C^{(t)}(j) \leftarrow \arg \min_i \|\mu_i - x_j\|^2$

- Recenter: μ_i becomes centroid of its point:

- $\mu_i^{(t+1)} \leftarrow \arg \min_{\mu} \sum_{j:C(j)=i} \|\mu - x_j\|^2$

Does K-means converge???

Part 1

- Optimize potential function:

$$\min_{\mu} \min_C F(\mu, C) = \min_{\mu} \min_C \sum_{i=1}^k \sum_{j:C(j)=i} \|\mu_i - x_j\|^2$$

- Fix μ , optimize C

Does K-means converge???

Part 2

- Optimize potential function:

$$\min_{\mu} \min_C F(\mu, C) = \min_{\mu} \min_C \sum_{i=1}^k \sum_{j:C(j)=i} \|\mu_i - x_j\|^2$$

- Fix C, optimize μ

Vector Quantization, Fisher Vectors

Vector Quantization (for compression)

1. Represent image as grid of patches
2. Run k-means on the patches to build code book
3. Represent each patch as a code word.



FIGURE 14.9. *Sir Ronald A. Fisher (1890 – 1962) was one of the founders of modern day statistics, to whom we owe maximum-likelihood, sufficiency, and many other fundamental concepts. The image on the left is a 1024×1024 grayscale image at 8 bits per pixel. The center image is the result of 2×2 block VQ, using 200 code vectors, with a compression rate of 1.9 bits/pixel. The right image uses only four code vectors, with a compression rate of 0.50 bits/pixel*

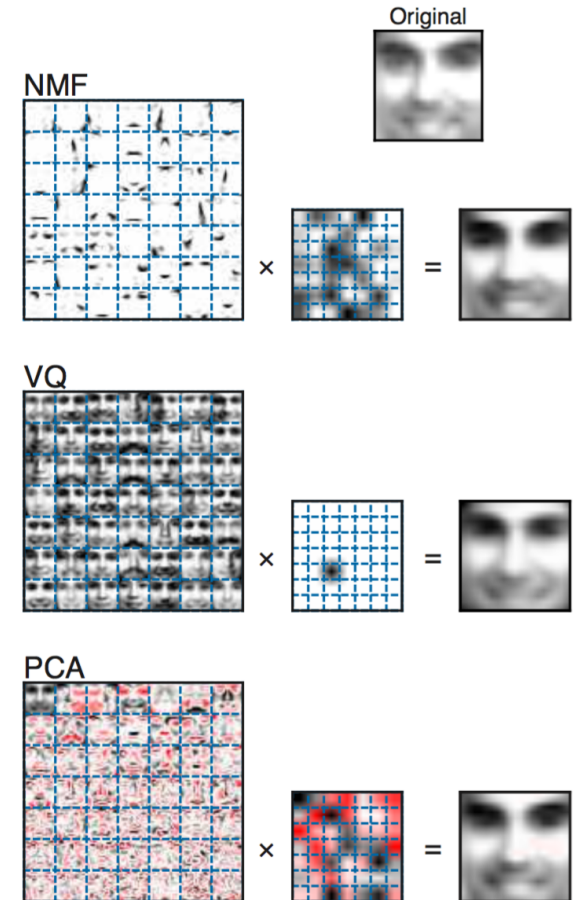
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Vector Quantization, Fisher Vectors

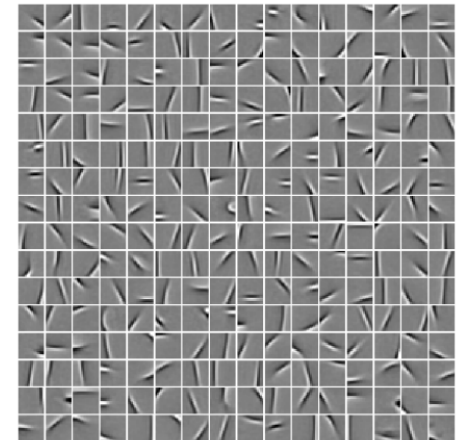
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Typical output of
on patches



Similar reduced representation can be used as a feature vector

Coates, Ng, *Learning Feature Representations with K-means*, 2012

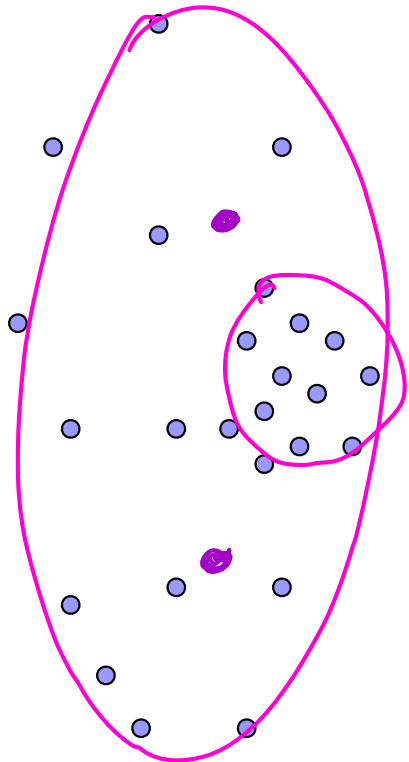
Mixtures of Gaussians

(One) bad case for k-means

$$\Sigma = \sum_{i=1}^d v_i v_i^T \lambda_i$$

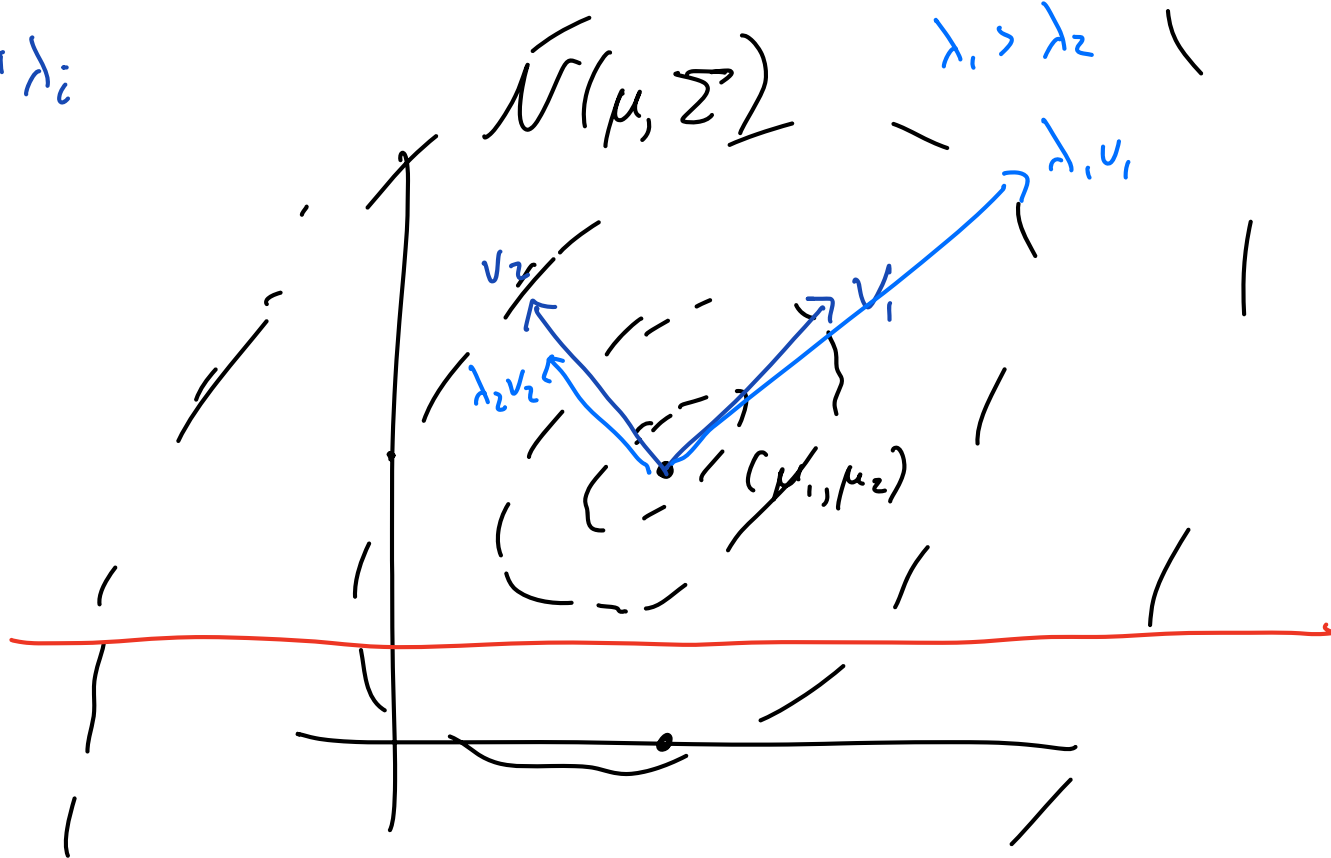
$$\Sigma = \mathbb{E}[(X-\mu)(X-\mu)^T]$$

$X \sim \mathcal{N}(\mu, \Sigma)$



$$x^T \Sigma x = \mathbb{E}[x^T (X-\mu)(X-\mu)^T x]$$

$$\approx \mathbb{E}[|x^T (X-\mu)|^2] \geq 0 \Rightarrow \Sigma \text{ is positive semi-definite.}$$



For matrix A
 $A^{1/2} = B$
 $B \cdot B = A$

$$X \sim \mathcal{N}(\mu, \Sigma)$$

$$Z \sim \mathcal{N}(0, I)$$

$$X' = \mu + \Sigma^{1/2} Z$$

$$\mathbb{E}[X'] = \mu$$

$$\begin{aligned} \mathbb{E}[(X' - \mu)(X' - \mu)^T] &= \mathbb{E}[\Sigma^{1/2} Z Z^T (\Sigma^{1/2})^T] = \Sigma^{1/2} \cdot \Sigma^{1/2} \\ &= \Sigma \end{aligned}$$

$$[Z Z^T]_{i,j} = z_i z_j$$

$$\mathbb{E}[Z Z^T] = I$$

$$\begin{aligned} \Sigma &= V \Lambda V^T \\ &= \sum_i v_i v_i^T \lambda_i \end{aligned}$$

$$\Sigma^{1/2} = \sum_i v_i v_i^T \sqrt{\lambda_i}$$

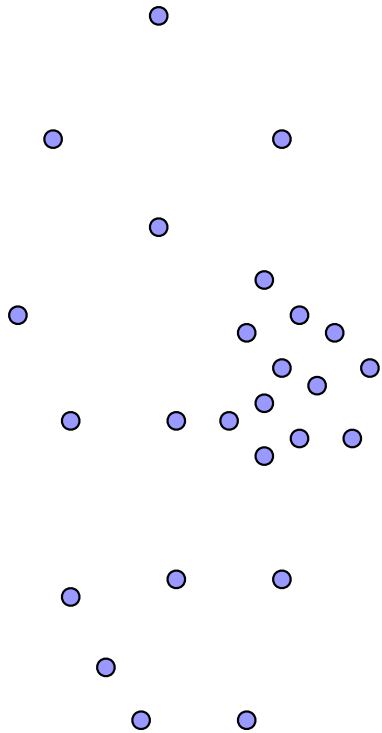
$$\Sigma^{1/2} \cdot \Sigma^{1/2} = \sum_i v_i v_i^T \lambda_i$$

$$v_i^T v_j = \begin{cases} 1 & \text{if } i=j \\ 0 & \text{o.w.} \end{cases}$$

$$\Rightarrow X' = X \quad \square$$

(One) bad case for k-means

- Clusters may overlap
- Some clusters may be “wider” than others



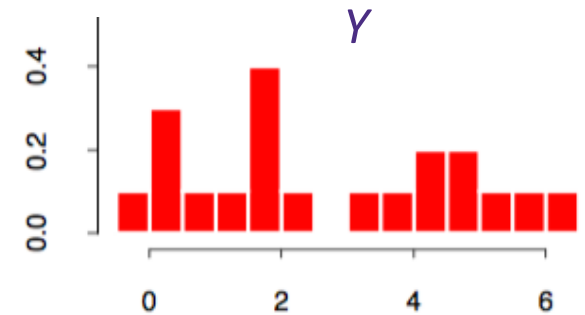
Mixture models

$$Y_1 \sim N(\mu_1, \sigma_1^2),$$

$$Y_2 \sim N(\mu_2, \sigma_2^2),$$

$$Y = (1 - \Delta) \cdot Y_1 + \Delta \cdot Y_2,$$

$$\Delta \in \{0, 1\} \text{ with } \Pr(\Delta = 1) = \pi$$



$\mathbf{Z} = \{y_i\}_{i=1}^n$ is observed data

If $\phi_\theta(x)$ is Gaussian density with parameters $\theta = (\mu, \sigma^2)$ then

$$\ell(\theta; \mathbf{Z}) = \sum_{i=1}^n \log[(1 - \pi)\phi_{\theta_1}(y_i) + \pi\phi_{\theta_2}(y_i)]$$

Mixture models

$$Y_1 \sim N(\mu_1, \sigma_1^2),$$

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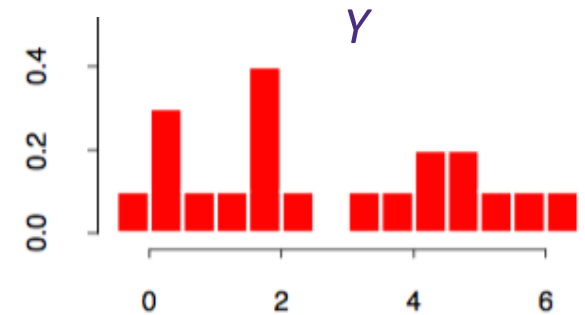
$$\Delta \in \{0, 1\} \text{ with } \Pr(\Delta = 1) = \pi$$

$$\theta = (\pi, \theta_1, \theta_2) = (\pi, \mu_1, \sigma_1^2, \mu_2, \sigma_2^2)$$

If $\phi_\theta(x)$ is Gaussian density with parameters $\theta = (\mu, \sigma^2)$ then

$$\ell(\theta; y_i, \Delta_i = 0) =$$

$$\ell(\theta; y_i, \Delta_i = 1) =$$



$\mathbf{Z} = \{y_i\}_{i=1}^n$ is observed data

$\mathbf{\Delta} = \{\Delta_i\}_{i=1}^n$ is unobserved data

Mixture models

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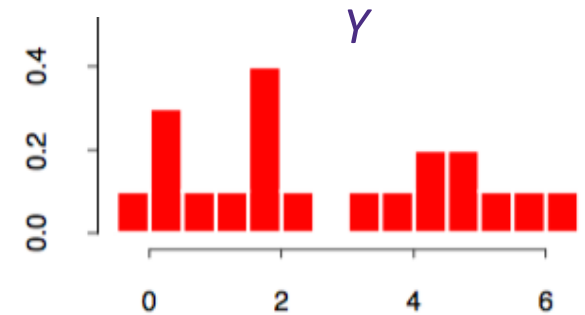
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If $\phi_\theta(x)$ is Gaussian density with parameters $\theta = (\mu, \sigma^2)$ then

$$\ell(\theta; \mathbf{Z}, \mathbf{\Delta}) = \sum_{i=1}^n (1 - \Delta_i) \log[(1 - \pi)\phi_{\theta_1}(y_i)] + \Delta_i \log(\pi\phi_{\theta_2}(y_i))$$

If we knew $\mathbf{\Delta}$, how would we choose θ ?



$\mathbf{Z} = \{y_i\}_{i=1}^n$ is observed data

$\mathbf{\Delta} = \{\Delta_i\}_{i=1}^n$ is unobserved data

Mixture models

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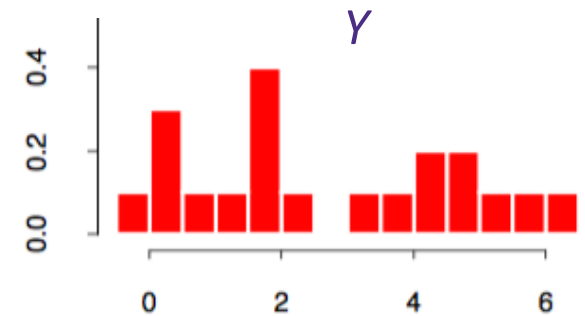
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If we knew θ , how would we choose $\mathbf{\Delta}$?



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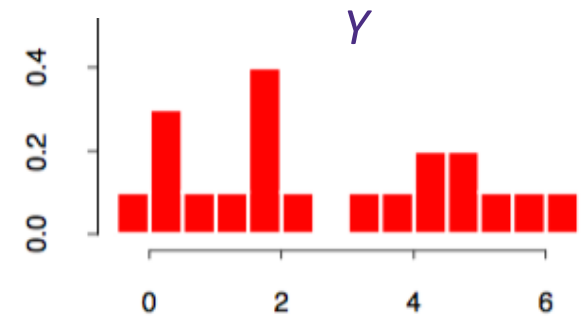
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If $\phi_\theta(x)$ is Gaussian density with parameters $\theta = (\mu, \sigma^2)$ then

$$\ell(\theta; \mathbf{Z}, \mathbf{\Delta}) = \sum_{i=1}^n (1 - \Delta_i) \log[(1 - \pi)\phi_{\theta_1}(y_i)] + \Delta_i \log(\pi\phi_{\theta_2}(y_i))$$

$$\gamma_i(\theta) = \mathbb{E}[\Delta_i | \theta, \mathbf{Z}] =$$



$\mathbf{Z} = \{y_i\}_{i=1}^n$ is observed data

$\mathbf{\Delta} = \{\Delta_i\}_{i=1}^n$ is unobserved data

Mixture models

Algorithm 8.1 *EM Algorithm for Two-component Gaussian Mixture.*

1. Take initial guesses for the parameters $\hat{\mu}_1, \hat{\sigma}_1^2, \hat{\mu}_2, \hat{\sigma}_2^2, \hat{\pi}$ (see text).

2. *Expectation Step*: compute the responsibilities

$$\hat{\gamma}_i = \frac{\hat{\pi} \phi_{\hat{\theta}_2}(y_i)}{(1 - \hat{\pi}) \phi_{\hat{\theta}_1}(y_i) + \hat{\pi} \phi_{\hat{\theta}_2}(y_i)}, \quad i = 1, 2, \dots, N. \quad (8.42)$$

3. *Maximization Step*: compute the weighted means and variances:

$$\begin{aligned} \hat{\mu}_1 &= \frac{\sum_{i=1}^N (1 - \hat{\gamma}_i) y_i}{\sum_{i=1}^N (1 - \hat{\gamma}_i)}, & \hat{\sigma}_1^2 &= \frac{\sum_{i=1}^N (1 - \hat{\gamma}_i) (y_i - \hat{\mu}_1)^2}{\sum_{i=1}^N (1 - \hat{\gamma}_i)}, \\ \hat{\mu}_2 &= \frac{\sum_{i=1}^N \hat{\gamma}_i y_i}{\sum_{i=1}^N \hat{\gamma}_i}, & \hat{\sigma}_2^2 &= \frac{\sum_{i=1}^N \hat{\gamma}_i (y_i - \hat{\mu}_2)^2}{\sum_{i=1}^N \hat{\gamma}_i}, \end{aligned}$$

and the mixing probability $\hat{\pi} = \sum_{i=1}^N \hat{\gamma}_i / N$.

4. Iterate steps 2 and 3 until convergence.

