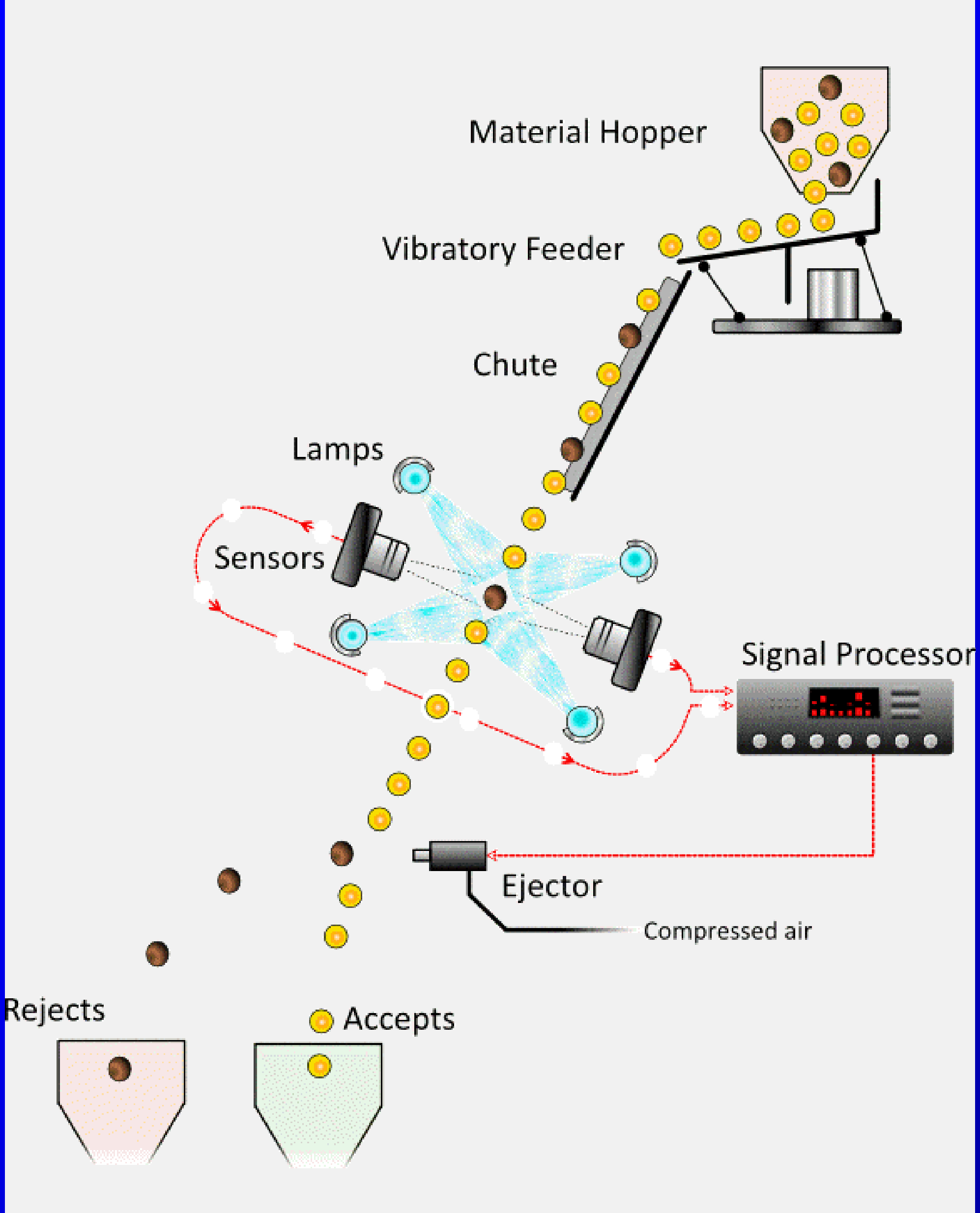
Seismic Attributes - from Interactive Interpretation to Machine Learning

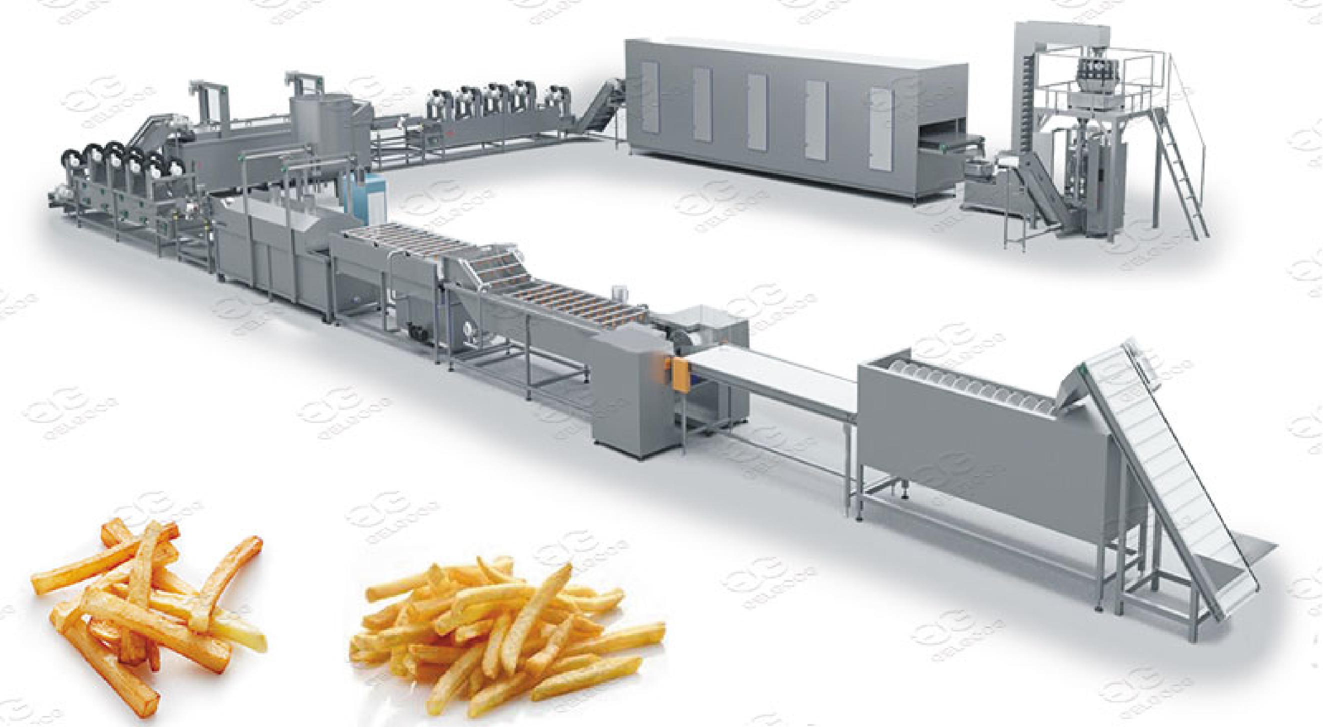
David Lubo-Robles and Kurt J. Marfurt

Machine Learning and Unsupervised Multiattribute Clustering

k-means

Examples of pattern recognition in manufacturing





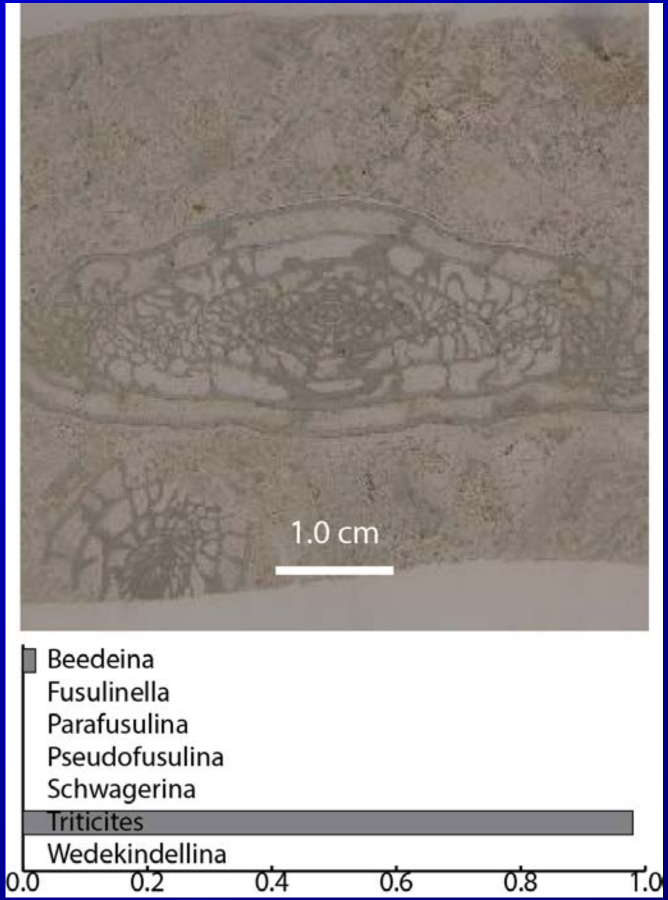
French fry production line
Step 1:
Is this a potato?
Or is this a rock shaped like a potato?

https://www.satake-europe.com/optical-sorting/principles-of-optical-sorting
https://www.snackfoodm.com/french-fries-production-line/

Machine learning:

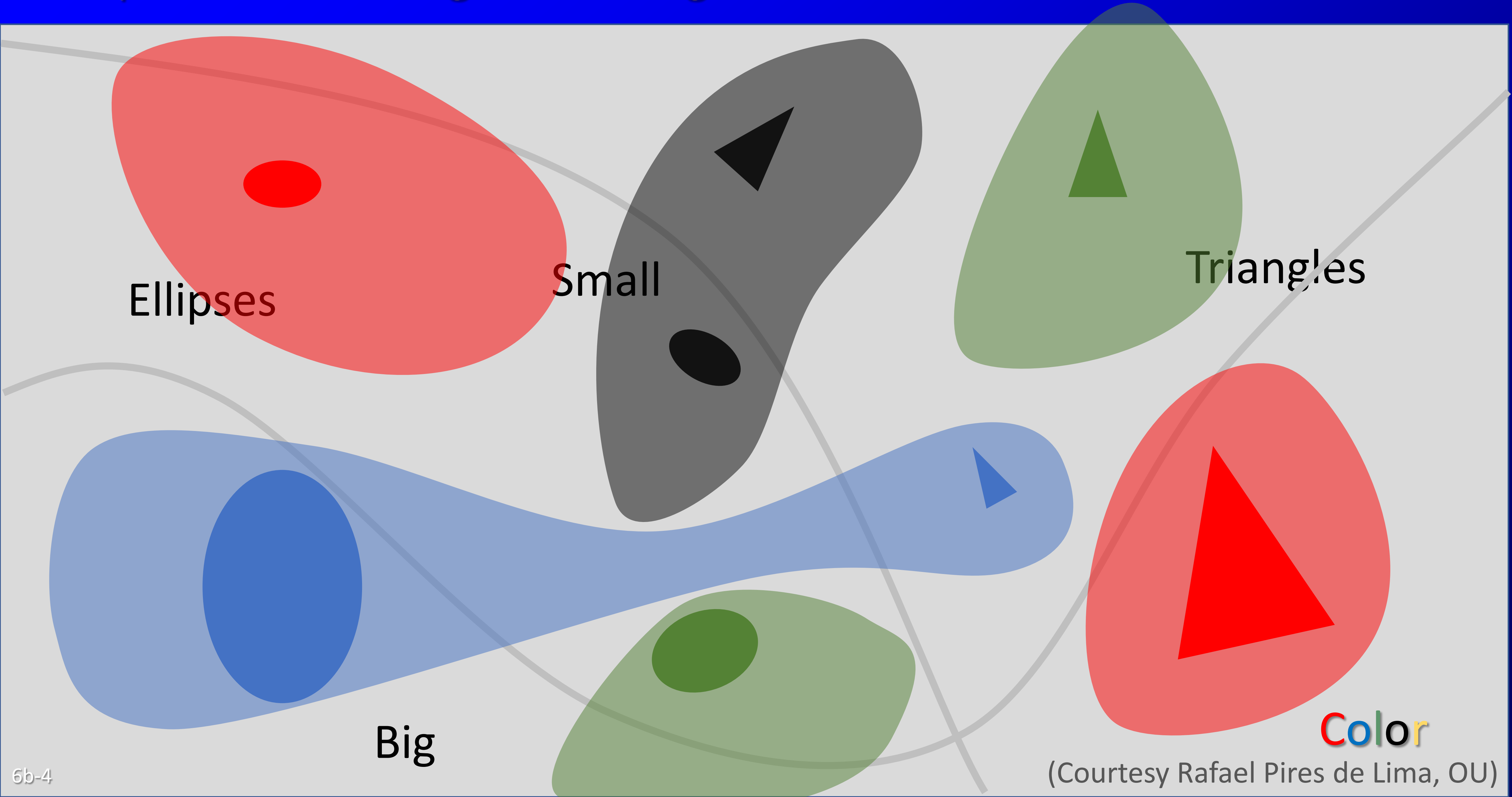
A computer algorithm that improves automatically through experience and performs tasks without explicit programming

Original algorithm program to classify living animals



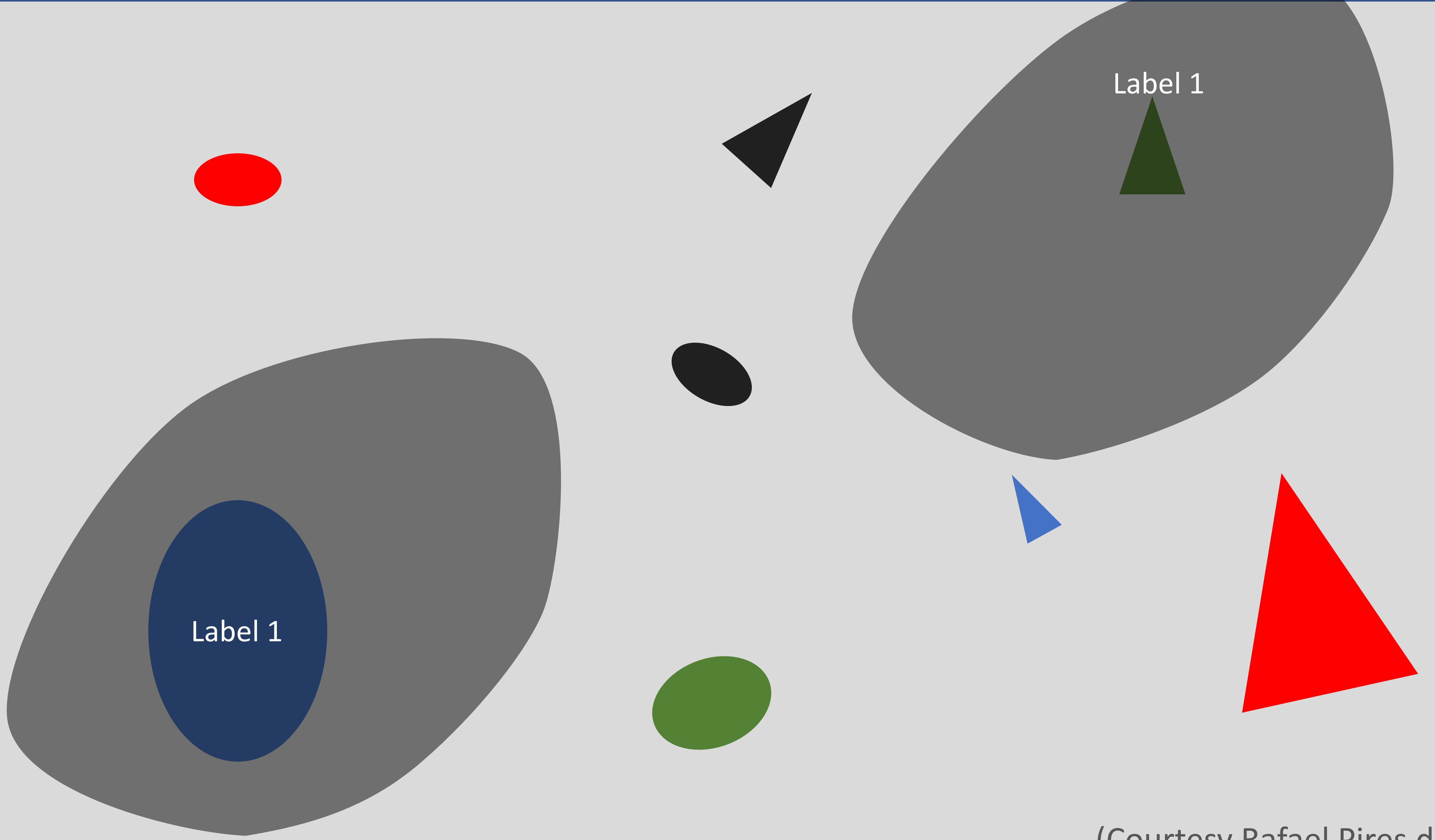
Algorithm repurposed to classify Upper Paleozoic fusilinids

Unsupervised learning - clustering



(Courtesy Rafael Pires de Lima, OU)

Supervised learning using interpreter supplied labels



(Courtesy Rafael Pires de Lima, OU)

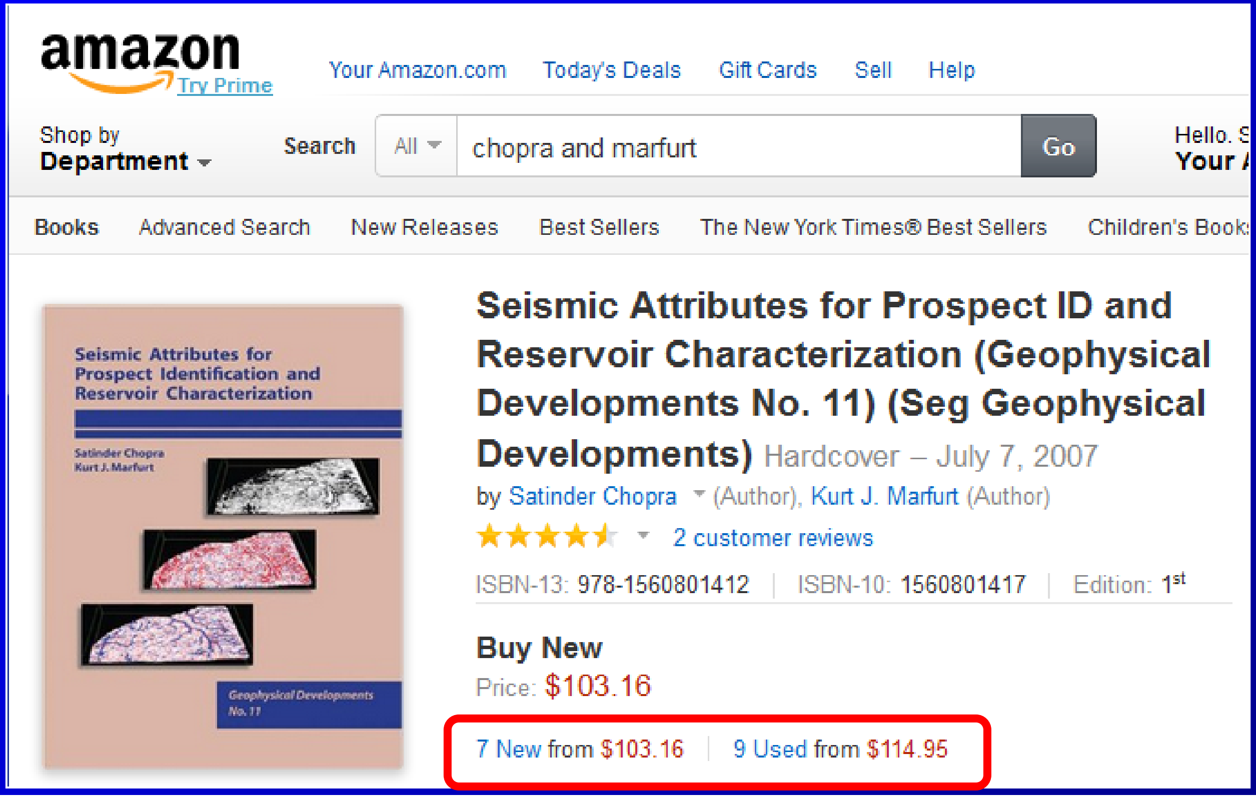
"Can machines think?" – Alan Turing

Nazi Enigma Machine

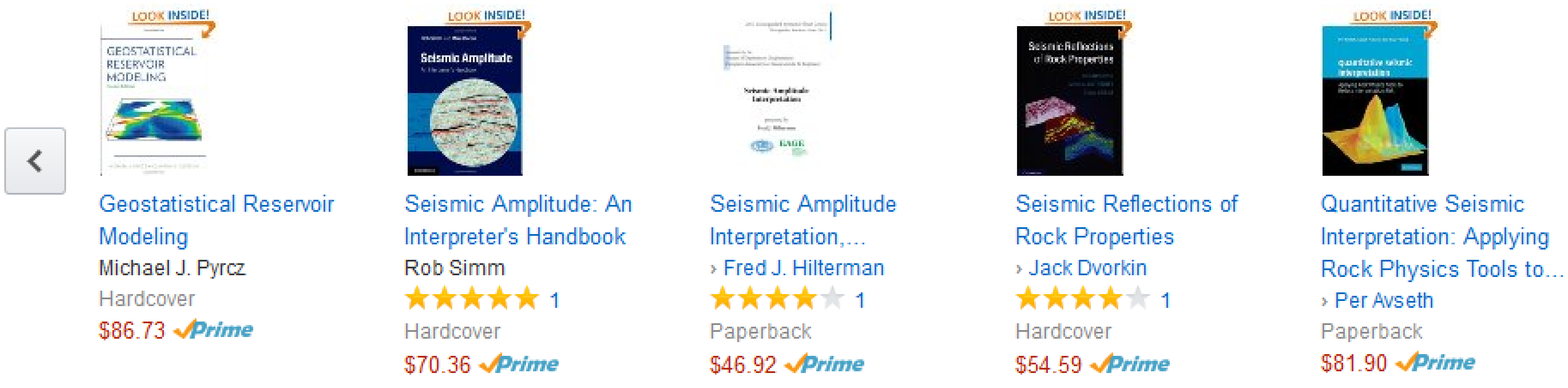
Turing's "Bombe"

(Bletchely Park Museum, UK)

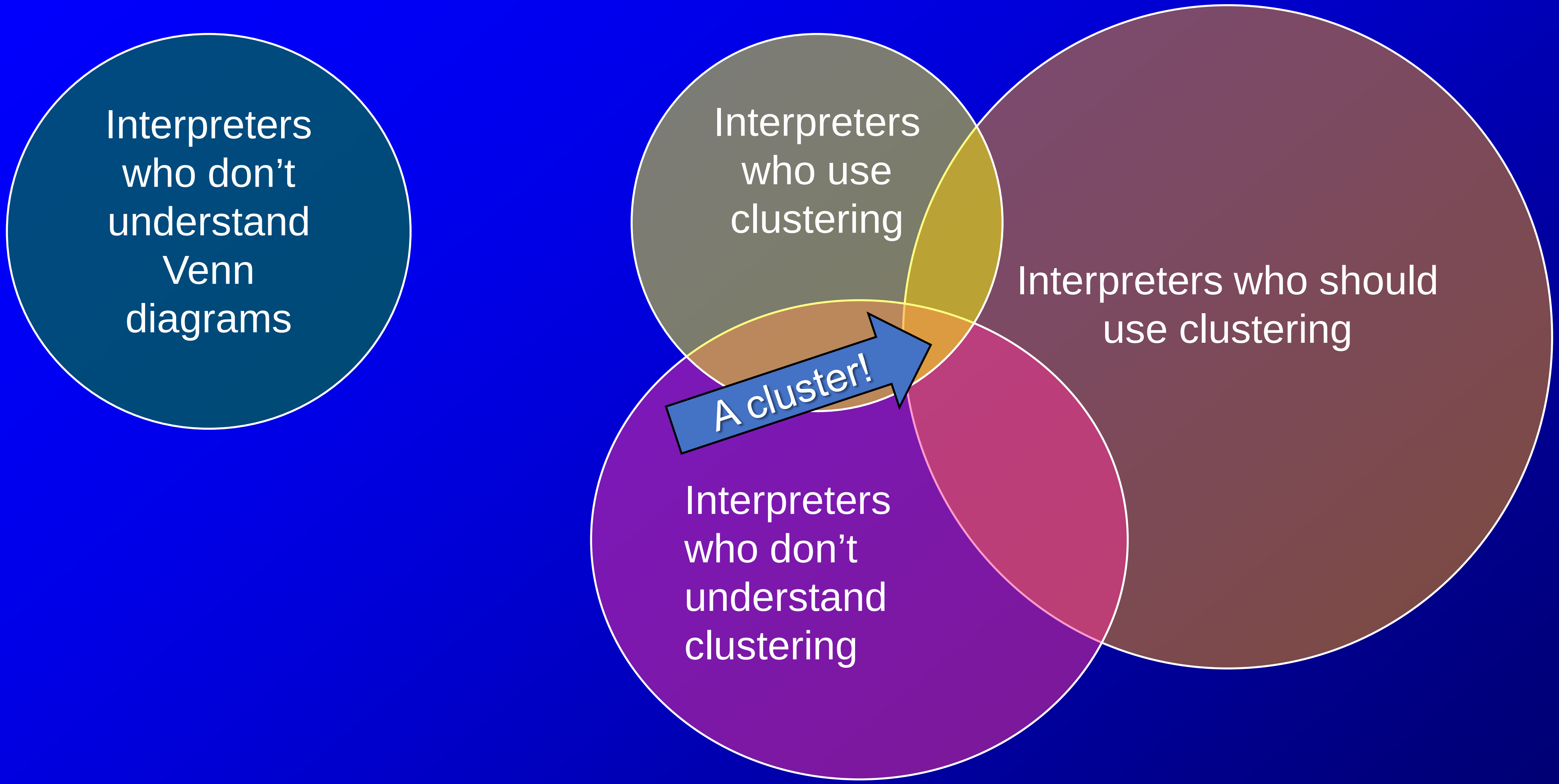
Everyday data mining…



Customers Who Bought This Item and Don't Have a Life also Bought



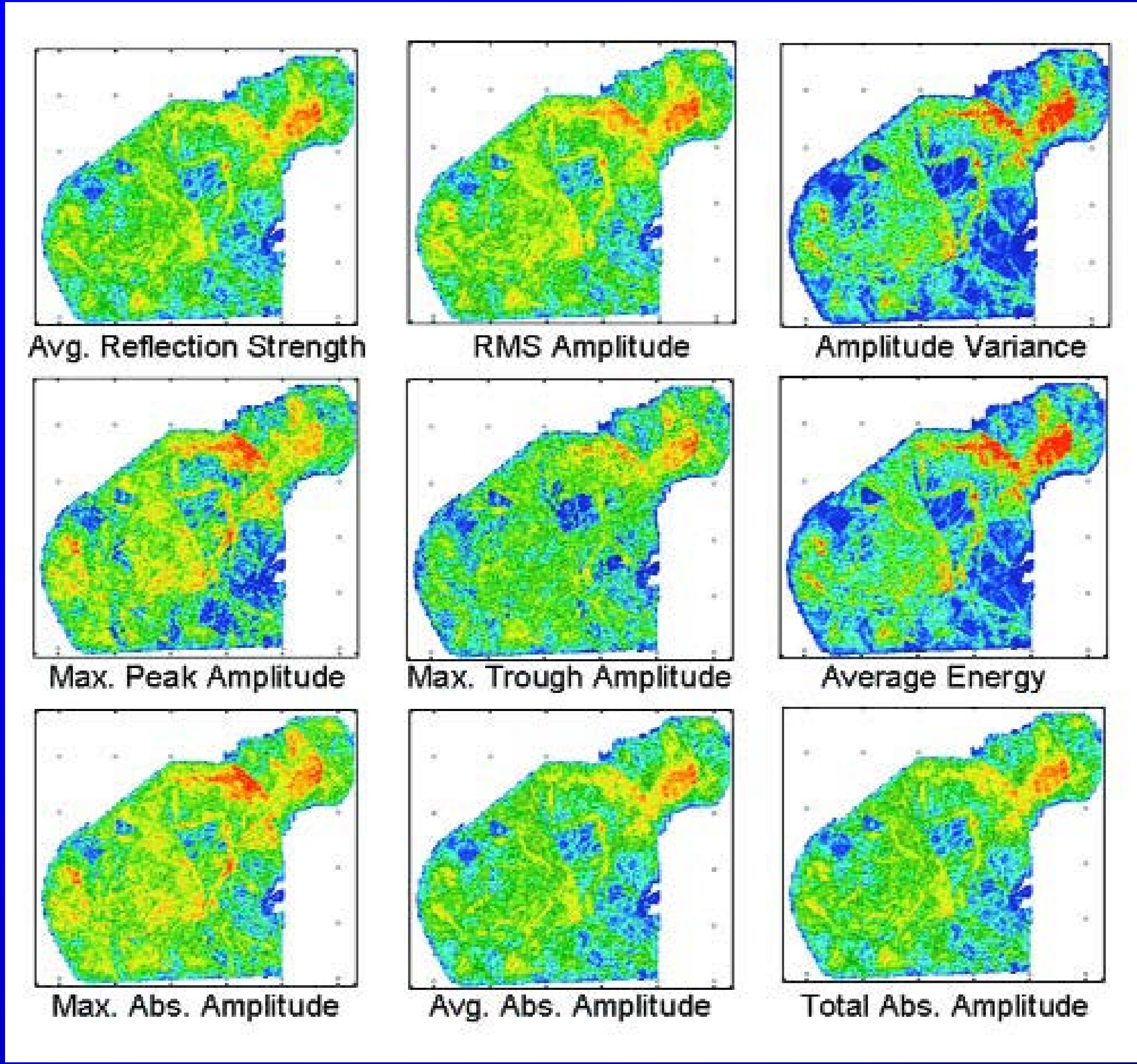
An Example of Clustering



Effective Clustering Strategies

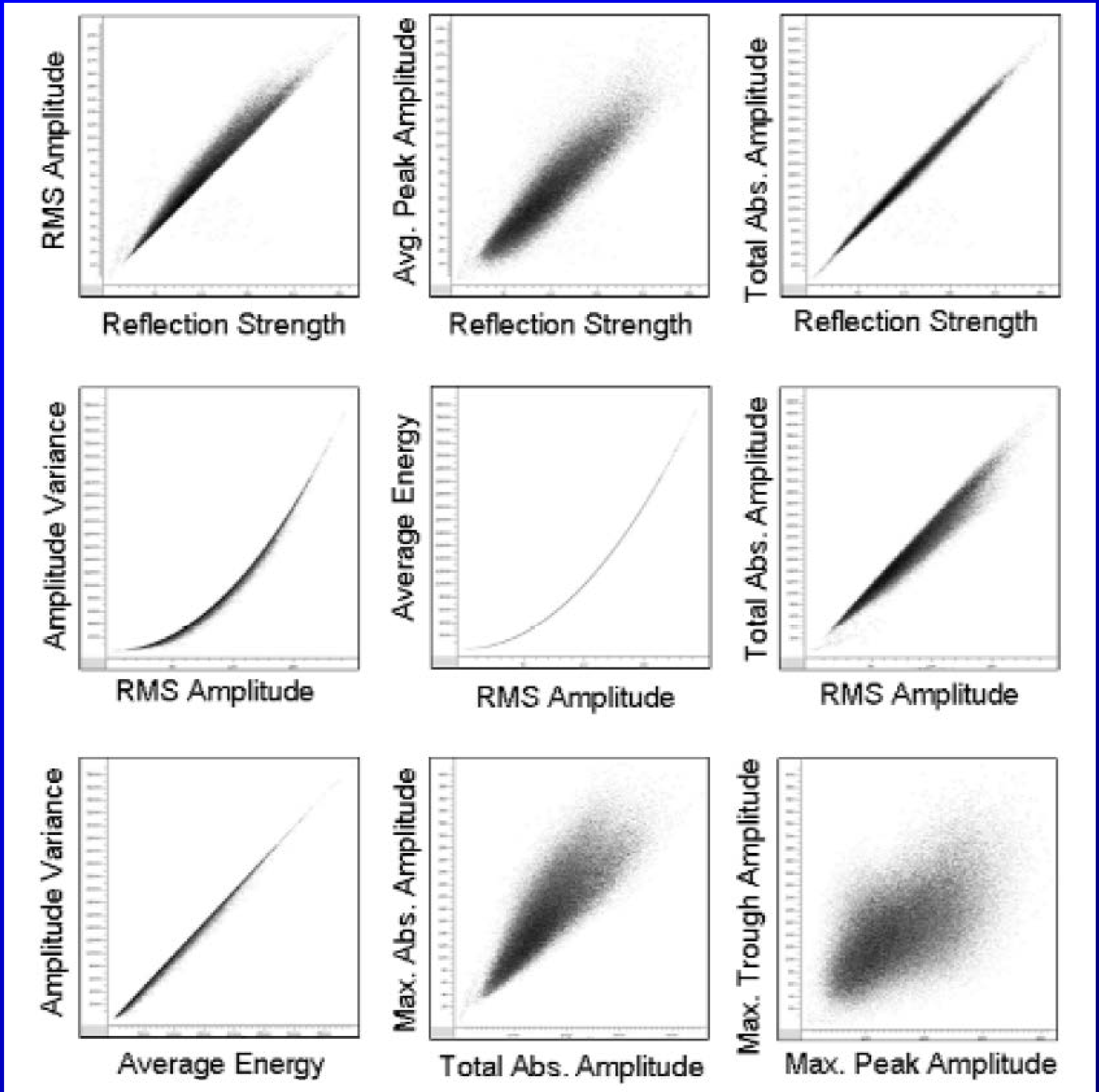
- Avoid using attributes that are mathematically correlated
- Choose attributes that are geologically correlated
- Whenever possible, choose attributes that differentiate lithologies or facies of interest (e.g. limestone vs. dolomite, turbidites vs. mass transport complexes)
- Clustering favors dominant populations. It may be necessary to explicitly define a cluster that represents an anomalous feature of interest.

Example of highly correlated attributes



(Barnes,2006)

Example of highly correlated attributes



(Barnes,2006)

Multiattribute Analysis Tools

Interpreter-Driven Multiattribute Analysis

Visual Decision Making

- Crosscorrelation Maps
- Corendering
- Spreadsheets
- Crossplotting and Geobodies
- Connected Component Labeling

Projection Techniques

- Principal Component Analysis
- Independent Component Analysis

Statistical Analysis

- Analysis of Variance (ANOVA, MANOVA)
- Multilinear Regression
- Kriging with external drift
- Collocated co-kriging

Machine Learning Multiattribute Analysis

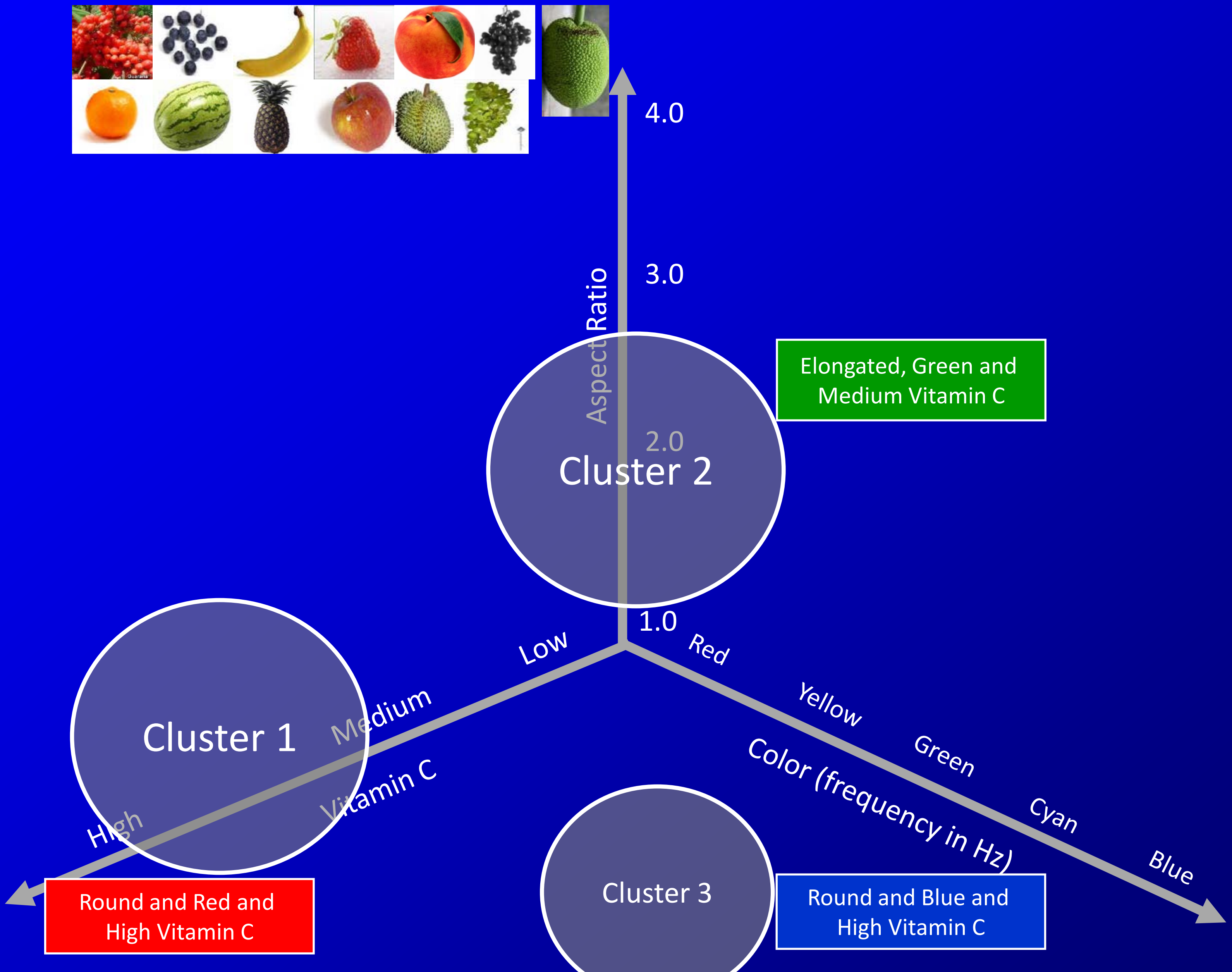
Unsupervised Learning

- K-means
- Gaussian Mixture Models
- Kohonen Self-Organizing Maps
- Generative Topographical Maps

Supervised Learning

- Probabilistic Neural Networks
- Multilinear Feedforward Neural Networks
- Support Vector Machines
- Random Forest Decision Trees
- Generative Adversarial Networks

An example of self-organization



(Roy et al., 2011)

Alternative 'distance' calculations

In geometry, x and y are both measured in meters, so we use the Pythagorean distance:

$$r^2 = (\mathbf{x}-\mathbf{m})^{\mathrm{T}}(\mathbf{x}-\mathbf{m})$$
$$= (x_1\text{-}x_m)(x_1\text{-}x_m) + (y_1\text{-}y_m)(y_1\text{-}y_m)$$

A better measure is the standardized distance:

$$r^2 = \left(\frac{\mathbf{x}-\mathbf{m}}{\sigma}\right)^{\mathrm{T}}\left(\frac{\mathbf{x}-\mathbf{m}}{\sigma}\right)$$

Alternative ‘distance’ calculations

In the attribute world, each attribute may have different units, so that we need to somehow normalize them. To do so, we calculate the Mahalanobis distance:

$$r^2 = (\mathbf{a} - \mathbf{m})^{\mathrm{T}} \mathbf{C}^{-1} (\mathbf{a} - \mathbf{m})$$

Calculating the covariance matrix, C

1. Calculate the mean of each attribute, p, over the map:

$$m_p = \frac{1}{N_{line} N_{cdp}} \sum_{j=1}^{N_{line}} \sum_{k=1}^{N_{cdp}} a_p(x_j, y_k)$$

2. Cross-correlate each attribute map with itself and all other attribute maps:

$$C_{pq} = \frac{1}{N_{line} N_{cdp}} \sum_{j=1}^{N_{line}} \sum_{k=1}^{N_{cdp}} [a_p(x_j, y_k) - m_p][a_q(x_j, y_k) - m_q]$$

Note that the diagonal of C is the variance of each attribute:

$$C_{pp} = \sigma_p^{\,2}$$

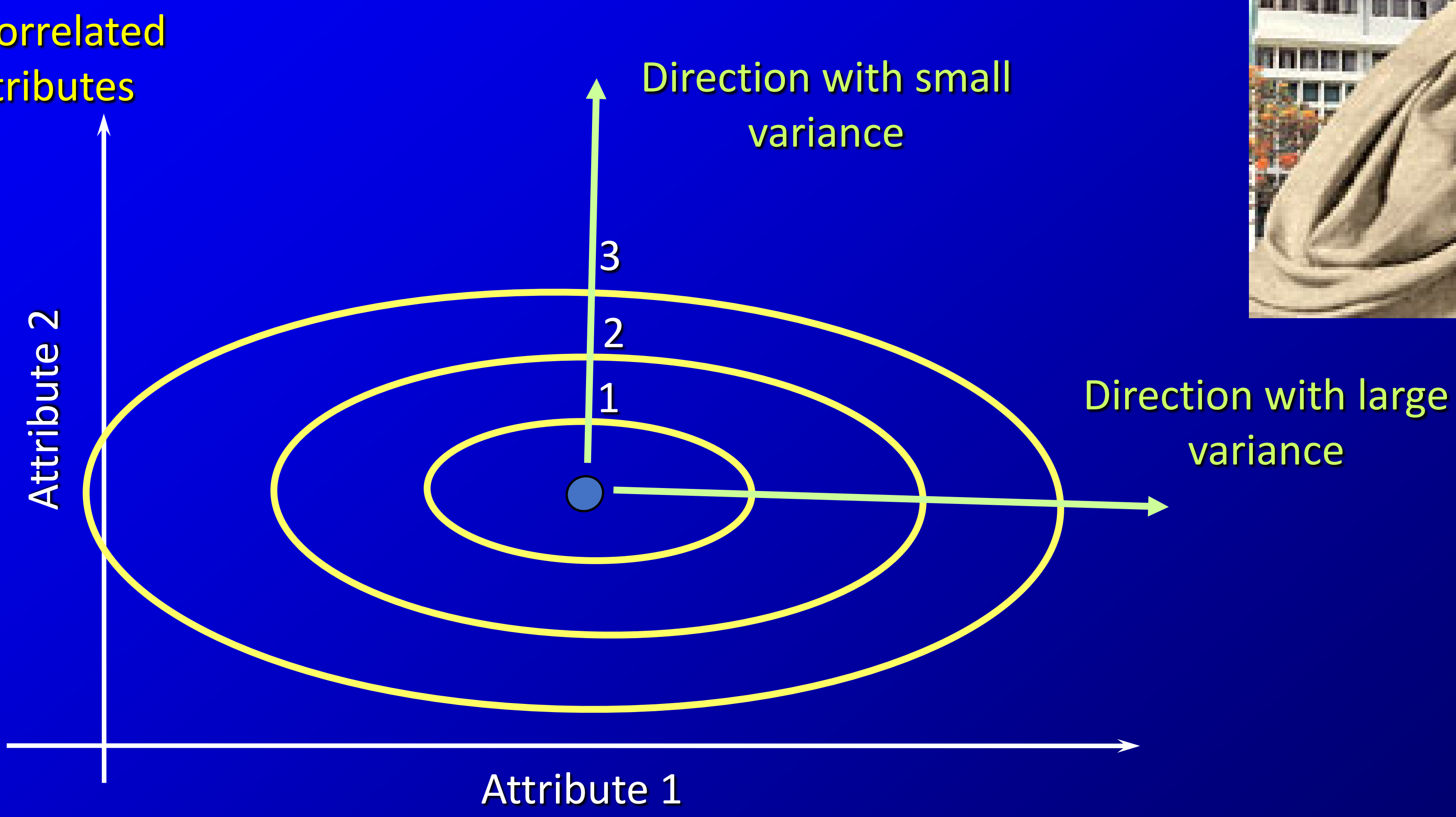
and:

$$\left|C_{pq}\right| <= \sigma_p \sigma_q$$

Mahalanobis distance:

Compensates for different variance of each attribute

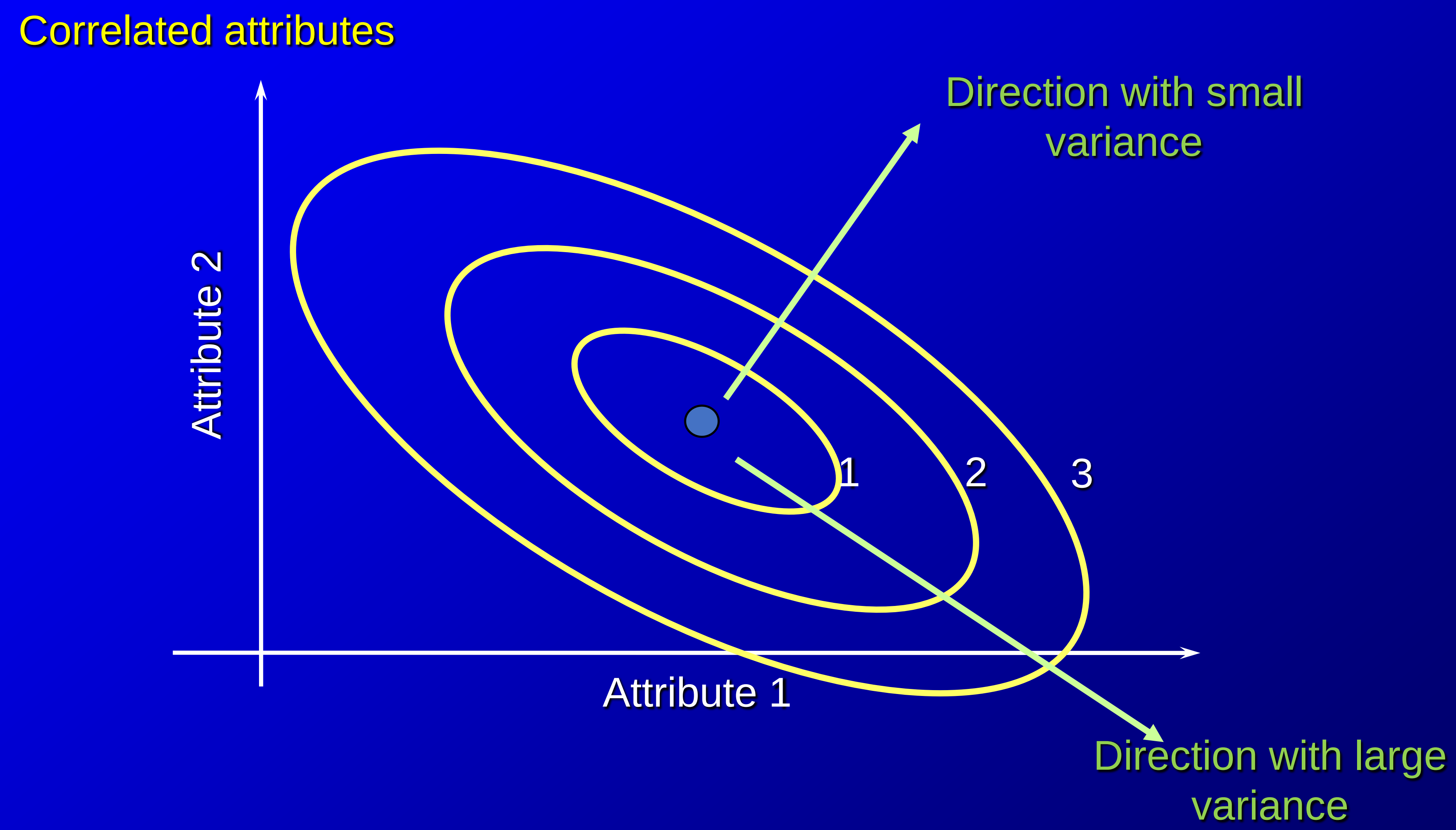
Compensates for correlation of attributes



Mahalanobis distance:

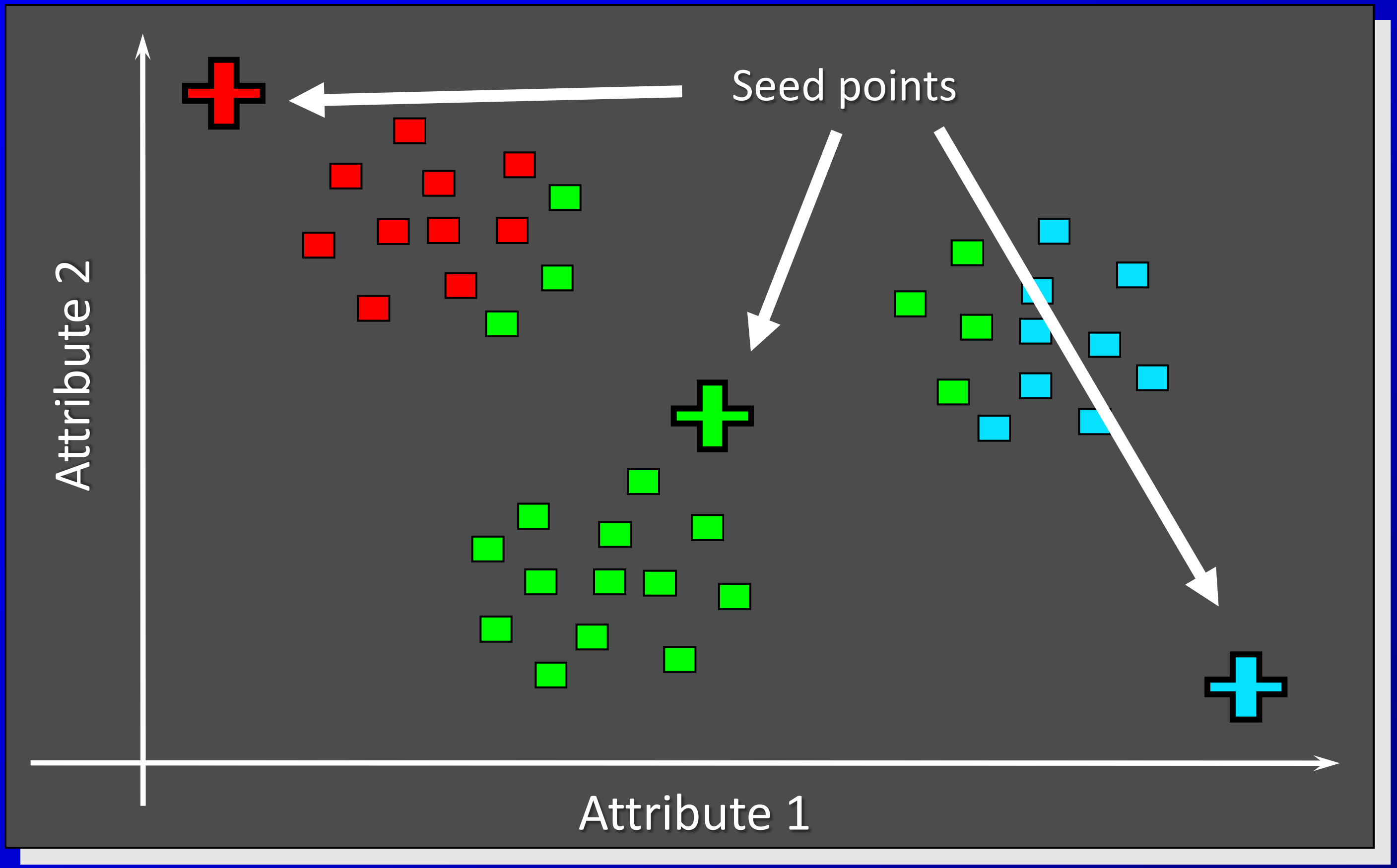
Compensates for different variance of each attribute

Compensates for correlation of attributes



K-means analysis

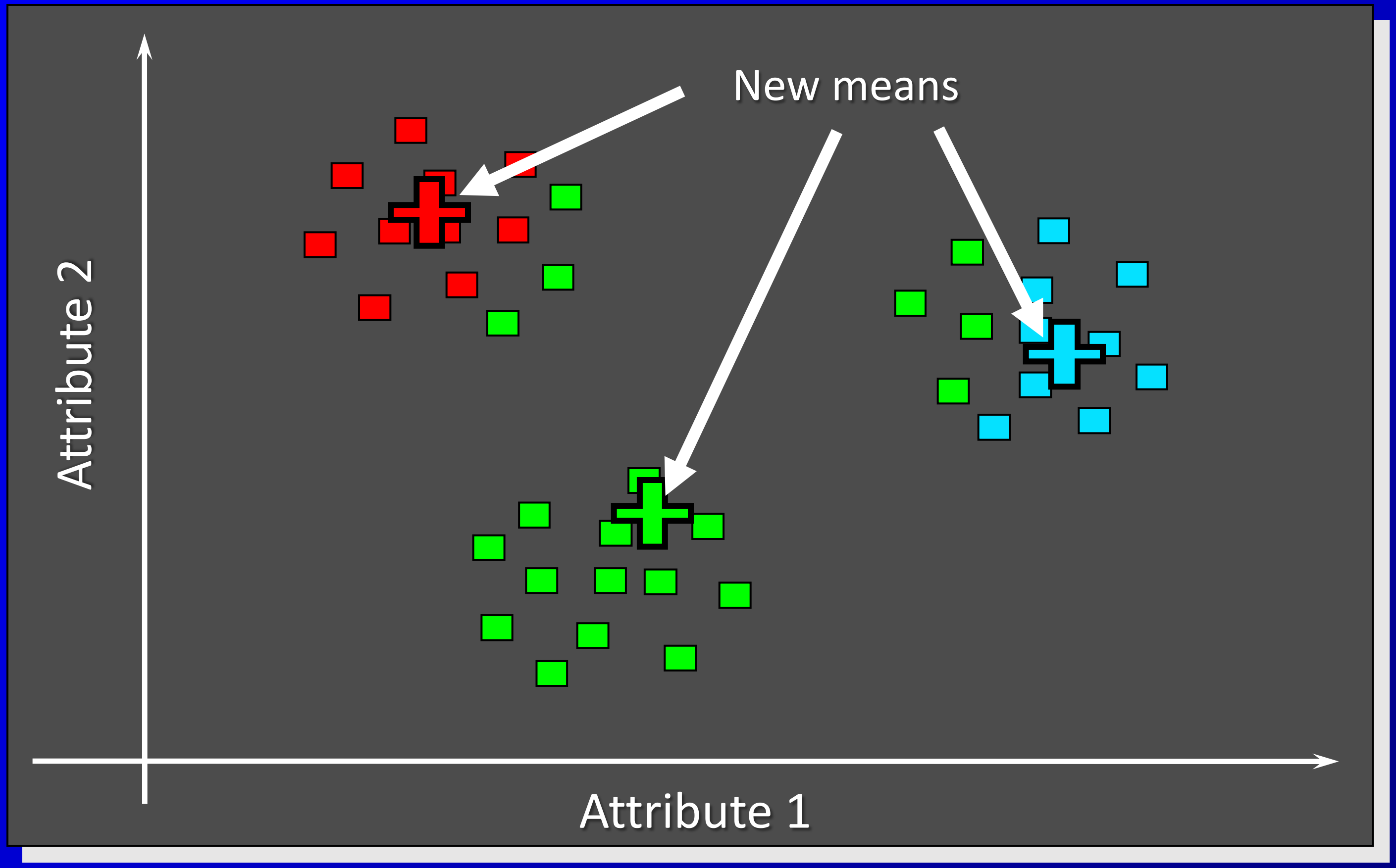
1. Cluster according to distance.



(Courtesy Scott Pickford)

K-means analysis

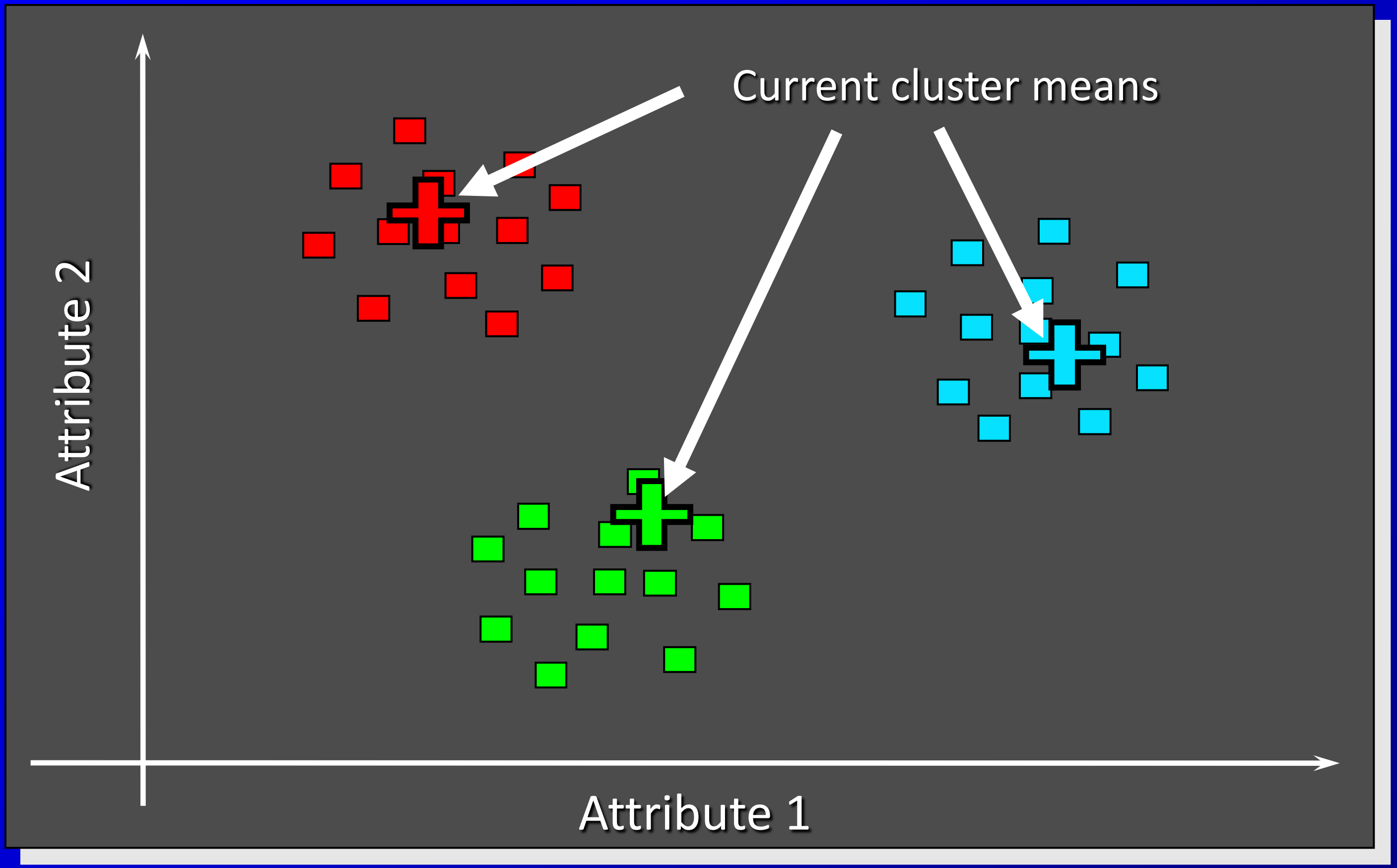
2. Recalculate mean.



(Courtesy Scott Pickford)

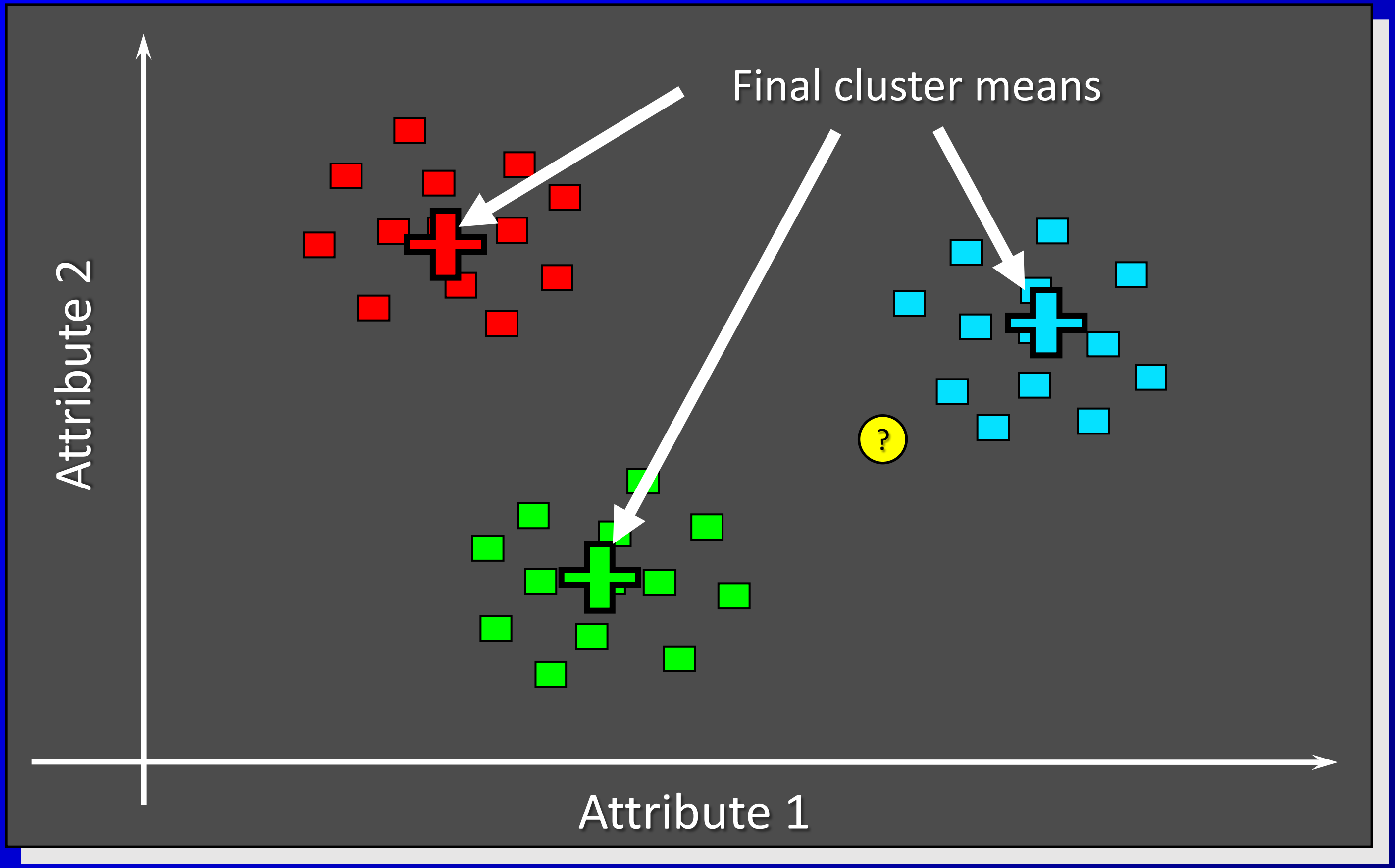
K-means analysis

3. Recalculate distances and recluster.



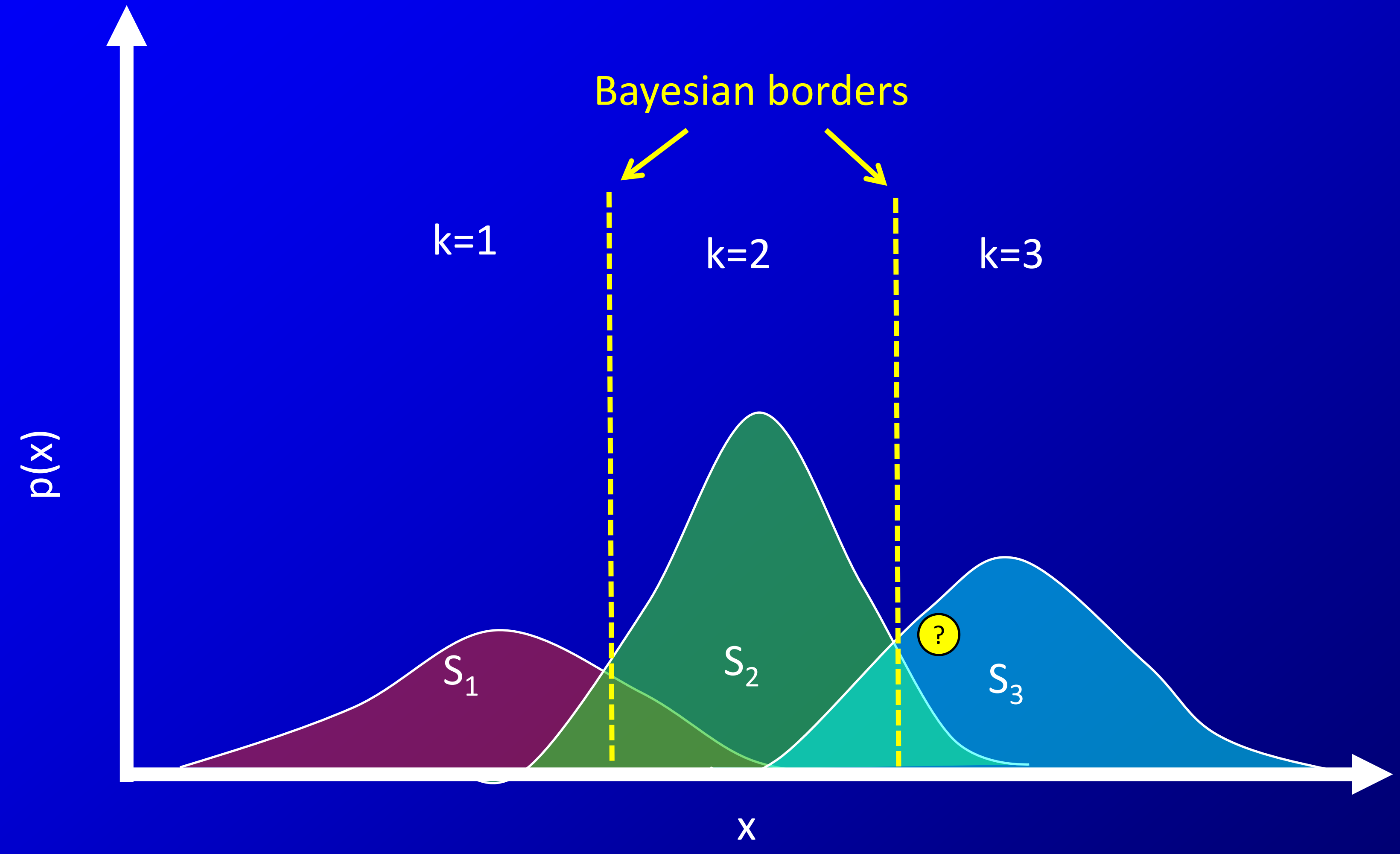
(Courtesy Scott Pickford)

K-means analysis
(*n*: iterate until convergence)



(Courtesy Scott Pickford)

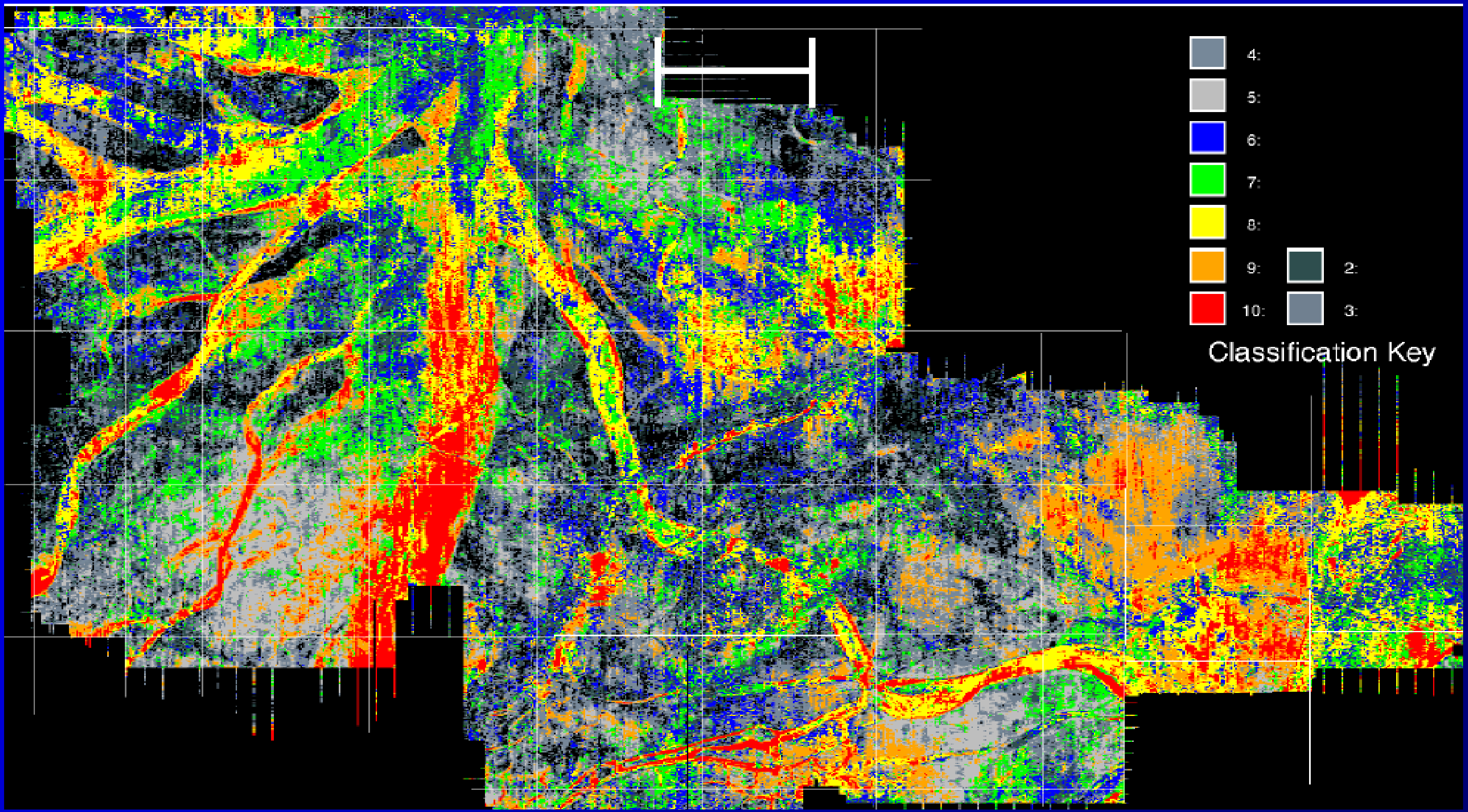
Bayes classifier



Bayesian boundaries for three different probability densities

(Taner et al. 2001)

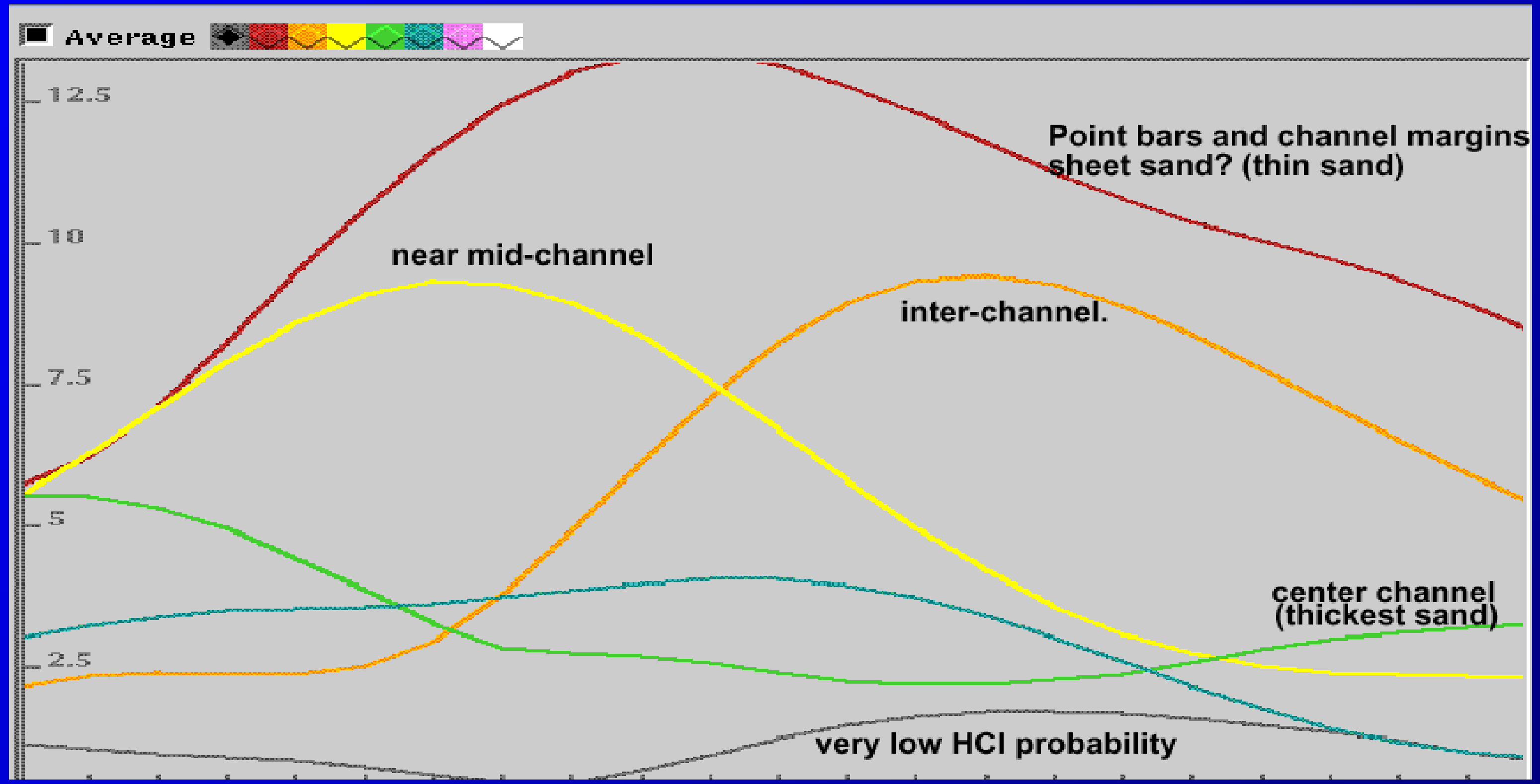
k-means unsupervised cluster analysis using 10 classes



(Wessels et al., 1996)

Post classification interpretation (spectrum of features)

Relative amplitude



10

Frequency (Hz)

80

(Wessels et al., 1996)

Unsupervised Multiattribute Clustering: *k*-means

In Summary

- k-means is perhaps the simplest and most widely available classification techniques

- Using unscaled attributes exhibiting different units biases the result towards the attributes having the largest numerical range

- Scaling the attributes using the Mahalanobis distance (or simpler Z-score) normalizes the importance of each attribute

- In general, use attributes that are mathematically independent but correlated for different seismic facies by the underlying geology