MACHINE LEARNING: CLUSTERING, AND CLASSIFICATION

Steve Tjoa
kiemyang@gmail.com
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Review from Day 2

Supervised vs. Unsupervised

- Unsupervised – “clustering”
- Supervised – binary classifiers (2 classes)
- Multiclass is derived from binary

Clustering

- Unsupervised learning – find pockets of data to group together
- Statistical analysis techniques

Clustering

- K = # of clusters

- Choosing the number of clusters – note that choosing the “best” number of clusters according to minimizing total squared distance will always result in same # of clusters as data points.

Clustering

The basic goal of clustering is to divide the data into groups such that the points within a group are close to each other, but far from items in other groups.

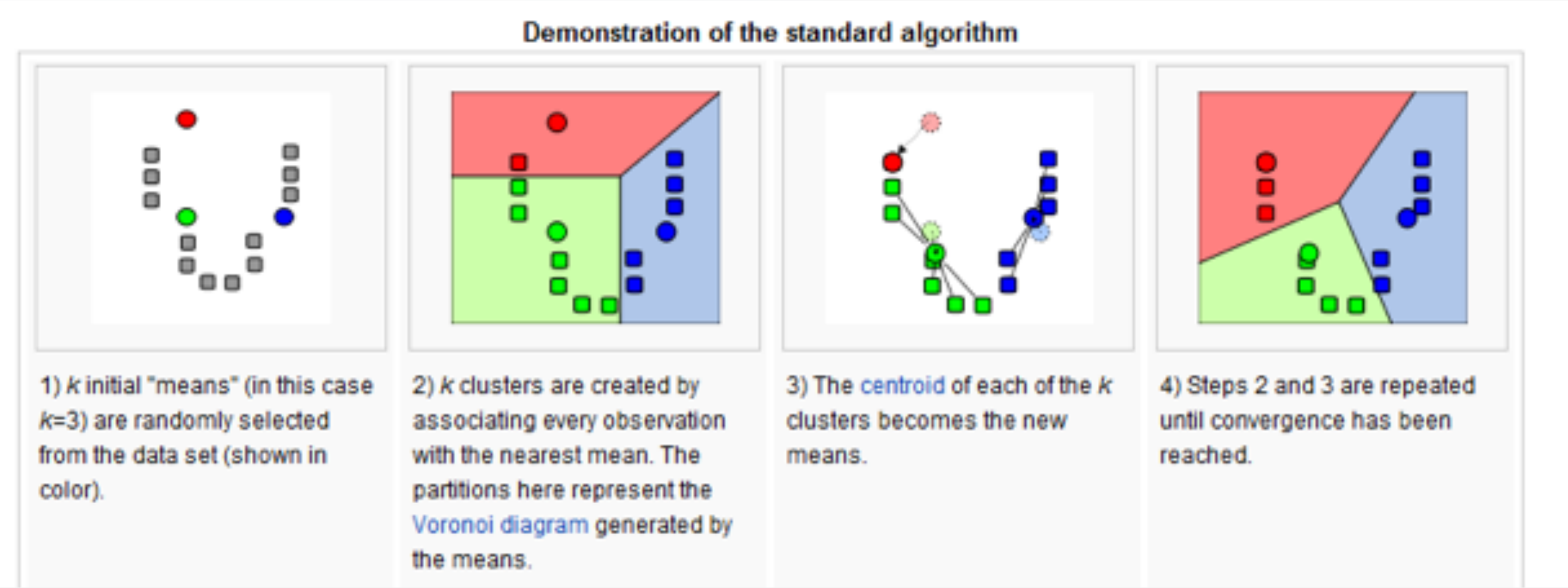
Hard clustering – each point is assigned to one and only one cluster.

K-Means

- procedure for clustering unlabelled data;
- requires a pre-specified number of clusters;
- minimizes within-cluster variance
- Guaranteed to converge (eventually)
- Clustering solution is dependent on the initialization

Demo

- YouTube demo: Bishma Stornelli



K-Means

Initialization methods:

- Choose random data points as cluster centers
- Randomly assign data points to K clusters and compute means as initial centers
- Choose data points with extreme values
- Find the mean for the whole data set then perturb into k means
- Find ground-truth for data

ANALYSIS AND DECISION MAKING: GMMS

Mixture Models (GMM)

- K-means = hard clusters.
- GMM = soft clusters.

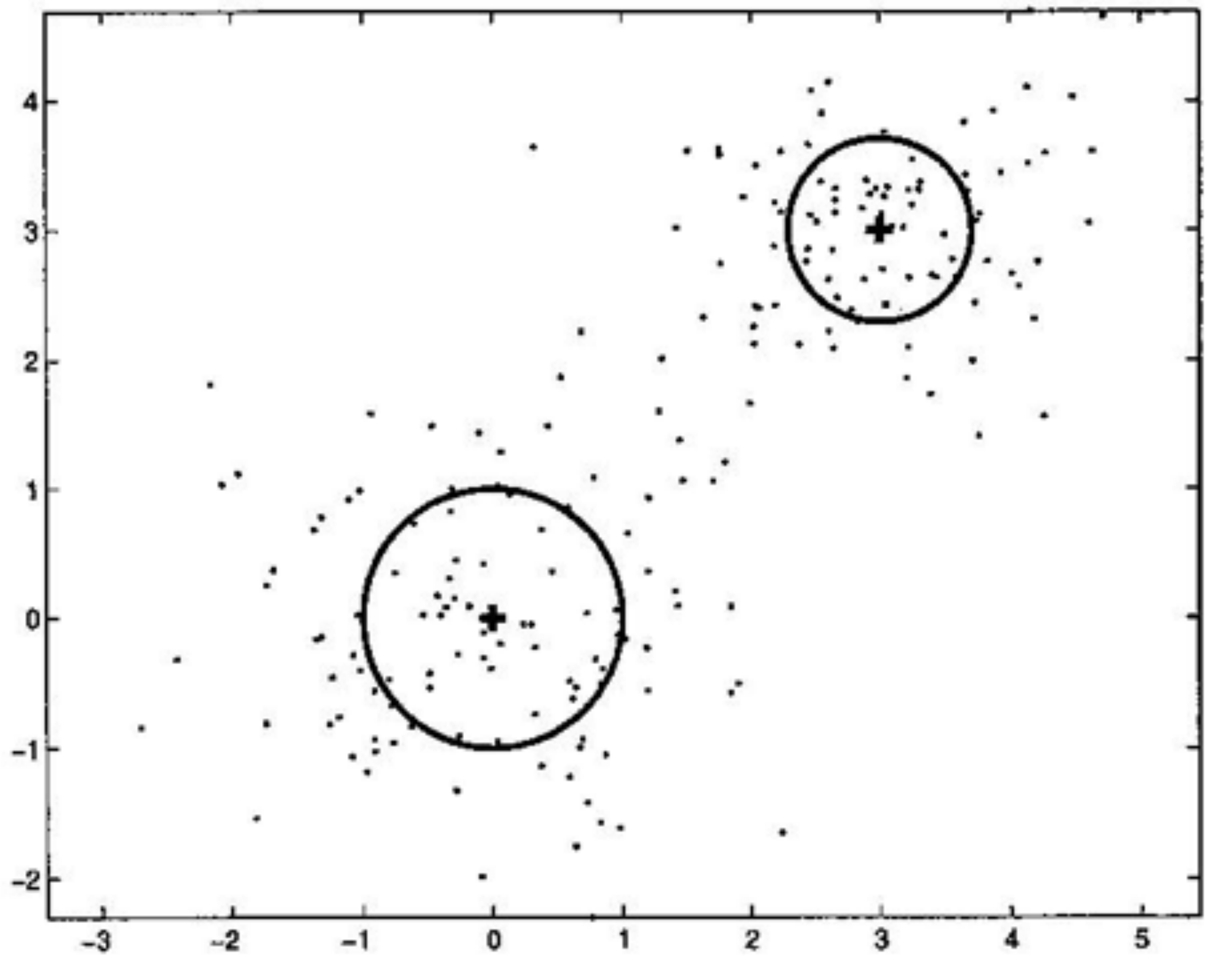


Fig. 3.1. Spherical covariance mixture model. Sampled data (*dots*), **centres** (*crosses*) and one standard deviation error bars (*lines*).

Mixture Models (GMM)

- GMM is good because:
  1. Can approximate any pdf with enough components
  2. EM makes it easy to find components parameters
     - EM – the means and variances adapt to fit the data as well as possible
  3. Compresses data considerably

- Can make softer decisions (decide further downstream given additional information)

GMM Parameters

Input

- Number of components (Gaussians)
  - e.g., 3
- Mixture coefficients (sum = 1)
  - e.g., [0.5 0.2 0.3]
  - “Priors” or “Prior probabilities”
  - Priors are “the **original** probability that each point came from a given mixture.”
  - “A prior is often the purely subjective assessment of an experienced expert.”
- Initialized centers, means, variances. (optional)

Output

- Component centers/means, variances, and mixture coeff.
- Posterior probabilities
  - “Posterior probabilities are the responsibilities which the Gaussian components have for each of the data points.”

Query

- Obtain similarity via Likelihood

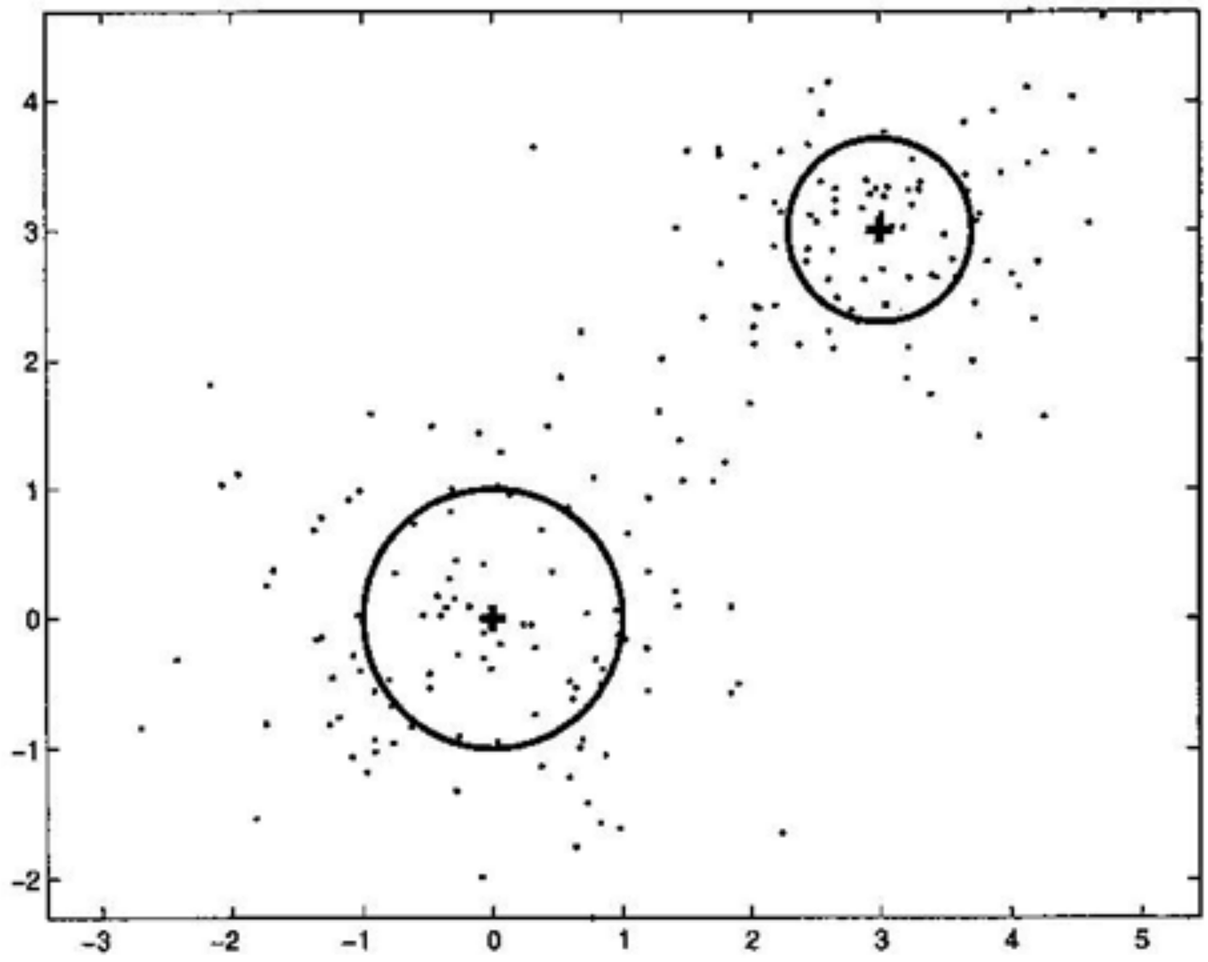
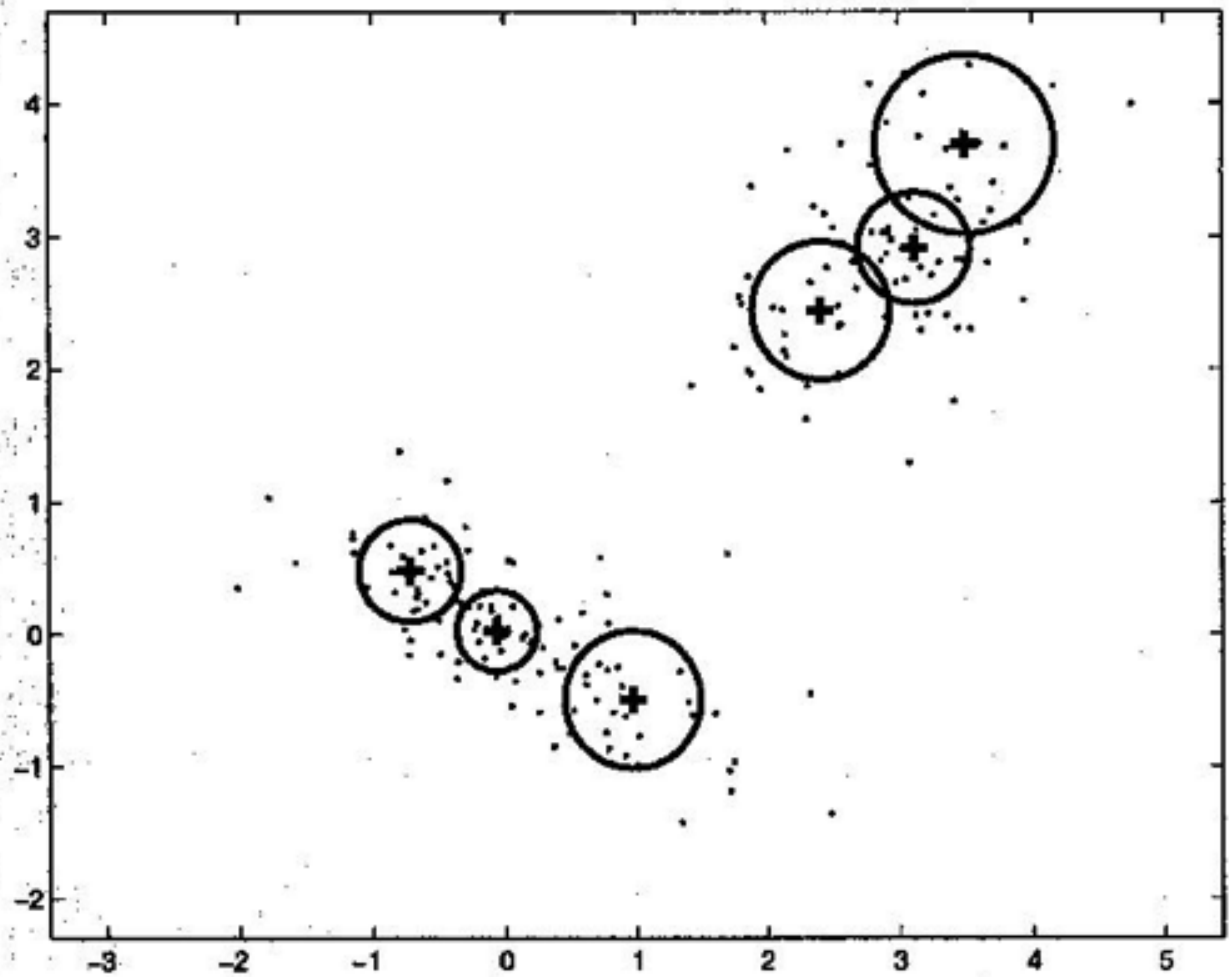


Fig. 3.1. Spherical covariance mixture model. Sampled data (*dots*), **centres** (*crosses*) and one standard deviation error bars (*lines*).



4. Spherical covariance mixture model with six components fitted to the mpled from the full covariance two-component model in Fig. 3.3. Sampled ots), centres (*crosses*) and one standard deviation error bars (*lines*).

- From Netlab (p82–83)

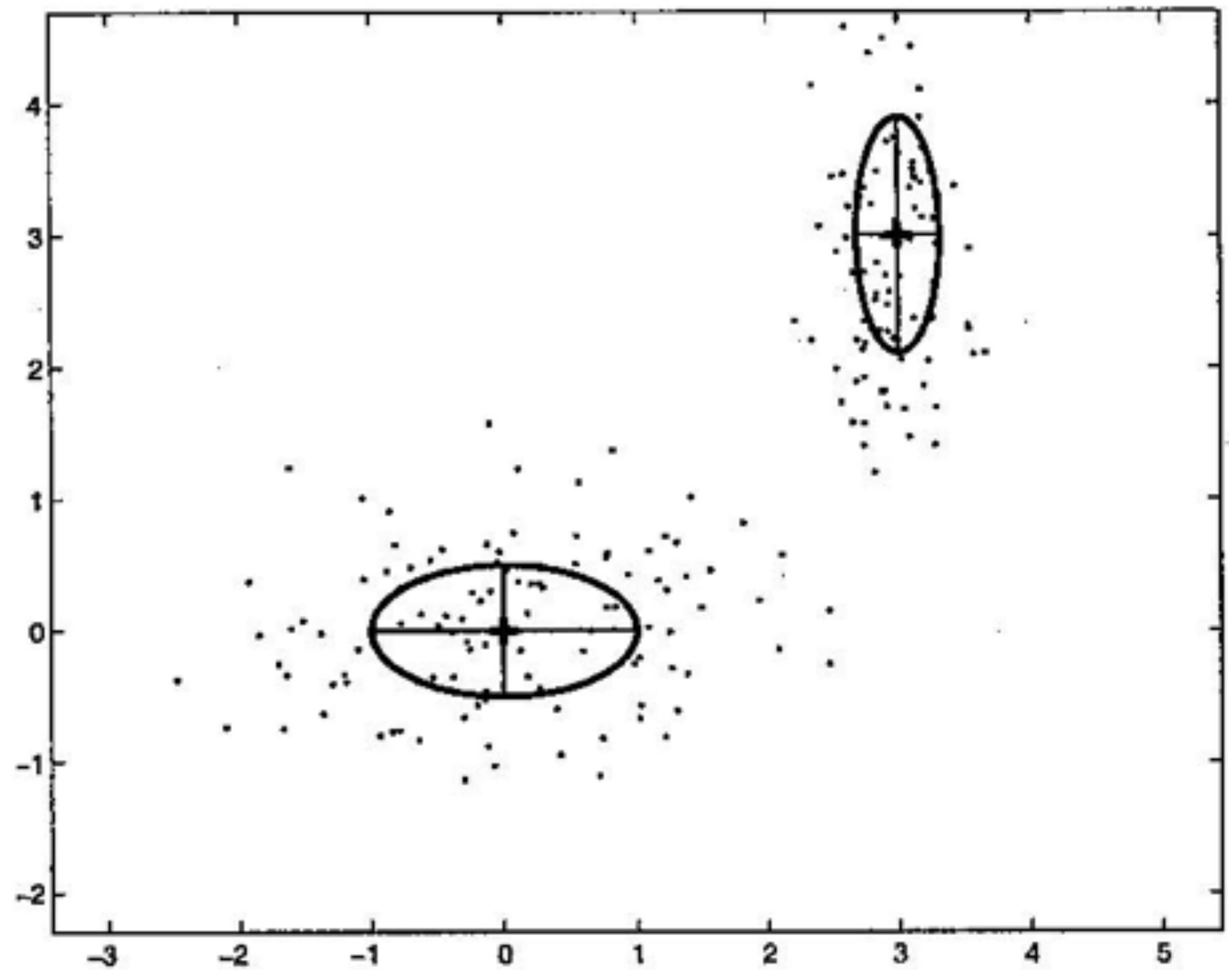
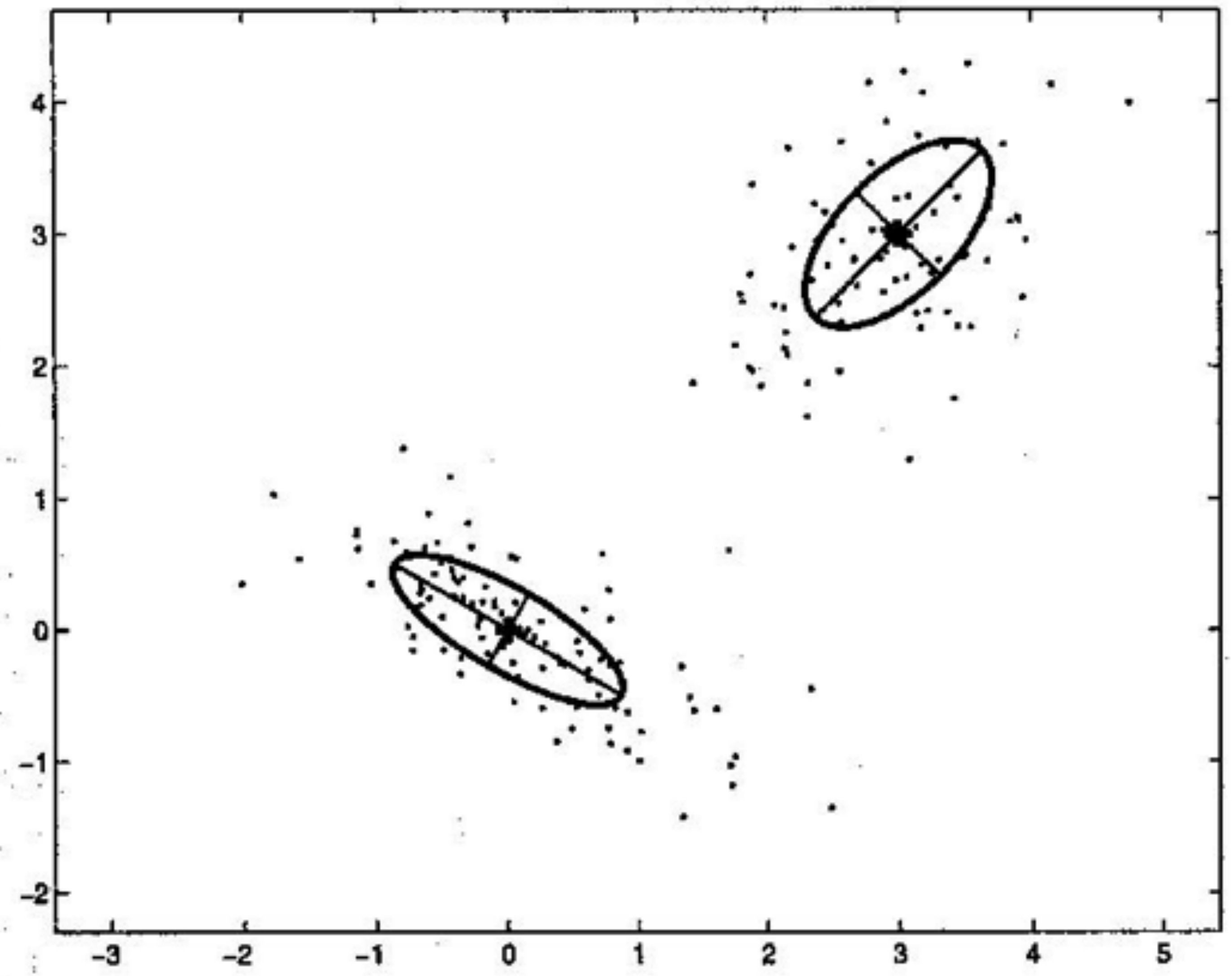


Fig. 3.2. Diagonal covariance mixture model. Sampled data (*dots*), centres (*crosses*), covariance axes (*thin lines*) and one standard deviation error bars (*thick lines*).



3. Full covariance mixture model. Sampled data (*dots*), centres (*crosses*), nce axes (*thin lines*) and one standard deviation error bars (*thick lines*).

GMM

- “Pooled covariance" – using a single covariance to describe all clusters (saves on parameter computation)

GMM: Likelihood

1. Evaluate the probability of that mixture modeling your point.

```
likelihoodgm1 = gmmprob(gm1,testing_features)
likelihoodgm2 = gmmprob(gm2,testing_features);
loglikelihood  = log(likelihoodKick ./ likelihoodSnare )
```

- Log-function is “order-preserving” – maximizing a function vs. maximizing its log

Minimization Problems

>Demgmm1

- EM is gradient-based – it does not find the global maximum in the general case, unless properly initialized in the general region of interest.

- Error wants to be -inf, which occurs when Gaussian is fit for each data point. (mean = data point and variance = 0)

- "There are often a large number of local minima which correspond to poor models. Solution is to build models from many different initialization

GMM

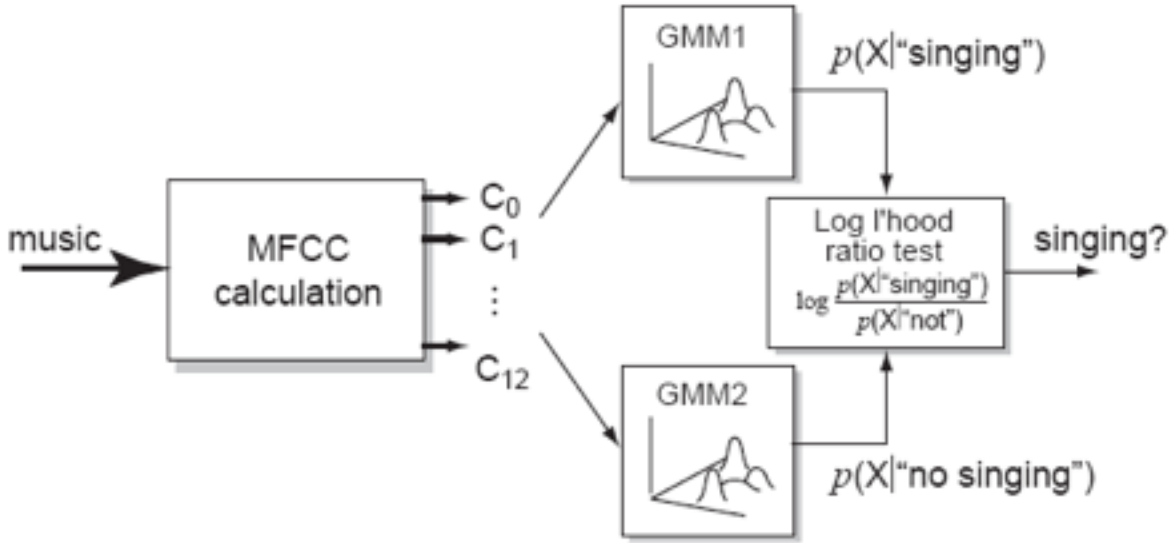
- Application:
  - State-of-the-art speech recognition systems
  - estimate up to 30,000 separate GMMs, each with about 32 components. This means that these systems can have up to a million Gaussian components!! All the parameters are estimated from (a lot of) data by the EM algorithm.

Application:

Speaker Recognition

GMM System

- **Separate models for $p(x|sing)$, $p(x|no\ sing)$**
  - combined via likelihood ratio test



- **How many Gaussians for each?**
  - say 20; depends on data & complexity
- **What kind of covariance?**
  - diagonal (spherical?)

Genre

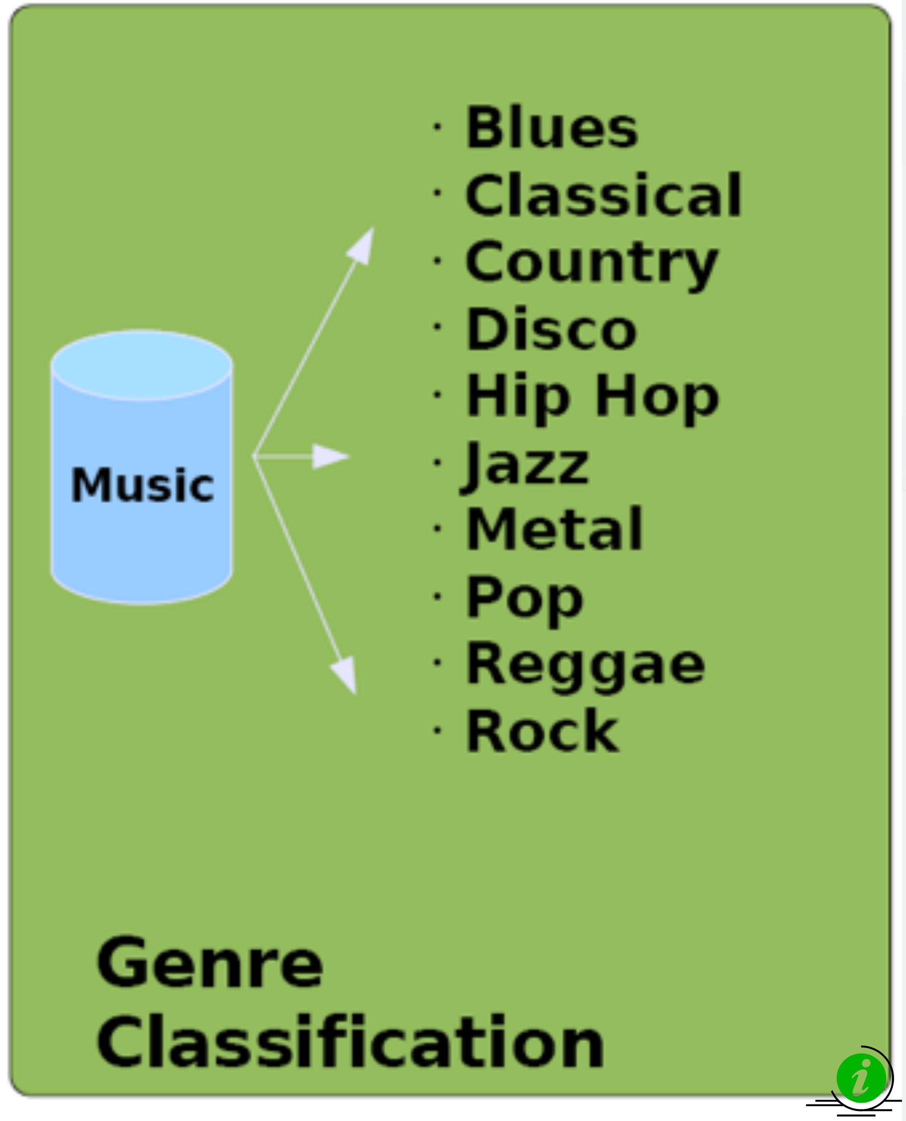
"Because feature vectors are computed from short segments of audio, an entire song induces a cloud of points in feature space."

"The cloud can be thought of as samples from a distribution that characterizes the song, and we can model that distribution using statistical techniques. Extending this idea, we can conceive of a distribution in feature space that characterizes the entire repertoire of each artist."

A. Berenzweig, B. Logan, D. Ellis, and B. Whitman. A large-scale evalutation of acoustic and subjective music similarity measures. In Proceedings of 4th International Symposium on Music Information Retrieval,

- **Genre Classification**:
  - Manual : 72% (Perrot/Gjerdigen)
  - Automated (2002) 60% (Tzanetakis)
  - Automated (2005) 82% (Bergstra/Casagrande/Eck)
  - Automated (2007) 76%

From ISMIR 2007 Music Recommender Tutorial (Lamere & Celma)



How?

- Version 1 – One feature vector per song
  - High-level features extracted from data
    - Timbral (MFCCs, etc), Rhythmic content (beat histogram, autocor, tempos), Pitch info
    - Sampling of the frames in the song
  - Statistics of features extracted from a piece (includes means, weights, etc)
  - Representative of MFCC spectral shape
  - Could further use “Anchor space” where classifiers are training to represent musically meaningful classifiers. (Euclidean distance between anchor space)

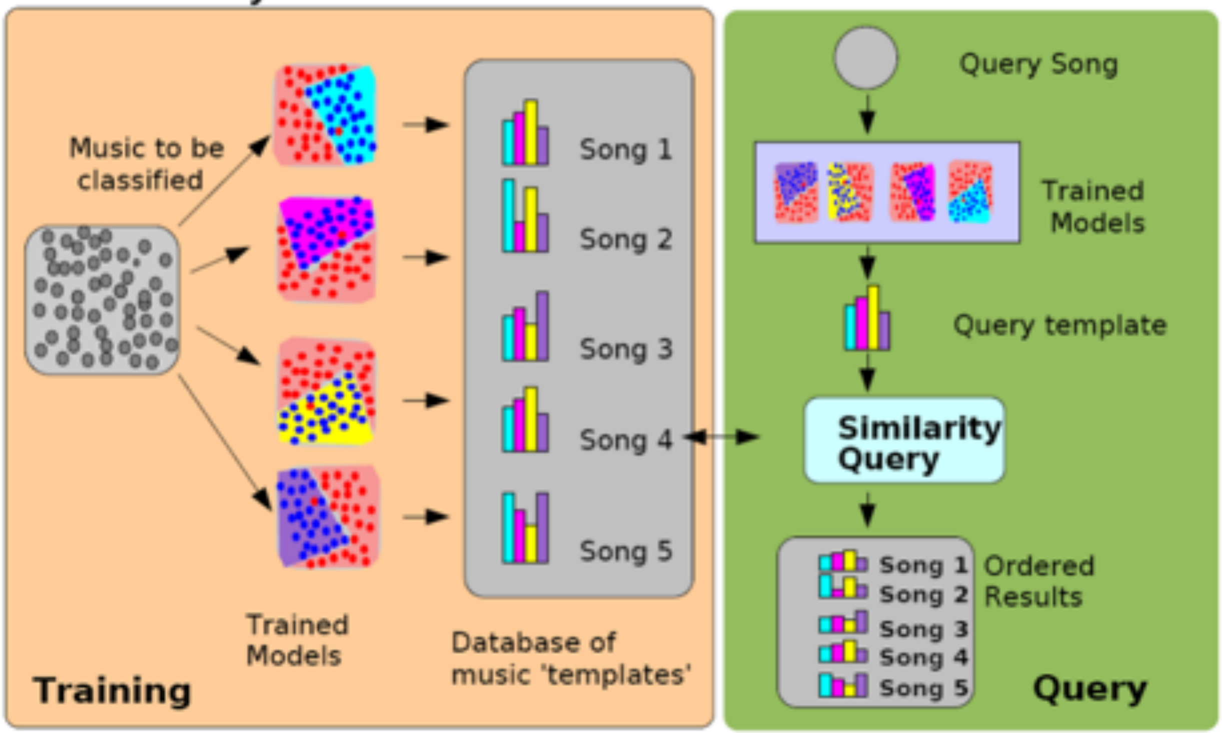
- Version 2 – Cloud of points
  - Extract audio every N frames
  - K-Means or GMM representing a “cloud of points” for song
    - Clusters: mean, covariance and weight of each cluster = signature for song/artist/genre

Music Recommendation

- Cloud of points from frames of song
  - High-level features extracted from data
  - Classifier: Weighted attribute nearest neighbors or fast distance measures.
  - k-Means or GMM used to create clusters.
  - The mean, covariance and weight of each cluster = signature for the song.

  - Compare distance between other songs (signature) using various techniques to measure distance between probability distributions. (Most similar = closest distance)

- Automatic annotation
  - Similarity based on classification



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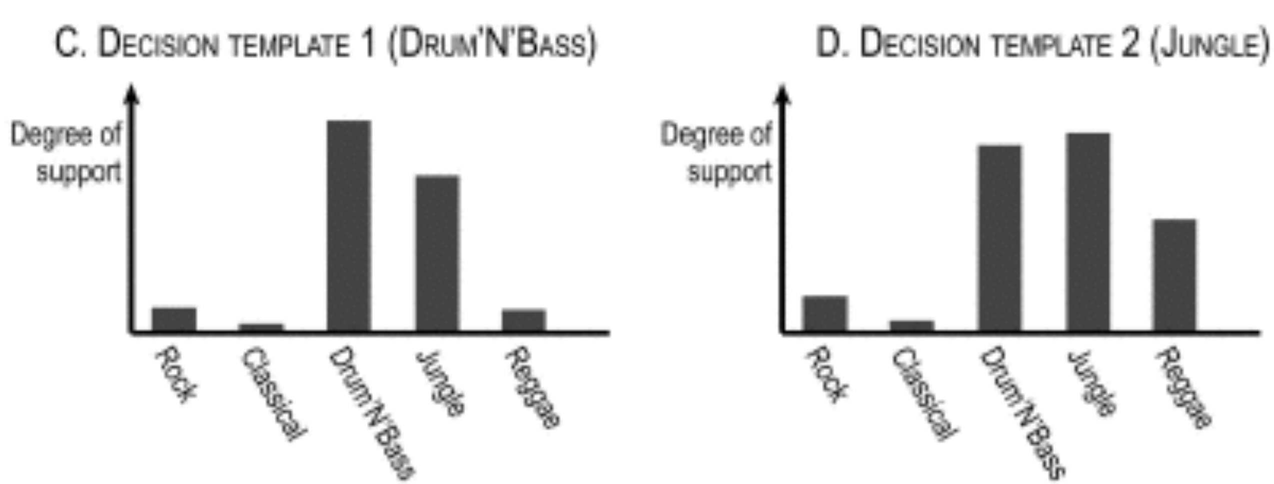
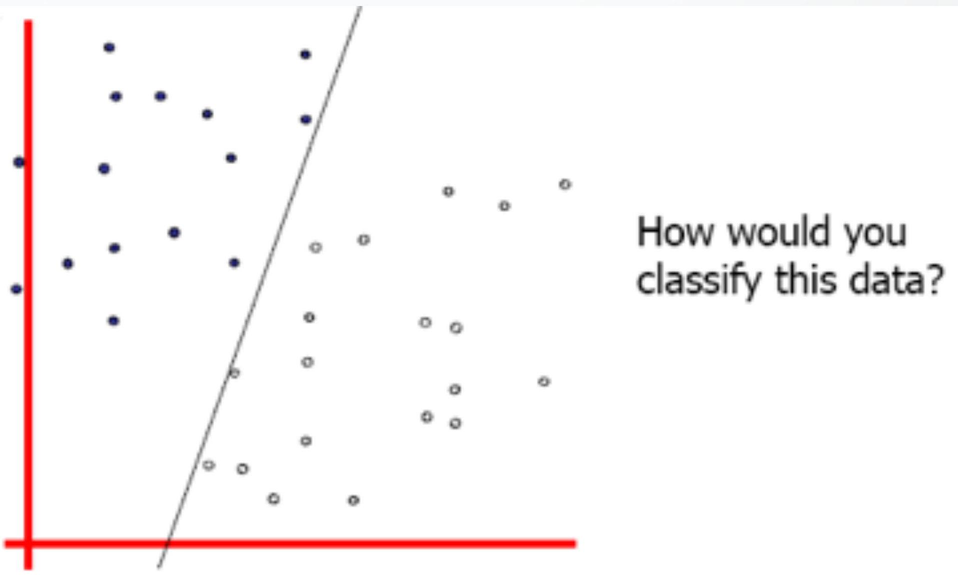
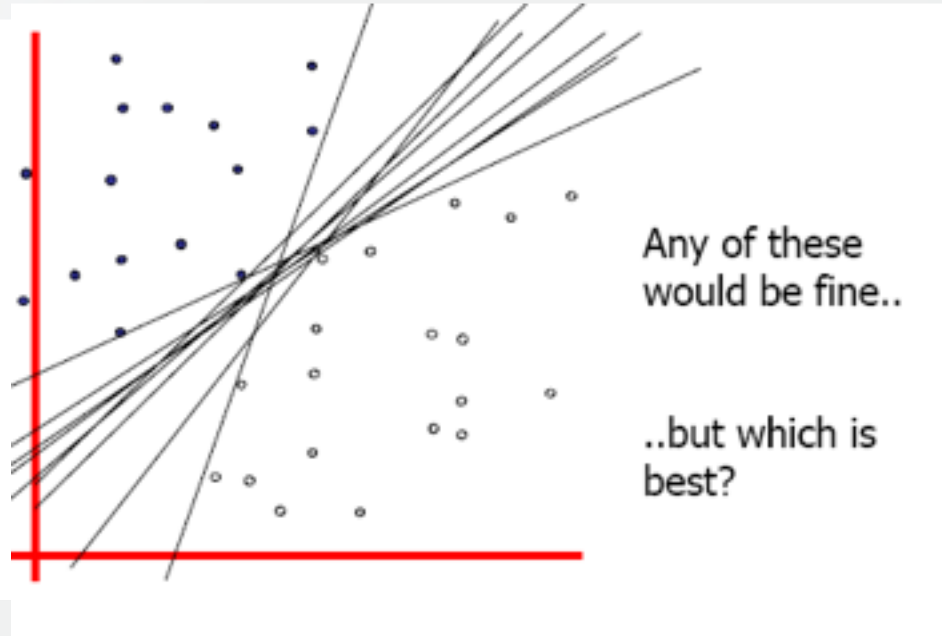
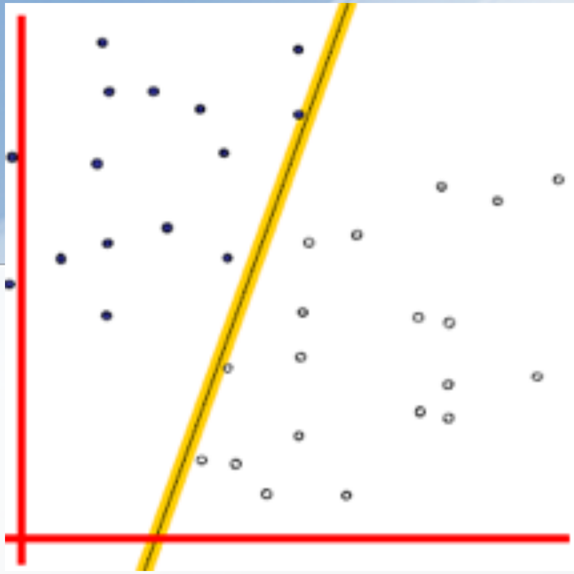


SUPPORT VECTOR MACHINES (SVM)

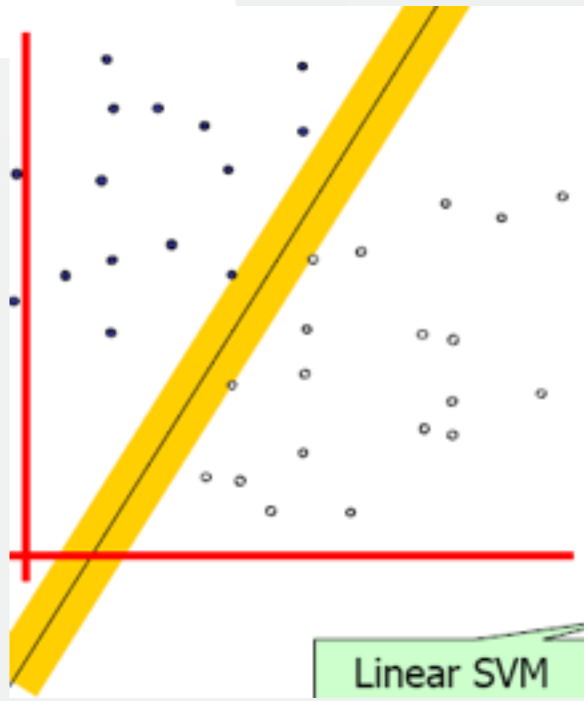




From : http://www.autonlab.org/tutorials/



Define the margin of a linear classifier as the width that the boundary could be increased by before hitting a datapoint.



The maximum margin linear classifier is the linear classifier with the, um, maximum margin.

This is the simplest kind of SVM (Called an LSVM)

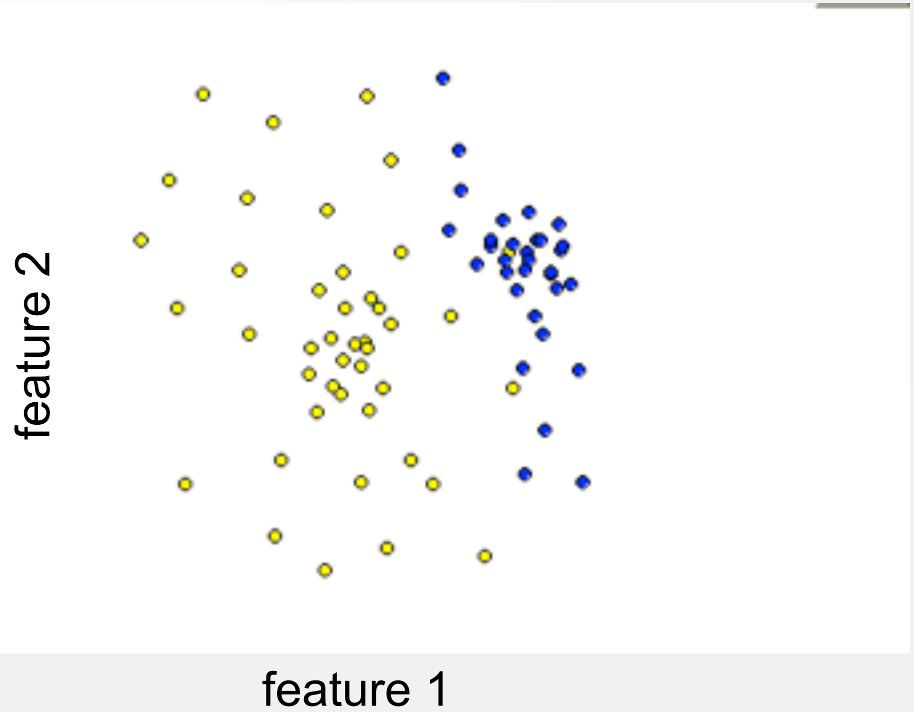
From : http://www.autonlab.org/tutorials/

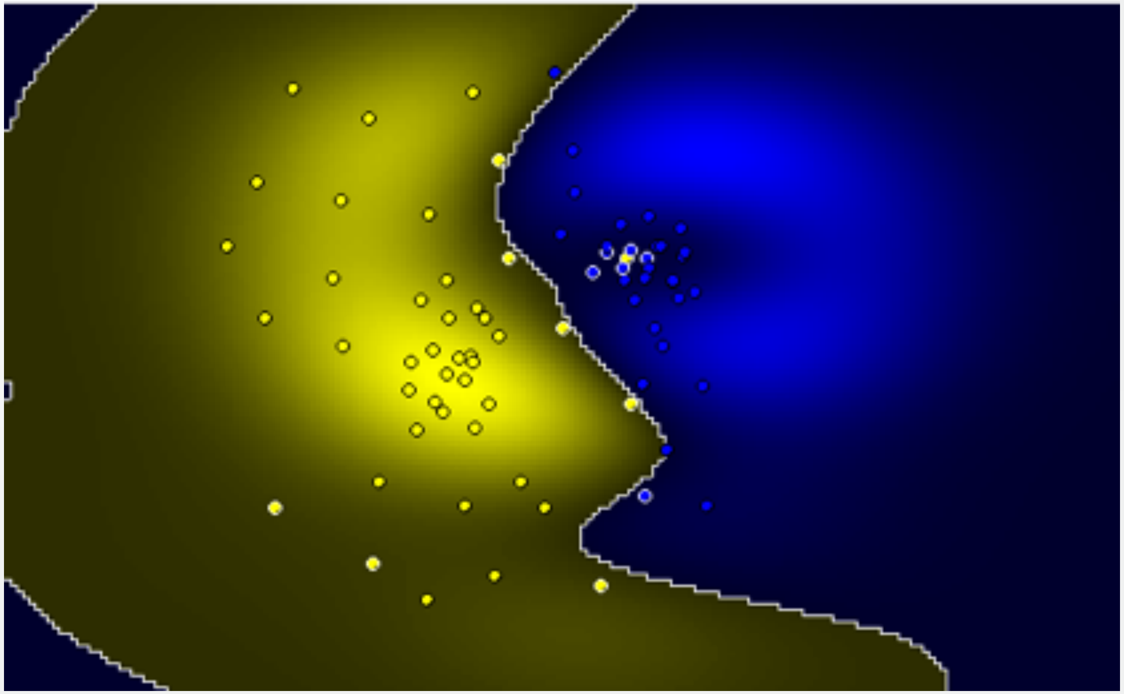
SVM

- Hyperplane separates the data from the two classes with a "maximum margin".
- Support Vectors – are those data points that the margin pushes up against
- SVM training is guaranteed to find the global minimum of the cost function.
- Less experience needed – fewer parameters to tune

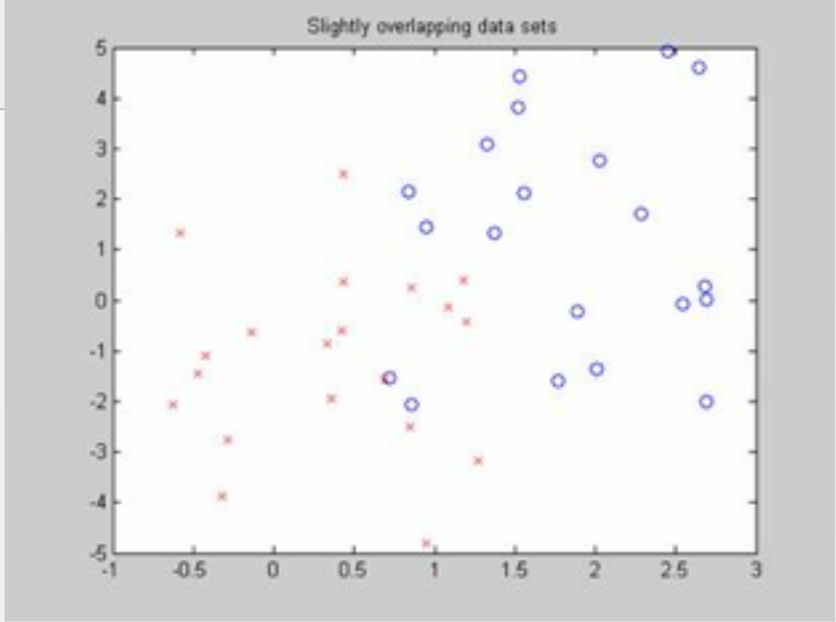
SVM with polynomial kernel visualization by Udi Aharoni

- http://www.youtube.com/watch?v=3liCbRZPrZA


feature 2
feature 1



SVM Parameters



What effect do the parameters of an radial-basis-function SVM have on the separating the two data sets?

RBF kernel parameters:
gamma = degree of curviness of the hyperplane / complexity of the contour
C = allowance for points to overlap into each other's class

RBF Parameters: C and gamma

- Grid search using cross-validation to find the best one. Coarse then fine grid search.
- e.g., 2–5, 2–3, … 2+15, gamma = 2–15, 2–13, 2+3
- Why grid search
  - Psychological (If you have time for brute force… why chance it on approximations or heuristics)
  - Since there are only 2 params, grid search isn’t all the different from advanced estimation techniques
  - Easily parallelized (C and gamma are

Practical Guide to SVM: The Lab

- Feature selection?
- Scale feature data
  - Save scaling stats so we can scale the test data to be in the same range
- Feature format
- Class labels {1,-1} or {0,1}
- Kernels (linear, polynomial, RBF, sigmoid)
- Find best C and gamma (cross-validation)
- Train with entire training set
- Test with validation or test set