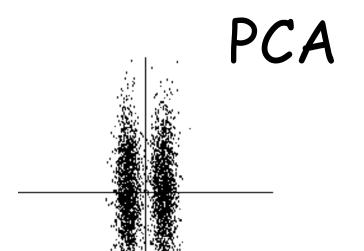
Linear Discriminant Analysis (LDA)

Ahmet Sacan

PCA



- The data is clearly divided into two clusters and each cluster has gaussian distribution
- PCA chooses the vertical axis as the principal component because of higher variance
 - Clustering information is lost
- Which projection would be more "interesting"?

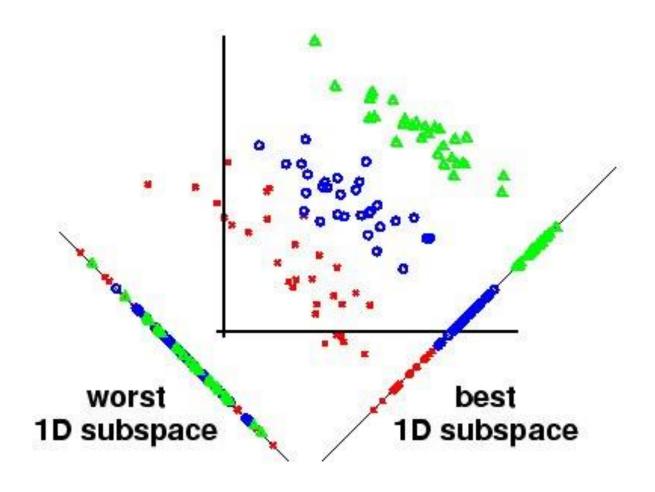
Projection based on Interestingness (Projection Pursuit)

- Specify the projection index function $I(x,\alpha)$ that maximizes the interestingness of the projection
 - Measure of variation (PCA)
 - Departure from normality (negative entropy)
 - Class seperability (LDA, Bhattacharyya)

— ...

• Solve for α by maximizing $I(x,\alpha)$

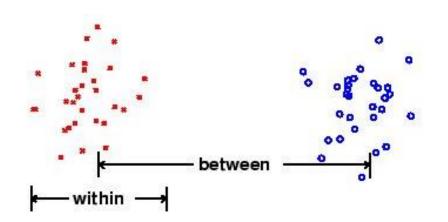
LDA



Within/between class scatter

• Within-class scatter (Sw)

$$S_w = \sum_j \text{cov}_j$$
$$= \sum_j (X_j - \mu_j)(X_j - \mu_j)^T$$



- where j is one of the red/blue classes.
- Between-class scatter (Sb)

$$S_b = \sum_{j} (\mu_j - \mu_*) (\mu_j - \mu_*)^T$$

LDA Criterion

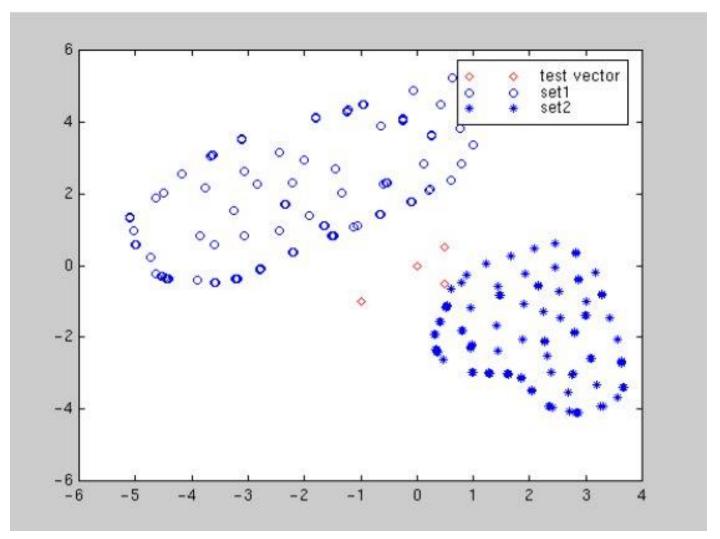
 Maximize ratio of overall variance to within class variance:

$$criterion = \frac{S_b}{S_w}$$

Two LDA approaches

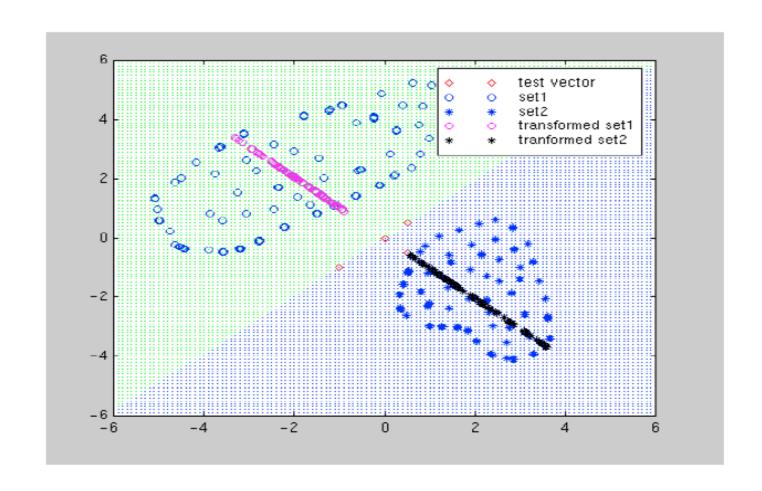
- · Class-independent transformation
 - All data is transformed using the same transformation, regardless of their class
 - Maximize ratio of overall between class variance to overall within class variance $criterion = \frac{S_b}{S_w}$
- · Class-dependent transformation
 - Transform data from each class separately
 - Maximize ratio of overall between class variance to within class variance of a specific j'th class.
 - $criterion_j = \frac{S_b}{cov_j}$

LDA

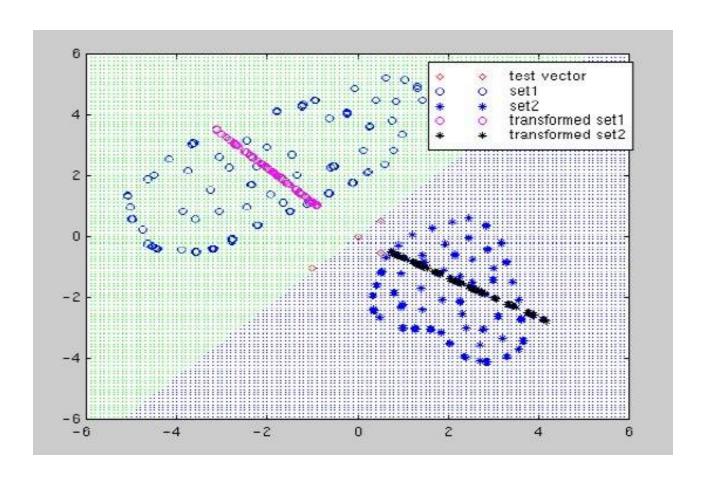


Balakrishnama and Ganapathiraju

Class-Independent LDA



Class-Dependent LDA



Thoughts on LDA

- The goal in LDA is typically classification. We typically don't show the projections.
- LDA does not work well for:
 - complex problems with nonlinear patterns.
 - high dimensional data
- One solution to high dimensional data:
 - Perform PCA first, reduce to a few dimensions.
 - Then perform LDA