### E9 205 Machine Learning for Signal Processing

**Dimensionality Reduction - I** 

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# Principal Component Analysis

- \* Reducing the data  $\mathbf{x}_n$  of dimension D to lower dimension M < D
- Projecting the data into subspace which preserves maximum data variance
  - \* Maximize variance in projected space
- \* Equivalent formulated as minimizing the error between the original and projected data points.

### Minimum Error Formulation - PCA



## Principal Component Analysis

\* First *M* eigenvectors of data covariance matrix

$$S = \frac{1}{N} \sum_{n=1}^{N} (\mathbf{x}_n - \bar{\mathbf{x}}) (\mathbf{x}_n - \bar{\mathbf{x}})^T$$

Residual error from PCA

$$J = \sum_{i=M+1}^{D} \lambda_i$$

### PCA

#### Handwritten digits used for PCA training...



### PCA



## PCA - Reconstruction



#### **PCA - Reconstruction**



## Whitening the Data



## Linear Discriminant Analysis

### Without the Within Class Factor



### Linear Discriminant Analysis

Find a linear transform  $f(\mathbf{x}) = \mathbf{w}^T \mathbf{x}$  with a criterion which maximizes the class separation

• Maximize the between class distance in the projected space while minimizing the within class covariance

$$J = \frac{\mathbf{w}^T \boldsymbol{S}_b \mathbf{w}}{\mathbf{w}^T \boldsymbol{S}_w \mathbf{w}}$$

 $\boldsymbol{S}_b = \sum_{k=1}^{K} N_k (\boldsymbol{\mathbf{m}}_k - \boldsymbol{m}) (\boldsymbol{\mathbf{m}}_k - \boldsymbol{m})^T \quad \boldsymbol{S}_w = \sum_{k=1}^{K} \sum_{n \in C_k} (\boldsymbol{\mathbf{x}}_n - \boldsymbol{m}_k) (\boldsymbol{\mathbf{x}}_n - \boldsymbol{m}_k)^T$ 

- Generalized Eigenvalue problem
- \* Eigenvectors of  $S_w^{-1}S_b$

PRML - C. Bishop (Sec. 4.1.4, Sec. 4.1.6)

## Linear Discriminant Analysis



PRML - C. Bishop (Sec. 4.1.4, Sec. 4.1.6)

### PCA versus LDA



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