

# SMAI-M20-L13: PCA(Cont.)

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# Class Review

Consider the vector  $\mathbf{w} = [w_1, w_2]^T$  and the objective function to be minimized as:

$$\min_{\mathbf{w}} (3w_1 + 4w_2 - 12)^2 + \lambda g(\mathbf{w})$$

If  $g(\mathbf{w})$  is  $L_p$  norm of  $\mathbf{w}$ , what is the optimal value of  $\mathbf{w}$ ?

- for various  $p$ ?
- for various  $\lambda$ ?



# Recap:

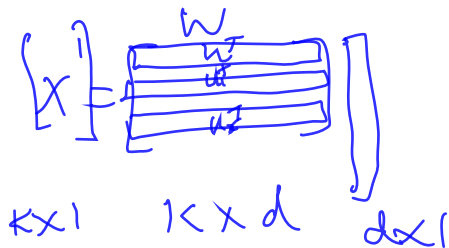
- Problem Space:
  - Learn a function  $y = f(\mathbf{W}, \mathbf{x})$  from the data.
  - Dimensionality Reduction and Representation ( Feature Selection, PCA, Neural Embeddings)
  - Matrix Factorization for Data Matrices: (LSI, Matrix Completion, Recommendation Systems)
- Supervised Learning:
  - Notions of Training, Validation and Testing; Loss Function and Optimization
  - Generalization, Overfitting, Occam's razor, Model Complexity, Bias and Variance, Regularization.
  - Performance Metrics, Estimating error using validation set.
- Algorithms:
  - Nearest Neighbour Algorithm
  - Linear Classification; Linear Regression
  - Decide as  $\omega_1$  if  $P(\omega_1|\mathbf{x}) \geq P(\omega_2|\mathbf{x})$  else  $\omega_2$

# This Lecture:

- ① PCA as Compression
  - Dimensionality reduction that allow minimal loss in the data.
- ② Intuitive Intro to Gradient Descent
  - An iterative optimization algorithm for minimizing loss functions.
- ③ Feature Normalization
  - Dimensions to be brought to some common scale and variation/range; Numerical and practical advantages.

**Questions? Comments?**

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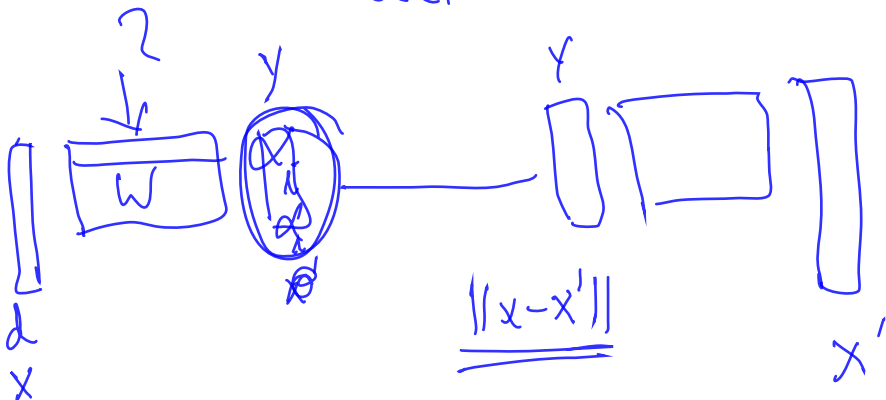


$$x \quad d \times 1$$

$$\sum d \times d$$

$$u \quad d \times 1$$

$$\boxed{a^T b = b^T a}$$

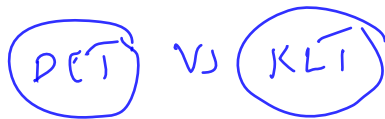




# Discussions Point - I

- It is common to represent signal/data using some orthogonal basis. Discrete Fourier Transform (DFT) is an example that use complex exponential basis.
- Discrete Cosine Transform(DCT) (a close friend of DFT) is popular in the compression standards such as JPEG. We retain only a small number of coeff; rest as zero; thus obtain compression.
- The optimal linear transform to do this is popularly known as KL Transform (where eigen vectors of the covariance form the basis). Our PCA is a close relative.

Why is PCA/KL-Transform based compression algorithms not yet popular in the standards we all use?









## Discussions Point - II

Comment about the effectiveness of GD for optimizing the loss functions. Initialization is also shown.







## Discussions Point - III

Consider a two dimensional representation with each dimensions as  $x_1$  and  $x_2$ . i.e.,  $\mathbf{x} = [x_1, x_2]^T$ .

We know that we need to do a feature normalization to obtain

$$\mathbf{x}' = [x'_1, x'_2]^T$$

A  $x'_i = \frac{x_i}{\alpha_i}$

B  $x'_i = x_i - \alpha_i$  (after the class?)

How do we represent

- 1  $\mathbf{x}' = \mathbf{L}\mathbf{x}$  ? What is  $\mathbf{L}$
- 2 What should be the matrix  $\mathbf{A}$  such that the Euclidean distance in  $\mathbf{x}'$  is same as Mahalanobis distance in  $\mathbf{x}$ . i.e.,

$$[\mathbf{x} - \mathbf{y}]^T \mathbf{A}^{-1} [\mathbf{x} - \mathbf{y}] = [\mathbf{x}' - \mathbf{y}']^T [\mathbf{x}' - \mathbf{y}']$$







## What Next:? (next three)

- ① Application of PCA
- ② Perceptron Algorithms
- ③ Analysis of Gradient Descent Algorithm
- ④ Implementation of Gradient Descent
- ⑤ Analysis of Perceptron Algorithm