



# SMAI-M20-L08:SVD; MLE and MSE

C. V. Jawahar

IIIT Hyderabad

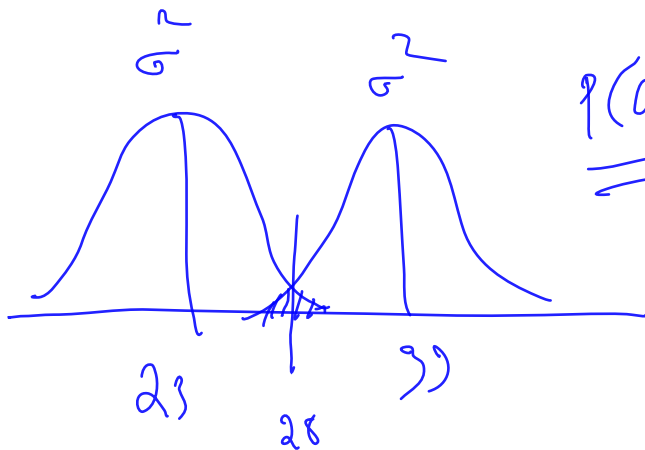
August 26, 2020

# Announcements:

- Class Review Questions (wish to do in the lecture session:5-10 mins):
  - Five objective questions;; An average of 1 to 1.5 min per questions;
  - Submission (QA) will be now on Shiksha.
  - Enough buffer for missing lecture sessions/connectivity (only 80%)
  - Quick clarifications in the class; detailed doubts/queries in an OH.
- Home works:
  - Regular (we are lagging behind), handwritten or some programming.
  - Only 80% is required. Buffer for connectivity/personal schedules.
  - Assume by now: Comfortable with python and jupyter notebooks.
- MS Teams/Communication/Connectivity:
  - use smai.m2020@gmail.com for direct communication
  - use channels to post queries
  - avoid submission closest to the deadlines.
- Office Hours/Queries on:
  - 1 Chapter 2, 3 and 5 of the book
  - 2 Class Review Questions: L01-L08
  - 3 Micro-Lecture Videos: L01-L08

## Review Questions: Let us submit in the first 10 mins

- ① Numerically computing rank of a  $3 \times 3$  matrix
- ② The system of linear equations  $Ax = b$  has?
- ③ Suppose a disease is prevalent in 1% of the population. Its medical diagnosis is 90% accurate in both directions. Given that a person tested positive, what is the chance, he actually has the disease (rounded to nearest integer)?
- ④ We know that the optimal classifier for two equally probable (equal Prior probability) classes (days of months)  $N(23, \sigma^2)$  and  $N(33, \sigma^2)$  is 28.  
If the variance of the second class becomes double, then the the optimal classification threshold will increase or decrease?
- ⑤ A man is known to speak truth 2 out of 3 times. He throws a die and reports that number obtained is a four. Find the probability that the number obtained is actually a four.



$$\underline{\underline{p(w) = p(w)}}$$

# Recap:

- Problem Space:
  - Learn a function  $y = f(\mathbf{W}, \mathbf{x})$  from the data.
    - for classification
    - for regression
  - Learn useful features
    - feature transformations
    - dimensionality reduction
    - feature selection, feature extraction
- Supervised Learning:
  - Notion of Training and Testing
  - Notion of Loss Function and Optimization
  - Need of generalization and Worry of Overfitting
- Classification 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  $\omega_2$
  - Performance Metrics
- Mathematical Foundations: Linear Algebra, Probability, Optimization

# This Lecture:

- SVD: Singular Value Decomposition

- Connect to Eigen Decomposition
- Connect to Data Matrix
- Follow ups to come.

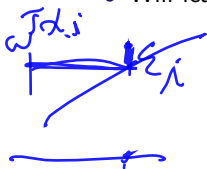
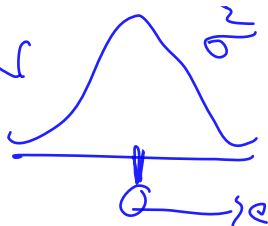
- MSE as MLE

- Appreciate MLE as a general step.
- Probabilistic interpretation of an intuitive expression.

- Geometry of Gaussians

- Eigen Decomposition
- Will lead to PCA.

~~max~~  $\sum (y_i - \omega^T x_i)^2$

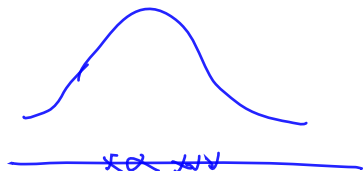


$$\epsilon_i = y_i - \omega^T x_i$$

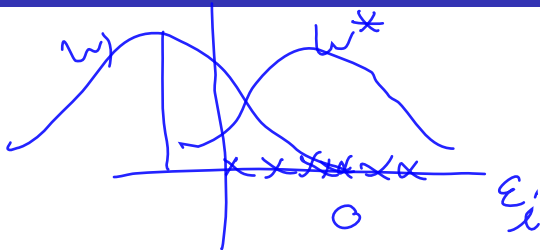
$$-||x||^2$$

# Blank

MLE



Find  
 $\mu, \sigma^2$



$$e_i = y_i - c^T x_i$$

**Questions? Comments?**





## Discussions Point -I

Consider a situation when we continue to get one sample at a time. We have mean ( $\mu_N$ ) and variance ( $\sigma_N^2$ ) computed and available at sample  $N$ .

Now we get the  $N + 1$  sample. How do we compute the new mean? Ans:

$$\text{Ans : } \mu_{N+1} = \frac{\mu_N \times N + x_{N+1}}{N + 1}$$

$$\mu_N = \frac{\sum_{i=1}^N x_i}{N}$$

How do we compute  $\sigma_{N+1}^2$ ?

Where do we need such “online” computations?

$$\mu = \frac{1}{n} \sum x_i$$

$$\sigma^2 = \frac{1}{n} \sum_{i=1}^n (x_i - \mu)^2$$

$$\sum_i (x_i - \mu)^2$$

$$\underbrace{\sum_i x_i^2}_{\checkmark} + \underbrace{\sum_i \mu^2}_{\checkmark} - \underbrace{\sum_i \mu \cdot x_i}_{\checkmark}$$

# Discussion Point - II

We know that:

- Eigen Decomposition of Symmetric Matrix  $\mathbf{S}$

$$\mathbf{S} = \mathbf{Q} \mathbf{\Lambda} \mathbf{Q}^T = \sum_{i=1}^n \lambda_i \mathbf{q}_i \mathbf{q}_i^T$$

- SVD of  $\mathbf{A}$   $n \times n$

$$\mathbf{A} = \mathbf{U} \mathbf{D} \mathbf{V}^T = \sum_{i=1}^n d_i \mathbf{u}_i \mathbf{v}_i^T$$

- How do we compute  $\mathbf{S}^{-1}$  and  $\mathbf{A}^{-1}$

- If  $\mathbf{A} = \mathbf{p} \mathbf{q}^T$  is a  $3 \times 3$  matrix, what is the SVD of  $\mathbf{A}$ ?

$$\mathbf{Q}^T = \mathbf{Q}^T$$

$$(\mathbf{Q} \mathbf{\Lambda} \mathbf{Q}^T)^T$$

$$\mathbf{Q}^T \mathbf{\Lambda}^T \mathbf{Q}^T$$

$$\mathbf{Q}^T \mathbf{\Lambda} \mathbf{Q}^T$$

$$\mathbf{Q} \mathbf{\Lambda} \mathbf{Q}^T$$

$$\mathbf{U} \mathbf{D} \mathbf{V}^T$$

$$\begin{bmatrix} \lambda_1 & 0 & 0 \\ 0 & \lambda_2 & 0 \\ 0 & 0 & \lambda_3 \end{bmatrix}$$

$$\mathbf{A} = \begin{bmatrix} p & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} q \\ 0 \\ 0 \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

$$b. \quad A = U D V^T$$

$$p \quad 3 \times 1$$

$$q \quad 3 \times 1$$

$$A^T = (V^T)^T D^T U^T$$

$$= \underline{\underline{V D^T U^T}}$$

$$A = \begin{bmatrix} \underline{\underline{p_1}} & \underline{\underline{0}} & \underline{\underline{0}} \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} q_1 \\ 0 \\ 0 \end{bmatrix} \begin{bmatrix} q_1 & q_2 & q_3 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$

$$\begin{matrix} 3 \times 1 & 3 \times 3 & 3 \times 1 \\ \begin{bmatrix} p_1 \\ p_2 \\ 0 \end{bmatrix} & & \end{matrix}$$

## Discussion Point - III

We are worried about outliers in the regression. Let us give a score  $\gamma_i$  as the “importance” or “confidence” of a sample that this is an inlier. We can now modify the loss/objective as:

$$\frac{1}{2} \sum_{i=1}^N \gamma_i (y_i - \mathbf{w}^T \mathbf{x}_i)^2$$

Handwritten notes:  $\gamma_i$  is circled with an arrow pointing to the matrix form. To the right, a box contains the matrix form:  $\mathbf{w} = (\mathbf{X}^T \mathbf{\Gamma} \mathbf{X})^{-1} \mathbf{X}^T \mathbf{\Gamma} \mathbf{y}$ . Above this box, there is a handwritten expression:  $[y - \mathbf{X}\mathbf{w}]^T [\mathbf{I} - \mathbf{H}]$ .

- Write down the objective in matrix form. (Hint: use  $\mathbf{\Gamma} = \text{Diag}(\gamma_i)$ ).

a What is the final closed form expression for the  $\mathbf{w}$ ?

- (Advanced) Consider a two step Iterative algorithm:

- Assign  $\gamma_i$  as inversely proportional to the distance from the line. (distance = 0  $\rightarrow$   $\gamma$  as 1 and high distance  $\rightarrow$   $\gamma$  as 0)
- Compute  $\mathbf{w}$  using the closed form expression (Q1).

If we iterate the above two steps? (i) will it converge? (ii) will it take care of outliers? (Later: Try it out on a toy data of yours <sup>1</sup>)

<sup>1</sup>A similar treatment in a different area: read “Sample weighted Clustering Methods”, CMA, 2011

$$[y - xw]^T [y - xw]$$

$$[y - \underline{\underline{[r]}} xw]^T [y - \underline{\underline{[r]}} xw]$$

$$\frac{\partial}{\partial w} [y - xw]^T [y - xw] = 0$$

$n \times n$   
 $1 \times n$   
 $n \times 1$   
 $n + 1$

## What Next:? (next three)

- Application of SVD and Eigen Decomposition
- More Insights into Supervised Learning
- Bayesian View and Optimal Classification
- Practical Issues in Optimization