

SMAI-M20-L10: LSI etc.

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Class Review Questions

- 1 If $A = UDV^T$, then $A^T A$ is
- (i) always a rank deficient matrix (ii) VD^2V^T (iii) UD^2U^T (iv) A square matrix (v) is always full rank (vi) can some times be full rank (vi) none of the above etc.
- 2 Consider a set of general vectors $\mathbf{a}_i \in R^d$. (assume all elements are some random numbers in the range of $[0, 1]$) \mathbf{b} is another such vector. Consider the matrix:

$$\mathbf{A} = \sum_{i=1}^k \alpha_i \mathbf{a}_i \mathbf{a}_i^T + \sum_{i=k+1}^d \beta_i \mathbf{b} \mathbf{b}^T$$

Comment on the effective rank of \mathbf{A} for various values of α_i and β_i

Announcements:

Post Your queries about:

- Chapters 2, 3 5 in the book.
- Class Reviews in L01-L08
- Micro-Lecture Videos L01-L08

Recap:

- Problem Space:
 - Learn a function $y = f(\mathbf{W}, \mathbf{x})$ from the data.
 - for classification
 - for regression
 - Learn useful features
- Supervised Learning:
 - Notion of Training and Testing
 - Notion of Loss Function and Optimization
 - Need of Generalization and Worry of Overfitting
 - Occam's razor and role of model complexity
 - Estimating error on validation set.
- Classification Algorithms:
 - Nearest Neighbour Algorithm
 - Linear Classification; Linear Regression
 - Decide as ω_1 if $P(\omega_1|\mathbf{x}) \geq P(\omega_2|\mathbf{x})$ else ω_2
 - Performance Metrics
- Mathematical Foundations: Linear Algebra, Probability, Optimization
 - SVD, Eigen Decomposition
 - MLE

This Lecture:



Micro-Lecture Videos

1 Rank of Term-Document Matrix and LSI

- Q: How do we compare documents? words?
- Appreciate "one-hot" representation of words.

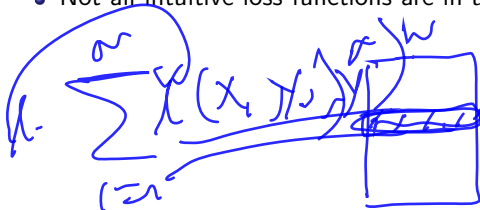


2 Bias and Variance

- Yet another balancing act to do while designing ML solution.

3 Loss Function

- Not all intuitive loss functions are in use due to practical difficulties.



Questions? Comments?

Discussions Point -I

Matrix completion: We know completion of rank 1 matrix as:

Given A , $\text{rank} \geq 1$
Find B

$$A = \begin{bmatrix} 7 & ? & ? \\ ? & 8 & ? \\ ? & 12 & 6 \\ ? & ? & 2 \\ 21 & 6 & ? \end{bmatrix} \Rightarrow \begin{bmatrix} 7 & 2 & 1 \\ 28 & 8 & 4 \\ 42 & 12 & 6 \\ 14 & 4 & 2 \\ 21 & 6 & 3 \end{bmatrix}$$

i, j available

Example Problem Formulation:

$$\min \sum_i \sum_j (A_{ij} - B_{ij})^2 \text{ s.t. } \text{rank}(B) = 1$$

Q: What is this summation over? What is the min over?

The rank constraint is not easy to enforce. See alternate formulations based on Nuclear norm¹ i.e., L1 norm over Diag(D) instead of L0 norm.

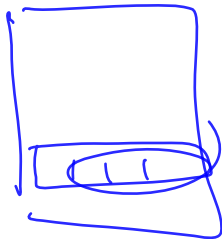
¹ Nuclear norm of a matrix is just the sum of the singular values of the matrix

$$\sum_{i,j, \text{visible}} (A_i - B_j)^2 \text{ s.t.}$$



$$\text{rank}(B) = 1$$

Ed = 300
350



Given A
with missing
elements and
rank constraint

Find B

Discussion Point - II

LSI has many applications ²

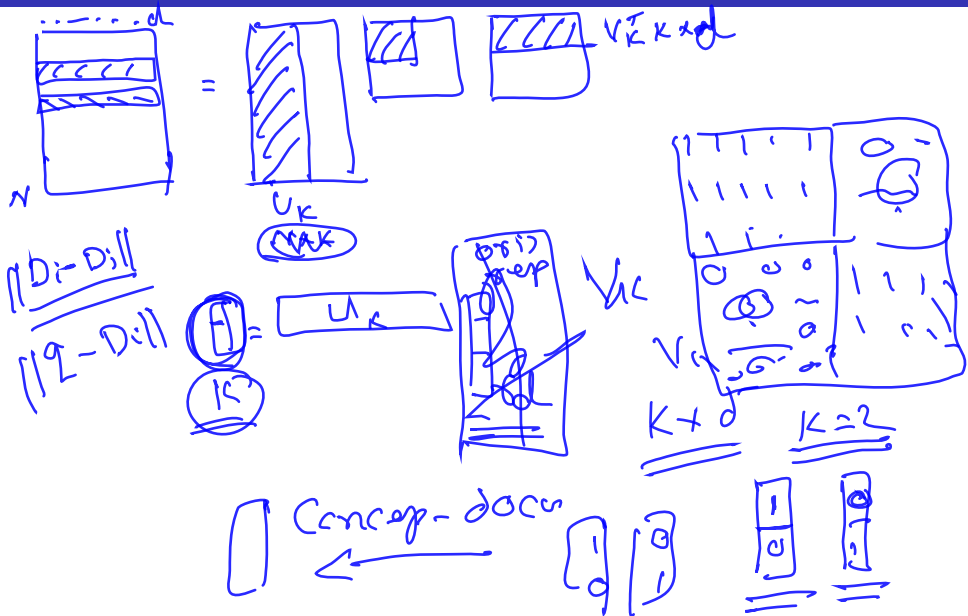
- Compare the documents in the low-dimensional space (data **clustering**, document classification).
- Find similar documents across languages, after analyzing a base set of translated documents (cross-language information retrieval).
- Find relations between terms (**synonymy** and polysemy).
- Given a query of terms, translate it into the low-dimensional space, and find matching documents (information retrieval).
- Find the best similarity between small groups of terms, in a semantic way.
- Expand the feature space of machine learning / text mining systems
- Analyze word association in text corpus

Q: **How does it help in Synonymy ?**

Q: **How does it help in Clustering documents ?**

²Read: https://en.wikipedia.org/wiki/Latent_semantic_analysis

Blank



Appreciate the fact that there is an important balancing act to be done to get good solutions. Why?

- ① overfitting and underfitting
- ② bias and variance
- ③ empirical error and model complexity

What Next:? (next three)

- Applications and insights into of SVD and Eigen Decomposition
- Supervised Learning: Regularization and Loss Functions
- Bayesian View and Optimal Classification
- PCA and Dimensionality Reduction

$$\underline{X^1 = U \Sigma^* V^T}$$