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1 Eigenchangers!

X is an $N \times D$ matrix over \mathbb{R} . An Singular Value Decomposition(SVD) of X is $X = U\Sigma V^T$, where-

1. The columns of U and V are orthonormal.

2. if $\Sigma = (\sigma_{ij})$ then $\sigma_{ij} = 0$ for $i \neq j$ and $\sigma_{11} \geq \sigma_{22} \geq \dots \geq 0$. Let $\sigma_{ii} = \sigma_i$ are called singular values of X .

Theorem: Let $X = U\Sigma V^T$ be an SVD of A . Then,

1. σ_i 's are the square roots of the eigenvalues of $X^T X$ (As well as XX^T).

2. The columns of V are the eigenvectors of $X^T X$.

3. The columns of U are the eigenvectors of XX^T

Proof:

Columns of V are (v_1, \dots, v_n)

Columns of U are (u_1, \dots, u_n)

$$\begin{aligned} X^T X v_i &= (U\Sigma V^T)^T U\Sigma V^T v_i \\ &= (V^T)^T \Sigma^T U^T U\Sigma V^T v_i \\ &= V\Sigma^T \Sigma V^T v_i = V\Sigma^T \Sigma e_i \\ &= V\Sigma_i^2 e_i = \sigma_i^2 v_i \end{aligned}$$

Here, We get the value of $\Sigma^T \Sigma$ as-

$$\begin{aligned} \Sigma^T \Sigma &= \begin{bmatrix} \sigma_1 & 0 & 0 & \dots & 0 \\ 0 & \sigma_2 & 0 & \dots & 0 \\ & & \dots & & \\ 0 & 0 & 0 & 0 & \sigma_r \\ & & \dots & & \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} \sigma_1 & 0 & 0 & \dots & 0 \\ 0 & \sigma_2 & 0 & \dots & 0 \\ & & \dots & & \\ 0 & 0 & 0 & 0 & 0 \\ & & \dots & & \\ 0 & 0 & 0 & \sigma_r & 0 \end{bmatrix} e_i \\ &= \begin{bmatrix} \sigma_1^2 & 0 & 0 & \dots & 0 \\ 0 & \sigma_2^2 & 0 & \dots & 0 \\ & & \dots & & \\ 0 & 0 & 0 & \sigma_r^2 & 0 \\ & & \dots & & \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}_i = \sigma_i^2 \times e_i \end{aligned}$$

$\therefore v_i$ is an eigenvector of $X^T X$ with eigenvalue σ_i^2

The diagonal entries of Σ are the roots of the eigenvalues of $X^T X$.

Same argument shows that u_i 's are the eigenvectors of XX^T with eigenvalues σ_i^2 .

All the columns of U and V are linearly independent(as they are orthogonal). So, U and V invertible.

$$XV = U\Sigma \quad [V^T = V^{-1}]$$

$$\begin{aligned}
&= (u_1, \dots, u_m) \Sigma \\
&= (\sigma u_1, \sigma u_2, \dots, \sigma u_m) \\
&\therefore X v_i = \sigma_i u_i
\end{aligned}$$

$$\boxed{u_i = \frac{X v_i}{\sigma_i}}$$

Advantage: Determining the eigenvalue of $XX^T (N \times N)$ will take $O(N^3)$ and for $X^T X (D \times D)$ it will take $O(D^3)$. As $N \leq D$, the time complexity will be less for XX^T case.

2 A General Activation Function

1. $\beta = kx$ where $k \rightarrow \infty$ will approximate the Identity function.
2. $\beta \rightarrow \infty$ then $h(x)$ will approximate ReLU.

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QUESTION

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My solution to problem 3

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QUESTION

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My solution to problem 4

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QUESTION

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My solution to problem 5

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QUESTION

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My solution to problem 6