We know that solution to the problem of Maximize $\mathbf{w}^T\mathbf{A}\mathbf{w}$ subject to $||\mathbf{w}|| = 1$ is the eigen vector corresponding to the largest eigen value.

Note that we assume that a typical eigen value computation assumes to be returning (i) eigen values arranged in non-increasing order (ii) eigen vectors have unit L2 norm.

What is the solution to the problem of Maximize $\mathbf{w}^T\mathbf{A}\mathbf{w}$ subject to $||\mathbf{w}||_2^2 = 2$

(A) Eigen vector correspond to the second eigen value.

(B) Eigen vector correspond to the first eigen value.

(C) 2***u** where **u** is the eigen vector correspond to the first eigen value.

(D) **[Ans]** $\sqrt{2} * \mathbf{u}$ where **u** is the eigen vector correspond to the first eigen value.

(E) None of the above.

We are working with N samples each of d dimension. Consider $N < d$

(A) Solution to the problem of linear regression as a closed form can not be computed because the matrices are no longer compatble for multiplication.

(B) **[Ans]** Solution to the problem of linear regression as a closed form can not be computed because the matrix can not be inverted.

(C) Solution to the problem of ridge regularized linear regression as a closed form can not be computed because the matrix can not be inverted.

(D) None of the above

We are working with N samples each of d dimension. Consider $N \leq d$

(A) PCA can not be computed

(B) While computing Eigen values, we will see d zero eigen values.

(C) **[Ans]** While computing Eigen values, we will see at least $d - N$ zero eigen values.

(D) **[Ans]** While computing Eigen values, we will see at max $d - N$ zero eigen values.

(E) **[Ans]** We can not use eigen value/vector computation. We need to use SVD.

(F) None of the above.

We know the weighted Euclidean distance

$$\tau = [\mathbf{x} - \mathbf{y}]^T[\mathbf{A}][\mathbf{x} - \mathbf{y}]$$

Where $\mathbf{x}$ is a vector in d dimension $\mathbf{A}$ is a square matrix

(A) **[Ans]** If $\mathbf{A}$ is a non-identity diagonal matrix. Then "dist" is a scaled version of Euclidean distance or "$\tau = \alpha$ Euclidean distance"

(B) If $k < d$ and $A = \sum_{i=1}^{k} \mathbf{u}_i \mathbf{u}_i^T$, with $\mathbf{u}_i$s as orthonormal. Then A is rank deficient and Euclidean τ can not be computed.

(C) **[Ans]** If $k < d$ and $A = \sum_{i=1}^{k} \mathbf{u}_i \mathbf{u}_i^T$, with $\mathbf{u}_i$s as orthonormal. Then τ is equivalent to dimensioality reduction $\mathbf{x}' = \mathbf{W}\mathbf{x}$ with $\mathbf{W}$ as $k \times d$ matrix with $\mathbf{u}_i^T$ as the i th row.

(D) When $\mathbf{A}$ is non-diagonal matrix, τ can not be a metric.

(E) None of the above.

Consider the covariance matrix Σ

(A) **[Ans]** Σ is symmetric

(B) **[Ans]** Σ is PSD

(C) Σ is Diagonal if the distribution is Normal.

(D) Σ can not be Diagonal if the distribution is Normal.

(E) None of the above