

# Linear Algebra Review Assignment 1

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1.)

$$A = \begin{pmatrix} a_{11} & \dots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{m1} & \dots & a_{mn} \end{pmatrix}, B = \begin{pmatrix} b_{11} & \dots & b_{1m} \\ \vdots & \ddots & \vdots \\ b_{n1} & \dots & b_{nm} \end{pmatrix}$$

$$\text{tr}(AB) = (a_{11}b_{11} + \dots + a_{1n}b_{n1}) + (a_{21}b_{12} + \dots + a_{2n}b_{n2}) + \dots + (a_{m1}b_{1m} + \dots + a_{mn}b_{nm})$$

$$= \sum_{i=0}^m \sum_{j=0}^n a_{ij} b_{ji} = \sum_{i=0}^m \sum_{j=0}^n b_{ji} a_{ij}$$

$$= (b_{11}a_{11} + b_{12}a_{21} + \dots + b_{1m}a_{m1}) + \dots + (b_{n1}a_{1n} + \dots + b_{nm}a_{mn}) = \text{tr}(BA)$$

This is valid because of the associativity and commutativity in  $\mathbb{R}$ .

2.)

$$G = A^T A$$

We know from linear algebra:

$$(Ax)^T = x^T A^T$$

$$x^T G x = x^T A^T A x = (Ax)^T (Ax)$$

Let  $Ax$  be  $y$ .

$$y^T y = \sum_{i=0}^n y_i y_i = \sum_{i=0}^n y_i^2 \succeq 0$$

3.)

Let's assume singularity :

$$\exists x \in \text{Ker}(A) \neq 0 : Ax = 0$$

$$\Rightarrow x^T Ax = x^T 0 = 0$$

what is a contradiction to the definition of positive definite:

$$x^T Ax > 0$$

$$\Rightarrow \nexists x \in \text{Ker}(A) \neq 0 : Ax = 0$$

$$\Rightarrow \text{Ker}(A) = \{0\}$$

A is nonsingular.

4.)

$$A \in \mathbb{R}^{n \times n} \quad Ax_i = \lambda_i x_i$$

For the following we use the knowledge that A is regular and symmetrical, in other words eigendecomposable where no eigenvalue is zero.

$$A = QDQ^{-1}, \quad A^{-1} = QD^{-1}Q^{-1}$$

where D is diagonal. Now  $D^{-1}$  is the diagonal matrix to  $A^{-1}$  where the eigenvalues of  $A^{-1}$  are on the diagonal. We also know that the eigenvalue  $\lambda_i$  is on the matrix entry  $D_{ii}$

$$D_{ii}^{-1} = \lambda_i^{-1} = \frac{1}{\lambda_i}$$

$$A^{-1}x_i = \frac{1}{\lambda_i}x_i \quad \square$$

5.)

$$A = x_i y_i^T \in \mathbb{R}^{n \times m}$$

$$A_{ij} = x_i x_j$$

$$\text{col}_i = \left\{ \begin{pmatrix} x_1 y_i \\ \vdots \\ x_n y_i \end{pmatrix} \right\}$$

All columns are linearly dependent from one column since column i can be retrieved by  $\text{col}_j / y_j \cdot y_i$ . Therefore the rank of this matrix is 1.

$$\begin{pmatrix} x_1 y_i \\ \vdots \\ x_n y_i \end{pmatrix} \Rightarrow \begin{pmatrix} x_1 \\ \vdots \\ x_n \end{pmatrix} \Rightarrow \begin{pmatrix} x_1 y_j \\ \vdots \\ x_n y_j \end{pmatrix}$$

$$\Rightarrow A = \sum_{i=0}^m x_i y_i^T \Rightarrow \text{col}_i = \begin{pmatrix} x_{11}y_{1i} \\ \vdots \\ x_{1n}y_{1i} \end{pmatrix} + \dots + \begin{pmatrix} x_{m1}y_{mi} \\ \vdots \\ x_{mn}y_{mi} \end{pmatrix}$$

$$A = \sum_{i=0}^m G_i : G_i = x_i y_i^T$$

This means that A is a linear combination of m matrices each of rank 1. Therefore the rank cannot exceed m:  $\text{rank}(A) \leq m$

6.)

We know from linear algebra that the column rank is the same as the row rank. Following from this the rank cannot exceed the amount of BOTH rows AND columns and must therefore be the minimum of these.

Proof Lemma:

$A \in R^{m \times n}$ . Let the row rank be r. Therefore the dimension of the row space is also r. Now let  $x_1, \dots, x_r$  be a basis of this row space. Now consider a linear homogeneous relation with these vectors and scalar coefficients  $c_1, \dots, c_r$ .

$$0 = c_1 A x_1 + \dots + c_r A x_r = A(c_1 x_1 + \dots + c_r x_r) = A v$$

with  $v = c_1 x_1 + \dots + c_r x_r$ . Now v is obviously a linear combination of vectors of the row space in A, which implies that v belongs to this row space. Furthermore since  $A v = 0$ , v is orthogonal to every row vector of A. These facts together imply that v is orthogonal to itself, which means that  $c_1 x_1 + \dots + c_r x_r = 0$ . Recall now that the  $x_i$  are a basis and therefore linearly independent. Therefore it must be true that  $c_1 = \dots = c_r = 0$ . Therefore  $A x_1, \dots, A x_r$  are also linearly independent. Now each  $A x_i$  is a vector in the column space of A, so the  $A x_i$  are linearly independent vectors in the column space and therefore the column rank must at least be as big as r. Now you can do this exact same process with  $A^T$  what leads to reverse equality and concludes this proof.

7.)

a) We know now that the rank, even though it's full, cannot exceed the minimum of n and m. So we're gonna have either linear dependent rows or columns. So there exists a vector v and coefficients c (not all zero) with

$$c_1 v_1 + \dots + c_r v_r = 0$$

$$\Rightarrow M c = c_1 v_1 + \dots + c_r v_r = 0$$

We also know that  $M 0 = 0$ . So if  $M^{-1}$  existed the following two things would be given:

$$0 = M^{-1}0, c = M^{-1}0$$

But it is given that  $c$  cannot be zero and therefore  $M^{-1}$  cannot exist.

In the case  $m = n$ , the matrix is regular. Therefore singularity is not guaranteed.

b) Singular, since there are rows in this matrix that are linearly dependent and we know that a matrix is regular if all rows are linearly independent. Furthermore a lemma states that a matrix is singular iff  $|A| \neq 0$

c) orthogonal matrices have the property that all rows and columns are linearly independent. Therefore it is clear that this matrix must also be regular.

d) Suppose  $A$  is square matrix and has an eigenvalue of 0. For the sake of contradiction, let's assume  $A$  is invertible.

Consider,  $Av = \lambda v$ , with  $\lambda = 0$  means there exists a non-zero vector  $v$  such that  $Av = 0$ . This implies  $Av = 0v \Rightarrow Av = 0$ . For an invertible matrix  $A$ ,  $Av = 0$  implies  $v = 0$ . So,  $Av = 0 = A \cdot 0$ . Since  $v$  cannot be 0, this means  $A$  must not have been one-to-one. Hence, our contradiction,  $A$  must not be invertible. So we know that a matrix is invertible if and only if it has no eigenvalue equal to zero.

e) As we stated before, as long as the matrix has no eigenvalue equal to zero it is regular. In all other cases it is singular.