1 Symmetric Matrix

Definition

$$A = A^T$$

Properties
1) The eigenvectors associate with distinct eigenvalues (v_1, v_2, v_n)of a symmetric matrix are orthogonal. So let V be the matrix whose columns are the eigenvectors of A, then $VV^T = I$, $V^{-1} = V^T$. If with same eigenvalues, then the eigenvector may not be orthogonal, we can do Gram-Schmit transformation to make it orthogonal.
2) The diagonal factorization of an symmetric matrix is

$$\begin{aligned}
A =& VCV^T \\
=& AI \\
=& A\sum_i v_i v_i^T \\
=& \sum_i c_i v_i v_i^T
\end{aligned}$$

3) Maximum value of As quadratic form

$$\begin{aligned}
& x^T Ax \\
=& x^T \sum_i c_i v_i v_i^T x \\
=& \sum_i b^T V^T v_i v_i^T V b c_i \\
=& \sum_i b_i^2 c_i \\
<=& max(c_i) b^T b \\
=& max(c_i) x^T x
\end{aligned}$$

2 Hermitian Matrix

A = A*(where A* is the complex conjugate of A)
1) The eigenvalues are real.

3 Orthogonal Matrix

Definition
$A{-}1 = A^T$ **Intuition**

Orthogonal matrix arise from dot product. Consider vector u , and a matrix Q. When we apply the matrix Q to v, we get $v^{'} = Qv$. We would like to have the dot product preserved, namely

$$v^T v = v^{'T} v^{'} = (Qv)^T (Qv) = v^T Q^T Q v$$

So $Q^T Q = 1$, $Q^T = Q^{-1}$.
Properties
Orthogonal matrices imply orthogonal transformations. Examples include rotations, reflections and combinations
Examples
1) Rotation Matrix

$$\begin{pmatrix} cos\theta & -sin\theta \\ sin\theta & cos\theta \end{pmatrix}$$

2) Reflection Matrix

$$\begin{pmatrix} 1 & 0 \\ 0 & -1 \end{pmatrix}$$

4 Idempotent Matrix

Definition
$A^2 = A$
Properties
1) Its eigenvalues are either 0 or 1. Because the eigenvalues of A^2 are the squares of the eigenvalues of A. 2) Any vector in the columns space of an idempotent matrix A is an eigenvector of A 3) The number of eigenvalues that are 1 is the rank of an idempotent matrix. $tr(A) = rank(A)$

5 Symmetric Positive Definite

Definition
A symmetric positive definite matrix satisfies for any non-zero vector x, $x^T Ax > 0$
Properties 1) Positive definite matrix is non-singular.
Proof: If A is singular, it means there is a non-zero vector x so that Ax=0. Therefore $x^T Ax = 0$, which is a contradiction.
2) All the eigenvalues are positive.
3) Its leading principal minors are all positive.
4) It has a unique Cholesky decomposition.