

Matrix Theory
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Lecture 57
Hermitian and symmetric matrix

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Hermitian and Symmetric Matrices

1. $f: \mathcal{D} \rightarrow \mathbb{R}$ twice continuously differentiable
Hessian: $H(x) = [h_{ij}(x)] = \left[\frac{\partial^2 f}{\partial x_i \partial x_j} \right] \in \mathbb{R}^{n \times n}$
 $\frac{\partial^2 f}{\partial x_i \partial x_j} = \frac{\partial^2 f}{\partial x_j \partial x_i} \quad \forall i, j = 1, 2, \dots, n$
 $\Rightarrow H(x) = (H(x))^T$ i.e., symmetric.

2. Quadratic form: $A \in \mathbb{R}^{n \times n}, x \in \mathbb{R}^n$

Quadratic form.
 $Q(x) = x^T A x$
 $A = \frac{1}{2}(A + A^T) + \frac{1}{2}(A - A^T)$
 $\Rightarrow Q(x) = \frac{1}{2} x^T (A + A^T) x + \frac{1}{2} \underbrace{x^T (A - A^T) x}_{x^T A x - x^T A^T x = 0}$
 $= \frac{1}{2} x^T (A + A^T) x$ (scalar)^T = (scalar)
 $\Rightarrow A$ and $\frac{1}{2}(A + A^T)$ generate the same quadratic form.
 \Rightarrow Suffices to study quadratic forms generated by symmetric matrices!!

And now, we move on to chapter 4 in Horn and Johnson which is Hermitian and symmetric matrices. So, Hermitian and symmetric matrices are special matrices which are, I mean distinguishing them only in terms of complex versus real Hermitian matrix is one where A conjugate transpose equals A and a symmetric matrix is a real-valued matrix where A is equal to A transpose, but these arise naturally in a variety of applications.

So, for example, if you are looking at the, looking at a function f , which is defined from some n -dimensional real space, which I call D to the real line, then and suppose it is twice

continuously differentiable. We define the Hessian of, Hessian matrix for this f as a matrix H of x which is an n cross n matrix whose entries are h_{ij} of x and each h_{ij} is the second partial derivative of this f with respect to x_i and x_j . So, this is a function of n variables, you take the second partial derivative with respect to x_i and x_j and this is a matrix that will be in \mathbb{R} to the n cross n .

And a key property of this is very important in optimization and especially in optimization, differential equations, and so on. But, the key property of this partial derivatives is that $\frac{d^2 f}{dx_i dx_j}$ is equal to $\frac{d^2 f}{dx_j dx_i}$, is the fundamental property of these partial derivatives for every i, j equal to $1, 2, \dots, n$. And as a consequence, H is equal to H^T , that is it is symmetric. Similarly, if we look at what is known as the quadratic form.

So, suppose we are given A in \mathbb{R} to the n cross n and x in \mathbb{R} to the n , then consider Q of x which could be one example of this function f here, Q of x is equal to $x^T A x$. So, note that we can always write A as one half of A plus A^T plus one half of A minus A^T , this can always be written, basically half a transpose cancels with minus half a transpose, and a half A and half A add up to give A .

So, this is always true. So, if I substitute for this in here that means that Q of x is equal to half $x^T A$ plus $A^T x$ plus half $x^T A$ minus $A^T x$ and if A is a symmetric matrix, then A may not even be symmetric here. So, if you just examine this $x^T A$ minus $A^T x$ this is equal to $x^T A x$ minus $x^T A x$, but this is a scalar. So, its transpose is equal to itself. So, for any scalar, this is equal to scalar.

And so, the transpose of this is $x^T A^T x$ and so these two are always going to be equal. So, this is equal to 0. And so, this Q of x is equal to one half $x^T A$ plus $A^T x$ times x . Now, what that means is that A and one-half A plus A^T generate the same quadratic form. So, basically that means, this is a very, very crucial point. So, that means that if you are interested in studying quadratic forms, it is sufficient to study quadratic forms generated by symmetric matrices. So, we will be studying quadratic forms generated by symmetric matrices.

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$x^T A x = x^T \frac{1}{2} (A + A^T) x$
 $(\text{scalar})^T = (\text{scalar})$
 $\Rightarrow A \text{ and } \frac{1}{2} (A + A^T) \text{ generate the same quadratic form.}$
 $\Rightarrow \text{Suffices to study quadratic forms generated by symmetric matrices!!}$
3. Graph theory: $A = [a_{ij}]$
 $a_{ij} = \begin{cases} 1 & \text{if } \exists \text{ edge bet}^n \text{ nodes } i \& j \\ 0 & \text{else} \end{cases} \quad \longleftrightarrow$
 $A = A^T \text{ for undirected graphs.}$

And finally, a third example is that I am out of time, so I will just very briefly mentioned it in graph theory. We define an adjacency matrix A graph is defined by a set of vertices and edges and an edge exists, so the set of vertices you can denoted by 1 to n . So, if there are n vertices in the graph, then you can label those vertices as 1 to n and edges are pairs of indices, pairs of vertices i, j, i_1, j_1, i_2, j_2 , etcetera.

And an edge exists if the two nodes i and j are connected to each other. And we define an adjacency matrix to be a matrix A , which contains entries a_{ij} , where a_{ij} equals 1 if there exists an edge between nodes i and j and 0 otherwise. And if the graph is undirected, undirected means the edges do not have a direction associated with them.

So, you have two nodes, you define an edge like this, not with an arrow going like this. It is an undirected graph, undirected graphs. So, these are three examples where symmetric matrices arise. And so, with this background, we will start in the next class studying about Hermitian and symmetric matrices. They have lots of very intricate very beautiful properties and so we will cover them.