CO 367

272284444

September 2023

Contents

1 Introduction

1.1 Lecture 1-Preliminaries

Definition 1.1 – Quadratic Form

Let A be a symmetric matrix and $x = \begin{pmatrix} x_1 \\ \vdots \\ x_n \end{pmatrix}$. The **quadratic form** Q of the matrix A is defined as

$$Q = x^T A x$$

Problem 1.1 – Example

Consider the matrix $A = \begin{bmatrix} 5 & -5 \\ -5 & 1 \end{bmatrix}$. The quadratic form of A is

$$Q(x) = 5x_1^2 - 10x_1x_2 + x_2^2$$

Definition 1.2 – Classification of Quadratic Forms

Let Q be a quadratic form of a matrix A. Then Q is

1. positive definite if $Q(x) > 0$ for all non-zero vectors x, and $Q(x) = 0$ if and only if $x = 0$. Or all eigenvalues of A are positive.
2. positive semidefinite if $Q(x) \geq 0$ for all vectors x, with $Q(x) = 0$ occurring for some non-zero vectors x. Or all eigenvalues of A are non-negative.
3. negative definite if $Q(x) < 0$ for all non-zero vectors x, and $Q(x) = 0$ if and only if $x = 0$. Or all eigenvalues of A are negative.
4. negative semidefinite if $Q(x) \leq 0$ for all vectors x, with $Q(x) = 0$ occuring for some non-zero vectors x. Or all eigenvalues of A are non-negative.
5. indefinite if $Q(x)$ can be positive or negative. Or there are positive and negative eigenvalues for A.

Definition 1.3 – Big O and little o

Big O is basically the rate of growth of that function. A function $f(n)$ is of order 1, or $O(1)$ if there exists some non zero constant c such that

$$\frac{f(n)}{c} \to 1$$

as $n \to \infty$.

Little o is the upper bound of the rate of growth of that function. Therefore, a function $f(n)$ is of order 1, or $o(1)$ if for all constants $c > 0$,

$$\frac{f(n)}{c} \to 0$$

as $n \to \infty$.

Definition 1.4 – Differentiability Based on Big o and Little o

If f is differentiable at $x = a$, then

$$f(a + h) = f(a) + f'(a)h + o(h)$$

Conversely, if there exists constants A and B such that

$$f(a+h) = A + Bh + o(h)$$

then f is differentiable at $x = a$. Moreover, $A = f(a)$ and $B = f'(a)$.

Definition 1.5 – Product Rule
If f, g are differentiable at $x = a$, then

$$f(a+h) = f(a) + f'(a)h + o(h), \quad g(a+h) = g(a) + g'(a)h + o(h)$$

Then

$$\begin{aligned} p(a+h) &= f(a+h)g(a+h) \\ &= f(a)g(a) + [f(a)g'(a) + g(a)f(a)]h + o(h) \end{aligned}$$

Then by above theorem, $p = fg$ is differentiable at $x = a$, and $p'(a) = f(a)g'(a) + g(a)f'(a)$.

Definition 1.6 – Chain Rule
WIP

Definition 1.7 – Inner Product Space
Let $x \in \mathbb{R}^n$, represented as:

$$x = \begin{pmatrix} x_1 \\ \vdots \\ x_n \end{pmatrix}$$

The inner product space is defined as:

$$\langle x, y \rangle = x^T y = \sum_{i=1}^{n} x_i y_i \quad \text{(dot product)}$$

The angle between vectors x and y is given by $\cos(\theta) = \frac{\langle x,y \rangle}{\|x\|}$.
With corresponding norm to be the Euclidean Norm

Definition 1.8 – Open ball
Given $\delta > 0$, $\bar{x} \in \mathbb{R}^n$, the open ball $B_\delta(\bar{x}) = \{x \in \mathbb{R}^n \,|\|x - \bar{x}\| < \delta\}$

Definition 1.9 – map
Suppose the map $f : \mathbb{R}^n - > \mathbb{R}$.

Definition 1.10 – open set
Let D $\subset \mathbb{R}^n$, D open set. $\forall x \in D$, $\exists \delta > 0$, s.t $B_\delta(x) \subset D$

Definition 1.11 – differ
We define f to be in C^1, C^2 on an open set $D \subseteq \mathbb{R}^n$, denoted $f \in C^1(D), C^2(D)$, respectively, if the partial first $\frac{\partial f(x)}{\partial x_i}$ and second $\frac{\partial^2 f(x)}{\partial x_i \partial x_j}$ derivatives exist and are continuous for all i, j, respectively. We then get the gradient vector in $\mathbb{R}^n$ and the $n \times n$ symmetric Hessian matrix, respectively denoted as:

$$\nabla f(x) = \left(\frac{\partial f(x)}{\partial x_i}\right) \in \mathbb{R}^n, \quad \nabla^2 f(x) = \left[\frac{\partial^2 f(x)}{\partial x_i \partial x_j}\right] \in \mathbb{S}^n.$$

Here, $\mathbb{S}^n$ is the vector space of $n \times n$ symmetric matrices.

Definition 1.12 – General Nonlinear opt. function NLO
The general problem of nonlinear optimization, denoted NLO, is defined as follows: Given C^2-smooth functions $f, g_i, h_j : D \subseteq \mathbb{R}^n \to \mathbb{R}$ for $i = 1, \ldots, m$ and $j = 1, \ldots, p$, where D is an open subset of $\mathbb{R}^n$, the objective is to find the optimal value p^* and an optimum x^* of NLO, represented as:

$$p^* := \min f(x) \text{s.t.} \quad g_i(x) \leq 0, \quad \forall i = 1, \ldots, m h_j(x) = 0, \quad \forall j = 1, \ldots, p x \in D$$

If f, g_i, h_i are all **affine** function and D=R^2, then we have an LP

Definition 1.13 – affine

$$f(x) = Ax + b \tag{1}$$

where b≠0

Definition 1.14 – Types of Minimality
Consider $f : \mathbb{R}^n \to \mathbb{R}$ and $D \subset \mathbb{R}^n$. Then $\bar{x} \in D$ is:

- a *global minimizer* for f on D if $f(\bar{x}) \leq f(x)$ for all $x \in D$.
- a *strict global minimizer* for f on D if $f(\bar{x}) < f(x)$ for all $x \in D$ where $x \neq \bar{x}$.
- a *local minimizer* for f on D if there exists $\delta > 0$ such that $f(\bar{x}) \leq f(x)$ for all $x \in D \cap B_\delta(\bar{x})$.
- a *strict local minimizer* for f on D if there exists $\delta > 0$ such that $f(\bar{x}) < f(x)$ for all $x \in D \cap B_\delta(\bar{x})$ where $x \neq \bar{x}$.

Definition 1.15 – Linear Approximation
Suppose f is a function that is differentiable on an interval I containing the point a. The **linear approximation** to f at a is the linear function

$$L(x) = f(a) + f'(a)(x - a)$$

for $x \in I$.

Definition 1.16 – Quadratic Approximation
Similar as above, the **quadratic approximation** to f at a is the quadratic function

$$Q(x) = f(a) + f'(a)(x - a) + \frac{1}{2} f''(a)(x - a)^2$$

for $x \in I$.

Definition 1.17 – Formal Definition of Derivative
The **derivative** of f at a is defined as

$$f'(a) = \lim_{x \to a} \frac{f(x) - f(a)}{x - a}$$

if the limit exists.
An alternate definition is

$$f'(a) = \lim_{h \to 0} \frac{f(a+h) - f(a)}{h}$$

1.2 Lecture 2

Definition 1.18 – General NLO/NLP
A **Non-linear Optimization Problem** (NLP) is of the following form:

$$\underbrace{p^*}_{\text{Optimal Value}} = \min \underbrace{f(x)}_{\text{Objective function}}$$

s.t.

$$g(x) = (g_i(x)) \leq 0 \in \mathbb{R}^m$$
$$h(x) = (h_j(x)) = 0 \in \mathbb{R}^p$$

Problem 1.2 – Example

$$\min(x_1 - 2)^2 + (x_2 - 1)^2$$

s.t.

$$x_1^2 - x_2 \leq 0 \qquad (g_1(x) \leq 0)$$
$$x_1 + x_2 - 2 \leq 0 \qquad (g_2(x) \leq 0)$$

Definition 1.19 – Contour
For $\alpha \in \mathbb{R}$, the **contour** of a function f is

$$C_\alpha = \{x \in \mathbb{R}^n : f(x) = \alpha\}$$

Definition 1.20 – Feasible Set
The **feasible set** is

$$F = \{x \in \mathbb{R}^n : g(x) \leq 0, h(x) = 0, x \in D\}$$

(Is D the domain??)

Definition 1.21 – Gradient

The **gradient** of f is

$$\nabla f(x) = \begin{pmatrix} \frac{\partial f(x)}{\partial x_1} \\ \vdots \\ \frac{\partial f(x)}{\partial x_n} \end{pmatrix}$$

For the optimal solution x^*, we have

$$\alpha \nabla f(x^*) = \lambda_1 \nabla g_1(x^*) + \lambda_2 \nabla g_2(x^*)$$

for some $\alpha, \lambda_1, \lambda_2 \in \mathbb{R}$.
We will see later that we can choose $\alpha = 1$ and we need $\lambda_1 \geq 0, \lambda_2 \geq 0$.

Problem 1.3 – Max-cut Problem
Given a weighted graph $G = (\underbrace{V}_{\text{vertices}}, \underbrace{E}_{\text{edges}}, \underbrace{w}_{\text{weight}})$, a **cut** is $U \subseteq V, U \neq \emptyset$. The objective function

$$\max \quad \frac{1}{2} \sum_{\substack{i \in U, j \notin U \\ (i,j) \in E}} w_{i,j}$$

maximizes the sum of edges in a cut.
Formulating as an NLP, we introduce variables $x_i \in \{\pm 1\}, i = 1, \dots, n$. Then the Max-cut problem (MC) is as follows:

$$\max \quad \frac{1}{2} \sum_{ij \in E} w_{ij}(1 - x_i x_j)$$

Why 1/2 s.t.

$$x_i \in \{\pm 1\} \quad (\text{equivalent to } x_i^2 = 1) \quad \forall i = 1, \dots, n$$

This works because

$$1 - x_i x_j = \begin{cases} 0 & \text{if } x_i = x_j \quad (i, j \text{ in the same set, } U \text{ or } U^c) \\ 2 & \text{otherwise} \end{cases}$$

MC is a **quadratically constrained quadratic program** (QOP) since each constraint $x_i \in \{-1, 1\}$ is equivalent to the quadratic constraint $x_i^2 = 1$. Note that MC is an NP-hard problem.

2 Unconstrained Optimization

2.1 Lecture 2

Problem 2.1 – Simplest Case - No Constraints
Let $\Omega \subseteq \mathbb{R}^n$ be an open set. Assume f is sufficiently smooth (differentiable) then the NLP with no constraints is

$$\min_{x \in \Omega} \quad f(x)$$

Theorem 2.1 – Taylor's Theorem on the real line
¡¡¡¡¡¡ HEAD Is it true? Let $f : (a, b) \to \mathbb{R}$, and $\bar{x}, x \in (a, b)$, then there exists z strictly between $x, \bar{x}$ such that

$$f(x) = f(\bar{x}) + f'(\bar{x})(x - \bar{x}) + \frac{f''(z)}{2}(x - \bar{x})^2$$

or equivalently
$$f(\bar{x}+\delta x) = \underbrace{f(x) + f'(x)\delta x}_{\text{Linear approximation}} + o(|\delta x|)(\text{little O})$$

======= Let $f : (a, b) \to \mathbb{R}$, and $\bar{x}, x \in (a, b)$. Then the Taylor's series centered at $\bar{x}$ (approximation near $\bar{x}$) is
$$f(x) = f(\bar{x}) + f'(\bar{x})(x - \bar{x}) + \frac{f''(z)}{2}(x - \bar{x})^2$$
where z is between x and $\bar{x}$ that gives the largest value of $f''(z)$. The term $\frac{f''(z)}{2}(x - \bar{x})^2$ is the **error term**
Equivalently,
$$f(\bar{x}+\Delta x) = \underbrace{f(x) + f'(x)\Delta x}_{\text{Linear approximation}} + o(|\Delta x|)(\text{little O})$$
This formula emphasizes its use in approximating changes in f for small changes in x, denoted Δx. $o(|\Delta x|)$, the error term, means that the error goes to 0 faster than $|\Delta x|$ as Δx goes to 0. Therefore, this is saying that the linear approximation becomes more and more accurate for smaller Δx.

Definition 2.1 – Secant Line
A secant line is a line that connects two points on a function.

Theorem 2.2 – Chain Rule (2 dimensions)
Let $f : \mathbb{R}^2 \to \mathbb{R}$, and two other functions $x(t) : \mathbb{R} \to \mathbb{R}$ and $y(t) : \mathbb{R} \to \mathbb{R}$. Let $\phi(t) = f(x(t), y(t))$. The chain rule then states
$$\frac{d\phi}{dt} = \frac{\partial f}{\partial x}\frac{dx}{dt} + \frac{\partial f}{\partial y}\frac{dy}{dt}$$
¿¿¿¿¿¿¿ 9996c8d83e9addfdf8c2bcebb3927782cfc8e160

Problem 2.2 – Example of Chain Rule in 2 Dimensions
Let $f(x, y) = x^2 + y^2$. We want to find the rate of change of f along a curve defined by $x(t) = t$ and $y(t) = 2t$. The partial derivatives of f are:
$$\frac{\partial f}{\partial x} = 2x, \quad \frac{\partial f}{\partial y} = 2y$$
The derivatives of $x(t)$ and $y(t)$ are
$$\frac{dx}{dt} = 1, \quad \frac{dy}{dt} = 2$$
Then we get
$$\begin{aligned}\frac{d}{dt}f(x(t), y(t)) &= \frac{\partial f}{\partial x}\frac{dx}{dt} + \frac{\partial f}{\partial y}\frac{dy}{dt} \\ &= 2x \cdot 1 + 2y \cdot 2 \\ &= 2(t) \cdot 1 + 2(2t) \cdot 2 \\ &= 10t\end{aligned}$$

Lemma 2.1 – Directional Derivative
Let $f : \mathbb{R}^n \to \mathbb{R}, \bar{x}, d \in \mathbb{R}^n$ where d is the direction. We define
$$\phi(\epsilon) = f(\bar{x} + \epsilon d) : \mathbb{R} \to \mathbb{R}$$

the value of the function f at a point that is displaced from $\bar{x}$ by a distance of ϵ in the direction d. Then the **directional derivative**, denoted $f'(x;d)$ of f at x at the direction d is

$$f'(x;d) = \phi'(0) = \lim_{\epsilon \to 0} \frac{f(x+\epsilon d) - f(x)}{\epsilon} = \nabla f(x)^T d$$

Definition 2.2 – Directional Derivative (Different notation)
The directional derivative of f at a point $\bar{x}, \in \mathbb{R}^n$ in the direction d is

$$f'(\bar{x};d) = \frac{d}{ds} f(\bar{x}+sd)\bigg|_{s=0}$$

Theorem 2.3
If f is differentiable at $\bar{x}$, then

$$f'(\bar{x};d) = \nabla f(\bar{x})^T d$$

Proof. We only prove in the case where $\bar{x} = (a,b) \in \mathbb{R}^2$.

$$\begin{aligned}
f'(\bar{x};d) &= \frac{d}{ds} f(\bar{x}+sd)\bigg|_{s=0} \\
&= \frac{d}{ds} f(\underbrace{a+sd_1}_{x}, \underbrace{b+sd_2}_{y})\bigg|_{s=0} \\
&= \left[\frac{\partial f}{\partial x}\frac{dx}{ds} + \frac{\partial f}{\partial y}\frac{dy}{ds}\right]_{s=0} && \text{Chain rule} \\
&= \left[\frac{\partial}{\partial x} f(a+sd_1, b+sd_2)\cdot d_1 + \frac{\partial}{\partial y} f(a+sd_1, b+sd_2)\cdot d_2\right]_{s=0} \\
&= \frac{\partial f}{\partial x}(a,b)\cdot d_1 + \frac{\partial f}{\partial y}(a,b)\cdot d_2 \\
&= \left(\frac{\partial f}{\partial x}(a,b), \frac{\partial f}{\partial y}(a,b)\right)\cdot(d_1,d_2) \\
&= \nabla f(a,b)\cdot d
\end{aligned}$$

□

Problem 2.3

Let $f(x,y,z) = x^2 z + y^3 z^2 - xyz$ with $d = \begin{pmatrix}-1\\0\\3\end{pmatrix}$ Then the **directional derivative** in the direction d is

$$\nabla f(x,y,z)^T d = \begin{pmatrix}2xz - yz\\ 3y^2z^2 - xz\\ x^2 + 2y^3z - xy\end{pmatrix}^T \begin{pmatrix}-1\\0\\3\end{pmatrix} = -2xz + yz + 3x^2 + 6y^3z - 3xy$$

Corollary 2.1
Let $f : (a,b) \to \mathbb{R}$

1. If $\bar{x}$ is a **local minimizer** of f on (a,b), then $f'(\bar{x}) = 0$ and $f''(\bar{x}) \geq 0$.

2. If $f(\bar{x}) = 0, f''(\bar{x}) > 0$ then $\bar{x}$ is a **strict local minimizer** of f.

Definition 2.3 – Hessian

The **Hessian** of f at $x = \begin{pmatrix} x_1 \\ \vdots \\ x_n \end{pmatrix}$ is the matrix

$$\nabla^2 f(x) = \begin{bmatrix} \frac{\partial f(x)}{\partial x_1^2} & \frac{\partial f(x)}{\partial x_1 \partial x_2} & \cdots & \frac{\partial f(x)}{\partial x_1 \partial x_n} \\ \frac{\partial f(x)}{\partial x_2 \partial x_1} & \frac{\partial f(x)}{\partial x_2^2} & \cdots & \frac{\partial f(x)}{\partial x_2 \partial x_n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial f(x)}{\partial x_n \partial x_1} & \frac{\partial f(x)}{\partial x_n \partial x_2} & \cdots & \frac{\partial f(x)}{\partial x_n^2} \end{bmatrix}$$

Theorem 2.4 – Multivariate Taylor
Consider a C^2-smooth function $f : U \to \mathbb{R}$ on an open set $U \subset \mathbb{R}^n$. If $\bar{x}$ and x are such that the segment $[\bar{x}, x] := \{\bar{x} + t(x - \bar{x}) : t \in [0, 1]\}$ is contained in U, then the Taylor series expansion of f centered around $\bar{x}$ is

$$f(x) = f(\bar{x}) + \langle \nabla f(\bar{x}), x - \bar{x} \rangle + \frac{1}{2} \langle \nabla^2 f(z)(x - \bar{x}), (x - \bar{x}) \rangle$$

where z is between x and $\bar{x}$.

Lemma 2.2
Let $v \in \mathbb{R}^n$. Then

$$v = 0 \iff \langle v, d \rangle = 0, \quad \forall d \in \mathbb{R}^n$$

2.2 Lecture 3

Definition 2.4 – Matrix Norm

$$\|Q\| = max_{\|x\|=1} \|Qx\| = \text{Largest singular value of A}$$

Definition 2.5
Define $f, D, \bar{x}, D$ is an open set Then:

1. Nec: If $\bar{x}$ is a local minimum for f on D, then $\nabla f(\bar{x}) = 0$ and $\nabla^2 f(\bar{x}) \succeq 0$ is positive semidefinite.
2. Suff: If $\nabla f(\bar{x}) = 0, \nabla^2 f(\bar{x}) \succ 0$ is positive definite then $\bar{x}$ is a strict local minimum of f on D.

Proof. 1. updated later after I confirmed some details with the professor □

Definition 2.6 – Critical/Stationary Points
A point $\bar{x} \in U$ is a critical point of a function $f : U \to \mathbb{R}$ if $\nabla f(\bar{x})$ exists and satisfies $\nabla f(\bar{x}) = 0$.

Problem 2.4 – Algorithm to Find Local Minimizer
Given $f : \mathbb{R} \to \mathbb{R}$ and $f'(\bar{x}) \neq 0$, then $x_{new} = \bar{x} - (\text{step}) * f'(\bar{x})$.
The idea is that if $f'(\bar{x}) > 0$, then we know that the function is increasing at $\bar{x}$, so we want to move to the left to obtain the minimum. Similarly, if $f'(\bar{x}) < 0$, then we know that the function is decreasing at $\bar{x}$, so we want

to move to the right to obtain the minimum.

Problem 2.5
Given f:$\mathbb{R}^n \implies \mathbb{R}, \phi(\epsilon) = f(\bar{x} + \epsilon d)$
using tylar expansion $f(\bar{x} + \epsilon d)$= $f(\bar{x})$+ϵ $\nabla f(\bar{x})^T d$ +$o(\|\epsilon\|)$ shouldnt be ϵd? or d is the unit vector
let $d = -\nabla f(\bar{x})$, f($\bar{x}$)-$\epsilon\|f(\bar{x})\|^2$+$o(\epsilon)$. $< f(x)$ (if $\nabla f(\bar{x}) \neq 0$)
i.e test nec condition
If $\nabla f(\bar{x}) \neq 0$, then $x_{new} = \bar{x} + \epsilon(-\nabla f(\bar{(x)}))$ Move to the deapest direction

Definition 2.7 – Cauchy's method of steepest descant
https://www.math.usm.edu/lambers/mat419/lecture10.pdf $x_0 \in \mathbb{R}^n$.

$$Is \nabla f(x_k) \approxeq 0 \text{?IF yes Stop}$$

.

$$O.W, \text{ find a Stop} \alpha > 0$$

$$x_{k+1} = x_k - \alpha \nabla f(x_k)$$

$$repeat$$

Problem 2.6 – Example of finding global and local minimizers
Find global and local minimizers of $f(x, y) = x^3 - 12xy + 8y^3$.

We first find the gradient and the Hessian:

$$\nabla f(x, y) = \begin{pmatrix} 3x^2 - 12y \\ -12x + 24y^2 \end{pmatrix}$$

$$\nabla^2 f(x, y) = \begin{bmatrix} -6x & -12 \\ -12 & 48y \end{bmatrix}$$

We can find the critical points when we solve for $\nabla f(x, y) = 0$. Solving it, we get solutions $(0, 0)$ or $(2, 1)$.
The Hessian at $(0, 0)$ is

$$\nabla^2 f(0, 0) = \begin{bmatrix} 0 & -12 \\ -12 & 0 \end{bmatrix}$$

The eigenvalues of $\nabla^2 f(0, 0)$ are $-12, 12$. Therefore it is indefinite. So $(0, 0)$ is a saddle point.
The Hessian at $(2, 1)$ is

$$\nabla^2 f(2, 1) = \begin{bmatrix} -12 & -12 \\ -12 & 48 \end{bmatrix}$$

Checking all leading principal minors, we see that they are all positive. So $\nabla^2 f(2, 1)$ is positive definite. So $(2, 1)$ is a local minimizer.

2.3 Lecture 4

Definition 2.8 – Principal Submatrices
Let

$$A = \begin{bmatrix} 1 & 1 & 2 & 7 \\ 1 & 1 & 4 & 6 \\ 2 & 4 & 7 & 8 \\ 7 & 6 & 8 & 1 \end{bmatrix}, \quad I = \{1, 3\}, \quad A[I] = \begin{bmatrix} 1 & 2 \\ 2 & 7 \end{bmatrix}$$

Then $A[I]$ is a **principal submatrix** of A.

Definition 2.9 – Principal Minors
Let $A \in \mathbb{S}^n$, where $\mathbb{S}^n$ is the set of all symmetric $n \times n$ matrices.

1. $\det(A[I])$ is called the **principal minor** of A.
2. If $I = \{1, \ldots, k\}$ then $\det(A[I])$ is called the **leading principal minor** of A.

Proposition 2.1 – Characterizing Positive Definiteness with Principal Minors
Let $A \in \mathbb{S}^n$. Then

1. $A \succeq 0 \iff \det(A[I]) \geq 0$ for all principal minors $\det(A[I])$.
2. $A \succ 0 \iff \det(A[I]) > 0$ for all **leading** principal minors $\det(A[I])$.

Definition 2.10 – Eigenvectors and Eigenvalues
$0 \neq v \in \mathbb{R}^n$ is an **eigenvector** of A if there exists $\lambda \in \mathbb{R}$ such that $Av = \lambda v$. The number λ is called an **eigenvalue** of A.

Theorem 2.5 – Finding Eigenvectors and Eigenvalues
Let A be a matrix.

1. Set up the characteristic equation. We find
$$\det(A - \lambda I) = 0$$
2. Solve for λ. These are the eigenvalues.
3. Plug eigenvalues $\lambda_1, \ldots, \lambda_n$ into $(A - \lambda I)v = 0$ and solve for v. These are the eigenvectors.

Theorem 2.6 – Orthogonal Spectral Decomposition
Let $A \in \mathbb{S}^n$. Then A has an **orthogonal spectral decomposition**

$$A = \sum_i \lambda_i u_i u_i^T = UDU^T$$

where U is orthogonal with the orthogonal eigenvectors u_i as columns and D is a diagonal matrix with real eigenvalues on the diagonal.

Corollary 2.2
Let $A \in \mathbb{S}^n$. Then

1. $A \succeq 0$ (positive semidefinite) iff all eigenvalues of A are nonnegative.
2. $A \succ 0$ (positive definite) iff all eigenvalues of A are positive.

Proposition 2.2
Let $A \in \mathbb{S}^n$. The following are equivalent (Positive definite):

1. $A \succ 0$.
2. All the eigenvalues of A are in $\mathbb{R}^n_{++}$, the interior of the nonnegative orthant.
3. A has a real symmetric positive definite square root, $A = SS, S \in \mathbb{S}^n_{++}$.
4. A has a lower triangular factorization, a Cholesky factorization, $A = LL^T$ and L has positive diagonal elements.
5. All principal minors of A are positive.
6. All leading principal minors of A are positive.

And the following are equivalent (Positive semidefinite):

1. $A \succeq 0$.
2. All the eigenvalues of A are in $\mathbb{R}^n_{+}$, the nonnegative orthant.
3. A has a real symmetric square root, $A = SS, S \in \mathbb{S}^n$.
4. A has a lower triangular factorization, a Cholesky factorization, $A = LL^T$.
5. All principal minors of A are nonnegative.

Problem 2.7 – Motivation
When can we guarantee that global minimizers of $f : \mathbb{R}^n \to \mathbb{R}$ exist?
For example, the real valued function on $\mathbb{R}$ $f(x) = e^x$ is bounded below by 0 but has no minimizers. The minimum value is 0 but is not attained.

Proposition 2.3 – Weierstrass Extreme Value Theorem
If $f : \mathbb{R}^n \to \mathbb{R}$ is continuous, and if $D \subset \mathbb{R}^n$ is a closed and bounded set, then f is bounded below and the minimum value is attained on D.

Definition 2.11 – Coercive function
A continuous function $f : \mathbb{R}^n \to \mathbb{R}$ is **coercive** if for any sequence x_i with $\|x_i\| \to \infty$, it must be the case that $f(x_i) \to +\infty$. In other words,

$$\lim_{\|x\| \to \infty} f(x) = +\infty$$

Here are some examples:

1. $f_1(x) = x^2$ is coercive.
2. $g(x) = x$ is not coercive (because as $x \to -\infty$, $g(x) \to -\infty \neq \infty$).
3. $h(x) = e^x$ is not coercive.

Proposition 2.4 – Coercive Functions and Minimizers
A coercive function $f : \mathbb{R}^n \to \mathbb{R}$ has a global minimizer.

Definition 2.12 – Level Sets
Let $f : \mathbb{R}^n \to \mathbb{R}$ be a function and let $\alpha \in \mathbb{R}$. An α-level set of f is defined by

$$L_\alpha = \{x \in \mathbb{R}^n : f(x) = \alpha\}$$

That is, all points x such that $f(x) = \alpha$.

- When $n = 2$, we call this a level curve.
- When $n = 3$, we call this a level surface.
- When $n > 3$, we call this a level hypersurface.

Definition 2.13 – Sub-level set
Let $f : \mathbb{R}^n \to \mathbb{R}$ be a function and let $\alpha \in \mathbb{R}$. An α-sublevel set of f is defined by

$$S_\alpha(f) = \{x \in \mathbb{R}^n : f(x) \leq \alpha\}$$

That is, all points x below the line $f(x) = \alpha$.

3 Linear Least Squares & Solving Linear Systems

3.1 Lecture 5

Problem 3.1 – Motivation For Least Squares
Suppose we have a series of observed values from an experiment:

$$\{(t_1, s_1), (t_2, s_2), \dots, (t_m, s_m)\}$$

where t_i is the time and s_i is the observed value at time t_i. We want to find a polynomial function

$$p(t) = x_0 + x_1 t + \cdots + x_n t^n$$

that fits the data. So we want to find coefficients $x_0, \dots x_n$ such that $p(t_i) \approx s_i$ for all i. More formally, we want to minimize the absolute value of the error of each term. The error (ℓ_1 norm) is defined as

$$|e_i| = |p(t_i) - s_i|$$

This can be formulated into a ℓ_1 norm minimization problem:

$$\min \left\{ \sum_{i=1}^{m} |p(t_i) - s_i| : (x_0, \dots, x_n) \in \mathbb{R}^{n+1} \right\}$$

This is a non-differentiable optimization problem since we have absolute values which make it not smooth. So we can be reformualte it as a linear program:

$$\min \quad \sum_{i=1}^{m} \lambda_i$$

s.t.

$$\begin{aligned} s_i - p(t_i) &\le \lambda_i && \text{for all } i = 1, \dots, m \\ p(t_i) - s_i &\le \lambda_i && \text{for all } i = 1, \dots, m \end{aligned}$$

This minimization problem is called **compressive sensing**.

Definition 3.1 – Vandermonde Matrix
Let

$$A = \begin{bmatrix} 1 & t_1 & t_1^2 & \cdots & t_1^n \\ 1 & t_2 & t_2^2 & \cdots & t_2^n \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & t_m & t_m^2 & \cdots & t_m^n \end{bmatrix} \in \mathbb{R}^{m \times (n+1)}, \quad b = \begin{pmatrix} s_1 \\ s_2 \\ \vdots \\ s_m \end{pmatrix}, \quad x = \begin{pmatrix} x_0 \\ x_1 \\ \vdots \\ x_n \end{pmatrix}$$

A is called a **Vandermonde matrix**.

Theorem 3.1

The Vandermonde Matrix

$$A = \begin{bmatrix} 1 & t_1 & t_1^2 & \cdots & t_1^n \\ 1 & t_2 & t_2^2 & \cdots & t_2^n \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & t_m & t_m^2 & \cdots & t_m^n \end{bmatrix} \in \mathbb{R}^{m\times(n+1)}, \quad b = \begin{pmatrix} s_1 \\ s_2 \\ \vdots \\ s_m \end{pmatrix}, \quad x = \begin{pmatrix} x_0 \\ x_1 \\ \vdots \\ x_n \end{pmatrix}$$

is full column rank if $n+1 \le m$ and the points t_i are distinct.

Definition 3.2 – ℓ_1 and ℓ_2 Norm
The ℓ_1 norm of a vector x is defined to be

$$\|x\| = \sum |x_i|$$

The ℓ_2 norm of a vector x is defined to be

$$\|x\| = \sqrt{\sum x_i^2}$$

Problem 3.2 – Linear Least Squares Problem
Recall our ℓ_1 norm minimization problem:

$$\min \left\{ \sum_{i=1}^{m} |p(t_i) - s_i| : (x_0, \dots, x_n) \in \mathbb{R}^{n+1} \right\}$$

We can instead use ℓ_2 norm defined as $\|e\|_2 = \sqrt{\sum e_i^2}$. So our ℓ_2 minimization problem is

$$\min \left\{ \sum_{i=1}^{m} (p(t_i) - s_i)^2 : (x_0, \dots, x_n) \in \mathbb{R}^{n+1} \right\}$$

where $p(t) = x_0 + x_1 t + \cdots + x_n t^n$. Using the Vandermonde matrix, we can rewrite our problem to be

$$\min \frac{1}{2}\|Ax - b\|^2$$

where

$$A = \begin{bmatrix} 1 & t_1 & t_1^2 & \cdots & t_1^n \\ 1 & t_2 & t_2^2 & \cdots & t_2^n \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & t_m & t_m^2 & \cdots & t_m^n \end{bmatrix} \in \mathbb{R}^{m\times(n+1)}, \quad b = \begin{pmatrix} s_1 \\ s_2 \\ \vdots \\ s_m \end{pmatrix}, \quad x = \begin{pmatrix} x_0 \\ x_1 \\ \vdots \\ x_n \end{pmatrix}$$

The objective function is $g(x) = \frac{1}{2}\|Ax - b\|^2$. Let's first expand $g(x)$:

$$\begin{aligned} g(x) &= \frac{1}{2}\|Ax - b\|^2 \\ &= \frac{1}{2}(Ax - b)^T(Ax - b) \\ &= \frac{1}{2}(Ax)^T Ax - (Ax)^T b + \frac{1}{2}\|b\|^2 \\ &= \frac{1}{2}x^T A^T Ax - x^T A^T b + \frac{1}{2}\|b\|^2 \end{aligned}$$

Then, using the definition of linear transformation definition of the gradient (WTF is this), we have

$$\nabla g(x) = A^T Ax - A^T b$$

To find the critical points, we solve for $\nabla g(x) = 0$. So the critical points are x^* that satisfy the equation

$$A^T Ax = A^T b$$

This is also called a **normal equation**.
also something about the condition number, i dont really understand.

Definition 3.3 – Singular Values of a Matrix
The singular values of a matrix A are the square roots of the eigenvalues of the matrix $A^T A$. They are always non-negative real numbers.
The number of non-zero singular values of a matrix equals the rank of that matrix.

Definition 3.4 – Condition Number of a Matrix
Suppose $A \in \mathbb{R}^{m\times n}, m > n$ is full column rank. The condition number of the matrix A, cond(A), is the ratio of the largest to smallest nonzero singular values of A. Let $\sigma_{\max}$ be the largest singular value and $\sigma_{\min}$ be the smallest singular value. Then

$$\text{cond}(A) = \frac{\sigma_{\max}}{\sigma_{\min}}$$

Definition 3.5 – Frechet Derivative
Let $h : U \to W$, where U is an open subset of V, and V, W are finite dimensional vector spaces. The function h is **Frechet differentiable** at $x \in U$ if there exists a linear transformation $A : V \to W$ such that

$$\lim_{d\to 0} \frac{\|h(x+d) - h(x) - Ad\|}{\|d\|} = 0$$

idk

3.2 Lecture 6

Goal: Solving normal equation/non linear case

Definition 3.6 – SVD Decomposition
Let A be an $m \times n$ matrix. Then A can be factored into

$$\underbrace{A}_{m\times n} = \underbrace{U}_{m\times m} \underbrace{\Sigma}_{m\times n} \underbrace{V^T}_{n\times n}$$

where

- U is an $m \times m$ orthogonal matrix consisting of eigenvectors of AA^T
- V^T is the transpose of an $n \times n$ matrix containing the eigenvectors of $A^T A$
- Σ is a diagonal matrix with $r = \text{rank}(A)$ positive eigenvalues of AA^T (Singular values of A) on the diagonal.

there is a section on piazza posted lecture notes that shows why using SVD decomposition to solve normal equation is a bad idea. Not sure if i should include here

Definition 3.7 – Orthogonal Matrix
A matrix Q is orthogonal if $Q^T Q = I$.

Definition 3.8 – Orthonormal Columns
A matrix Q has orthonormal columns if each column vector is a unit vector (norm is 1), and any two distinct columns are orthogonal (inner product is 0).

Definition 3.9 – QR Factorization
For any $m \times n$ matrix A, there there exists an $m \times m$ orthogonal matrix Q ($QQ^T = I$) and an $m \times n$ upper triangular matrix R ($R_{i,j} = 0, \forall i < j$) satisfying $A = QR$. Moreover, if the columns of A are linearly independent then we can get

$$\begin{aligned} A &= QR \\ &= Q \begin{bmatrix} R_1 \\ 0 \end{bmatrix} \\ &= \begin{bmatrix} Q_1 & Q_2 \end{bmatrix} \begin{bmatrix} R_1 \\ 0 \end{bmatrix} \\ &= Q_1 R_1 \end{aligned}$$

where

- R_1 is an invertible $n \times n$ upper triangular matrix
- 0 is an $(m - n) \times n$ zero matrix
- Q_1 is an $m \times n$ matrix with orthonormal columns
- Q_2 is an $m \times (m - n)$ matrix with orthonormal columns

Theorem 3.2 – QR Factorization on Normal Equation
Assuming that the columns of A are linearly independent, then the normal equation $A^T A x = A^T b$ can be solved by applying QR factorization to A:

$$\begin{aligned} (A^T A)x &= A^T b \\ ((Q_1 R_1)^T Q_1 R_1)x &= (Q_1 R_1)^T b \\ (R_1^T Q_1^T Q_1 R_1)x &= R_1^T Q_1^T b \\ R_1^T R_1 x &= R_1^T Q_1^T b && \text{Since } Q_1 \text{ is orthogonal} \\ R_1 x &= Q_1^T b && \text{Since } R_1 \text{ is invertible} \end{aligned}$$

Definition 3.10 – Methods of Solving General Linear Systems
Suppose we are given a linear system $Bx = b$, and we know that this system has a solution, i.e. $b \in \text{range}(B)$. There are 3 important algorithms/factorizations used to find x:

- Gaussian Elimination (LU factorization) ($PB = LU$)
- QR factorization
- SVD, singular value decomposition

Problem 3.3 – Solving Large Positive Definite Systems
Suppose we have a linear system, $Ax = b$, with A postive definite. If x^* is a solution, then $Ax^* - b = 0$. Then this is equivalent to minimizing the function

$$f(x) = \frac{1}{2}\|A_x - b\|^2, \nabla f(x) = Ax - b = 0$$

Dont understand this and the part after as well. You will have to add more notes here. Link to notes HERE

Theorem 3.3 – Conjugate Gradient Method
The first search direction is the negative gradient,

$$v_0 = -\nabla q(x_0)$$

with $q = f$. At the kth iteration:

$$v_{k+1} = -\nabla q(x_k) + \beta_k v_k$$

where β_k is chosen to ensure $\langle Av_{k+1}, v_k\rangle = 0$. This guarantees that the directions are A-conjugate wtf is A conjugate. We then set

$$x_{k+1} = x_k + \alpha_{k+1} v_{k+1}$$

where α_{k+1} is chosen from an exact line search (what is line search).

3.3 Lecture 7

Definition 3.11 – Nonlinear Least Square
Suppose we have $F : \mathbb{R}^n \to \mathbb{R}^m$ where

$$F(x) = \begin{pmatrix} f_1(x) \\ f_2(x) \\ \vdots f_m(x) \end{pmatrix}$$

Then the nonlinear least squares problem is

$$\min\{h(x)\}$$

where

$$h(x) = \frac{1}{2}\|F(x)\|^2 = \frac{1}{2}\langle F(x), F(x)\rangle = \frac{1}{2}\sum_{i=1}^{m} f_i^2(x)$$

Definition 3.12 – Jacobian Matrix
Let F be defined as above, then the Jacobian matrix is $J(x) = F'(x)$ where

$$F'(x) = \begin{bmatrix} \nabla f_1(x)^T \\ \nabla f_2(x)^T \\ \vdots \\ \nabla f_m(x)^T \end{bmatrix}$$

Problem 3.4 – Solving Nonlinear Least Squares
For the nonlinear least squares problem defined above, we consider the special case $m = n$. Then we can consider the problem as solving the square system of nonlinear equations $F(x) = 0$. Recall that for current

approximation x_c,

$$0 = F(x_c + d) \approx F(x_c) + \underbrace{F'(x_c)}_{\text{Jacobian}} \underbrace{d}_{\text{search direction}}$$

So we solve

$$F'(x_c)d = -f(x_c)$$

which is called the Newton equation. Then we can take a step in the search/Newton direction d to get a new approxiamtion $x_{c+1} = x_c + \alpha d$ for appropriate step length α.

Definition 3.13 – Argmin and argmax
argmin $f(x)$ is the set of all minimizers of $f(x)$, similarly argmax $f(x)$ is the set of all maximizers of $f(x)$.

4 Iterative Methods for Unconstrained Optimization

4.1 Lecture 8

Before, we have iterative methods to solve linear and linear least squares system.
Goal: Solve more general problems of minimization.
An iterative algorithm is a procedure that produces an (infinite) sequence of points $\{x_k\}$, in $\mathbb{R}^n$ such that our sequence converges to a critical point of f or to a point that satisfies the second order necessary conditions of optimality.

Theorem 4.1 – Cauchy-Schwarz Inequality
Let $x, y \in \mathbb{R}^n$. Then

$$|\langle x, y\rangle| \leq \|x\|\|y\|$$

Line Search Strategy

Main Idea: At a point x_k, we find the direction with the steepest descent(in the gradient direction) and move in that direction to a new point x_{k+1}.
How do we choose step size? We first set

$$g(\alpha) = f(x_k + \alpha\nabla f(x_k))$$

for step size α, so we are traveling in the direction of the gradient (steepest descent). So now we have a one dimensional problem, then we can just solve for $g'(\alpha) = 0$ to find the critical point in the direction of the gradient. After finding α, we can obtain the next point $x_{k+1} = x_k + \alpha\nabla f(x_k)$.

Definition 4.1 – Line Search Strategy
At each iteration k, we choose a vector (search direction) $v_k \neq 0 \in \mathbb{R}^n$, then choose $\alpha_k > 0$ (step length) that approximately solves

$$\alpha_k \in \text{argmin } f(x_k + \alpha v_k)$$

Then we update $x_{k+1} = x_k + \alpha_k v_k$.

Definition 4.2 – Descent Direction
Let $x \in U \subseteq \mathbb{R}^n$ with U being an open set. Then $d \in \mathbb{R}^n$ is a descent direction for f at x if there exists $\bar{\alpha} > 0$ such that

$$x + \alpha d \in U, f(x + \alpha d) < f(x)$$

for all $0 < \alpha < \bar{\alpha}$.

Lemma 4.1
Let f be sufficiently smooth on an open set U and let $\bar{x} \in U$. Let $d \in \mathbb{R}^n$ satisfy

$$\langle d, \nabla f(\bar{x}) \rangle < 0$$

Then d is a descent direction for f at x.

Trust Region Strategy

The difference in trust region strategy and line search strategy is that in line search strategy, we first choose the direction, then choose step size. In trust region, we first choose the step size, then we choose the direction.

Definition 4.3 – Trust Region Strategy
In each iteration, we construct a model of f. That is, in each step we consider $m_k : \mathbb{R}^n \to \mathbb{R}$ that is a simple function that approximates f well on some simple set Ω_k (the trust region) around our current approximation x_k. Then we find the new approximation

$$\hat{x} = \text{argmin } m_k(x) \quad x \in \Omega_k$$

A common model is the quadratic model

$$m_k(x) = f(x_k) + \langle \nabla f(x_k), x - x_k \rangle + \frac{1}{2} \langle x - x_k, B_k(x - x_k) \rangle$$

where $B_k \approx \nabla^2 f(x_k)$ approximates the Hessian. If the values $f(\hat{x})$ and $m_k(\hat{x})$ are close, then we declare $x_{k+1} = \hat{x}$. Otherwise, we shrink the size of the trust region Ω_k and repeat the process.
Usually Ω_k is a ball, ellipsoid, or a box around x_k.
The main points are how to choose a model function m_k, and how to choose a trust region Ω_k.

Problem 4.1 – Lagrange Multiplier Example
Maximize $f(x, y) = x^2 y$ subject to $g(x, y) = x^2 + y^2 = 1$. By using Lagrange multipliers, we know that the maximizer, (x^*, y^*) satisfies

$$\nabla f(x^*, y^*) = \lambda \nabla g(x^*, y^*)$$

We have

$$\nabla g(x, y) = \begin{bmatrix} 2x \\ 2y \end{bmatrix}$$
$$\nabla f(x, y) = \begin{bmatrix} 2xy \\ x^2 \end{bmatrix}$$

Then, using Lagrange multipliers, we solve

$$\begin{bmatrix} 2xy \\ x^2 \end{bmatrix} = \lambda \begin{bmatrix} 2x \\ 2y \end{bmatrix}$$

Since we also have the constraint $x^2 + y^2 = 1$, we solve the system of equations

$$\begin{aligned} 2xy &= 2\lambda x \\ x^2 &= 2\lambda y \\ x^2 + y^2 &= 1 \end{aligned}$$

Solving it, we get

$$(x, y) = \left(\pm\sqrt{\frac{2}{3}}, \pm\sqrt{\frac{1}{3}}\right), \quad \lambda = y$$

Testing each point, we get that $\left(\sqrt{\frac{2}{3}}, \sqrt{\frac{1}{3}}\right)$ is the maximizer of f.

Proposition 4.1
Suppose $\langle d, \nabla f(\bar{x})\rangle < 0$. Then there exists $B \succ 0$ that satisfies $d = -B^{-1}\nabla f(\bar{x})$.