Lecture 1 -Mathematical Preliminaries

The Space $\mathbb{R}^n$

- $\mathbb{R}^n$ - the set of n-dimensional column vectors with real components endowed with the component-wise addition operator:

$$\begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{pmatrix} + \begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{pmatrix} = \begin{pmatrix} x_1 + y_1 \\ x_2 + y_2 \\ \vdots \\ x_n + y_n \end{pmatrix},$$

and the scalar-vector product

$$\lambda \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{pmatrix} = \begin{pmatrix} \lambda x_1 \\ \lambda x_2 \\ \vdots \\ \lambda x_n \end{pmatrix},$$

- $\mathbf{e}_1, \mathbf{e}_2, \ldots, \mathbf{e}_n$ - standard/canonical basis.
- $\mathbf{e}$ and $\mathbf{0}$ - all ones and all zeros column vectors.

Important Subsets of $\mathbb{R}^n$

- nonnegative orthant:

$$\mathbb{R}^n_+ = \left\{ (x_1, x_2, \ldots, x_n)^T : x_1, x_2, \ldots, x_n \geq 0 \right\}.$$

- positive orthant:

$$\mathbb{R}^n_{++} = \left\{ (x_1, x_2, \ldots, x_n)^T : x_1, x_2, \ldots, x_n > 0 \right\}.$$

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- If $\mathbf{x}, \mathbf{y} \in \mathbb{R}^n$, the closed line segment between $\mathbf{x}$ and $\mathbf{y}$ is given by

$$[\mathbf{x}, \mathbf{y}] = \{\mathbf{x} + \alpha(\mathbf{y} - \mathbf{x}) : \alpha \in [0, 1]\}.$$

- the open line segment $(\mathbf{x}, \mathbf{y})$ is similarly defined as

$$(\mathbf{x}, \mathbf{y}) = \{\mathbf{x} + \alpha(\mathbf{y} - \mathbf{x}) : \alpha \in (0, 1)\}$$

  for $\mathbf{x} \neq \mathbf{y}$ and $(\mathbf{x}, \mathbf{x}) = \emptyset$

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  for $\mathbf{x} \neq \mathbf{y}$ and $(\mathbf{x}, \mathbf{x}) = \emptyset$
- unit-simplex:

$$\Delta_n = \left\{\mathbf{x} \in \mathbb{R}^n : \mathbf{x} \geq \mathbf{0}, \mathbf{e}^T\mathbf{x} = 1\right\}.$$

The Space $\mathbb{R}^{m \times n}$

- The set of all real valued matrices is denoted by $\mathbb{R}^{m \times n}$.
- $\mathbf{I}_n$ - $n \times n$ identity matrix.
- $\mathbf{0}_{m \times n}$ - $m \times n$ zeros matrix.

Inner Products

Definition An inner product on $\mathbb{R}^n$ is a map $\langle \cdot, \cdot \rangle : \mathbb{R}^n \times \mathbb{R}^n \to \mathbb{R}$ with the following properties:

1. **(symmetry)** $\langle \mathbf{x}, \mathbf{y} \rangle = \langle \mathbf{y}, \mathbf{x} \rangle$ for any $\mathbf{x}, \mathbf{y} \in \mathbb{R}^n$.
2. **(additivity)** $\langle \mathbf{x}, \mathbf{y} + \mathbf{z} \rangle = \langle \mathbf{x}, \mathbf{y} \rangle + \langle \mathbf{x}, \mathbf{z} \rangle$ for any $\mathbf{x}, \mathbf{y}, \mathbf{z} \in \mathbb{R}^n$.
3. **(homogeneity)** $\langle \lambda \mathbf{x}, \mathbf{y} \rangle = \lambda \langle \mathbf{x}, \mathbf{y} \rangle$ for any $\lambda \in \mathbb{R}$ and $\mathbf{x}, \mathbf{y} \in \mathbb{R}^n$.
4. **(positive definiteness)** $\langle \mathbf{x}, \mathbf{x} \rangle \geq 0$ for any $\mathbf{x} \in \mathbb{R}^n$ and $\langle \mathbf{x}, \mathbf{x} \rangle = 0$ if and only if $\mathbf{x} = \mathbf{0}$.

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Examples

- the "dot product"

$$\langle \mathbf{x}, \mathbf{y} \rangle = \mathbf{x}^T \mathbf{y} = \sum_{i=1}^{n} x_i y_i \text{ for any } \mathbf{x}, \mathbf{y} \in \mathbb{R}^n.$$

- the "weighted dot product"

$$\langle \mathbf{x}, \mathbf{y} \rangle_{\mathbf{w}} = \sum_{i=1}^{n} w_i x_i y_i,$$

  where $\mathbf{w} \in \mathbb{R}^n_{++}$.

Vector Norms

Definition. A norm $\|\cdot\|$ on $\mathbb{R}^n$ is a function $\|\cdot\|:\mathbb{R}^n \to \mathbb{R}$ satisfying

- **(Nonnegativity)** $\|\mathbf{x}\| \geq 0$ for any $\mathbf{x} \in \mathbb{R}^n$ and $\|\mathbf{x}\| = 0$ if and only if $\mathbf{x} = \mathbf{0}$.
- **(positive homogeneity)** $\|\lambda \mathbf{x}\| = |\lambda| \|\mathbf{x}\|$ for any $\mathbf{x} \in \mathbb{R}^n$ and $\lambda \in \mathbb{R}$.
- **(triangle inequality)** $\|\mathbf{x} + \mathbf{y}\| \leq \|\mathbf{x}\| + \|\mathbf{y}\|$ for any $\mathbf{x}, \mathbf{y} \in \mathbb{R}^n$.

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- **(triangle inequality)** $\|\mathbf{x} + \mathbf{y}\| \leq \|\mathbf{x}\| + \|\mathbf{y}\|$ for any $\mathbf{x}, \mathbf{y} \in \mathbb{R}^n$.

- One natural way to generate a norm on $\mathbb{R}^n$ is to take any inner product $\langle\cdot,\cdot\rangle$ defined on $\mathbb{R}^n$, and define the associated norm

$$\|\mathbf{x}\| \equiv \sqrt{\langle \mathbf{x}, \mathbf{x} \rangle}, \text{ for all } \mathbf{x} \in \mathbb{R}^n,$$

- The norm associated with the dot-product is the so-called Euclidean norm or l_2-norm:

$$\|\mathbf{x}\|_2 = \sqrt{\sum_{i=1}^n x_i^2} \text{ for all } \mathbf{x} \in \mathbb{R}^n.$$

l_p-norms

- the l_p-norm $(p \geq 1)$ is defined by $\|\mathbf{x}\|_p \equiv \sqrt[p]{\sum_{i=1}^n |x_i|^p}$.
- The l_∞-norm is
$$\|\mathbf{x}\|_\infty \equiv \max_{i=1,2,\ldots,n} |x_i|.$$
- It can be shown that
$$\|\mathbf{x}\|_\infty = \lim_{p\to\infty} \|\mathbf{x}\|_p.$$

Example: $l_{1/2}$ is **not** a norm. **why?**

The Cauchy-Schwartz Inequality

Lemma: For any $\mathbf{x}, \mathbf{y} \in \mathbb{R}^n$:

$$|\mathbf{x}^T \mathbf{y}| \leq \|\mathbf{x}\| \cdot \|\mathbf{y}\|.$$

Proof: For any $\lambda \in \mathbb{R}$:

$$\|\mathbf{x} + \lambda \mathbf{y}\|^2 = \|\mathbf{x}\|^2 + 2\lambda \langle \mathbf{x}, \mathbf{y} \rangle + \lambda^2 \|\mathbf{y}\|^2$$

Therefore (why?),

$$4\langle \mathbf{x}, \mathbf{y} \rangle^2 - 4\|\mathbf{x}\|^2 \|\mathbf{y}\|^2 \leq 0,$$

establishing the desired result. □

Matrix Norms

Definition. A norm $\|\cdot\|$ on $\mathbb{R}^{m\times n}$ is a function $\|\cdot\|:\mathbb{R}^{m\times n}\rightarrow\mathbb{R}$ satisfying

1. **(Nonnegativity)** $\|\mathbf{A}\|\geq 0$ for any $\mathbf{A}\in\mathbb{R}^{m\times n}$ and $\|\mathbf{A}\|=0$ if and only if $\mathbf{A}=\mathbf{0}$.
2. **(positive homogeneity)** $\|\lambda\mathbf{A}\|=|\lambda|\|\mathbf{A}\|$ for any $\mathbf{A}\in\mathbb{R}^{m\times n}$ and $\lambda\in\mathbb{R}$.
3. **(triangle inequality)** $\|\mathbf{A}+\mathbf{B}\|\leq\|\mathbf{A}\|+\|\mathbf{B}\|$ for any $\mathbf{A},\mathbf{B}\in\mathbb{R}^{n}$.

Induced Norms

- Given a matrix $\mathbf{A} \in \mathbb{R}^{m \times n}$ and two norms $\|\cdot\|_a$ and $\|\cdot\|_b$ on $\mathbb{R}^n$ and $\mathbb{R}^m$ respectively, the induced matrix norm $\|\mathbf{A}\|_{a,b}$ (called (a,b)-norm) is defined by

$$\|\mathbf{A}\|_{a,b} = \max_{\mathbf{x}}\{\|\mathbf{A}\mathbf{x}\|_b : \|\mathbf{x}\|_a \leq 1\}.$$

- conclusion:

$$\|\mathbf{A}\mathbf{x}\|_b \leq \|\mathbf{A}\|_{a,b}\|\mathbf{x}\|_a$$

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- conclusion:

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- An induced norm is a norm (satisfies nonnegativity, positive homogeneity and triangle inequality).
- We refer to the matrix-norm $\|\cdot\|_{a,b}$ as the (a,b)-norm. When $a = b$, we will simply refer to it as an a-norm.

Matrix Norms Contd

- spectral norm: If $\|\cdot\|_a = \|\cdot\|_b = \|\cdot\|_2$, the induced (2,2)-norm of a matrix $\mathbf{A} \in \mathbb{R}^{m\times n}$ is the maximum singular value of $\mathbf{A}$

$$\|\mathbf{A}\|_2 = \|\mathbf{A}\|_{2,2} = \sqrt{\lambda_{\max}(\mathbf{A}^T\mathbf{A})} \equiv \sigma_{\max}(\mathbf{A}),$$

  This norm is called the spectral norm.

- l_1-norm: when $\|\cdot\|_a = \|\cdot\|_b = \|\cdot\|_1$, the induced (1,1)-matrix norm of a matrix $\mathbf{A} \in \mathbb{R}^{m\times n}$ is given by

$$\|\mathbf{A}\|_1 = \max_{j=1,2,\ldots,n} \sum_{i=1}^{m} |A_{i,j}|.$$

- l_∞-norm: when $\|\cdot\|_a = \|\cdot\|_b = \|\cdot\|_\infty$, the induced (∞,∞)-matrix norm of a matrix $\mathbf{A} \in \mathbb{R}^{m\times n}$ is given by

$$\|\mathbf{A}\|_\infty = \max_{i=1,2,\ldots,m} \sum_{j=1}^{n} |A_{i,j}|.$$

The Frobenius norm

$$\|\mathbf{A}\|_F = \sqrt{\sum_{i=1}^{m}\sum_{j=1}^{n} A_{ij}^2}, \quad \mathbf{A} \in \mathbb{R}^{m \times n}$$

The Frobenius norm is **not** an induced norm.
Why is it a norm?

Eigenvalues and Eigenvectors

- Let $\mathbf{A} \in \mathbb{R}^{n \times n}$. Then a nonzero vector $\mathbf{v} \in \mathbb{R}^n$ is called an eigenvector of $\mathbf{A}$ if there exists a $\lambda \in \mathbb{C}$ for which

$$\mathbf{A}\mathbf{v} = \lambda \mathbf{v}.$$

  The scalar λ is the eigenvalue corresponding to the eigenvector $\mathbf{v}$.
- In general, real-valued matrices can have complex eigenvalues, but when the matrix is symmetric the eigenvalues are necessarily real.

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- In general, real-valued matrices can have complex eigenvalues, but when the matrix is symmetric the eigenvalues are necessarily real.
- The eigenvalues of a symmetric $n \times n$ matrix $\mathbf{A}$ are denoted by

$$\lambda_1(\mathbf{A}) \geq \lambda_2(\mathbf{A}) \geq \ldots \geq \lambda_n(\mathbf{A}).$$

- The maximum eigenvalue is also denote by $\lambda_{\max}(\mathbf{A})(= \lambda_1(\mathbf{A}))$ and the minimum eigenvalue is also denote by $\lambda_{\min}(\mathbf{A})(= \lambda_n(\mathbf{A}))$.

The Spectral Factorization Theorem

Theorem. Let $\mathbf{A} \in \mathbb{R}^{n \times n}$ be an $n \times n$ symmetric matrix. Then there exists an orthogonal matrix $\mathbf{U} \in \mathbb{R}^{n \times n}$ ($\mathbf{U}^T\mathbf{U} = \mathbf{U}\mathbf{U}^T = \mathbf{I}$) and a diagonal matrix $\mathbf{D} = \text{diag}(d_1, d_2, \ldots, d_n)$ for which

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- The columns of the matrix $\mathbf{U}$ constitute an orthogonal basis comprising eigenvectors of $\mathbf{A}$ and the diagonal elements of $\mathbf{D}$ are the corresponding eigenvalues.
- A direct result is that $\mathrm{Tr}(\mathbf{A}) = \sum_{i=1}^n \lambda_i(\mathbf{A})$ and $\det(\mathbf{A}) = \Pi_{i=1}^n \lambda_i(\mathbf{A})$.

Basic Topological Concepts

- the open ball with center $\mathbf{c} \in \mathbb{R}^n$ and radius r:

$$B(\mathbf{c}, r) = \{\mathbf{x} : \|\mathbf{x} - \mathbf{c}\| < r\}.$$

- the closed ball with center $\mathbf{c}$ and radius r:

$$B[\mathbf{c}, r] = \{\mathbf{x} : \|\mathbf{x} - \mathbf{c}\| \le r\}.$$

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Definition. Given a set $U \subseteq \mathbb{R}^n$, a point $\mathbf{c} \in U$ is called an interior point of U if there exists $r > 0$ for which $B(\mathbf{c}, r) \subseteq U$.
The set of all interior points of a given set U is called the interior of the set and is denoted by $\mathrm{int}(U)$:

$$\mathrm{int}(U) = \{\mathbf{x} \in U : B(\mathbf{x}, r) \subseteq U \text{ for some } r > 0\}.$$

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Examples.

$$\begin{aligned} \mathrm{int}(\mathbb{R}^n_+) &= \mathbb{R}^n_{++}, \\ \mathrm{int}(B[\mathbf{c}, r]) &= B(\mathbf{c}, r) \quad (\mathbf{c} \in \mathbb{R}^n, r \in \mathbb{R}_{++}), \\ \mathrm{int}([\mathbf{x}, \mathbf{y}]) &= ? \end{aligned}$$

open and closed sets

- an open set is a set that contains only interior points. Meaning that $U = \text{int}(U)$.
- examples of open sets are open balls (hence the name...) and the positive orthant $\mathbb{R}^n_{++}$.

Result: a union of any number of open sets is an open set and the intersection of a finite number of open sets is open.

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Result: a union of any number of open sets is an open set and the intersection of a finite number of open sets is open.

- a set $U \subseteq \mathbb{R}^n$ is closed if it contains all the limits of convergent sequences of vectors in U, that is, if $\{\mathbf{x}_i\}_{i=1}^{\infty} \subseteq U$ satisfies $\mathbf{x}_i \to \mathbf{x}^*$ as $i \to \infty$, then $\mathbf{x}^* \in U$.
- a known result states that U is closed iff its complement U^c is open.
- examples of closed sets are the closed ball $B[\mathbf{c}, r]$, closed lines segments, the nonnegative orthant $\mathbb{R}^n_+$ and the unit simplex Δ_n.

What about $\mathbb{R}^n$?$\emptyset$?

Boundary Points

Definition. Given a set $U \subseteq \mathbb{R}^n$, a boundary point of U is a vector $\mathbf{x} \in \mathbb{R}^n$ satisfying the following: any neighborhood of $\mathbf{x}$ contains at least one point in U and at least one point in its complement U^c.

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Examples:

$$
\begin{aligned}
(\mathbf{c} \in \mathbb{R}^n, r \in \mathbb{R}_{++}), \mathrm{bd}(B(\mathbf{c}, r)) &= \\
(\mathbf{c} \in \mathbb{R}^n, r \in \mathbb{R}_{++}), \mathrm{bd}(B[\mathbf{c}, r]) &= \\
\mathrm{bd}(\mathbb{R}^n_{++}) &= \\
\mathrm{bd}(\mathbb{R}^n_{+}) &= \\
\mathrm{bd}(\mathbb{R}^n) &= \\
\mathrm{bd}(\Delta_n) &=
\end{aligned}
$$

Closure

- the closure of a set $U \subseteq \mathbb{R}^n$ is denoted by $\mathrm{cl}(U)$ and is defined to be the smallest closed set containing U:

$$\mathrm{cl}(U) = \bigcap \{ T : U \subseteq T, T \text{ is closed } \}.$$

- another equivalent definition of $\mathrm{cl}(U)$ is:

$$\mathrm{cl}(U) = U \cup \mathrm{bd}(U).$$

Examples.

$$\begin{aligned} \mathrm{cl}(\mathbb{R}^n_{++}) &= \qquad\qquad\qquad\qquad , \\ (\mathbf{c} \in \mathbb{R}^n, r \in \mathbb{R}_{++}), \mathrm{cl}(B(\mathbf{c}, r)) &= \\ (\mathbf{x} \neq \mathbf{y}), \mathrm{cl}((\mathbf{x}, \mathbf{y})) &= \end{aligned}$$

Boundedness and Compactness

- A set $U \subseteq \mathbb{R}^n$ is called bounded if there exists $M > 0$ for which $U \subseteq B(\mathbf{0}, M)$.
- A set $U \subseteq \mathbb{R}^n$ is called compact if it is closed and bounded.
- Examples of compact sets: closed balls, unit simplex, closed line segments.

Directional Derivatives and Gradients

Definition. Let f be a function defined on a set $S \subseteq \mathbb{R}^n$. Let $\mathbf{x} \in \text{int}(S)$ and let $\mathbf{d} \in \mathbb{R}^n$. If the limit

$$\lim_{t \to 0^+} \frac{f(\mathbf{x} + t\mathbf{d}) - f(\mathbf{x})}{t}$$

exists, then it is called the directional derivative of f at $\mathbf{x}$ along the direction $\mathbf{d}$ and is denoted by $f'(\mathbf{x}; \mathbf{d})$.

- For any $i = 1, 2, \ldots, n$, if the limit

$$\lim_{t \to 0} \frac{f(\mathbf{x} + t\mathbf{e}_i) - f(\mathbf{x})}{t}$$

  exists, then its value is called the i-th partial derivative and is denoted by $\frac{\partial f}{\partial x_i}(\mathbf{x})$.
- If all the partial derivatives of a function f exist at a point $\mathbf{x} \in \mathbb{R}^n$, then the gradient of f at $\mathbf{x}$ is

$$\nabla f(\mathbf{x}) = \begin{pmatrix} \frac{\partial f}{\partial x_1}(\mathbf{x}) \\ \frac{\partial f}{\partial x_2}(\mathbf{x}) \\ \vdots \\ \frac{\partial f}{\partial x_n}(\mathbf{x}) \end{pmatrix}.$$

Continuous Differentiability

A function f defined on an open set $U \subseteq \mathbb{R}^n$ is called continuously differentiable over U if all the partial derivatives exist and are continuous on U. In that case,

$$f'(\mathbf{x};\mathbf{d}) = \nabla f(\mathbf{x})^T \mathbf{d}, \quad \mathbf{x} \in U, \mathbf{d} \in \mathbb{R}^n$$

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Proposition Let $f : U \to \mathbb{R}$ be defined on an open set $U \subseteq \mathbb{R}^n$. Suppose that f is continuously differentiable over U. Then

$$\lim_{\mathbf{d} \to \mathbf{0}} \frac{f(\mathbf{x} + \mathbf{d}) - f(\mathbf{x}) - \nabla f(\mathbf{x})^T \mathbf{d}}{\|\mathbf{d}\|} = 0 \text{ for all } \mathbf{x} \in U.$$

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Another way to write the above result is as follows:

$$f(\mathbf{y}) = f(\mathbf{x}) + \nabla f(\mathbf{x})^T (\mathbf{y} - \mathbf{x}) + o(\|\mathbf{y} - \mathbf{x}\|),$$

where $o(\cdot) : \mathbb{R}^n_+ \to \mathbb{R}$ is a one-dimensional function satisfying $\frac{o(t)}{t} \to 0$ as $t \to 0^+$.

Twice Differentiability

- The partial derivatives $\frac{\partial f}{\partial x_i}$ are themselves real-valued functions that can be partially differentiated. The (i,j)-partial derivatives of f at $\mathbf{x} \in U$ (if exists) is defined by

$$\frac{\partial^2 f}{\partial x_i \partial x_j}(\mathbf{x}) = \frac{\partial \left(\frac{\partial f}{\partial x_j}\right)}{\partial x_i}(\mathbf{x}).$$

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- A function f defined on an open set $U \subseteq \mathbb{R}^n$ is called twice continuously differentiable over U if all the second order partial derivatives exist and are continuous over U. In that case, for any $i \neq j$ and any $\mathbf{x} \in U$:

$$\frac{\partial^2 f}{\partial x_i \partial x_j}(\mathbf{x}) = \frac{\partial^2 f}{\partial x_j \partial x_i}(\mathbf{x}).$$

The Hessian

The Hessian of f at a point $\mathbf{x} \in U$ is the $n \times n$ matrix:

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

- For twice continuously differentiable functions, the Hessian is a symmetric matrix.

Linear Approximation Theorem

Theorem. Let $f : U \to \mathbb{R}$ be defined on an open set $U \subseteq \mathbb{R}^n$. Suppose that f is twice continuously differentiable over U. Let $\mathbf{x} \in U$ and $r > 0$ satisfy $B(\mathbf{x}, r) \subseteq U$. Then for any $\mathbf{y} \in B(\mathbf{x}, r)$ there exists $\xi \in [\mathbf{x}, \mathbf{y}]$ such that:

$$f(\mathbf{y}) = f(\mathbf{x}) + \nabla f(\mathbf{x})^T(\mathbf{y} - \mathbf{x}) + \frac{1}{2}(\mathbf{y} - \mathbf{x})^T \nabla^2 f(\xi)(\mathbf{y} - \mathbf{x}).$$

Quadratic Approximation Theorem

Theorem. Let $f : U \to \mathbb{R}$ be defined on an open set $U \subseteq \mathbb{R}^n$. Suppose that f is twice continuously differentiable over U. Let $\mathbf{x} \in U$ and $r > 0$ satisfy $B(\mathbf{x}, r) \subseteq U$. Then for any $\mathbf{y} \in B(\mathbf{x}, r)$:

$$f(\mathbf{y}) = f(\mathbf{x}) + \nabla f(\mathbf{x})^T(\mathbf{y} - \mathbf{x}) + \frac{1}{2}(\mathbf{y} - \mathbf{x})^T \nabla^2 f(\mathbf{x})(\mathbf{y} - \mathbf{x}) + o(\|\mathbf{y} - \mathbf{x}\|^2).$$