

Mathematical Analysis II

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Definition 0.0.1 (Tangent map). Let $f : M \rightarrow N$ be a map between manifolds, $v \in T_p M$. Let $\gamma : (-\varepsilon, \varepsilon) \rightarrow M$ be a parametrized curve with $\gamma(0) = p, \gamma'(0) = v$, then $f(\gamma(t))$ is a curve on N .

$$df(p)(v) = \left. \frac{d}{dt} f(\gamma(t)) \right|_{t=0} \in T_{f(p)} N.$$

Thus $df(p) : T_p M \rightarrow T_{f(p)} N$ is a map between tangent spaces.

In fact, if $f = F|_M$, then $df(p)(v) = dF(p) \cdot v$.

Definition 0.0.2 (Tangent bundle). Let M be a manifold, $\forall p \in M$, there's a tangent space $T_p M$. Define the **tangent bundle** of M to be

$$TM = \bigsqcup_{p \in M} T_p M.$$

If X is a map $M \rightarrow TM: p \mapsto X(p)$, with $X(p) \in T_p M$, then it's called a **tangent vector field**.

In other words, a tangent vector field is just to assign a tangent vector to every point in M .

Proposition 0.0.3

Let $M \subset \mathbb{R}^n$ be a manifold, all its tangent vector field form a C^∞ module $T(M, TM)$, i.e. $\forall f \in C^\infty(M)$, X, Y are smooth vector fields, then $fX, X + Y$ are both smooth vector fields.

Proposition 0.0.4

Let $M \subset \mathbb{R}^n$ be a smooth manifold, we have

$$TM = \{(x, v) \mid x \in M, v \in T_x M\}$$

is a smooth manifold in \mathbb{R}^{2n} , and $\dim TM = 2 \dim M$.

Proof. There exists a local homeomorphism $\phi : V \rightarrow U \subset \mathbb{R}^n$ s.t. $V \subset \mathbb{R}^d$, $\phi(V) = M \cap U$.

Define map $T\phi : V \times \mathbb{R}^n \rightarrow U \times \mathbb{R}^n$, $(x, v) \mapsto (\phi(x), d\phi(x) \cdot v)$. Since $T\phi$ is injective (ϕ is homeomorphism), and

$$dT\phi = \begin{pmatrix} d\phi & 0 \\ d(d\phi)(v) & d\phi \end{pmatrix}$$

is non-degenerate, so $T\phi$ is a bijection and hence differential homeomorphism.

Since the tangent space of V is just \mathbb{R}^d , so $T(U \cap M)$ is the image of $T\phi$ restricted on $V \times \mathbb{R}^d$. (Note that $d\phi(x) \cdot v \in T_{\phi(x)}M$) Thus TM is a manifold in \mathbb{R}^{2n} with dimension $2d$. \square

Definition 0.0.5 (Tangent maps). Earlier we know that $df(p)$ is a map $T_pM \rightarrow T_{f(p)}N$, combined with tangent bundle we can write $df : TM \rightarrow TN$, this map is called the **tangent map** or the **differentiation** of f .

If we have a vector field X and a smooth function $f : M \rightarrow \mathbb{R}^n$, consider

$$X(f)(p) = df(X)(p) := \left. \frac{d}{dt} f(\gamma(t)) \right|_{t=0}, \quad \gamma(0) = p, \gamma'(0) = X(p).$$

So X induces a smooth map $C^\infty(M) \rightarrow C^\infty(M)$.

Now we can generalize a well known result to manifolds:

Proposition 0.0.6

Let $M \subset \mathbb{R}^n$ be a smooth manifold, $f \in C^\infty(M)$. If f achieves a local extremum at $p \in M$, we must have $df(p) = 0$.

Proof. It suffices to prove $df(p)(v) = 0$, $\forall v \in T_pM$. Take γ s.t. $\gamma(0) = p$, $\gamma'(0) = v$, then $f(\gamma(t))$ achieves its extremum at $t = 0$, so $\left. \frac{d}{dt} f(\gamma(t)) \right|_{t=0} = 0 = df(p)(v)$. \square

§0.1 Conditional extremum problem

Consider a function $f(x_1, \dots, x_n) : \mathbb{R}^n \rightarrow \mathbb{R}$ and some constraint conditions

$$\begin{cases} g_1(x_1, \dots, x_n) = 0 \\ \vdots \\ g_m(x_1, \dots, x_n) = 0 \end{cases}$$

We want to compute the extremum of f under these conditions.

Well, you probably heard of *Lagrange multipliers*, i.e. let

$$L(x_1, \dots, x_n, \lambda_1, \dots, \lambda_m) = f(x) - \sum_{j=1}^m \lambda_j g_j(x).$$

But here we'll provide a different point of view. Let M be the manifold in \mathbb{R}^n under those conditions, Suppose $p \in M$ is a local extremum of f , then $T_pM \subset \ker df(p)$.

Also recall that $T_pM = \ker dg(p) = \bigcap_{j=1}^m \ker dg_j(p)$. This means that, $\exists \lambda_1, \dots, \lambda_m$ s.t.

$$df(p) = \sum_{j=1}^m \lambda_j dg_j(p).$$

Surprisingly, we get the same result of Lagrange multipliers! Hence what we've done is to give a geometrical comprehension of Lagrange multipliers.

Example 0.1.1

Let $g : \mathbb{R}^n \rightarrow \mathbb{R}$ be the constraint function, then f can achieve its extremum only if $df = \lambda dg$.

For example, let $f(x) = d(x, z)^2$, $df(x) = 2(x_1 - z_1, \dots, x_n - z_n)$, so $df = \lambda dg$ means the vector $df(p)$ is orthogonal to the tangent plane of $M = \{g = 0\}$.

Proposition 0.1.2 (Hadamard's inequality)

Let $v_1, \dots, v_n \in \mathbb{R}^n$, then

$$|\det(v_1, \dots, v_n)| \leq |v_1| \cdots |v_n|.$$

Proof. Let $f : \mathbb{R}^{n^2} \rightarrow \mathbb{R}$, $(v_1, \dots, v_n) \mapsto \det(v_1, \dots, v_n)$ with constraint $|v_i| = 1$. Let $v_{ij} \in \mathbb{R}$,

$$g_i(V) = -1 + \sum_{j=1}^n v_{ij}^2.$$

The manifold determined by g_i is $M = (S^{n-1})^n$. The extremum point of f in M must satisfy:

$$\frac{\partial f}{\partial v_{i_0 j}} - \lambda_{i_0} \frac{\partial g_{i_0}}{\partial v_{i_0 j}} = 0.$$

This implies $v_{i_0 j}^* = 2\lambda_{i_0} v_{i_0 j}$, where $v_{i_0 j}^*$ is the *cofactors* of $v_{i_0 j}$.

This means that $\sum_{j=1}^n v_{i_0 j} v_{kj} = 0$, so V must be an orthogonal matrix, so $|f| \leq 1$. \square

§0.2 Convex functions

Definition 0.2.1 (Hesse matrix). Let $f : \Omega \subset \mathbb{R}^n \rightarrow \mathbb{R}$ be a C^2 function, we call the Jacobi matrix of ∇f to be the **Hesse matrix** of f . (Also called Hessian matrix)

$$H_f(p) = \nabla^2 f(p) = \left(\frac{\partial}{\partial x_i} \frac{\partial}{\partial x_j} f(p) \right)_{i,j}.$$

Since the partial derivatives commute, so H_f is a symmetrical matrix, hence diagonalizable.

Proposition 0.2.2

Let $f \in C^2(\Omega)$, let x_0 be a minimum of f , then $\nabla f(x_0) = 0$, and $H_f(x_0)$ is semi positive definite.

Proof. By Taylor's expansion,

$$f(x) = f(x_0) + df(x_0)(x - x_0) + \frac{1}{2}(x - x_0)^T H_f(x_0)(x - x_0) + o(|x - x_0|^2).$$

If $H_f(x_0)$ has a negative eigenvalue $-\lambda$, with eigenvector v , then $f(x_0 + tv) = f(x_0) - \frac{1}{2}\lambda t^2 |v|^2 + o(|tv|^2)$, which contradicts with the minimality of x_0 . \square

Proposition 0.2.3

If $\nabla f(x_0) = 0$, $H_f(x_0)$ is positive definite, then x_0 is a local minimum of f .

Proof. Same as previous one. □

Definition 0.2.4 (Convex functions). If f and Ω satisfies:

$$\forall x, y \in \Omega, tx + (1-t)y \in \Omega, \quad f(tx + (1-t)y) \leq tf(x) + (1-t)f(y)$$

we say Ω is a **convex set** and f a **convex function**.

Theorem 0.2.5 (Jensen's inequality)

Let f be a convex function on Ω . Real numbers $t_i \geq 0$, $\sum_{i=1}^N t_i = 1$, for $x_i \in \Omega$,

$$f\left(\sum_{i=1}^N t_i x_i\right) \leq \sum_{i=1}^N t_i f(x_i).$$

Example 0.2.6 (Convex functions)

Linear functions $f(x) = Ax + b$ are convex.

The norm function $\|\cdot\| : \mathbb{R}^n \rightarrow \mathbb{R}$ is convex. Also let A be an $n \times n$ positive definite matrix, then $f(x) = x^T A x$ is convex.

Just like the one dimensional case, convex functions have nice properties.

Theorem 0.2.7

Let f be a convex function on an open convex set Ω , then f is continuous, and Lipschitz continuous in any compact set, i.e.

$$|f(x) - f(y)| \leq M|x - y|, \quad x, y \in U$$

where U is a compact set.

Proof. WLOG $0 \in \Omega$, take an orthogonal basis e_1, \dots, e_n . Let

$$x = \sum_{i=1}^n \lambda_i \bar{e}_i, \quad \bar{e}_i = e_i \text{ or } -e_i, \lambda_i \geq 0.$$

When $|x|$ sufficiently small, $\sum_{i=1}^n \lambda_i < 1$, so by Jensen's inequality,

$$f(x) \leq \sum_{i=1}^n \lambda_i f(\bar{e}_i) + \lambda f(0),$$

$$f(x) - f(0) \leq \sum_{i=1}^n \lambda_i (f(\bar{e}_i) - f(0)) \leq \left(\sum_{i=1}^n \lambda_i^2 \right)^{\frac{1}{2}} \left(\sum_{i=1}^n (f(\bar{e}_i) - f(0))^2 \right)^{\frac{1}{2}} \leq |x|C,$$

since we can change the length of e_i , and f is continuous on a straight line.

This means f is continuous. For the second part, let $\lambda_0 = \frac{1}{1+\sum_{i=1}^n \lambda_i}$, since $0 = \lambda_0 x + \sum_{i=1}^n \lambda_0 \lambda_i (-\bar{e}_i)$, by Jensen's inequality, we'll get the desired property. \square

Proposition 0.2.8

Let f be a differentiable function on a convex set Ω ,
 f is convex $\iff f(x) \geq f(x_0) + df(x_0)(x - x_0)$.

Proof. If f is convex, just use the definition and let $t \rightarrow 0$:

$$f(x_0) + f'(x_0)t(x - x_0) + o(t(x - x_0)) \leq tf(x) + (1 - t)f(x_0).$$

Conversely, let $z = tx + (1 - t)x_0$,

$$f(x) \geq f(z) + f'(z)(1 - t)(x - x_0), f(x_0) \geq f(z) + f'(z)t(x_0 - x).$$

Thus adding these together we get

$$tf(x) + (1 - t)f(x_0) \geq f(z).$$

\square

Theorem 0.2.9

Let $\Omega \subset \mathbb{R}^n$ be an open convex set, $f \in C^2(\Omega)$, f convex $\iff H_f(x)$ semi positive definite.

Proof. One direction can be proved using Taylor's expansion.

On the other hand, let $H(t) = f(x_0 + t(x - x_0)) - f(x_0) - t df(x_0)(x - x_0)$, then $H'(t) = df(x_0 + t(x - x_0))(x - x_0) - df(x_0)(x - x_0)$,

$$H''(t) = (x - x_0)^T H_f(p)(x_0 + t(x - x_0))(x - x_0) \geq 0.$$

So $H(t)$ is a convex function, $H(0) = 0, H'(0) = 0$. \square

§1 Integrals on surfaces

§1.1 Measures on manifolds

To define integrals, we need to define a measure on it first.

For example, let $v_1, \dots, v_d \in \mathbb{R}^n$ be linearly independent vectors, and unit vectors v_{d+1}, \dots, v_n complete them to a basis, satisfying $v_j \perp v_i, j > d, j > i$.

Let A be a linear map s.t. $Ae_i = v_i$, then the volume of $A(E)$ is $|\det A| = \sqrt{\det(G \cdot G^T)}$,

where $G = \begin{pmatrix} v_1 \\ \vdots \\ v_d \end{pmatrix}$ is a $d \times n$ matrix.

Since $AA^T = \begin{pmatrix} GG^T & 0 \\ 0 & I_{n-d} \end{pmatrix}$, $|\det A| = \sqrt{\det GG^T}$, we say GG^T is the **Gram matrix** of G .

Another example is the length of a curve. Recall that we have the formula

$$L(\gamma) = \int_0^1 |\gamma'(t)| dt.$$

The length of a curve is essentially the “volume” of a 1-dimensional manifold, so the idea of higher dimensional manifold is the same.

Definition 1.1.1. Let M be a manifold in \mathbb{R}^n . Let $\Phi : V \subset \mathbb{R}^d \rightarrow U \subset M$ be a smooth homeomorphism, $\text{rank } \Phi = d$. We can split U to many small regions and use the paraloids to approximate the volume of each region.

Thus we define:

$$m(U) = \int_V \sqrt{\det(d\Phi(x)^T d\Phi(x))} dx_1 dx_2 \cdots dx_d.$$

The above differential form inside the integral is called the **volume form**:

$$d\sigma(y) = \sqrt{\det(d\Phi^T d\Phi)} dy.$$

Moreover, with this measure we can define the integral of general measurable function f (measurable means locally measurable on \mathbb{R}^d):

$$\int_U f d\sigma = \int_V f(\Phi(x)) \sqrt{\det(d\Phi^T d\Phi)} dx.$$

Just like the length of a curve, the volume defined above is also a geometric quantity, i.e. independent of coordinates.

Example 1.1.2

Let $d = 1$, $\gamma : (-1, 1) \rightarrow \mathbb{R}^n$, $\gamma'(0) \neq 0$. For fixed $-1 < a < b < 1$ and a function f on γ , let C_a^b denote the curve between $\gamma(a), \gamma(b)$,

$$\int_{C_a^b} f d\sigma = \int_a^b f(\gamma(t)) |\gamma'(t)| dt$$

is called the **curve integral of the first type**.

Example 1.1.3

Let $d = n - 1$, $f : \mathbb{R}^{n-1} \rightarrow \mathbb{R}$, the graph of f is a hyper-surface $\Gamma_f = \{(x, f(x)) \mid x \in \mathbb{R}^{n-1}\}$. It has a parametrization $\Phi(x) = (x, f(x))$, so

$$d\Phi = \begin{pmatrix} I_{n-1} \\ \nabla f \end{pmatrix} \implies d\Phi^T d\Phi = I_{n-1} + \nabla f^T \cdot \nabla f.$$

Hence $\det(d\Phi^T d\Phi) = 1 + |\nabla f|^2$. (This can be obtained by looking at the eigenvectors)

Therefore for φ on \mathbb{R}^n , we have

$$\int_{\Gamma_f} \varphi d\sigma = \int_{\mathbb{R}^{n-1}} \varphi(x, f(x)) \sqrt{1 + |\nabla f|^2} dx.$$

Next we'll compute the surface area of unit sphere S^{n-1} .

Let c_n denote the volume of unit sphere in \mathbb{R}^n ,

$$c_n = \frac{\pi^{\frac{n}{2}}}{\Gamma(\frac{n}{2} + 1)}.$$

We claim in advance that the surface area of unit sphere $\omega_{n-1} = nc_n$. Here we use the sphere coordinates:

$$x_1 = r \prod_{k=1}^{n-1} \sin \theta_k, \quad x_i = r \sin \theta_{n-1} \cdots \sin \theta_i \cos \theta_{i-1}, 2 \leq i \leq n.$$

Let $F_n(r, \theta_1, \dots, \theta_{n-1}) = (x_1, \dots, x_n)$.

$$dF_n = \begin{pmatrix} \sin \theta_{n-1} dF_{n-1} & \cos \theta_{n-1} F_{n-1}^T \\ (\cos \theta_{n-1}, 0, \dots, 0) & -r \sin \theta_{n-1} \end{pmatrix}.$$

So we can compute its determinant (expand using the last row), note that the first column of dF_{n-1} is $r^{-1} F_{n-1}^T$,

$$\begin{aligned} \det dF_n &= -r \sin \theta_{n-1} (\sin \theta_{n-1})^{n-1} \det(dF_{n-1}) \\ &\quad + (-1)^{n-1} (\cos \theta_{n-1})^2 (-1)^{n-2} r (\sin \theta_{n-1})^{n-2} \det(dF_{n-1}) \\ &= -r (\sin \theta_{n-1})^{n-2} \det(dF_{n-1}). \end{aligned}$$

Hence $dx = r^{n-1} \sin^{n-2} \theta_{n-1} \cdots \sin \theta_2 dr d\theta_1 \cdots d\theta_{n-1} = r^{n-1} dr d\omega$.

Denote F_n^S to be the function F_n restricted to S^{n-1} . Then $dF_n = (r^{-1} F_n^T, dF_n^S)$. We can compute that the Gram determinant of dF_n^S is just $\det dF_n$ with $r = 1$.

The rest is some integrals with gamma function and beta function, which is left out.

§1.2 Stokes' formula

Intuitively, Stokes' formula states that: Let D be a region, $d\omega$ be a differential form, then

$$\int_D d\omega = \int_{\partial D} \omega.$$

Here ∂D means the "boundary" of D .

Of course we need some "regularity" requirements of D and ω , and it's the generalization of Newton-Lebniz formula into higher dimensions.

Definition 1.2.1 (Bounded regions with boundary). Let $\Omega \subset \mathbb{R}^n$ be a compact set, we say it's a **bounded region with boundary** if $\forall x \in \partial\Omega$, there exists open sets $U, V \subset \mathbb{R}^n$, $x \in U$ and a continuous homeomorphism $\Phi : U \rightarrow V$, such that

$$\Phi(U \cap \Omega) = V \cap \{x_n \geq 0\}, \quad \Phi(U \cap \partial\Omega) = V \cap \{x_n = 0\}.$$

If Φ is also C^1 , we say $x \in \partial\Omega$ is a **regular point**, otherwise a **singular point**.

Lemma 1.2.2

Let Ω be a bounded region with boundary, for all regular $p \in \partial\Omega$, there exists a unique unit vector $\nu(p) \in \mathbb{R}^n$, and $\varepsilon > 0$, s.t.

$$\nu(p) \perp T_p \partial\Omega, |\nu(p)| = 1, p - t\nu(p) \in \Omega, \forall 0 < t < \varepsilon.$$

We call $\nu(p)$ the **outward unit normal vector** of p .

Proof. By the definition of regular points, we may assume that:

$$\Omega \cap V = \{x \in V \mid f(x) \geq 0\}, \quad \partial\Omega \cap V = \{x \in V \mid f(x) = 0\}.$$

Where f is a C^1 function.

Since ∇f is nonzero, the tangent space $T_p \partial\Omega = \{v \mid v \cdot \nabla f = 0\}$.

Let $\nu(p) = -\frac{\nabla f}{|\nabla f|}$, then it's obvious $\nu(p)$ points outside of Ω . □

Now for a cuboid I and a C^1 function ϕ ,

$$\begin{aligned} \int_I \frac{d\phi}{dx_n} dx &= \int_{I_{n-1}} \phi(x_1, \dots, x_{n-1}, b_n) dx_1 \cdots dx_{n-1} - \int_{I_{n-1}} \phi(x_1, \dots, x_{n-1}, a_n) dx_1 \cdots dx_{n-1} \\ &= \int_{\partial I} \phi \cdot \nu_n d\sigma. \end{aligned}$$

Where σ is the measure on the boundary, ν is the outward unit normal vector.

Lemma 1.2.3

Let K be a compact set in \mathbb{R}^n , $U \supset K$ is open, there exists a smooth function f such that $\text{supp } f \subset U$, and $f|_K > 0$.

Proof. Let $\rho(x)$ be a smooth function s.t. $\rho(x) = 1$ for $|x| \leq 1$ and $\rho(x) = 0$ for $|x| \geq 2$. Let

$$g(x) = \int_{|y| \leq 2} f(x - \delta y) \rho(y) dy.$$

Then g is a smooth non-negative function. □

Theorem 1.2.4 (Unit decomposition on compact sets)

Let K be a compact set, $\{U_1, \dots, U_k\}$ is an open covering of K . There exists smooth functions f_1, \dots, f_k s.t.

$$1 = f_1(x) + f_2(x) + \cdots + f_k(x), \quad \text{supp } f_i(x) \subset U_i.$$

Proof. For $1 \leq i \leq k$, $\delta > 0$, define

$$K_i^\delta = \{x \in U_i \mid d(x, U_i^c) > \delta\}.$$

Note that $\{\bigcup_{i=1}^k K_i^{\frac{1}{m}}\}_{m=1}^\infty$ is also an open covering of K , thus there exists N s.t.

$$K \subset \bigcup_{i=1}^k K_i^{\frac{1}{N}}.$$

Hence by lemma we have g_i s.t. $\text{supp } g_i \subset U_i$ and $g_i > 0$ on the closure of $K_i^{\frac{1}{N}}$. Similarly we have a smooth function g s.t. $g(x) = 0$ on K , and $g > 0$ outside of the closure of $\bigcup_{i=1}^k K_i^{\frac{1}{N}}$.

Let $G(x) = g_1(x) + \cdots + g_k(x) + g(x) > 0$ on $\bigcup_{i=1}^k U_i$, then we can define $f_i(x) = \frac{g_i(x)}{G(x)}$ which satisfy the condition. □

Theorem 1.2.5

Let Φ be a C^1 homeomorphism from a cuboid I to Ω , then Ω satisfies Stokes' formula:

$\forall \phi \in C^1(\overset{\circ}{D}) \cap C(\overline{D})$, we have

$$\int_D \nabla \phi \, dx = \int_{\partial D} \phi \nu \, d\sigma.$$