

Lecture 1: Introductory Ideas

Goals: \Rightarrow equivalent to calculus but in \mathbb{R}^n

1. Define what a variational problem is.
 2. Discuss problems on finite dimensional spaces (\mathbb{R}^n).
 3. **Meat:** Examples of ill posed problems in infinite dimensional spaces.
- a.) non-uniqueness
 - b.) non-existence
 - c.) non-smooth solutions.

(*) \Rightarrow **Key Points:** $\nabla \cdot X \pm + (*)^2 = (x)^2$

1. coercivity \Rightarrow a measure of growth

2. compactness

3. lower semi-continuity

4. minimizing sequences.

1. Definitions:

The calculus of variations is concerned with problems of the following form:

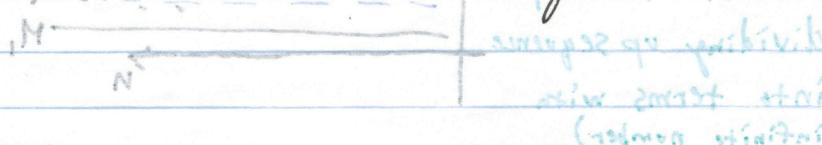
$$\inf_{\text{set}} I[f](x)$$

a.) ~~if~~ $I: A \rightarrow \mathbb{R}$ is called a functional.

b.) A is called the admissible set.

* The reason we say inf instead of min is the minimum may not exist.

This issue is not so trivial on general function spaces.



2. Finite Dimensional Spaces

Briefly we will look at functions $f: \mathbb{R}^n \rightarrow \mathbb{R}$.

Classic Approach: Intuitively a local minima

1. If f is smooth, solve $\nabla f = 0$, for \vec{x}^* .

2. Need to check convexity condition. (to M.E.)

$$\nabla^2 f = \begin{pmatrix} \frac{\partial^2 f}{\partial x_1^2} & \frac{\partial^2 f}{\partial x_1 \partial x_2} & \cdots & \frac{\partial^2 f}{\partial x_1 \partial x_n} \\ \vdots & \ddots & & \vdots \\ \frac{\partial^2 f}{\partial x_n \partial x_1} & \frac{\partial^2 f}{\partial x_n \partial x_2} & \cdots & \frac{\partial^2 f}{\partial x_n^2} \end{pmatrix} \geq 0$$

positive definite (d)
non-negative (d)

meaning $\vec{x}^T \cdot \nabla^2 f \cdot \vec{x} \geq 0$. Reason: in a neighbourhood around \vec{x}^* we have that

$$f(x) = f(\vec{x}^*) + \frac{1}{2} \vec{x}^T \cdot \nabla^2 f \cdot \vec{x} \Rightarrow f(x) \geq f(\vec{x}^*)$$

This approach assumes a lot of smoothness of the data.

Direct Method:

In terms of actually minimizing a function the above method is very impractical. (Solve n nonlinear equations). Here I will illustrate an important concept: the direct method.

1. Let \vec{x}_n be a minimizing sequence, i.e. a sequence satisfying $f(\vec{x}_n) \rightarrow \inf_{x \in \mathbb{R}^n} f(x)$. We can abstractly consider this existence since $f: \mathbb{R}^n \rightarrow \mathbb{R}$. We would like to show two things:

a.) There exists \vec{x}^* such that $\vec{x}_n \rightarrow \vec{x}^*$.

b.) For all $\vec{x} \in \mathbb{R}^n$, $f(\vec{x}^*) \leq f(\vec{x})$.

2. If f is coercive, meaning $|\vec{x}| \rightarrow \infty \Rightarrow |f(\vec{x})| \rightarrow \infty$

then there exists $M \in \mathbb{R}^n$ such that $|\vec{x}_n| \leq M$. By the Bolzano-Weierstrass Theorem (Compactness) there exists

a subsequence \vec{x}_{n_k} and \vec{x}^* such that $\vec{x}_{n_k} \rightarrow \vec{x}^*$.

(Proof of Bolzano-Weierstrass keep notes)

dividing up sequence into terms with infinite number



3. A function is lower semicontinuous if $x_n \rightarrow x$ implies $f(x) \leq \liminf f(x_n)$.

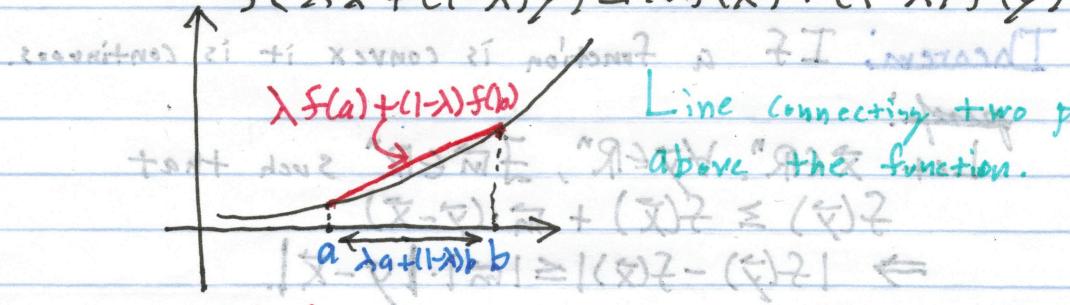
or

Summary:Coercivity + lower semicontinuity \Rightarrow existence of minimum.

These are the basic conditions we need for a well posed minimization problem on \mathbb{R}^n .

Convexity: A function $f: \mathbb{R}^n \rightarrow \mathbb{R}$ is convex if $\forall \vec{x}, \vec{y} \in \mathbb{R}^n$ and each $\lambda \in [0, 1]$:

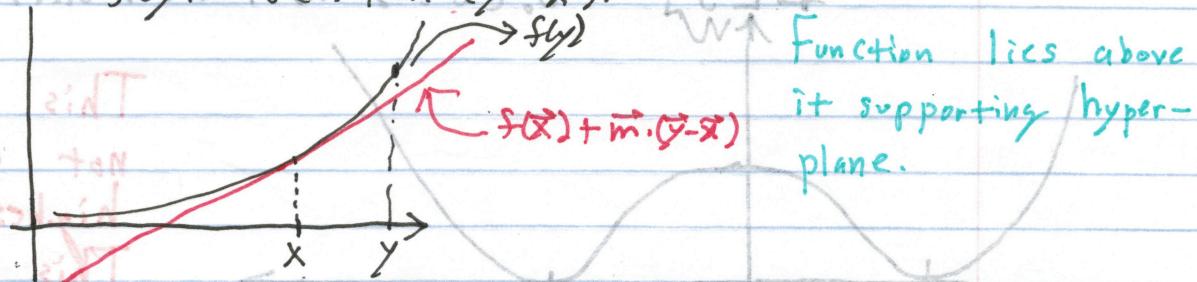
$$f(\lambda \vec{x} + (1-\lambda) \vec{y}) \leq \lambda f(\vec{x}) + (1-\lambda) f(\vec{y})$$



Caution: Convexity in terms of functions only makes sense on convex domains.

Theorem: Suppose $f: \mathbb{R}^n \rightarrow \mathbb{R}$ is convex, then for each $\vec{x} \in \mathbb{R}^n$ there exists $\vec{m} \in \mathbb{R}^n$ such that $\forall \vec{y} \in \mathbb{R}^n$

$$f(\vec{y}) \geq f(\vec{x}) + \vec{m} \cdot (\vec{y} - \vec{x}).$$



* If f is differentiable then $\vec{m} = \nabla f$.

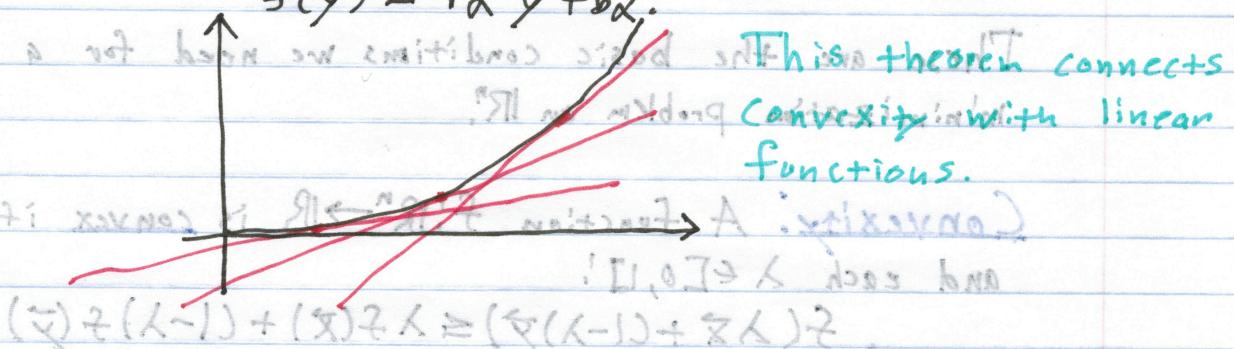
$$\mathcal{E}(1,0)^T \cdot \vec{w} \geq 23 = A$$

total [total sum of squares values] total $\|f\|_2$ of \vec{w}

Theorem: A function $f: \mathbb{R}^n \rightarrow \mathbb{R}_+$ is convex if and only if it can be written as the supremum of bounding hyperplanes:

$$f(\vec{x}) = \sup_{\alpha} \vec{r}_\alpha^\top \cdot \vec{x} + b_\alpha$$

where for all α and some indexing set and all $\vec{y} \in \mathbb{R}^n$

$$f(\vec{y}) \geq \vec{r}_\alpha^\top \vec{y} + b_\alpha.$$


Theorem: If a function is convex it is continuous.

proof:

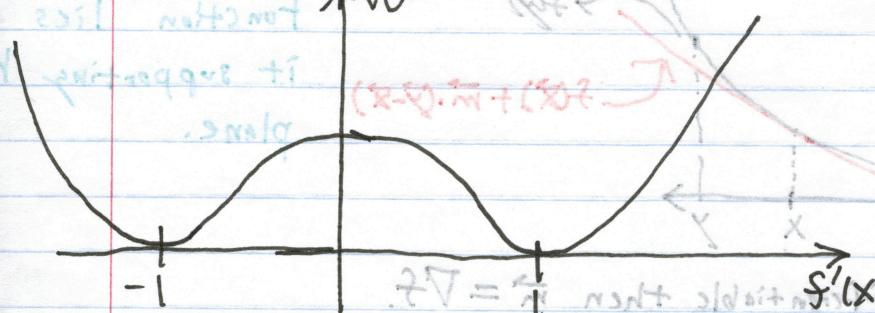
$$\begin{aligned} & \text{Let } \vec{x}, \vec{y} \in \mathbb{R}^n, \vec{m} \in \mathbb{R}^n \text{ such that} \\ & f(\vec{y}) \geq f(\vec{x}) + \vec{m} \cdot (\vec{y} - \vec{x}) \\ & \Rightarrow |f(\vec{y}) - f(\vec{x})| \leq |\vec{m}| \cdot |\vec{y} - \vec{x}|. \end{aligned}$$

Hence convexity \Rightarrow continuous \Rightarrow lower semicontinuous.

3 Examples

a.) Non-Convex

$$I[f] = \int_0^1 (f'(x)^2 - 1)^2 + f(x)^2 dx.$$



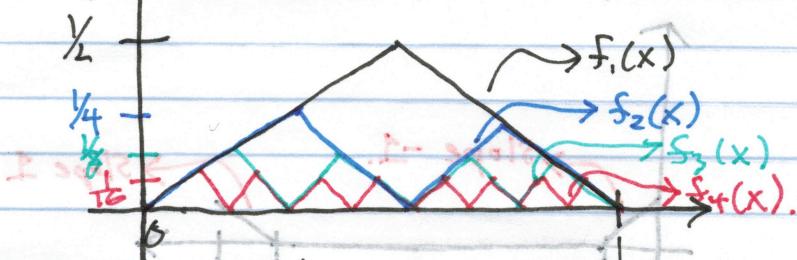
This functional is not convex in its highest derivative. This really means the integrand is not convex.

$$A = \{f \in W_0^{1,2}(0,1)\}$$

We will talk about Sobolev spaces in more detail later.

Sensitivity: Clearly, $I[f] \geq 0$. We construct a sequence of functions $f_n(x)$ such that $I[f_n] \rightarrow 0$.

$$f_1 = (0)^2, f_2 = (0)^2 + (1, 0)^2, f_3 = 2^2 = 1$$



$$I[f_n] = \int_0^1 f_n(x)^2 dx \leq \frac{1}{4n^2} \rightarrow 0.$$

However, if $I[f] = 0$ then $f(x) = 0$ a.e. and $f'(x) = \pm 1$ a.e. There is no minimum for this problem.

b.) Non-Coercive

$$I[f] = \int_0^1 \sqrt{f(x)^2 + f'(x)^2} dx.$$

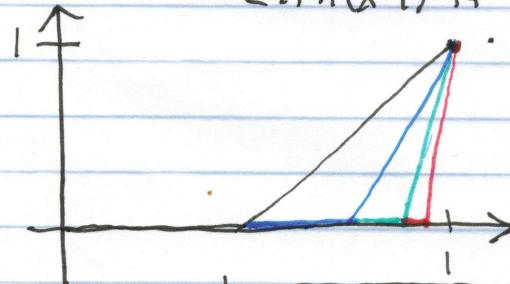
$$A = \{f \in W^{1,1}(0,1) : f(0) = 0 \text{ and } f(1) = 1\}.$$

We will show no minimum exists. Clearly,

$$I[f] = \int_0^1 \sqrt{f(x)^2 + f'(x)^2} dx \geq \int_0^1 |f'(x)| dx \geq \int_0^1 f'(x) dx = 1.$$

Now, construct a minimizing sequence as follows:

$$f_n(x) = \begin{cases} 0 & \text{if } x \notin [0, 1 - \frac{1}{n}] \\ 1+n(x-1) & \text{if } x \in [1 - \frac{1}{n}, 1] \end{cases}$$



(derivative concentrates at a point).

$$I[f_n] = \int_{1-\frac{1}{n}}^1 \sqrt{(1+n(x-1))^2 + n^2} dx \leq \int_{1-\frac{1}{n}}^1 \sqrt{1+n^2} dx = \frac{1}{n} \sqrt{1+n^2}$$

Therefore,

$$1 = I[f_n] \leq \frac{1}{n} \sqrt{1+n^2} \Rightarrow \lim_{n \rightarrow \infty} I[f_n] = 1.$$

This implies that $\inf_{f \in A} I[f] = 0$. Now, suppose that $\exists f^* \in A$ such that $I[f^*] = 1$. Then,

$$1 = \int_0^1 \sqrt{f^*(x)^2 + f'^*(x)^2} dx \geq \int_0^1 f'^*(x) dx = 1.$$

$\Rightarrow f^*(x) = 0$ which does not satisfy the boundary conditions.

C. Convex and Coercive (bad boundary conditions)

$$J \leftarrow [x_0^2] \quad I[f] = \int_0^1 f'(x)^2 dx \quad \text{to}$$

$$A = \{f \in W^{1,2}(0,1) : f'(0) = -1, f'(1) = 1\}.$$

(small ||f||)



$$J \leftarrow \frac{1}{n^2} \geq \int_0^1 f'(x)^2 dx = [x_0^2]$$

Therefore $I[f_n] = \frac{1}{n^2} \rightarrow 0$. However if $I[f] = 0$ then $f = \text{constant}$ which doesn't satisfy boundary conditions.

$$\text{sum} = n J(d)$$

$$\int_0^1 [x_0^2 + s(x)]^2 dx = [x_0^2]$$

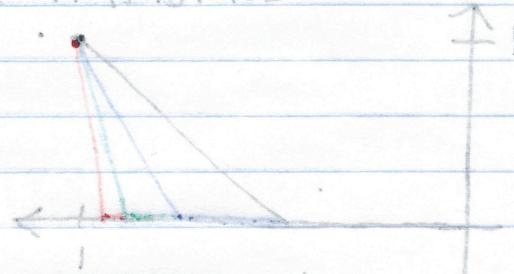
$$(1 = (1)^2 \text{ and } 0 = (0)^2 : (1, 0)^T \in W \ni 2^2 = 1)$$

$$x_0^2 \leq x_0^2 + s(x)^2 \leq x_0^2 + s(x)^2 = [x_0^2]$$

: small of sum up to minimize a function, well

$$[\frac{1}{n^2} - 1, 0] \ni x \ni 0 = (x)_n^2$$

$$[1, n^{-2}] \ni x \ni (1-x)n+1$$



(minimizing)

(minimizing A + B)

$$J = \int_0^1 [x_0^2 + s(x)]^2 dx \geq \int_0^1 [x_0^2 + ((1-x)n+1)]^2 dx = [x_0^2]$$

$$J = [x_0^2] \Leftarrow \int_0^1 [x_0^2] dx = [x_0^2] = 1$$

tant se qqq wll. $0 = [x_0^2]$ tant se ilgmi zidT

$$n > N \Rightarrow J = [x_0^2] + \text{tant se ilgmi zidT} \geq x_0^2$$

$$J = x_0^2 \leq x_0^2 + s(x)^2 = [x_0^2]$$

probando se qqq zidT se qqq wll. $0 = (x)^2 \Leftarrow$

se ilgmi zidT probando se qqq