

5. SUFFICIENT CONDITIONS FOR MINIMALITY

So far we have shown that solutions to a minimization problem for integral functionals also solve the associated EULER-LAGRANGE EQUATION.

**QUESTION:** Are solutions to (ELE) minimizers? If YES, how do we prove it?

**WARNING:** This is in general not true: we can have a sol. to (ELE) but not minimizer

To answer the above, we will analyze 4 methods:

- ① CONVEXITY
  - ② TRIVIAL LEMMA
- } NOW

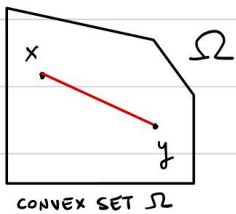
- ③ CALIBRATIONS
  - ④ WEIERSTRASS FIELDS
- } LATER in the course (if we have time!)

① CONVEXITY

If the Lagrangian  $L = L(x, s, p)$  is convex in  $s, p$ , we will prove that solutions to (ELE) are minimizers.

DEFINITION 5.1

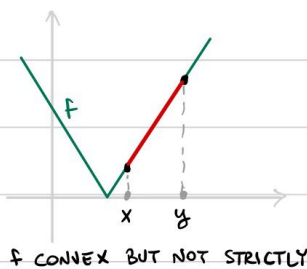
Let  $\Omega \subseteq \mathbb{R}^d$ . We say that  $\Omega$  is CONVEX if  $\lambda x + (1-\lambda)y \in \Omega, \forall x, y \in \Omega, \lambda \in [0, 1]$ .



Let  $f: \Omega \rightarrow \mathbb{R}$ , with  $\Omega$  convex. We say that  $f$  is CONVEX if

$$f(\lambda x + (1-\lambda)y) \leq \lambda f(x) + (1-\lambda)f(y),$$

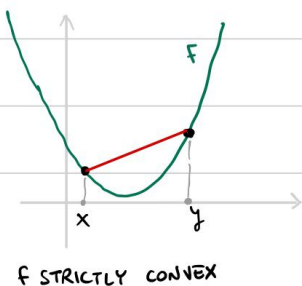
for all  $x, y \in \Omega, \lambda \in [0, 1]$ .



We say that  $f$  is STRICTLY CONVEX if

$$f(\lambda x + (1-\lambda)y) < \lambda f(x) + (1-\lambda)f(y),$$

for all  $x, y \in \Omega, s.t. x \neq y$  and  $\lambda \in (0, 1)$ .



For regular convex functions the following result holds:

**THEOREM 5.2** Let  $\Omega \subseteq \mathbb{R}^d$  be open convex,  $f: \Omega \rightarrow \mathbb{R}$ ,  $f \in C^1(\Omega)$ ,  
Then

1)  $F$  is convex iff

( $f$  above tangent planes)  $\rightsquigarrow f(y) \geq f(x) + \nabla f(x) \cdot (y-x)$ ,  $\forall x, y \in \Omega$

2)  $F$  is strictly convex iff

$$f(y) > f(x) + \nabla f(x) \cdot (y-x), \quad \forall x, y \in \Omega, x \neq y$$

Assume in addition that  $F \in C^2(\Omega)$

3)  $F$  is convex iff the HESSIAN  $\nabla^2 f$  is POSITIVE SEMI-DEFINITE, i.e.,

$$y^T \nabla^2 f(x) y \geq 0, \quad \forall x \in \Omega, y \in \mathbb{R}^d$$

4) Assume  $\nabla^2 f$  is POSITIVE DEFINITE, i.e.,

$$y^T \nabla^2 f(x) y > 0, \quad \forall x \in \Omega, y \in \mathbb{R}^d \setminus \{0\}$$

Then  $F$  is strictly convex.

(The proof is standard, from analysis courses. See B. Dacorogna - "INTRODUCTION TO THE CALCULUS OF VARIATIONS", IMPERIAL COLLEGE PRESS, 2004 - THEOREM 1.5)

WARNING: The converse of (4) does not hold.

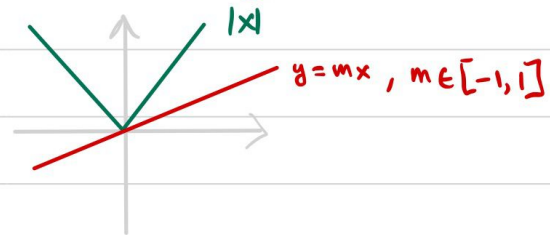
If instead we have no regularity, then we get:

**THEOREM 5.3** Let  $\Omega \subseteq \mathbb{R}^d$  be convex, and  $f: \Omega \rightarrow \mathbb{R}$  convex. Let  $\bar{x} \in \Omega$ . Then  $\exists m \in \mathbb{R}^d$  s.t.

$$f(y) \geq f(\bar{x}) + m \cdot (y - \bar{x}), \quad \forall y \in \Omega$$

(Proof is omitted. This result is saying that if  $f$  convex then  $\partial f(\bar{x}) \neq \emptyset$ , i.e., the SUBDIFFERENTIAL of  $f$  at  $\bar{x}$  is non-empty. For a proof see R.T. ROCKAFELLAR - "CONVEX ANALYSIS", PRINCETON UNIVERSITY PRESS, 1970 - THEOREM 23.4)

**NOTE:** For  $f: [a,b] \rightarrow \mathbb{R}$  one can take  $m \in [f'_-(\bar{x}), f'_+(\bar{x})]$  left and right derivatives.



### APPLICATION TO CONV

Let  $X := \{u \in C^1[a,b] \mid u(a) = \alpha, u(b) = \beta\}$ ,  $V := \{v \in C^1[a,b] \mid v(a) = v(b) = 0\}$ .

Let  $L: [a,b] \times \mathbb{R} \times \mathbb{R} \rightarrow \mathbb{R}$ ,  $L = L(x, s, p)$  and define  $F: X \rightarrow \mathbb{R}$  by

$$F(u) := \int_a^b L(x, u, u') dx.$$

**THEOREM 5.4** Suppose  $L \in C^1([a,b] \times \mathbb{R} \times \mathbb{R})$  and let  $\bar{u} \in X$  be a solution to ELE in INTEGRAL FORM, i.e.,

$$\otimes \int_a^b L_s(x, \bar{u}, \bar{u}') v + L_p(x, \bar{u}, \bar{u}') v' dx = 0, \quad \forall v \in V.$$

(1) If  $(s, p) \mapsto L(x, s, p)$  is CONVEX for all  $x \in [a, b]$  fixed, then  $\bar{u}$  is a minimizer for  $F$  in  $X$ .

(2) If  $(s, p) \mapsto L(x, s, p)$  is STRICTLY CONVEX for all  $x \in [a, b]$ , then  $\bar{u}$  is the unique minimizer of  $F$  in  $X$ .

**NOTE:** If  $u$  solves ELE in DIFFERENTIAL FORM then it solves ELE in INTEGRAL FORM

Proof (1) Let  $w \in X$  be arbitrary and set  $v := w - \bar{u}$ .

Then  $v \in V$  i.e.  $v(a) = v(b) = 0$ . We have

$$F(w) = F(\bar{u} + v) = \int_a^b L(x, \bar{u} + v, \bar{u}' + v') dx$$

As  $L$  is  $C^1$  and is convex in  $s, p$ , we can apply Theorem 5.2 and obtain

$$L(x, s + \tilde{s}, p + \tilde{p}) \geq L(x, s, p) + L_s(x, s, p) \tilde{s} + L_p(x, s, p) \tilde{p}, \quad \forall s, \tilde{s}, p, \tilde{p} \in \mathbb{R}, \quad \forall x \in [a, b]$$

Apply the above with  $s = \bar{u}$ ,  $\tilde{s} = v$ ,  $p = \bar{u}'$ ,  $\tilde{p} = v'$ ,

$$\begin{aligned} F(w) &= \int_a^b L(x, \bar{u} + v, \bar{u}' + v') dx \geq \\ &\geq \int_a^b L(x, \bar{u}, \bar{u}') dx + \underbrace{\int_a^b L_s(x, \bar{u}, \bar{u}') v + L_p(x, \bar{u}, \bar{u}') v' dx}_{= 0 \text{ by } (*), \text{ since } v \in V} \\ &= F(\bar{u}) \end{aligned}$$

showing that  $\bar{u}$  minimizes  $F$  over  $X$ .

(2) Assume  $\bar{u}$  and  $\hat{u}$  both minimize  $F$  over  $X$ . Set  $m := \min \{F(u) \mid u \in X\}$ .

Therefore  $F(\hat{u}) = F(\bar{u}) = m$ , and also  $F(u) \geq m$ ,  $\forall u \in X$ .

Define  $w := \frac{1}{2}\bar{u} + \frac{1}{2}\hat{u}$ , so  $w \in X$ . By convexity of  $L$  (just using the definition)

$$\begin{aligned} L(x, w, w') &= L\left(x, \frac{1}{2}\bar{u} + \frac{1}{2}\hat{u}, \frac{1}{2}\bar{u}' + \frac{1}{2}\hat{u}'\right) \\ &\leq \frac{1}{2} L(x, \bar{u}, \bar{u}') + \frac{1}{2} L(x, \hat{u}, \hat{u}') \end{aligned}$$

Integrating the above inequality we obtain

$$\begin{aligned} m &\leq F(w) = \int_a^b L(x, w, w') dx \leq \\ &\stackrel{\text{Since } w \in X}{=} \frac{1}{2} \int_a^b L(x, \bar{u}, \bar{u}') dx + \frac{1}{2} \int_a^b L(x, \hat{u}, \hat{u}') dx = \\ &= \frac{1}{2} F(\bar{u}) + \frac{1}{2} F(\hat{u}) \\ &= \frac{1}{2} m + \frac{1}{2} m = m \end{aligned}$$

Thus, all the inequalities in the above chain are actually equalities, and we get

$$\textcircled{*} \int_a^b \left\{ \frac{1}{2} L(x, \bar{u}, \bar{u}') + \frac{1}{2} L(x, \hat{u}, \hat{u}') - L(x, \frac{1}{2}\bar{u} + \frac{1}{2}\hat{u}, \frac{1}{2}\bar{u}' + \frac{1}{2}\hat{u}') \right\} dx = 0$$

Now, by convexity of  $L$ , the INTEGRAND in  $\textcircled{*}$  is always  $\geq 0$ . Hence, by continuity, we conclude that

$$L(x, \frac{1}{2}\bar{u} + \frac{1}{2}\hat{u}, \frac{1}{2}\bar{u}' + \frac{1}{2}\hat{u}') = \frac{1}{2} L(x, \bar{u}, \bar{u}') + \frac{1}{2} L(x, \hat{u}, \hat{u}'), \quad \forall x \in [a, b]$$

Since  $L$  is STRICTLY CONVEX, the above is possible iff  $\bar{u}(x) = \hat{u}(x)$  and  $\bar{u}'(x) = \hat{u}'(x)$ ,  $\forall x \in [a, b]$ .

Thus  $\bar{u} \equiv \hat{u}$  and the minimizer is unique.  $\square$

**EXAMPLE** Let  $L: \mathbb{R} \rightarrow \mathbb{R}$ ,  $L = L(p)$ . Assume  $L \in C^2(\mathbb{R})$ . Define

$$X := \{ u \in C^1[a, b] \mid u(a) = \alpha, u(b) = \beta \}$$

$$V := \{ v \in C^1[a, b] \mid v(a) = 0, v(b) = 0 \}$$

Consider  $F: X \rightarrow \mathbb{R}$  defined by

$$F(u) := \int_a^b L(\dot{u}) dx$$

We can then write **ELE** in **DIFFERENTIAL FORM**:

$$\begin{cases} \frac{d}{dx} [L_p(x, u(x), \dot{u}(x))] = L_s(x, u(x), \dot{u}(x)) & , \quad \forall x \in (a, b) \\ u(a) = \alpha, \quad u(b) = \beta \end{cases}$$

which in this case reads

$$(ELE) \quad \begin{cases} \frac{d}{dx} [L'(\dot{u}(x))] = 0 & , \quad \forall x \in (a, b) \\ u(a) = \alpha, \quad u(b) = \beta. \end{cases}$$

Now, the above ODE implies that

$$L'(\dot{u}) = \text{CONSTANT}$$

Therefore the straight line

$$\bar{u}(x) := \frac{\beta - \alpha}{b - a} (x - a) + \alpha$$

is **ALWAYS** a solution to **(ELE)**.

QUESTION When does  $\bar{u}$  also solve

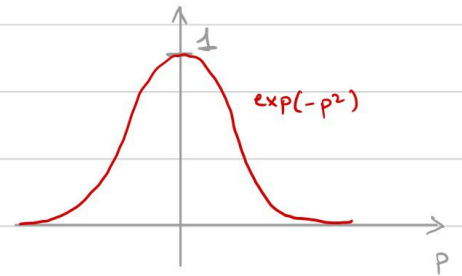
$$(P) \quad F(\bar{u}) = \min \{ F(u) \mid u \in X \} \quad ?$$

CASE 1 Assume  $L$  CONVEX. As  $\bar{u}$  solves (ELE), in particular it solves ELE in INTEGRAL FORM. Then by THEOREM 5.4 we have that  $\bar{u}$  solves (P).

CASE 2 If we do not assume convexity, then in general  $\bar{u}$  DOES NOT solve (P).  
For example let

$$L(p) := \exp(-p^2)$$

Let us consider the case with zero Dirichlet conditions, i.e.,



$$X = V = \{ u \in C^1[0,1] \mid u(0) = u(1) = 0 \}.$$

Note that in this setting our straight line is  $\bar{u} \equiv 0$ . Then  $\bar{u}$  solves (ELE), but is it solution to (P)?

Clearly  $L$  is not convex, so THEOREM 5.4 cannot be applied.

FACT The minimization problem (P) has NO SOLUTION and

$$m := \inf \{ F(u) \mid u \in X \} = 0$$

(This will be left as an exercise)

Therefore  $\bar{u} \equiv 0$  solves (ELE) but DOES NOT solve (P).

## ② TRIVIAL LEMMA

Given  $\bar{u}$  solution to ELE, we want to know if  $\bar{u}$  is also a minimizer. A possible way to answer this question is given by the following Lemma.

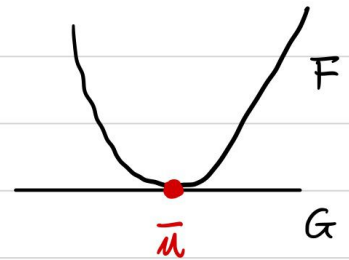
### LEMMA 5.5 (LEMMA TRIVIAL)

Let  $X$  be a set and  $F, G: X \rightarrow \mathbb{R}$  functionals. Assume that

$$(i) \quad F(u) \geq G(u), \quad \forall u \in X$$

(ii)  $\bar{u} \in X$  is a minimizer for  $G$  on  $X$

$$(iii) \quad F(\bar{u}) = G(\bar{u}).$$



Then  $\bar{u}$  is a minimizer for  $F$ . If in addition  $\bar{u}$  is the unique minimizer of  $G$ , then  $\bar{u}$  is the unique minimizer of  $F$ .

Proof Let  $u \in X$  be arbitrary. Then

$$F(u) \stackrel{(i)}{\geq} G(u) \stackrel{(ii)}{\geq} G(\bar{u}) \stackrel{(iii)}{=} F(\bar{u}),$$

showing that  $\bar{u}$  minimizes  $F$ .

Assume now that  $\bar{u}$  is the unique minimizer of  $G$ . Then, for the first part of the statement, we know that  $\bar{u}$  also minimizes  $F$ . Suppose that  $\bar{w} \in X$  is another minimizer for  $F$ . Then

$$G(\bar{w}) \stackrel{(i)}{\leq} F(\bar{w}) = F(\bar{u}) \stackrel{(iii)}{=} G(\bar{u})$$

↑  
minimality of  $\bar{u}$   
and  $\bar{w}$  for  $F$

Thus  $G(\bar{w}) = G(\bar{u})$ , being  $\bar{u}$  minimizer for  $G$ .  $\Rightarrow \bar{u} = \bar{w}$  as the minimizer of  $G$  is unique.  $\square$



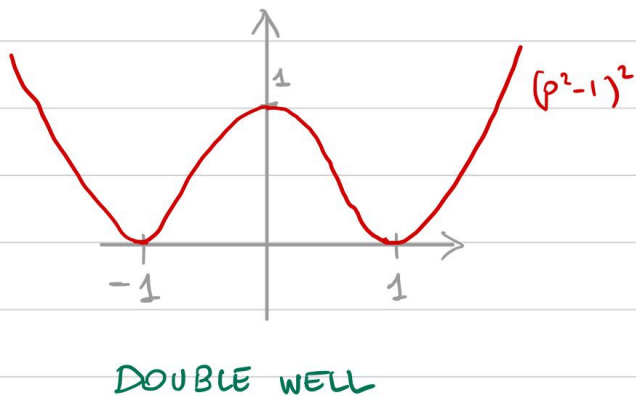
COMMENT: The above lemma requires to find a functional  $G$  satisfying (i), (ii), (iii). This is not always obvious. However in the future we will see a systematic way to construct  $G$  from  $F$ .

EXAMPLE 5.6  $X = \{ u \in C^1[0,1] \mid u(0) = 1, u(1) = 3 \}$

$F: X \rightarrow \mathbb{R}$  defined by

$$F(u) := \int_0^1 (u^2 - 1)^2 dx$$

Note that the Lagrangian is  $L = L(p) = (p^2 - 1)^2$ , which is not convex. Such Lagrangian is very typical and is named **DOUBLE WELL**.



The EDE for the minimum problem associated to  $F$  is

$$\begin{cases} \frac{d}{dx} L_p(u) = 0, \quad \forall x \in (0,1) \\ u(0) = 1, \quad u(1) = 3 \end{cases}$$

From  $L_p(u)' = 0$  we deduce  $L_p(u) = \text{CONSTANT}$ . Therefore the line

$$\bar{u}(x) := 2x + 1$$

satisfies the **BOUNDARY CONDITIONS** and **EDE**,

NOTE If  $L$  was **CONVEX** we could have concluded that  $\bar{u}$  minimizes  $F$ , by **THEOREM 5.4**. However  $L$  is not convex, so we need to proceed differently.

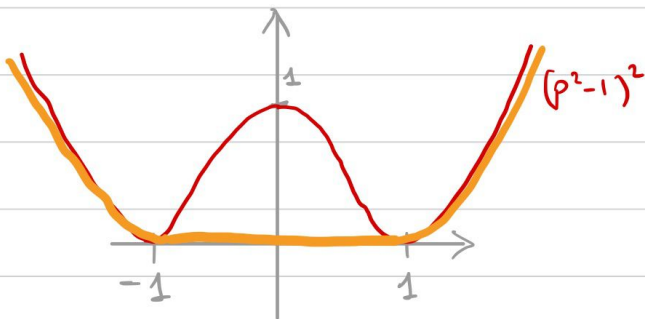
CLAIM  $\bar{u}$  is the unique minimizer of  $F$  in  $X$ .

Proof We make use of the TRIVIAL LEMMA. We need to find  $G$  satisfying the assumptions.

IDEA: Find a Lagrangian  $\hat{L}$  such that  $\hat{L} \leq L$  and that the functional

$$G(u) := \int_0^1 \hat{L}(u) dx, \quad u \in X$$

is likely to admit unique minimizer. Ideally we also want  $\hat{L}$  to be CONVEX, so we can apply THEOREM 5.4 to  $G$ .



A good idea is then to convexify  $L$ , by setting

$$\hat{L}(p) := \begin{cases} L(p) & \text{if } |p| \geq 1 \\ 0 & \text{if } |p| \leq 1 \end{cases}$$

Notice that  $\hat{L}$  is convex. We now verify (i), (ii), (iii) from LEMMA 5.5:

(i)  $F(u) \leq G(u)$ ,  $\forall u \in X$ : True because  $\hat{L} \leq L$  pointwise.

(ii)  $\bar{u}$  minimizes  $G$ : True because  $\hat{L}$  depends only on  $p$ . Therefore the line  $\bar{u}$  is solution of E-L-E for  $G$ :

$$\begin{cases} \frac{d}{dx} \hat{L}_p(\bar{u}') = 0 \\ \bar{u}(0) = 1, \bar{u}(1) = 2 \end{cases}$$

Therefore  $\bar{u}$  minimizes  $G$  by THEOREM 5.4,

as  $\hat{L}$  is CONVEX.

(iii)  $F(\bar{u}) = G(\bar{u})$ : True because  $\bar{u}' \equiv 2$ , and  $\hat{L}(2) = L(2)$  by definition.

Therefore  $\bar{u}$  minimizes  $F$  by LEMMA TRIVIAL 5.5.

Also note that  $\hat{L}$  is STRICTLY CONVEX in a neighborhood of  $p=2$  (that is, in a neighborhood of  $\bar{u}' \equiv 2$ ). Thus (by a slightly more general version of THEOREM 5.4 we conclude that  $\bar{u}$  is the unique minimizer of  $G$ .

By Lemma 5.5 we then have that  $\bar{u}$  is the unique minimizer of  $F$ .  $\square$

### EXAMPLE 5.7 (VARIATION ON EXAMPLE 5.6)

Let us consider the same Lagrangian  $L(p) = (p^2 - 1)^2$  as in EXAMPLE 5.6

However this time we look for a minimum of  $F$  over the set

$$X = \{ u \in C^1[a, b] \mid u(0) = 0, u(1) = 0 \}$$

Note: The only difference is we have changed the DIRICHLET BC

Let's try to show that the line passing through  $(0, 0)$  and  $(1, 0)$ , i.e.,

$$\bar{u}(x) \equiv 0$$

(which solves ELB associated to  $F$ ) is a minimizer for  $F$ .

We immediately see that the above strategy fails, because by definition

$$\hat{L}(0) = 0, \text{ while } L(0) = 1$$

Thus (iii) does not hold and we cannot apply LEMMA 5.5 to  $F, G$  and  $\bar{u}$ .

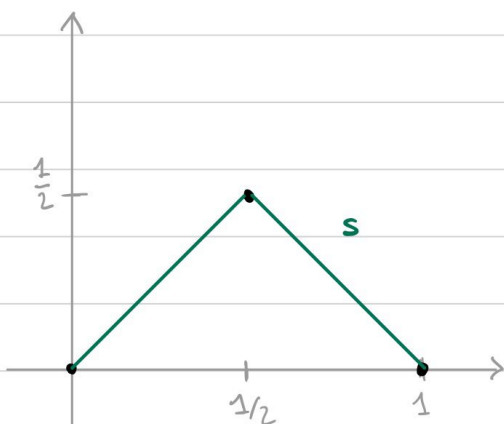
What is going on?

Since the constraints are  $u(0)=0, u(1)=0$ , then  $\bar{u}$  is NOT a minimizer for  $F$ . More in general:

CLAIM  $F$  admits no minimizer in  $X$ . Moreover

$$m := \inf \{ F(u) \mid u \in X \} = 0$$

Proof The idea is that, since  $L(1) = L(-1) = 0$ , we can construct a function  $\tilde{s} \in X$  s.t.  $|\tilde{s}'| \approx 1$  and so  $F(\tilde{s}) \approx 0$ . This is possible because the points  $(0,0), (1,0)$  are sufficiently close. To construct  $\tilde{s}$ , define  $s: [0,1] \rightarrow \mathbb{R}$  by



$$s(x) := \begin{cases} x & \text{if } 0 \leq x \leq \frac{1}{2} \\ -x+1 & \text{if } \frac{1}{2} \leq x \leq 1 \end{cases}$$

Notice that  $s(0)=0, s(1)=0$  and  $s' \in \{-1, 1\}$ . Thus  $F(s)=0$ .

The only problem is that  $s$  is not  $C^1$ . However, we can "ROUND the CORNER" at  $x=1/2$  by paying a small amount of energy (see WORKSHEET 3). Thus we can define  $\tilde{s}: [0,1] \rightarrow \mathbb{R}$  s.t.

$$\tilde{s} \in C^1[0,1], \tilde{s}(0)=\tilde{s}(1)=0, \tilde{s}'(x) = \pm 1 \text{ for } x \in [0,1] \setminus I, F(\tilde{s}) = \varepsilon$$

with  $I = (\frac{1}{2} - \delta, \frac{1}{2} + \delta)$  for some  $\delta > 0$  and  $\varepsilon > 0$  arbitrary. Then  $\tilde{s} \in X$ , so that  $m \leq F(\tilde{s}) = \varepsilon$ . As  $\varepsilon$  is arbitrary, we conclude  $m=0$  (as  $F \geq 0$ ).

Finally, to see that the infimum is not attained, if it existed  $\bar{u} \in X$  s.t.  $F(\bar{u}) = 0$ , then in particular

$$F(\bar{u}) = \int_0^1 ((\bar{u}')^2 - 1)^2 dx = 0 \Rightarrow \bar{u}' \in \{-1, 1\} \text{ for all } x \in [0, 1].$$

However, as  $\bar{u}'$  is continuous, we can only have  $\bar{u}' \equiv 1$ , or  $\bar{u}' \equiv -1$ , which are not possible since we must have  $\bar{u}(0) = \bar{u}(1) = 0$  by the DIRICHLET BC. Thus  $F$  admits no minimizer.  $\square$

**NOTE** In general if we define  $X := \{u \in C^1[0, 1] \mid u(0) = \alpha, u(1) = \beta\}$  and

$$F(u) := \int_0^1 (u^2 - 1)^2 dx, \quad u \in X.$$

then

- If  $|\beta - \alpha| > 1$ , then the unique minimizer of  $F$  is the straight line

$$\bar{u}(x) = (\beta - \alpha)x + \alpha$$

which can be shown as in EXAMPLE 5.6.

- If  $|\beta - \alpha| \leq 1$  then  $F$  admits no minimizers and the infimum is 0. This can be shown by adapting the arguments of EXAMPLE 5.7.

## SUMMARY OF INDIRECT METHOD

Given a minimization problem, the strategy is as follows:

- ① Finding necessary conditions for minimality: E-L + BC
- ② Solve E-L + BC (This is possible in very few cases: linear differential equations and not much more)
- ③ Prove that STATIONARY POINTS found in ② are minimizers:
  - Using CONVEXITY
  - Using TRIVIAL LEMMA

## 7. SOBOLEV SPACES

REFERENCE:

GIOVANNI LEONI - "A FIRST COURSE IN SOBOLEV SPACES"

AMERICAN MATHEMATICAL SOCIETY, 2017

So far our minimization problems were mostly set in  $C^1$ . Often a solution did not exist in  $C^1$ , however in many examples we saw that we could find an infimizing sequence converging to something piecewise  $C^1$ , i.e.,

$$C_{pw}^1[a,b] := \left\{ u \in C[a,b] \mid \exists \{x_0, \dots, x_N\} \subseteq [a,b] \text{ with } a = x_0 < x_1 < \dots < x_N = b, \right. \\ \left. u \in C^1[x_i, x_{i+1}], i = 0, \dots, N-1 \right\}$$

However these functional spaces are not very convenient to work with, due to their lack of completeness wRT weaker norms (e.g. the  $L^p$  convergence).

The default functional spaces for setting variational problems are (nowadays and in the past 60-70 years) SOBOLEV SPACES.

In order to define Sobolev spaces, we rely on previous knowledge about  $L^p$  spaces (LEBESGUE SPACES). A self-contained summary of definitions and properties can be found in SECTION 6 of these notes. ( $L^p$  SPACES REVISION)

Here we just recall the definition of  $L^p$  spaces, to establish some notation.

### $L^p$ SPACES

Let  $(X, \mathcal{A}, \mu)$  be a measurable space, where  $X$  set,  $\mathcal{A}$  is  $\sigma$ -algebra over  $X$  and  $\mu: \mathcal{A} \rightarrow [0, +\infty]$  is a measure.

For  $1 \leq p < +\infty$  and  $p = +\infty$  we set, respectively:

$$L^p(X, \mu) := \left\{ u: X \rightarrow \mathbb{R} \mid u \text{ measurable, } \int_X |u|^p d\mu < +\infty \right\}$$

$$L^\infty(X, \mu) := \left\{ u: X \rightarrow \mathbb{R} \mid u \text{ measurable, } \exists C > 0 \text{ s.t. } |u(x)| \leq C \text{ } \mu\text{-a.e. in } X \right\}$$

When we say  $\mu$ -a.e. we mean that a certain property holds in  $X \setminus E$ , where  $\mu(E) = 0$ .

**WARNING** The elements of  $L^p(X, \mu)$  and  $L^\infty(X, \mu)$  are NOT functions, but classes of equivalence of functions, where the equivalence is

$$u \sim v \iff u(x) = v(x) \text{ for } \mu\text{-a.e. } x \in X$$

This is not an issue, since in this case  $\int_X u d\mu = \int_X v d\mu$ .  
Therefore  $L^p(X, \mu)$  and  $L^\infty(X, \mu)$  have to be understood as

**QUOTIENT SPACES WRT  $\sim$**

**RECALL**  $L^p(X, \mu)$ ,  $L^\infty(X, \mu)$  are Banach spaces with the norms

$$\|u\|_p := \left( \int_X |u|^p d\mu \right)^{1/p}, \quad u \in L^p(X, \mu), \quad 1 \leq p < +\infty,$$

$$\|u\|_\infty := \inf \{ C : |u(x)| \leq C \text{ } \mu\text{-a.e. in } X \}, \quad u \in L^\infty(X, \mu)$$

Moreover  $L^2(X, \mu)$  is a Hilbert space with inner product

$$\langle u, v \rangle := \int_X u v d\mu, \quad u, v \in L^2(X, \mu)$$

**NOTE** In the following the definition of  $L^p$  will be employed in this setting:

- $X$  will always be an **OPEN SET OF  $\mathbb{R}^d$**
- $\mathcal{A}$  is the  $d$ -dimensional **LEBESGUE  $\sigma$ -Algebra**
- $\mu = dx = \mathcal{I}^d$  the  **$d$ -dimensional LEBESGUE MEASURE**

Thus we will always write  $L^p(X)$  in place of  $L^p(X, \mu)$ , as there is no ambiguity.

We need to introduce versions of the FLCV and DBR Lemma for  $L^p$  functions.  
For that we need tools to smoothen functions, i.e., convolutions.



# CONVOLUTIONS

DEFINITION 7.1 Let  $u, v: \mathbb{R} \rightarrow \mathbb{R}$ . The **CONVOLUTION** between  $u$  and  $v$ , is defined as

$$(u * v)(x) := \int_{\mathbb{R}} u(x-y) v(y) dy$$

for all  $x \in \mathbb{R}$  s.t. the RHS is FINITE.

REMARK It is immediate to check that, whenever the convolution is finite,

$$u * v = v * u \quad \text{and} \quad u * (v * w) = (u * v) * w$$

for  $u, v, w: \mathbb{R} \rightarrow \mathbb{R}$ .

The following Theorem gives a sufficient condition for  $u * v$  to be well-defined.

## THEOREM 7.2 (YOUNG)

Let  $u \in L^1(\mathbb{R})$ ,  $v \in L^p(\mathbb{R})$  for some  $1 \leq p \leq +\infty$ . Then for a.e.  $x \in \mathbb{R}$  the map  $y \mapsto u(x-y)v(y)$  is integrable, so that  $u * v$  is finite. Moreover  $u * v \in L^p(\mathbb{R})$ , with

$$(*) \quad \|u * v\|_p \leq \|u\|_1 \|v\|_p.$$

Proof •  $p = +\infty$  : this is immediate, since for a.e.  $x \in \mathbb{R}$

$$|(u * v)(x)| \leq \int_{\mathbb{R}} |u(x-y)| |v(y)| dy \leq \|v\|_{\infty} \int_{\mathbb{R}} |u(x-y)| dy = \|v\|_{\infty} \|u\|_1.$$

Taking the essential supremum in the above inequality we obtain  $(*)$

•  $p=1$ : Set  $\psi(x,y) := u(x-y)v(y)$ . For a.e.  $y \in \mathbb{R}$  we have

$$\int_{\mathbb{R}} |\psi(x,y)| dx = |v(y)| \int_{\mathbb{R}} |u(x-y)| dx = |v(y)| \|u\|_1 < +\infty$$

Integrating w.r.t.  $x$  we get

$$(**) \int_{\mathbb{R}} \left\{ \int_{\mathbb{R}} |\psi(x,y)| dx \right\} dy = \|v\|_1 \|u\|_1 < +\infty$$

Then  $\psi$  satisfies the assumptions of TONELLI'S THEOREM (THEOREM 6.9) and we infer  $\psi \in L^1(\mathbb{R} \times \mathbb{R})$  (where  $\mathbb{R} \times \mathbb{R}$  is equipped with the 2-dimensional Lebesgue measure). We can then apply FUBINI'S THEOREM (THEOREM 6.10) to get that

$$\int_{\mathbb{R}} |\psi(x,y)| dy < +\infty \quad \text{for a.e. } x \in \mathbb{R}.$$

and also

$$(**) \int_{\mathbb{R}} \left\{ \int_{\mathbb{R}} |\psi(x,y)| dy \right\} dx \stackrel{\text{FUBINI}}{=} \int_{\mathbb{R}} \left\{ \int_{\mathbb{R}} |\psi(x,y)| dx \right\} dy \stackrel{(**)}{=} \|v\|_1 \|u\|_1$$

Therefore

$$\int_{\mathbb{R}} |(u \star v)(x)| dx \stackrel{\text{def. of convolution}}{=} \int_{\mathbb{R}} \left| \int_{\mathbb{R}} u(x-y)v(y) dy \right| dx \leq \int_{\mathbb{R}} \left\{ \int_{\mathbb{R}} |u(x-y)v(y)| dy \right\} dx$$

$$\text{def of } \psi \rightarrow \int_{\mathbb{R}} \left\{ \int_{\mathbb{R}} |\psi(x,y)| dy \right\} dx \stackrel{(**)}{=} \|u\|_1 \|v\|_1,$$

which is exactly (\*).

•  $1 < p < +\infty$  : The functions  $|u|, |v|^p \in L^1(\mathbb{R})$ . Thus, from the case  $p=1$ ,

we know that  $y \mapsto |u(x-y)| |v(y)|^p$  belongs to  $L^1(\mathbb{R})$  for a.e.  $x \in \mathbb{R}$ .  
In particular

$$|u(x-\cdot)|^{1/p} |v(\cdot)| \in L^p(\mathbb{R}) \text{ for a.e. } x \in \mathbb{R}.$$

Moreover, as  $u \in L^1(\mathbb{R})$ , we also have

$$|u(x-\cdot)|^{1/p'} \in L^{p'}(\mathbb{R}) \text{ for a.e. } x \in \mathbb{R}$$

where we chose  $p'$  as the HÖLDER CONJUGATE, i.e.

$$p' := \frac{p}{p-1}, \text{ so that } \frac{1}{p} + \frac{1}{p'} = 1$$

From HÖLDER INEQUALITY (THEOREM 6.11) we get, for a.e.  $x \in \mathbb{R}$ ,

$$\begin{aligned} |(u * v)(x)| &\leq \int_{\mathbb{R}} |u(x-y)| |v(y)| dy \\ &= \int_{\mathbb{R}} \underbrace{|u(x-y)|^{1/p'}}_{\in L^{p'}} \underbrace{|u(x-y)|^{1/p} |v(y)|}_{\in L^p} dy \end{aligned}$$

$$\begin{aligned} \text{(HÖLDER)} \quad &\leq \left( \int_{\mathbb{R}} |u(x-y)| dy \right)^{1/p'} \left( \int_{\mathbb{R}} |u(x-y)| |v(y)|^p dy \right)^{1/p} \\ &= \|u\|_1^{1/p'} \cdot \left[ (|u| * |v|^p)(x) \right]^{1/p} \end{aligned}$$

Taking the  $p$ -power of the above we get

$$(**) | (u * v)(x) |^p \leq \|u\|_1^{p/p'} (|u| * |v|^p)(x) \quad \text{for a.e. } x \in \mathbb{R}$$

Now, as  $|u|, |v|^p \in L^1(\mathbb{R})$ , we can apply (\*) for the case  $p=1$  to get:

$$(***) \| |u| * |v|^p \|_1 \leq \|u\|_1 \| |v|^p \|_1 = \|u\|_1 \|v\|_p^p$$

By integrating (\*\*):

$$\int_{\mathbb{R}} | (u * v)(x) |^p dx \stackrel{(**)}{\leq} \|u\|_1^{p/p'} \int_{\mathbb{R}} (|u| * |v|^p)(x) dx$$

$$\text{and so} \quad = \|u\|_1^{p/p'} \| |u| * |v|^p \|_1$$

$$\stackrel{(***)}{\leq} \|u\|_1^{p/p'} \|u\|_1 \|v\|_p^p$$

$$\text{As } \frac{p}{p'} + 1 = p \rightarrow = \|u\|_1^p \|v\|_p^p.$$

Taking the  $\frac{1}{p}$ -power of the above inequality yields (\*). □

We now need the notion of **SUPPORT** for  $L^p$  functions. Indeed, as elements of  $L^p$  are actually equivalence classes, and thus defined a.e., the definition of support we used for continuous functions makes no sense:

**EXAMPLE**  $u := \chi_{\mathbb{Q}}$ . As the Lebesgue measure of  $\mathbb{Q}$  is zero,  $u$  belongs to the same equivalence class of  $v \equiv 0$ . Using the classical definition of support we get

$$\text{supp } u = \overline{\{x \in \mathbb{R} \mid u(x) \neq 0\}} = \overline{\mathbb{Q}} = \mathbb{R}, \quad \text{while } \text{supp } v = \emptyset.$$