

# A DUALITY PRINCIPLE FOR NON CONVEX VARIATIONAL PROBLEMS, NUMERICAL EXAMPLES

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# A non convex problem

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Let  $\Omega$  be a bounded domain of  $\mathbb{R}^N$ . We consider the problem

$$\mathcal{I}(\Omega) := \inf_{u \in H^1(\Omega)} \left\{ \int_{\Omega} (\varphi(\nabla u) + g(u)) \, dx : u = u_0 \text{ on } \partial\Omega \right\}, \quad (1)$$

where  $\varphi : \mathbb{R}^N \rightarrow [0, +\infty)$ ,  $g : \mathbb{R} \rightarrow [0, +\infty)$  are functions such that

- ▶  $\varphi(z)$  is convex continuous,  $\varphi(0) = 0$ ;
- ▶  $g(t)$  is lower semicontinuous and  $\exists M$  countable such that for  $t \in \mathbb{R} \setminus M$ ,  $\limsup_n g(t_n) \leq g(t)$  whenever  $t_n \rightarrow t$ ;
- ▶ there exist  $\alpha, \beta > 0 : \alpha|z|^2 \leq \varphi(z) + g(t) \leq \beta(1 + |z|^2)$ .

For simplicity, we assume that  $u_0 = 0$ .

We emphasize that  $g$  is not assumed to be convex.

## Example

$$\varphi(z) = \frac{|z|^2}{2}, \quad g(t) = \begin{cases} \lambda & \text{if } t > 0 \\ 0 & \text{if } t \leq 0 \end{cases},$$

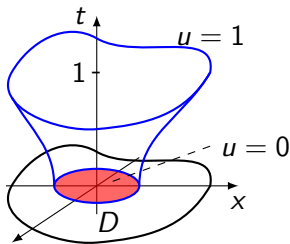
$$\mathcal{I}(\Omega) = \inf \left\{ \int_{\Omega} \left[ \frac{|\nabla u|^2}{2} + g(u) \right] dx : u = 1 \text{ on } \partial\Omega \right\}.$$

$\leadsto$  Free boundary Pb in term of  $D = \{u > 0\}$ ,  
 $u$  solves

$$\begin{cases} -\Delta u_D = 0 & \text{in } D \\ u_D = 1 & \text{on } \partial\Omega \\ u_D = 0 & \text{in } \Omega \setminus D. \end{cases}$$

$\leadsto$  Shape functional

$$J : D \rightarrow \lambda|D| + \frac{1}{2} \int_{\Omega} |\nabla u_D|^2.$$



## Pb in 1D case

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Let  $N = 1$ ,  $\Omega = (0, h)$ , the Pb is stated as

$$\mathcal{I}(\lambda, h) = \inf \left\{ \int_0^h \frac{u'^2}{2} dx + \lambda |\{u > 0\}| \left| \begin{array}{l} u(0) = 1 \\ u(h) = 1 \end{array} \right. \right\}. \quad (2)$$

Taking first integral of Euler's equation,  $-u'' + g'(u) = 0$ , we have

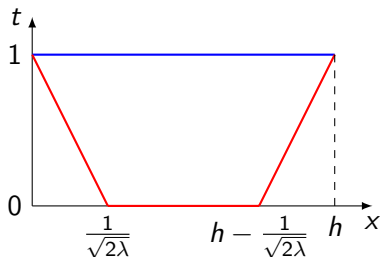
$$\begin{aligned} u' \varphi'(u') - [\varphi(u') + g(u)] &= \mu \\ \Leftrightarrow u' \cdot u' - \left( \frac{u'^2}{2} + \lambda 1_{\{u > 0\}} \right) &= \mu \\ \Leftrightarrow u' &= \pm \sqrt{2(\mu + \lambda 1_{\{u > 0\}})}. \end{aligned}$$

Solutions are piecewise affine functions of slopes in  $\{0, \pm\sqrt{2}\sqrt{\lambda}\}$ .

Thus, solutions are  $\bar{u}_0 \equiv 1$  or of the form:

$$\bar{u}_1(x) = \begin{cases} -\sqrt{2}\sqrt{\lambda}x + 1 & \text{if } 0 \leq x \leq \frac{1}{\sqrt{2}\sqrt{\lambda}} \\ 0 & \text{if } \frac{1}{\sqrt{2}\sqrt{\lambda}} < x < h - \frac{1}{\sqrt{2}\sqrt{\lambda}} \\ \sqrt{2}\sqrt{\lambda}x - (\sqrt{2}\sqrt{\lambda}h - 1) & \text{if } h - \frac{1}{\sqrt{2}\sqrt{\lambda}} \leq x \leq h. \end{cases}$$

The problem reaches its minimum:  $\mathcal{I}(\lambda, h) = \min\{\lambda h, 2\sqrt{2}\sqrt{\lambda}\}$ . As  $h = \frac{2\sqrt{2}}{\sqrt{\lambda}}$ , the problem has at least two solutions,  $\bar{u}_0$  and  $\bar{u}_1$ .



# Duality framework(Constrained flow optimization)

We set  $\mathcal{B}$  the class of fields  $\sigma = (\sigma^x, \sigma^t) \in (L^\infty(\Omega \times \mathbb{R}))^{N+1}$  satisfying the following conditions:

(s1)  $\operatorname{div} \sigma = 0$  in  $\Omega \times \mathbb{R}$ ;

(s2)  $\sigma(x, t) \in C(t)$  a.e.  $(x, t) \in \Omega \times \mathbb{R}$ ;

(s3)  $\forall t \in M, 0 \leq \sigma^t(x, t) + g(t)$  a.e.  $x \in \Omega$ . (\*)

Here  $C(t) = \{(q^x, q^t) \in \mathbb{R}^N \times \mathbb{R} \mid \varphi^*(q^x) - g(t) \leq q^t\}$ .

**Lemma 1 [Bouchitté, Fragalà]**

For every  $u \in H_0^1(\Omega)$  and for every  $\sigma \in \mathcal{B}$ , one has

$$-\int_{\Omega} \sigma^t(x, 0) dx \leq \int_{\Omega} [\varphi(\nabla u) + g(u)] dx$$

(\*) (s3) can be dropped if  $g$  is continuous,  $\sigma^t(\cdot, t)$  coincides with the normal flow across the hyperplane  $\{x_{N+1}\}$ .

# Geometrical interpretation

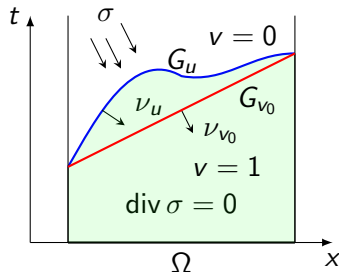
$$\varphi^*(\sigma^x) - g(t) \leq \sigma^t \text{ a.e. in } \Omega \times \mathbb{R}.$$

$$v = 1_u(x, t) = \begin{cases} 1 & \text{if } t \leq u(x) \\ 0 & \text{if } t > u(x) \end{cases}$$

$\nu_u = \frac{1}{\sqrt{1+|\nabla u|^2}}(\nabla u, -1)$  is the unit normal to the graph  $G_u$ .

$$\begin{aligned} - \int_{G_{v_0}} \sigma \cdot \nu_{v_0} dH^N &= \int_{\Omega \times \mathbb{R}} \sigma \cdot D1_u \\ &= \int_{\Omega} [\sigma^x(x, u(x)) \cdot \nabla u(x) - \sigma^t(x, u(x))] dx \\ &\leq \int_{\Omega} [\varphi^*(\sigma^x) + \varphi(\nabla u) - \sigma^t] dx \\ &\leq \int_{\Omega} [\varphi(\nabla u) + g(u)] dx \end{aligned}$$

If  $u_0 = 0$  then  $\int_{G_{v_0}} \sigma \cdot \nu_{v_0} dH^N = \int_{\Omega} \sigma^t(x, 0) dx.$



# Dual Pb holds in dimension $N + 1$

Let us define

$$\mathcal{S}(\Omega) := \sup_{\sigma \in \mathcal{B}} \left\{ - \int_{\Omega} \sigma^t(x, 0) dx \right\}. \quad (3)$$

Then  $\mathcal{I}(\Omega) \geq \mathcal{S}(\Omega)$  (Lemma 1).

## Theorem

It holds  $\mathcal{I}(\Omega) = \mathcal{S}(\Omega)$ .

Sketch of proof.

$u \rightsquigarrow v = 1_u(x, t) \in \mathcal{A}_0$  where

$$\mathcal{A}_0 = \left\{ v(x, t) : \Omega \times \mathbb{R} \rightarrow [0, 1] \left| \begin{array}{l} v(x, \cdot) \text{ is decreasing,} \\ v(x, +\infty) = 0, v(x, -\infty) = 1, \\ Dv \text{ is a bounded measure.} \end{array} \right. \right\}$$



- $\mathcal{I}(\Omega)$  can be reformulated as:  $\inf\{F(v), v \in \mathcal{A}_0\}$  where  

$$F(v) = \int_{\Omega \times \mathbb{R}} h(t, Dv), \quad h(t, p) := -p^t(\varphi(-\frac{p^x}{p^t}) + g(t)).$$
Let  $u_s(x) := \inf\{\tau \in \mathbb{R} : v(x, \tau) \leq s\}$  for  $s \in [0, 1]$ .

### Lemma 2

If  $F(v) < +\infty$ , for  $v \in \mathcal{A}_0$ , then for a.e.  $s \in [0, 1]$ , one has  $u_s \in H_0^1(\Omega)$  and  $F(v) = \int_0^1 (\int_{\Omega} [\varphi(\nabla u_s) + g(u_s)] dx) ds$ .

**Remark.** If  $v = 1_u$  then  $u_s = u$  for a.e.  $s \in [0, 1]$ .

### Consequence.

If  $v$  is solution of  $\inf\{F(v), v \in \mathcal{A}_0\}$  then  $\forall s \in [0, 1]$ ,  $u_s$  is solution of  $\mathcal{I}(\Omega)$ .

- $F(v)$  can be rewritten as  $F(v) = \sup \left\{ \int_{\Omega \times \mathbb{R}} \sigma \cdot Dv : \sigma \in \mathcal{B} \right\}$ .

$$\mathcal{I}(\Omega) = \inf_{v \in \mathcal{A}_0} \sup_{\sigma \in \mathcal{B}} \left\{ \int_{\Omega \times \mathbb{R}} \sigma \cdot Dv \right\} = \sup_{\sigma \in \mathcal{B}} \inf_{v \in \mathcal{A}_0} \left\{ \int_{\Omega \times \mathbb{R}} \sigma \cdot Dv \right\} = \mathcal{S}(\Omega)$$

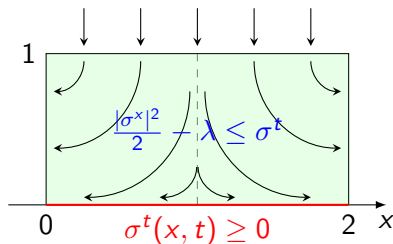
# Numerical computation of optimal flow

We treat the case

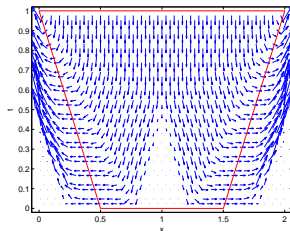
$$\Omega = [0, 2], \quad g(t) = \begin{cases} \lambda & \text{if } t > 0 \\ 0 & \text{if } t \leq 0, \end{cases} \quad \lambda = 2,$$

$$\mathcal{S}_\epsilon(\Omega) := \sup_{\sigma \in \mathcal{B}} \left\{ - \int_{\Omega} \sigma^t(x, 1) dx - \epsilon \int_{\Omega \times [0, 1]} |\sigma|^2 : \epsilon \geq 0 \right\}.$$

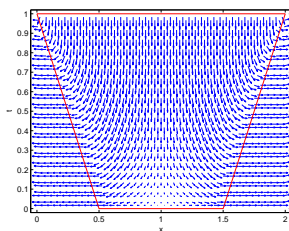
- ▶  $\epsilon = 0$  the critical dual Pb
- ▶  $\epsilon > 0$  viscosity term ( $\leadsto$  uniqueness of solution)



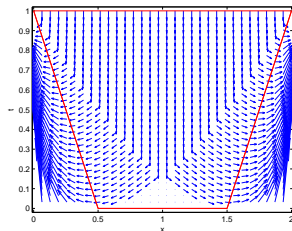
# Numerics (Matlab toolbox + 2D Finite element)



(a)  $\epsilon = 0$



(b)  $\epsilon > 0$



(c) Singular solution

- Singular solution (c) is constructed by symmetrization of gradient rotated,  $\sigma = (\partial_t V, -\partial_x V)$ , of value function:

$$V(x, t) := \inf \left\{ \int_0^x \frac{u'^2}{2} dx + \lambda |\{u > 0\}| \mid u(0) = 1, u(x) = t \right\}.$$

- Time of computation is very high. Matlab toolbox is not good for non linear constrained optimization Pb.

# Min-max Formulation

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Let  $L(v, \sigma) := \int_{\Omega \times \mathbb{R}} \sigma \cdot Dv$ .

As we have known

$$\mathcal{I}(\Omega) = \inf_{v \in \mathcal{A}_0} \sup_{\sigma \in \mathcal{B}} L(v, \sigma) = \sup_{\sigma \in \mathcal{B}} \inf_{v \in \mathcal{A}_0} L(v, \sigma) = \mathcal{S}(\Omega)$$

We now seek the saddle point of min-max problem

$$\inf_{v \in \mathcal{A}_0} \sup_{\sigma \in \mathcal{B}} L(v, \sigma)$$

Recall that  $(\bar{v}, \bar{\sigma})$  is solution of the problem min-max if

$$L(\bar{v}, \sigma) \leq L(\bar{v}, \bar{\sigma}) \leq L(v, \bar{\sigma}), \forall v \in \mathcal{A}_0, \sigma \in \mathcal{B}$$

**Remark.** Once when  $\bar{v}$  is determined, we will obtain  $u_s$  as optimal solution of  $\mathcal{I}(\Omega)$  (Lemma 2).

# Discretization settings

Back to the previous Free boundary Pb.

Let  $\Omega = (0, 2)$ ,  $\Sigma = \Omega \times (0, 1)$ . Note that

$$\int_{\Sigma} \sigma \cdot Dv = \int_{\Sigma} \sigma \cdot D(v-1) = \int_{\Sigma} -(v-1) \operatorname{div} \sigma + \int_{\partial \Sigma} (v-1)(\sigma \cdot n) ds.$$

$$A = \left\{ v(x, t) \in BV(\Sigma) \left| \begin{array}{l} v(\cdot, 0) = 1, v(\cdot, 1) = 0, \\ v(0, \cdot) = v(h, \cdot) = 1 \end{array} \right. \right\}.$$

The min-max problem reads

$$\begin{aligned} & \sup_{\sigma} \inf_{v \in A} \left\{ \int_{\Sigma} -(v-1) \operatorname{div} \sigma - \int_{\Omega} \sigma^t(x, 1) dx \right\} \\ &= \sup_{\sigma} \left\{ - \int_0^h \sigma^t(x, 1) dx : \operatorname{div} \sigma = 0 \right\}. \end{aligned}$$

## Discretization settings:

We consider a two-dimensional Cartesian grid  $G^h$  of size  $n_x \times n_t$ . Let  $h_x, h_t$  are steps and  $(i, j)$  is location on the grid.

$$G^h = \{(ih_x, jh_t) : 0 \leq i < n_x, 0 \leq j < n_t\}$$

$$A^h = \left\{ v^h \in \mathbb{R}^{n_x n_t} : v_{i,0}^h = 1, v_{i,n_t-1}^h = 0, v_{0,j}^h = v_{n_x-1,j}^h = 1 \right\}$$

$$B^h = \left\{ \sigma^h \in (\mathbb{R}^2)^{n_x n_t} : (\sigma^h)_{i,j} \in C(jh_t) \right\}$$

The discrete minimax Pb

$$\min_{v^h \in A^h} \max_{\sigma^h \in B^h} \left\langle \nabla^h v^h, \sigma^h \right\rangle$$

# Orthogonal projections

Consider the projection

$$\begin{cases} \sigma_{n+1}^h = \text{Proj}_{B^h}(\sigma_n^h + \alpha \nabla^h \bar{v}_n^h) \\ v_{n+1}^h = v_n^h - \beta(\text{div}^h \sigma_{n+1}^h) \\ \bar{v}_{n+1}^h = 2v_{n+1}^h - v_n^h \end{cases}$$

where  $\alpha\beta L^2 < 1$ ,  $\text{div}^h$  is adjoint to  $\nabla^h$ , and  $L$  is given by

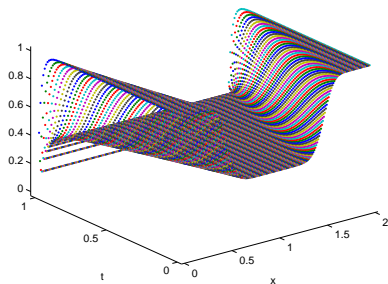
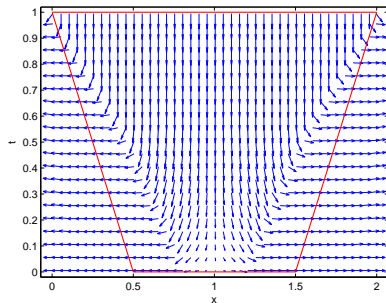
$$L = \|\nabla^h\| = \sup_{\|v^h\| \neq 0} \frac{\|\nabla^h v^h\|}{\|v^h\|} = \sqrt{\frac{4}{h_x^2} + \frac{4}{h_t^2}}$$

The projection  $\bar{\sigma}^h = (\bar{\sigma}^x, \bar{\sigma}^t)$  of  $\sigma^h \notin B^h$  is given by

$$\begin{cases} \bar{\sigma}^x &= \frac{1}{1+\theta} \sigma^x \\ \bar{\sigma}^t &= \sigma^t + \theta \\ q^x &= \sigma^x \\ qt^t &= \sigma^t + \lambda \\ 0 &= \theta^3 + (2 + q^t)\theta^2 + (1 + 2q^t)\theta + q^t - \frac{1}{2}|q^x|^2 \end{cases}$$

# Scheme MAC + Orthogonal projections

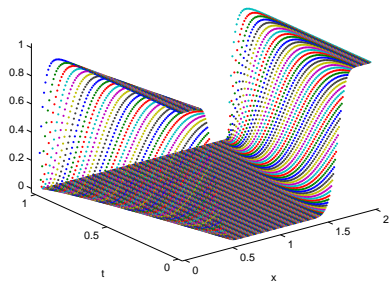
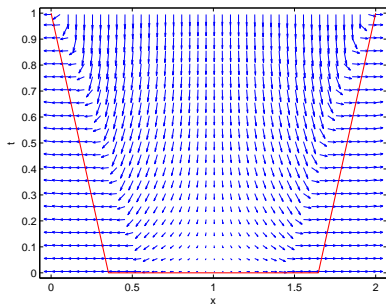
Scheme MAC is adaptive to this method. Here are some results.



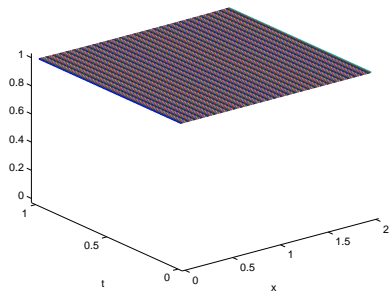
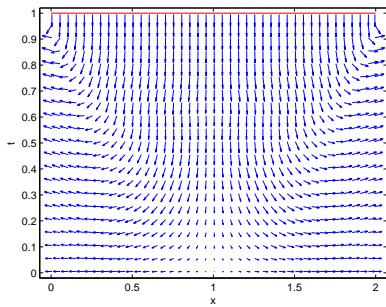
- In case of  $\lambda = 2$ .

Optimal  $v$  exhibits two plateaus corresponding to solution  $u_0$  and  $u_1$





- In the case of  $\lambda = 4$ .  
Optimal  $v$  exhibits two plateaus corresponding to solution  $u_1$ .



- In the case of  $\lambda = 1$ .  
Optimal  $v$  has only one plateau corresponding to solution  $u_0$ .

THANK YOU!