

Hamilton - Jacobi Equations

$$(1) \quad \begin{cases} u_t + H(Du) = 0 \\ u(x, 0) = g(x) \end{cases} \quad \begin{array}{l} \text{in } \mathbb{R}^n \times (0, \infty) \\ x \in \mathbb{R}^n \end{array}$$

$H: \mathbb{R}^n \rightarrow \mathbb{R}$ called the Hamiltonian

our goal of w/ the conservation laws is to continue the solution past the time when characteristics cross. To do so it will be ~~the~~ necessary, as before, to select the correct weak solution ~~convergence~~ by using ~~the~~ physical principle.

We will find that (1) PDE is associated w/ an optimal control problem.

Characteristics for (1) are

$$\begin{cases} \dot{x} = D_p H(p, x) \\ \dot{p} = -D_x H(p, x) \end{cases} \quad \text{called } \underline{\text{Hamilton's ODEs}}$$

these ODE arise in classical mechanics.

from a variational principle

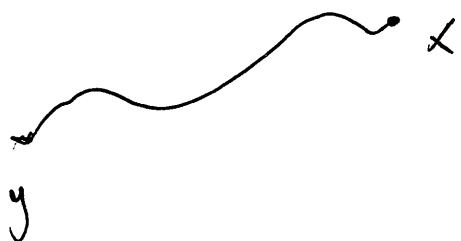
Let $L: \mathbb{R}^n \rightarrow \mathbb{R}$ a given smooth function
 called the Lagrangian or Running Cost. We write $L(\dot{q}, x)$.

fix $x, y \in \mathbb{R}^n$ and $t > 0$ the action
 or cost functional is defined

$$I[w] = \int_0^t L(\dot{w}(s), w(s)) ds \quad \text{defined for}$$

$$w \in \mathcal{A} = \{w(\cdot) \in C^1([0, t]; \mathbb{R}^n) : w(0) = y, w(t) = x\}$$

smooth paths from y to x



We wish to find the

minimal cost/action path from
 y to x .

$$I[x(\cdot)] = \min_{w \in \mathcal{A}} I[w(\cdot)]$$

let us assume we can find such a path,

$$x(\cdot)$$

then Φ

Then (Euler-Lagrange Eqs) The x solves

$$\left[-\frac{d}{ds} (D_v L(\dot{x}, x)) + D_x L(\dot{x}, x) = 0 \quad 0 \leq s \leq t. \right]$$

proof: as we did for previous variational principle
we look at the "directional derivative"
of I in direction $\phi \in \text{tangent } A$.

let v smooth $[0, t] \rightarrow \mathbb{R}^n$,

$$\phi(0) = \phi(t) = 0 \quad \text{so that}$$

$$w = x + \varepsilon \phi \in A$$

~~$I[w]$~~ $I[x] \leq I[w] \quad \forall \varepsilon > 0.$

so $\tilde{I}(\varepsilon) = I[x + \varepsilon \phi]$ has a min at $\varepsilon = 0$

$$\Rightarrow \tilde{I}'(0) = 0 \quad \text{if it exists.}$$

$$\tilde{I}(\varepsilon) = \int_0^t L(\dot{x} + \varepsilon \dot{\phi}, x + \varepsilon \phi) ds \quad \text{so}$$

$$\tilde{I}'(\varepsilon) = \int_0^t D_v L(\dot{x} + \varepsilon \dot{\phi}, x + \varepsilon \phi) \dot{\phi} + D_x L(\dot{x} + \varepsilon \dot{\phi}, x + \varepsilon \phi) \phi ds$$

setting

$$\varepsilon = 0$$

$$0 = \delta' I(0) = \int_0^t D_q L(\dot{x}, x) \delta \dot{x} + D_x L(\dot{x}, x) \delta x \, ds$$

and integrate by parts using

$$\delta x(0) = \delta x(t) = 0$$

$$= \int_0^t \left(-\frac{d}{ds} (D_q L(\dot{x}, x)) + D_x L(\dot{x}, x) \right) \delta x \, ds$$

Since this is zero for all $\delta x \in C_c^2([0, t]; \mathbb{R}^n)$

we obtain

$$\begin{cases} -\frac{d}{ds} (D_q L(\dot{x}, x)) + D_x L(\dot{x}, x) = 0 \\ \text{for } s \in (0, t) \end{cases}$$

□

Example 1: $L(q, \dot{q}) = \frac{1}{2} m |\dot{q}|^2 - \phi(q)$
kinetic energy potential energy

E-L eqn is Newton's law

$$m \ddot{x} = -\nabla \phi(x)$$

Example 2: $L(q, \dot{q}) = \begin{cases} 0 & |\dot{q}| \leq 1 \\ \infty & |\dot{q}| > 1 \end{cases}$

cost functional is minimal time to move from y to x
 w/ speed ≤ 1 . E-L eqn is harder to interpret.

A: payoff problem

define

$$u(x, t) = \inf \left\{ \int_0^t L(\dot{w}(s)) ds + g(\overset{\text{the running cost}}{\underset{\text{the payoff / terminal cost}}{\cancel{w(t)}}} \overset{y}{x}) \mid w(0)=y, w(t)=x \right\}$$

$\uparrow$ the value function

optimal trajectories solve the Euler-Lagrange Eqn

$$\frac{d}{ds} (D_v L(x)) = 0 \quad 0 \leq s < t$$

dynamic programming principle, $\forall 0 < t \leq t_1$

$$u(x, t) = \inf \left\{ \int_s^t L(\dot{w}(\tau), w(\tau)) d\tau + u(y, s) \mid w(s)=y, w(t)=x \right\}$$

using the DPP infinitesimally

$$u(x, t+h) = \inf_w \left\{ \int_t^{t+h} L(\dot{w}(\tau), w(\tau)) d\tau + u(y, t) \mid w(t)=y, w(t+h)=x \right\}$$

$$= \inf_v \left\{ h L(v, x) + u(x-hv, t) \right\} + O(h^2)$$

$$= \inf_v \left\{ h L(v, x) + u(x, t) - h v \cdot D_v u(x, t) \right\} + O(h^2)$$

$$= u(x, t) + h \inf_v \left\{ -v \cdot D_v u(x, t) + L(v, x) \right\} + O(h^2)$$

on

$$\partial_t u = \inf_v \{ -v \cdot Du(x,t) + L(v,x) \}$$

or

$$\partial_t u + \sup_v \{ v \cdot Du(x,t) - L(v,x) \} = 0$$

$\underbrace{\hspace{10em}}_{=: H(Du, x)}$

proof of DPP

$$u(x,t) = \inf \left\{ \int_0^t L(\bar{w}, w) ds + g(y) \mid w(0)=y, w(t)=x \right\}$$

(9) let $y \in \mathbb{R}^n$, take w_s optimal for $u(y,s)$, i.e.

$$u(y,s) = \int_0^s L(\bar{w}_s, w_s) dt + g(w_s(0))$$

and let $\bar{w}_{st} = \begin{cases} w(\tau) & s \leq \tau \leq t \\ w_s(\tau) & 0 \leq \tau \leq s \end{cases}$

with w any path s.t. $w(s)=y, w(t)=x$

then $u(x,t) \leq \int_0^t L(\bar{w}, \bar{w}) ds + g(\bar{w}(0))$

$$= u(y,s) + \int_s^t L(\bar{w}(\tau), w(\tau)) d\tau$$

taking inf over w yields

$$u(x,t) \leq \inf \left\{ \int_s^t L(\bar{w}(\tau), w(\tau)) d\tau + u(y,s) \mid w(s)=y, w(t)=x \right\}$$

for the other direction let w_* optimal

$$\text{for } u(x, t) = \int_0^t L(\dot{w}_*, w_*) d\tau + g(w_*(0))$$

$$= \int_s^t L(\dot{w}_*, w_*) d\tau + \int_0^s L(\dot{w}_*, w_*) d\tau + g(w_*(0))$$

$$\geq \int_s^t L(\dot{w}_*, w_*) d\tau + u(w_*(s), s)$$

$$\Rightarrow u(x, t) \geq \inf \left\{ \int_s^t L(\dot{w}, w) d\tau + u(y, s) : \right. \\ \left. w(s) = y, w(t) = x \right\}$$

□

Hamilton's ODE's

Suppose that x is an action minimizer
(or critical point) call

$$p(s) = D_v L(\dot{x}(s), x(s)) \quad 0 \leq s \leq t.$$

$p(-)$ is called the generalized momentum
 x - position, $\dot{x}$ - velocity.

Now we suppose that $\forall x, p \in \mathbb{R}^n$

$$\left\{ \begin{array}{l} p = D_v L(v, x) \text{ can be uniquely solved} \\ \text{for } v \text{ as a smooth fn of } p, x \\ v = v(p, x) \end{array} \right.$$

Def The Hamiltonian associated with the Lagrangian

L is

$$H(p, x) = p \cdot v(p, x) - L(v(p, x), x)$$

Legendre Transform

Now we put some additional assumptions

(1) $v \mapsto L(v)$ is convex

(2) $\lim_{|v| \rightarrow \infty} \frac{L(v)}{|v|} = +\infty$ coercivity

Def The Legendre transform of L is

$$L^*(p) = \sup_{q \in \mathbb{R}^n} \{ p \cdot q - L(q) \} \quad (p \in \mathbb{R}^n)$$

—
suppose the supremum is achieved by $q_* \in \mathbb{R}^n$

$$L^*(p) = p \cdot q_* - L(q_*) \quad \text{and}$$

$$q \mapsto p \cdot q - L(q) \text{ has maximum at } q_*$$

then $p = DL(q)$ is solvable for q
(q_* solves) although not necessarily

uniquely $L^*(p) = \cancel{p \cdot q(p) - L(q(p))}$
 $p \cdot q(p) - L(q(p))$

which is the Hamiltonian H associated w/ L .

We thus call $H = L^*$.

Now conversely given Hamiltonian H

can we find L ?

Thm (Convex duality) Assume L convex, coercive

and define $H = L^*$ then

(1) H is convex and coercive

(2) $H^* = L$

Rem: We call H and L convex dual functions

Proof:

$p \mapsto p \cdot q - L(q)$ is linear

so $H(p) = \sup_{q \in \mathbb{R}^n} \{ p \cdot q - L(q) \}$ is convex.

$$H(p) = \sup_{q \in \mathbb{R}^n} \{ q \cdot p - L(q) \}$$

$$\text{take } q = \frac{Rp}{|p|} \geq R|p| - L\left(\frac{Rp}{|p|}\right)$$

$$\geq R|p| - \max_{B(0,R)} L$$

(coercive)

$$\Rightarrow \lim_{|p| \rightarrow \infty} \frac{H(p)}{|p|} \geq R \quad \text{for every } R > 0$$

(duality) :

$\forall$

p, q

$$H(p) + L(q) \geq p \cdot q$$

$$\text{so } L(q) \geq \sup_{p \in \mathbb{R}^n} \{ p \cdot q - H(p) \} = H^*(q)$$

and

$$\begin{aligned} H^*(q) &= \sup_{p \in \mathbb{R}^n} \left\{ p \cdot q - \sup_{r \in \mathbb{R}^n} \{ r \cdot p - L(r) \} \right\} \\ &= \sup_{p \in \mathbb{R}^n} \inf_{r \in \mathbb{R}^n} \{ p \cdot (q - r) + L(r) \} \end{aligned}$$

Since L convex $\Rightarrow$ it has a supporting
hyperplane at q , $\exists$ $s \in \mathbb{R}^n$ s.t.

$$L(r) \geq L(q) + s \cdot (r - q) \quad \forall r \in \mathbb{R}^n$$

taking $p = s$ in the supremum

$$H^*(q) \geq \inf_{r \in \mathbb{R}^n} \{ s \cdot (q - r) + L(r) \}$$

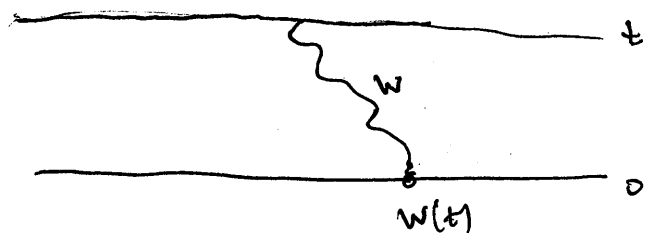
$$\geq L(q) \quad \text{from choice of } s.$$

$\mathbb{R}$

the Hopf-Lax formula

define

$$(1) \quad u(x, t) = \inf \left\{ \int_0^t L(\dot{w}(s)) ds + g(y) \mid w(0) = y, w(t) = x \right\}$$



will turn out to solve (in a sense)

$$\begin{cases} u_t + H(Du) = 0 & \text{in } \mathbb{R}^n \times (0, \infty) \\ u(x, 0) = g(x) \end{cases}$$

where $H \geq L^*$ or $L = H^*$ depending

on our starting point.

Then (Hopf-Lax formula)

let $x \in \mathbb{R}^n$, $t > 0$ then u as in (1) is

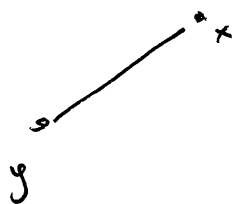
$$u(x, t) = \min_{y \in \mathbb{R}^n} \left\{ t L\left(\frac{x-y}{t}\right) + g(y) \right\}$$

(i.e. optimal trajectories in (1) are straight lines)

proof of half-lax formula:

one direction is easy

take $w(s) = y + \frac{s}{t}(x-y)$ $0 \leq s \leq t$



$$\begin{aligned} u(x,t) &\leq \int_0^t L(\tilde{w}(s)) ds + g(y) \\ &= \int_0^t L\left(\frac{x-y}{t}\right) ds + g(y) \\ &= t L\left(\frac{x-y}{t}\right) + g(y) \end{aligned}$$

take inf over $y \in \mathbb{R}^n$ or obtain

$$u(x,t) \leq \inf_{y \in \mathbb{R}^n} \left\{ t L\left(\frac{x-y}{t}\right) + g(y) \right\}$$

if w is any c' for $w(t) = x$ then

calling $y = w(0)$

$$L\left(\frac{1}{t} \int_0^t L(\tilde{w}(s)) ds\right) \leq \frac{1}{t} \int_0^t L(\tilde{w}(s)) ds \quad (\text{Jensen})$$

so

$$u(x,t) \geq \inf_{y \in \mathbb{R}^n} \left\{ t L\left(\frac{1}{t} \int_0^t \tilde{w}(s) ds\right) + g(y) \right\}$$

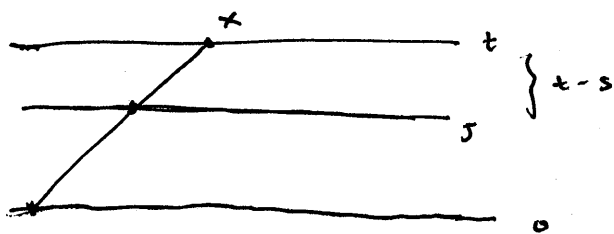
$$= \inf_{y \in \mathbb{R}^n} \left\{ t L\left(\frac{x-y}{t}\right) + g(y) \right\}$$

(use) Super-linear growth of L to show inf is achieved. $\square$

LEM (Dynamic Programming Principle)

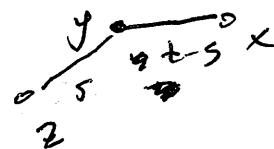
For each $x \in \mathbb{R}^n$, $0 \leq s < t$ we have

$$u(x, t) = \min_{y \in \mathbb{R}^n} \left\{ (t-s) L\left(\frac{x-y}{t-s}\right) + u(y, s) \right\}$$



Proof: 1. Fix $y \in \mathbb{R}^n$, $0 < s < t$ and choose z so

$$u(y, s) = s L\left(\frac{y-z}{s}\right) + g(z)$$



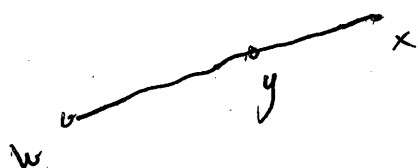
Since L convex, $\frac{x-z}{t} = (1-\frac{s}{t}) \frac{x-y}{t-s} + \frac{s}{t} \frac{y-z}{s}$

$$L\left(\frac{x-z}{t}\right) \leq (1-\frac{s}{t}) L\left(\frac{x-y}{t-s}\right) + \frac{s}{t} L\left(\frac{y-z}{s}\right) \quad \text{so}$$

$$\begin{aligned} u(x, t) &\leq t L\left(\frac{x-z}{t}\right) + g(z) \leq (t-s) L\left(\frac{x-y}{t-s}\right) + s L\left(\frac{y-z}{s}\right) + g(z) \\ &= (t-s) L\left(\frac{x-y}{t-s}\right) + u(y, s) \end{aligned}$$

for each $y \in \mathbb{R}^n$.

Now choose w s.t. $u(x, t) = t L\left(\frac{x-w}{t}\right) + g(w)$



$$\text{at } y = \frac{s}{t} x + (1-\frac{s}{t}) w$$

Lemma (Lipschitz estimate) The function u is Lipschitz continuous in $\mathbb{R}^n \times (0, \infty)$ and $u = g$ on $\mathbb{R}^n \times \{t=0\}$

proof: fix $t > 0$, $x, \hat{x} \in \mathbb{R}^n$. Let $y \in \mathbb{R}^n$ s.t.

$$t L\left(\frac{x-y}{t}\right) + g(y) = u(x, t)$$

then

$$u(\hat{x}, t) - u(x, t) = \inf_z \left\{ t L\left(\frac{\hat{x}-z}{t}\right) + g(z) \right\} - t L\left(\frac{x-y}{t}\right) - g(y)$$

$$\left(\text{take } z = \hat{x} - x + y \right) \leq g(\hat{x} - x + y) - g(y) \leq \text{Lip}(g) |\hat{x} - x|$$

$$\text{interchanging roles of } \hat{x}, x \Rightarrow |u(\hat{x}, t) - u(x, t)| \leq \text{Lip}(g) |\hat{x} - x|$$

Now for time continuity, we just prove at $t=0$.

Let $t > 0$. Choosing $y = x$ in Hopf-Lax

$$u(x, t) \leq t L(0) + g(x) \quad \text{and}$$

$$u(x, t) = \min_{y \in \mathbb{R}^n} \left\{ t L\left(\frac{x-y}{t}\right) + g(y) \right\}$$

$$\geq g(x) + \min_{y \in \mathbb{R}^n} \left\{ -\text{Lip}(g) |x-y| + t L\left(\frac{x-y}{t}\right) \right\}$$

$$\begin{aligned} \left(z = \frac{x-y}{t} \right) &= g(x) - t \max_{z \in \mathbb{R}^n} \left\{ \text{Lip}(g) |z| - L(z) \right\} \\ &= g(x) - t \max_{w \in \mathbb{R}^n, \text{Lip}(g)} \max_{z \in \mathbb{R}^n} \{ w \cdot z - L(z) \} \end{aligned}$$

$$= g(x) - t \max_{w \in B(0, \text{lip}(g))} H(w)$$

$$\text{so } |u(x, t) - g(x)| \leq Ct \quad \forall$$

$$C = \max(|H(0)|, \max_{B(0, \text{lip}(g))} |H|)$$

Using dynamic programming principle and Lipschitz continuity in space of $u(x, t)$ to yield time Lipschitz continuity. $\square$

Now by Rademacher's theorem Lipschitz functions are differentiable a.e.

Then let $x \in \mathbb{R}^n$, $t > 0$ and u defined by Hopf-Lax formula differentiable at (x, t) . Then

$$u_t(x, t) + H(D_x u(x, t)) = 0$$

Proof: ~~$u(x, t)$~~ Fix $q \in \mathbb{R}^n$, $h > 0$, by DPP

$$u(x + hq, t + h) = \min_{y \in \mathbb{R}^n} \left\{ H\left(\frac{x + hq - y}{h}\right) + u(y, t) \right\}$$



Subsolution :

$$u(x+hq, t+h) = \min_{y \in \mathbb{R}^n} \left\{ h L\left(\frac{x+hq-y}{h}\right) + u(y, t) \right\}$$

$$(y=x) \quad \leq h L(q) + u(x, t)$$

$$\text{So} \quad \frac{u(x+hq, t+h) - u(x, t)}{h} \leq L(q)$$

Since u is differentiable at x, t

$$q \cdot Du(x, t) + u_t(x, t) \leq L(q)$$

valid for all q so

$$u_t(x, t) + \max_{q \in \mathbb{R}^n} \{ q \cdot Du(x, t) - L(q) \} \leq 0$$

$$H(Du(x, t))$$

$$\text{So} \quad u_t(x, t) + H(Du(x, t)) \leq 0$$

Supersolution : Choose z s.t.

$$u(x, t) = t L\left(\frac{x-z}{t}\right) + g(z)$$

Fix $L > 0$ and let $s = t-h$, $y = \frac{s}{t}x + (1-\frac{s}{t})z$

$$\text{then} \quad \frac{x-z}{t} = \frac{y-z}{s} \quad \text{and}$$

$$u(x, t) - u(y, s) \geq t L\left(\frac{x-z}{t}\right) + g(z) - \left[s L\left(\frac{y-z}{s}\right) + g(z) \right]$$

$$u(x, t) - u(y, s) \geq (t-s) L\left(\frac{x-z}{t}\right) \quad \text{or}$$

$$\frac{u(x, t) - u\left(x - \frac{h}{t}(x-z), t-h\right)}{h} \geq L\left(\frac{x-z}{t}\right)$$

letting $h \rightarrow 0$

$$\text{at } \frac{x-z}{t} \cdot Du(x, t) + u_t(x, t) \geq L\left(\frac{x-z}{t}\right)$$

and therefore

$$\begin{aligned} u_t(x, t) + H(Du(x, t)) &= u_t(x, t) + \max_{v \in \mathbb{R}^n} \{v \cdot Du(x, t) - L(v)\} \\ &\geq u_t(x, t) + \frac{x-z}{t} \cdot Du(x, t) - L\left(\frac{x-z}{t}\right) \\ &\geq 0 \end{aligned}$$

$\square$

Thm The function u given by Hopf-Lax is Lipschitz continuous, differentiable a.e. in $\mathbb{R}^n \times (0, \infty)$ and solves the PVP

$$\begin{cases} u_t + H(Du) = 0 & \text{a.e. in } \mathbb{R}^n \times (0, \infty) \\ u = g & \text{on } \mathbb{R}^n \times \{t=0\} \end{cases}$$

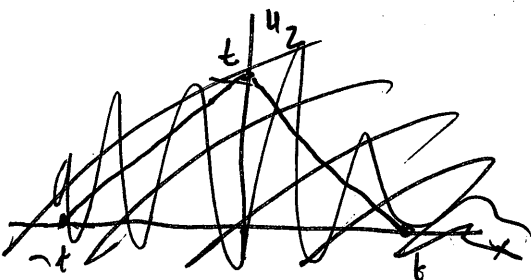
Ex (Non-uniqueness of a.e. solutions)

$$\begin{cases} u_t + \frac{1}{2} |u_x|^2 = 0 & \text{in } \mathbb{R} \times (0, \infty) \\ u = 0 & \text{on } \mathbb{R} \times \{t=0\} \end{cases}$$

$$u_1(x, t) = 0$$

solves

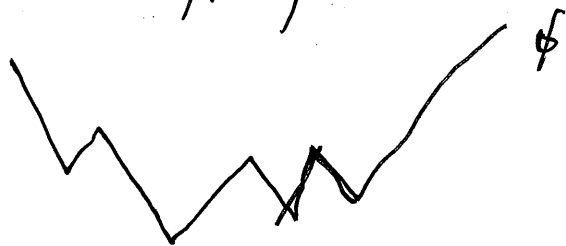
also $u_2(x, t) = \begin{cases} \frac{x-t}{2} & 0 \leq x \leq t \\ \frac{x+t}{2} & -t \leq x \leq 0 \\ 0 & |x| \geq t \end{cases}$



only a solution a.e.
~~doesn't solve~~ not differentiable
 or $x = 0, \pm t$

or

anything like



$$w/ |\phi'| \geq 1$$

a.e.

$$\text{and } \phi \geq 0$$

$$u(x, t) = (\phi(x-t))_- \quad \text{satisfies } u(x, 0) = 0$$

$$\text{and } \partial_t u + H(\partial_x u) = 0 \quad \text{a.e. in } \mathbb{R}^n \times (0, \infty)$$

Some Examples of HS eqns

Level set evolutions:

Then We are interested in making a formulation of

hypersurface Γ_t

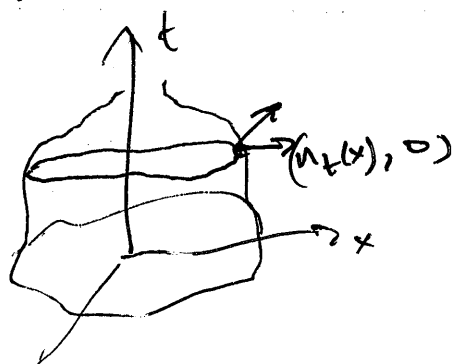
bdry of domain Ω_t

outer normal $n_{\Gamma_t}: \Gamma_t \rightarrow \partial B(0,1)$

want to solve a PDE, Γ_t moves w/ normal velocity

$$V_n = c(x,t)$$

how to interpret this PDE?



$$\Omega_{0,T} = \bigcup_{0 \leq t \leq T} \Omega_t$$

w/ $\mathbb{R}^n \times \mathbb{R}$ outer normal

$$V(x,t) = \frac{(n_t(x), m(x,t))}{\sqrt{1 + m(x,t)^2}}$$

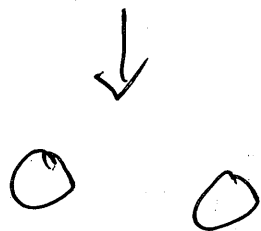
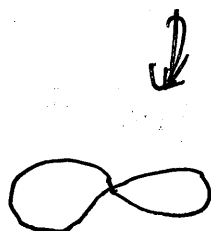
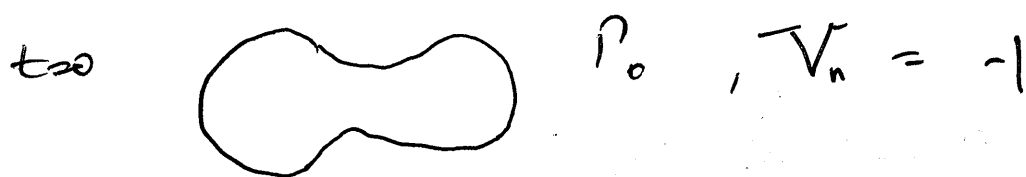
$-m$ is the outward normal velocity of Γ_t

another interpretation:

Σ_t any path lying in Γ_t through $\Sigma_{t_0} = x_0$

then $\dot{\Sigma}_{t_0} \cdot n_{t_0}(x_0)$ is the outward normal velocity of Γ_t at x_0 .

The problem w/ this sort of solution

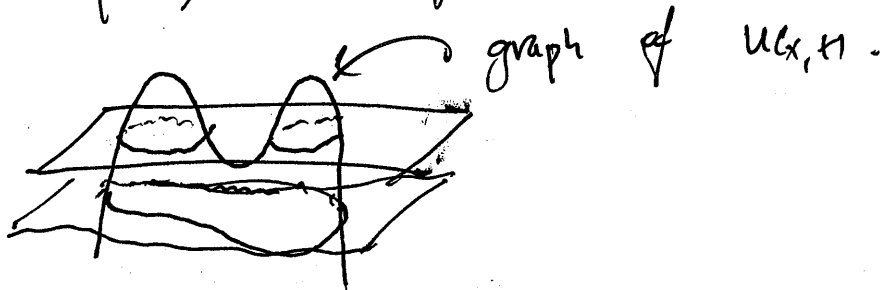


topological changes
~~which~~
 are difficult to
 deal with.

The idea is to view Γ_t as the zero level set of a fn $u(x,t) : \mathbb{R}^n \times (0, \infty) \rightarrow \mathbb{R}$.

$$\Gamma_t = \{x \in \mathbb{R}^n : u(x,t) = 0\}$$

topological changes are easy -



how is outward normal velocity encoded in u ?

$\mathcal{X}_t$ path in $\mathbb{R}^n$ w/ $\mathcal{X}_t = x$

$$0 = \frac{d}{dt} u(\mathcal{X}_t, t) = u_t + \dot{\mathcal{X}}_t \cdot \nabla u(\mathcal{X}_t, t)$$

$$= u_t(\mathcal{X}_t, t) + \dot{\mathcal{X}}_t \cdot \nabla u(\mathcal{X}_t, t)$$

$$= u_t(\mathcal{X}_t, t) + \dot{\mathcal{X}}_t \cdot \frac{\nabla u}{|\nabla u|} |\nabla u|(\mathcal{X}_t, t)$$

Case 1: $u \rightarrow 0$ as $|x| \rightarrow \infty$

in Ω_t , $u \rightarrow 0$ as $|x| \rightarrow \infty$ in $\mathbb{R}^n$ (or)

$$\frac{\nabla u}{|\nabla u|} \Big|_{\mathcal{X}_t} = +n_{\mathcal{X}_t}(x)$$

$$= u_t(\mathcal{X}_t, t) + V_n |\nabla u|(\mathcal{X}_t, t)$$

$$\text{so } \boxed{\frac{u_t}{|\nabla u|}(x, t) = -V_n}$$

so

$$V_n = c(x, t)$$

$$\longrightarrow -\frac{u_t}{|\nabla u|} = c(x, t)$$

or

the H-J eqn

$$u_t + c(x, t) |\nabla u| = 0$$

example

$$u_t + |Du| = 0 \quad w/ \quad u(x, 0) = \begin{matrix} 0 \\ \text{sgn}(x) \end{matrix}$$

Hopt-Lax (formal) solution

$$\begin{aligned} L(v) = H^*(v) &= \sup_{p \in \mathbb{R}^n} \{ v \cdot p - H(p) \} = \sup_{p \in \mathbb{R}^n} \{ v \cdot p - |p| \} \\ &= \begin{cases} 0 & |v| \leq 1 \\ +\infty & |v| > 1 \end{cases} \end{aligned}$$

so the associated variational problem is

$$u(x, t) = \inf \left\{ g(y) : \begin{array}{l} w \text{ smooth path w/} \\ |w'| \leq 1 \text{ on } [0, t] \\ w(0) = y, w(t) = x \end{array} \right\}$$

Hopt-Lax

$$u(x, t) = \inf_{y \in \mathbb{R}^n} \left\{ t L\left(\frac{x-y}{t}\right) + g(y) \right\} = \inf_{|y-x| \leq t} g(y)$$

Suppose $g(x) = \text{sign dist}(x, \Gamma_0) = \begin{cases} \text{dist}(x, \Omega^c) & x \in \Omega^c \\ -\text{dist}(x, \Omega^c) & x \in \Omega \end{cases}$

then
$$u(x, t) = \inf_{|y-x| \leq t} \text{sign dist}(x, \Gamma_0)$$

Claim:
$$u(x, t) = (\text{sign dist}(x, \Gamma_0) - t) \vee \left(\min_{y \in \mathbb{R}^n} g(y) \right)$$

proof of claim

clearly $u(x, t) = \inf_{|y-x| \leq t} g(y) \geq \inf_{\mathbb{R}^n} g$

and if $x_* = \arg \min_{\mathbb{R}^n} g$ satisfies $|x_* - x| \leq t$

then $u(x, t) = \min_{\mathbb{R}^n} g$

Call ~~otherwise~~ $E = \{x \in \mathbb{R}^n : g(x) = \min_{\mathbb{R}^n} g\}$

Note that $\text{signedist}(x, E) = \text{dist}(x, E) + \min_{\mathbb{R}^n} g$

$$u(x, t) = \min_{|y-x| \leq t} \text{signedist}(x, E) = \min_{|y-x| \leq t} \text{dist}(x, E) + \min_{\mathbb{R}^n} g$$

$$= \begin{cases} \text{dist}(x, E) - t & \text{if } \text{dist}(x, E) \geq t \\ 0 & \text{if } \text{dist}(x, E) < t \end{cases} + \min_{\mathbb{R}^n} g$$

Viscosity solutions of H-J Eqs

~~def~~

We need to make some definitions first

$$D_+ u(x) = \left\{ p \in \mathbb{R}^n : \cancel{u(y) \leq u(x)} \quad u(y) \leq u(x) + p \cdot (y-x) + o(|y-x|) \right\} \text{ as } y \rightarrow x$$

Supersolution

$$D_- u(x) = \left\{ p \in \mathbb{R}^n : u(y) \geq u(x) + p \cdot (y-x) + o(|y-x|) \right\} \text{ as } y \rightarrow x$$

Subsolution

From the proof of Hopf-Lax solution solves

$$u_t + H(Du) = 0$$

where u is differentiable

We actually could have shown

$$(p, \tau) \in D_+^{*u}(x, t) \Rightarrow \tau + H(p) \leq 0 \quad \text{"subsolution"}$$

$$(p, \tau) \in D_-^{*u}(x, t) \Rightarrow \tau + H(p) \geq 0 \quad \text{"supersolution"}$$

Lemma (properties) (i) ~~iff~~ u is diff'able at x ,

$$\Leftrightarrow D_+ u(x) = D_- u(x) = \{Du(x)\}$$

(ii) ~~iff~~ $D_+ u(x)$, $D_- u(x)$ both convex sets

(iii) if $D_+ u(x)$ non-empty

$\Rightarrow$ either $D_+ u(x) = D_- u(x) = \{Du(x)\}$

or $D_- u(x) = \emptyset$

~~We say~~

Statements are a bit easier for non-time dependent

$$(H-J) \quad \begin{cases} H(Du) = 0 & \text{in } U \\ \text{bdry data} \end{cases}$$

Def u is a viscosity soln of $(H-J)$ if
 u is continuous and

(i) subsolution, $\forall p \in D_+ u(x)$

$$H(p) \leq 0$$

(ii) supersolution, $\forall p \in D_- u(x)$

$$H(p) \geq 0$$

Rem 1: This is in a sense the ∞ version of
the weak solution condition we saw before.

~~Rem 2:~~

Rem 2: Although it is not immediately obvious from this definition, the definition of viscosity solution essentially says that u satisfies a "local comparison principle" with respect to C^1 test functions.

Def 2 u is a viscosity solution of (H-J) $\Leftrightarrow$ if
 for every ~~$\phi \in C^1(\mathbb{R}^n \times (0, \infty))$~~ $(x, t) \in \mathbb{R}^n \times (0, \infty)$
 every parabolic cylinder $Q_r(x, t) = \{ (y, s) : |y - x| \leq r, t-r \leq s \leq t \}$
 and any $\phi \in \text{smooth } C^1(\overline{Q}_r(x, t))$

(i) if ϕ touches u from below at (x, t)
 in $Q_r(x, t)$ then
 $\phi_t + H(D\phi) \geq 0$

(ii) if ϕ touches u from above at (x, t)
 in $Q_r(x, t)$ then
 $\phi_t + H(D\phi) \leq 0$

example: $\begin{cases} |Du| \leq 1 & \text{in } (0,1) \\ u=0 & \text{at } \{0,1\} \end{cases}$

$u(x) = \frac{1}{2} - |x - \frac{1}{2}|$ satisfies

u diffable at $x \in (0,1) \setminus \{\frac{1}{2}\}$

$|Du(x)| = 1$

ok ✓

at $x = \frac{1}{2}$

$D_+ u(\frac{1}{2}) = [-1, 1]$

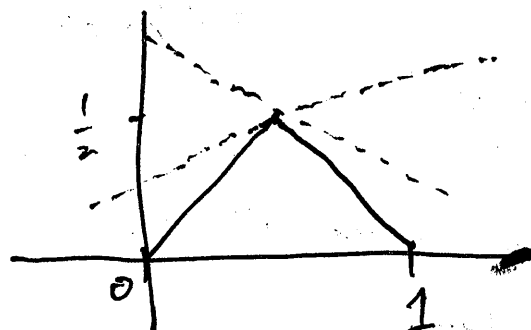
$D_- u(\frac{1}{2}) = \emptyset$

$\forall p \in [-1, 1]$

$|p| - 1 \leq 0$

✓

subsoln condition



Thm: if u , viscosity subsolution, v viscosity supersoln

of (HJ) in $\mathbb{R}^n \times (0, \infty)$ w/

$u(x,0) \leq v(x,0)$

then

$u(x,t) \leq v(x,t)$

$\forall t \geq 0.$