

Hamilton-Jacobi equation in metric spaces and applications

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The Classical Hamilton-Jacobi (HJ) Equation

The solution (in some sense) of the Hamilton-Jacobi equation

$$\begin{cases} \partial_t u(t, x) = -\frac{1}{2} |\nabla_x u(t, x)|^2 & t > 0, x \in \mathbb{R}^n \\ u(0, x) = f(x) & x \in \mathbb{R}^n \end{cases}$$

is given by the celebrated Hopf-Lax formula

$$u(t, x) = Q_t f(x) := \inf_{y \in \mathbb{R}^n} \left\{ f(y) + \frac{1}{2t} |x - y|^2 \right\}$$

- $|x| := \sqrt{\sum x_i^2}$ is the Euclidean distance
- $(Q_t)_{t \geq 0}$ is a semi-group: $Q_{t+s} = Q_t(Q_s)$ also called inf-convolution operator

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For example if f is Lipschitz, i.e. $Lip(f) := \sup_{x \neq y} \frac{|f(x) - f(y)|}{|x - y|} < \infty$, then

- $(t, x) \mapsto Q_t f(x)$ is Lipschitz (on $[0, \infty) \times \mathbb{R}^n$)
- $Q_0 f(x) = f(x)$ for all $x \in \mathbb{R}^n$
- Everywhere where this makes sense (so a.e. in (t, x) by Rademacher) $Q_t f(x)$ satisfies $\partial_t Q_t f(x) = -\frac{1}{2} |\nabla_x Q_t f(x)|^2$

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One can replace $\frac{1}{2} |\cdot|^2$ by a convex function L in the Hopf-Lax formula (plugging $tL(|x - y|/t)$). It becomes a solution of the HJ Equation

$$\partial_t u(t, x) = -L^*(|\nabla_x u(t, x)|)$$

with $L^*(x) = \sup_y \{xy - L(y)\}$.

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Hamilton Jacobi Equation In Metric Space - setting

- (X, d) is a metric space, complete, separable and for which balls are compact.
- If for all $x, y \in X$ there exists a path $\gamma: [0, 1] \rightarrow X$ such that $\gamma(0) = x$, $\gamma(1) = y$ and for all $s, t \in [0, 1]$, $d(\gamma(s), \gamma(t)) = |t - s|d(x, y)$, then X is called a **geodesic space**.

For $f: X \rightarrow \mathbb{R}$, define the length of the gradient

$$|\nabla^- f|(x) := \begin{cases} 0 & \text{if } x \text{ is an isolated point} \\ \limsup_{y \rightarrow x} \frac{[f(y) - f(x)]_-}{d(x, y)} & \text{otherwise} \end{cases}$$

where $[A]_- := \max(-A, 0)$.

- If f is Lipschitz then $|\nabla^- f|(x) \leq \text{Lip}(f) < \infty$
- If X is a Riemannian manifold $|\nabla^- f|(x)$ coincides with the length of the vector $\nabla f(x)$ in the tangent space at x .

Main Theorem

Theorem (Ambrosio-Gigli-Savaré '14, Gozlan-R-Samson '14)

Let $f: X \rightarrow \mathbb{R}$ be continuous and bounded. Then

$$\begin{cases} \frac{d}{dt_+} Q_t f(x) \leq -\frac{1}{2} |\nabla^- Q_t f|(x)^2 & \forall t > 0, \quad \forall x \in X \\ \frac{d}{dt_+} Q_t f(x)|_{t=0} \geq -\frac{1}{2} |\nabla^- f|(x)^2 & t = 0, \quad \forall x \in X \end{cases}$$

where $Q_t f(x) := \inf_{y \in X} \left\{ f(y) + \frac{1}{2t} d(x, y)^2 \right\}$. $\lim_{t \rightarrow 0} Q_t f = f$.

If in addition X is geodesic, then $\frac{d}{dt_+} Q_t f(x) = -\frac{1}{2} |\nabla^- Q_t f|(x)^2$ for all $t \geq 0$ and all $x \in X$.

- Lott-Villani '07 if (X, d, μ) is a compact **measured** geodesic space with μ satisfying a local Poincaré inequality + doubling condition. Result holds for all t and for μ -almost all $x \in X$. Result holds for all t and all x under some additional curvature condition + finite dim.
- If X is a Riemannian manifold, Villani '09 get the result for all t, x .

Where The Audience Is Asked To Choose Between Application I and II

- Application I : Otto-Villani's theorem (in metric spaces).
- Application II : Concentration versus the Poincaré Inequality (in metric spaces).

Application I: Introduction - Talagrand's inequality

Given two probability measures ν_1, ν_2 on X , set

$$T_2(\nu_1, \nu_2) := \inf_{\pi} \iint \frac{1}{2} d(x, y)^2 \pi(dx, dy)$$

where the inf runs over all couplings (i.e. prob. meas. on $X \times X$) π with first marginal ν_1 and second marginal ν_2 .

A probability measure μ satisfies the Talagrand transport-entropy inequality (with constant C) if

$$T_2(\nu, \mu) \leqslant CH(\nu|\mu) \quad \forall \nu \text{ prob. meas.}$$

where $H(\nu|\mu) := \begin{cases} \int \frac{d\nu}{d\mu} \log \frac{d\nu}{d\mu} d\mu & \text{if } \nu \ll \mu \\ +\infty & \text{otherwise} \end{cases}$ is the relative

entropy of ν with respect to μ .

Ex: For $\mu = \gamma_n$ the standard Gaussian on $X = \mathbb{R}^n$ satisfies the inequality with $C = 1$ (optimal) Talagrand '96.

Application I: Transport and inf-convolution operator

Recall Talagand's inequality: $T_2(\nu, \mu) \leq CH(\nu|\mu)$ for all ν .

Theorem (Bobkov-Gotze '99)

μ satisfies the Talagrand transport-entropy inequality with constant C iff for all $f: X \rightarrow \mathbb{R}$ continuous and bounded

$$\int e^{\frac{Q_1 f}{C}} d\mu \leq e^{\frac{1}{C} \int f d\mu}$$

where $Q_1 f(x) = \inf_y \{f(y) + \frac{1}{2}d(x, y)^2\}$.

Application I: log-Sobolev inequality

μ satisfies the log-Sobolev inequality, with constant C , if for all $f: X \rightarrow \mathbb{R}$, say Lipschitz,

$$\text{Ent}_\mu(e^f) \leq \frac{C'}{2} \int |\nabla^- f|^2 e^f d\mu$$

where

$$\text{Ent}_\mu(g) := \int g d\mu H\left(\frac{g d\mu}{\int g d\mu} \mid \mu\right) = \int g \log g d\mu - \int g d\mu \log \int g d\mu.$$

Ex: if $\mu = \gamma_n$ and $X = \mathbb{R}^n$ then $C' = 1$ (optimal) Stam '59, Gross '75. Applications:

- Hypercontractivity Gross '75.
- Concentration Herbst 70s.
- Gaussian Isoperimetry, Bakry-Ledoux '96.

Application I: Otto-Villani's Theorem

Talagrand: $T_2(\nu, \mu) \leq CH(\nu|\mu)$

Log-Sobolev: $\text{Ent}_\mu(e^f) \leq \frac{C'}{2} \int |\nabla f|^2 e^f d\mu$

Theorem (Gozlan-R-Samson '14)

Assume that μ satisfies the log-Sobolev inequality with some constant C' . Then μ satisfies the Talagrand transport-entropy Inequality with constant $C \leq C'$.

- Otto-Villani '00.
- Bobkov-Gentil-Ledoux '01, alternative proof based on HJ .
- Extensions in many directions Gentil-Guillin-Miclo '05, Wang '04 (path spaces), Lott-Villani '07 (geodesic spaces), Balogh-Engoulatov-Hunziker-Maasalo '09.
- In the general setting of metric spaces Gozlan '09 (Large deviation), Gozlan-R-Samson '12 (tensorisation), Gigli-Ledoux '11 (Gradient flow).
- Talagrand $\not\Rightarrow$ log-Sob, Cattiaux-Guillin' 06.

Application I: Otto-Villani's Theorem

Talagrand: $T_2(\nu, \mu) \leq CH(\nu|\mu)$

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Proof of Otto-Villani's Theorem

Recall Bobkov-Gotze dual characterization: $\int e^{\frac{Q_1 f}{c}} d\mu \leq e^{\frac{1}{c} \int f d\mu}$

We will prove better, namely that

$$\|e^{Q_t f}\|_{a+\frac{t}{c'}} \leq \|e^f\|_a \quad \forall t, a \geq 0, \forall f$$

In fact if this is true, then choose $t = 1$ and send a to 0 to obtain

$$\left(\int e^{\frac{Q_1 f}{c'}} d\mu \right)^{c'} \leftarrow \|e^{Q_1 f}\|_{a+\frac{1}{c'}} \leq \|e^f\|_a \rightarrow e^{\int f d\mu}$$

which is precisely the dual characterization of Talagrand transport-entropy inequality.

Proof of Otto-Villani's Theorem

In order to prove

$$\|e^{Q_t f}\|_{a+\frac{t}{C'}} \leq \|e^f\|_a \quad \forall t, a \geq 0, \forall f$$

we set $F(t) := \log \|e^{Q_t f}\|_{k(t)}$ with $k(t) = a + \frac{t}{C'}$ and differentiate:

$$F'(t) = \frac{k'(t)}{k(t)} \frac{1}{\int e^{k(t)Q_t f} d\mu} \left[\text{Ent}_\mu(e^{k(t)Q_t f}) + \frac{k^2(t)}{k'(t)} \int \frac{d}{dt_+} Q_t f e^{k(t)Q_t f} d\mu \right]$$

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The log-Sobolev inequality $\text{Ent}_\mu(e^g) \leq \frac{C'}{2} \int |\nabla^- g|^2 e^g d\mu$ applied to $g = k(t)Q_t f$ guarantees that the r.h.s. is non positive, hence F is non-increasing and therefore

$$\|e^{Q_t f}\|_{a+\frac{t}{C'}} = e^{F(t)} \leq e^{F(0)} = \|e^f\|_a,$$

ending the proof.

Application II: Introduction (Concentration)

- Define on X^n the ℓ_2 -product distance

$$d^{(n)}(x, y) := \left(\sum_{i=1}^n d(x_i, y_i)^2 \right)^{1/2}$$

- Given a Borel set $A \subset X^n$, we define its enlargement as

$$A_r^{(n)} := \{x \in X : d^{(n)}(x, A) \leq r\} \quad \text{Notation } A_r = A_r^{(1)}$$

- A probability measure μ on X satisfies a *concentration inequality*, with concentration profile α (non-increasing), if

$$\mu(A_r) \geq 1 - \alpha(r) \quad \forall A \subset X \text{ with } \mu(A) \geq 1/2,$$

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- A probability measure μ on X satisfies a **dimension free concentration inequality**, with concentration profile α (non-increasing), if

$$\mu^n \left(A_r^{(n)} \right) \geq 1 - \alpha(r) \quad \forall A \subset X^n \text{ with } \mu^n(A) \geq 1/2, \quad \forall n$$

We denote by $Cl_2(\alpha)$ and $Cl_2^\infty(\alpha)$ respectively such properties.

Application II: Introduction (The Poincaré Inequality)

A probability measure μ on X satisfies the Poincaré Inequality if there exists $\lambda > 0$ such that for all f Lipschitz it holds

$$\int f^2 d\mu - \left(\int f d\mu \right)^2 =: \text{Var}_\mu (f) \leq \frac{1}{\lambda} \int |\nabla^- f|(x)^2 d\mu$$

Ex: if $X = \mathbb{R}^n$ and $\mu = \gamma_n$ the standard Gaussian measure, then $\lambda = 1$ (optimal).

Theorem (Gromov-Milman '83)

Assume that μ satisfies a Poincaré inequality with constant $\lambda > 0$. Then $IC_2^\infty(\alpha)$ holds with $\alpha(r) := be^{-a\sqrt{\lambda}r}$, $r \geq 0$:

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Poincaré versus dimension free concentration.

$CI_2^\infty(\alpha): \mu^n(A_r^{(n)}) \geq 1 - \alpha(r)$, for all A with $\mu^n(A) \geq 1/2, \forall r, n$. Poincaré: $\text{Var}_\mu(f) \leq \frac{1}{\lambda} \int |\nabla f(x)|^2 d\mu$.

Theorem (Gozlan-R-Samson '15)

If μ satisfies $CI_2^\infty(\alpha)$, then the Poincaré Inequality holds with

$$\lambda = \sup_{r>0:\alpha(r)\leq\frac{1}{2}} \left\{ \frac{\bar{\Phi}^{-1}(\alpha(r))}{r} \right\}^2 \text{ where } \bar{\Phi}(x) = \int_x^\infty \frac{e^{-u^2/2}}{\sqrt{2\pi}} du.$$

i.e. $CI_2^\infty(\alpha) \Leftrightarrow$ Poincaré (for non trivial α : note that $\bar{\Phi}^{-1}(\frac{1}{2}) = 0$).

- (self-improvement. Talagrand '91) If μ satisfies $CI_2^\infty(\alpha)$ with a "minimal" profile $\alpha = \frac{1}{2}\mathbb{1}_{[0,r_0]} + a_0\mathbb{1}_{(r_0,\infty)}$, $r_0 > 0$, $a_0 \in (0, \frac{1}{2})$, then μ satisfies $CI_2^\infty(\alpha)$ with $\alpha(r) = be^{-ar}$.
- In case of the Gaussian measure γ_n , $CI_2^\infty(\bar{\Phi})$ holds so that the theorem leads to $\lambda = 1$ which is optimal.
- If $\alpha(r)$ goes too fast to 0 (such as be^{-ar^k} with $k > 2$) then $\lambda = +\infty$ and μ is a Dirac mass.
- Extension to the convex situation. See also Adamczak-Strzelecki '17, Gozlan-R-Samson-Shu-Tetali '15, Feldheim-Marsiglietti-Nayar-Wang '15.

Proof. A key Lemma: concentration and inf-convolution operator

Lemma (Gozlan-R-Samson '11)

The following are equivalent

(i) $Cl_2(\alpha)$ holds: $\mu(A_r) \geq 1 - \alpha(r)$ for all $A \subset X$, all $r \geq 0$.

(ii) For any $f: X \rightarrow \mathbb{R} \cup \{+\infty\}$ bounded below and such that $\mu(\{f = +\infty\}) < \frac{1}{2}$ ($m(f)$ being a median of f)

$$\mu(Q_t f > m(f) + r) \leq \alpha(\sqrt{2rt}) \quad \forall r, t > 0.$$

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The following are equivalent

- (i) $Cl_2(\alpha)$ holds: $\mu(A_r) \geq 1 - \alpha(r)$ for all $A \subset X$, all $r \geq 0$.*
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$$\mu(Q_t f > m(f) + r) \leq \alpha(\sqrt{2rt}) \quad \forall r, t > 0.$$

- Let $h: X \rightarrow \mathbb{R}$ be bounded, Lipschitz with $\int h d\mu = 0$.
Set $f_n(x) = h(x_1) + \dots + h(x_n)$, $x = (x_1, \dots, x_n) \in X^n$.
- Apply (ii) of the Lemma to μ^n , f_n , $t = \frac{1}{\sqrt{n}}$ and $r = \frac{\sqrt{nu}}{2}$

$$\mu^n \left(Q_{\frac{1}{\sqrt{n}}} f_n > m(f_n) + \frac{\sqrt{nu}}{2} \right) \leq \alpha(\sqrt{u})$$

with $Q_t^{(n)} f_n(x) = \inf \{ f_n(y) + \frac{1}{2t} \sum_1^n d^2(x_i, y_i) \} = \sum_1^n Q_t h(x_i)$.

Proof

$$\mu^n \left(Q_{\frac{1}{\sqrt{n}}}^{(n)} f_n > m(f_n) + \frac{\sqrt{nu}}{2} \right) \leq \alpha(\sqrt{u}) \text{ and } Q_t^{(n)} f_n = \sum Q_t h(x_i).$$

$$\text{Set } \sigma_n := \sqrt{\text{Var}_\mu \left(Q_{\frac{1}{\sqrt{n}}} h \right)}.$$

$$\mu^n \left(Q_{\frac{1}{\sqrt{n}}}^{(n)} f_n > m(f_n) + \frac{\sqrt{nu}}{2} \right) = \mu^n \left(\frac{\sum_{i=1}^n \left[Q_{\frac{1}{\sqrt{n}}} h(x_i) - \int Q_{\frac{1}{\sqrt{n}}} h d\mu \right]}{\sqrt{n}\sigma_n} > \frac{m(f_n)}{\sqrt{n}\sigma_n} + \frac{u}{\sigma_n} + \frac{\sqrt{n}}{2\sigma_n} \int h - Q_{\frac{1}{\sqrt{n}}} h d\mu \right)$$

Proof

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Observe that, in the limit $n \rightarrow \infty$, $\sigma_n \rightarrow \sqrt{\text{Var}_\mu(h)}$, $\frac{m(f_n)}{\sqrt{n}} \rightarrow 0$
 $\sqrt{n}[h(x) - Q_{\frac{1}{\sqrt{n}}} h(x)] \rightarrow -\frac{d}{dt_+} Q_t h(x)|_{t=0} \leq \frac{1}{2} |\nabla^- h|(x)^2$ by HJ.

By the CLT we get

$$\bar{\Phi} \left(\frac{u}{\text{Var}_\mu(h)} + \frac{\int |\nabla^- h|^2 d\mu}{4\text{Var}_\mu(h)} \right) \leq \alpha(\sqrt{u})$$

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We obtained $\bar{\Phi} \left(\frac{u}{\text{Var}_\mu(h)} + \frac{\int |\nabla^- h|^2 d\mu}{4\text{Var}_\mu(h)} \right) \leq \alpha(\sqrt{u})$.

Given u so that $\alpha(\sqrt{u}) < 1/2$, we have, for $k(u) := \bar{\Phi}^{-1}(\alpha(\sqrt{u}))$

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This ends the proof.

Open question

Consider $d_p^{(n)}(x, y) := (\sum_i d(x_i, y_i)^p)^{1/p}$, $p \geq 1$ and the corresponding enlargement $A_{r,p}^{(n)} := \{x \in X^n : d_p^{(n)}(x, A) \leq r\}$ and the corresponding dimension free concentration inequality $CI_p^\infty(\alpha)$

$$\mu^n(A_{r,p}^{(n)}) \geq 1 - \alpha(r) \quad \forall n, \forall A \text{ with } \mu^n(A) \geq 1/2.$$

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