

Anisotropic congested transport

Lorenzo Brasco

LATP – Aix-Marseille Université

lbrasco@gmail.com — <http://www.latp.univ-mrs.fr/~brasco/>

Sankt-Peterburg, 04/06/2012



References

Part of the results here presented are contained in

1. L. B., G. Carlier, F. Santambrogio, *On certain anisotropic elliptic equations arising in optimal transport: local gradient bounds*, 90% completed

Outline

Introduction to the problem and goal of the talk

Some continuous models

Equilibrium issues

Regularity results

Congested transport: introduction

From an overall point of view...

Optimal Transport Problem, where the *infinitesimal cost* obeys

“spreading the mass during the transport, we save cost”

in a point, if our transport accumulates an amount of mass m , we pay

$H(m)$ where H **convex and superlinear** (given)

The **total cost** is something of the type $\int H(m(x))dx$

Congested transport: introduction

From an overall point of view...

Optimal Transport Problem, where the *infinitesimal cost* obeys

“spreading the mass during the transport, we save cost”

in a point, if our transport accumulates an amount of mass m , we pay

$H(m)$ where H **convex and superlinear** (given)

The **total cost** is something of the type $\int H(m(x))dx$

...and from an individual one

A **game** with many players going from certain **sources** to their **destinations** using a system of roads

“travel time on a road increasingly depends on the traffic ”

i.e. my satisfaction is affected by **choices of the other players**

Anisotropic transport costs

The typical costs we will consider are of the form

$$(C) \quad H(m) = H_1(m_1) + \cdots + H_N(m_N)$$

where $m_i =$ mass transported in direction \mathbf{e}_i

Anisotropic transport costs

The typical costs we will consider are of the form

$$(C) \quad H(m) = H_1(m_1) + \cdots + H_N(m_N)$$

where m_i = mass transported in direction \mathbf{e}_i

Motivation

The model we are going to present is a **continuous version** of a classical discrete model settled on **networks**. Question: do the discrete models “converge” to the continuous one, for very dense networks?

Anisotropic transport costs

The typical costs we will consider are of the form

$$(C) \quad H(m) = H_1(m_1) + \cdots + H_N(m_N)$$

where $m_i =$ mass transported in direction \mathbf{e}_i

Motivation

The model we are going to present is a **continuous version** of a classical discrete model settled on **networks**. Question: do the discrete models “converge” to the continuous one, for very dense networks? **Yes**, if the network is a regular grid of size $\varepsilon \ll 1$, with a cost that at each node distinguish between the mass entering with different directions (Baillon-Carlier)

The limit continuous model has a cost of the form (C), which “keeps memory” of the geometry of the approximating problems

Goals of the talk

From an overall point of view...

Prove **existence** of an **optimal transport**, i.e. existence of a way to accomplish the transport which minimizes the total cost and show **regularity properties** for this optimizer.

Goals of the talk

From an overall point of view...

Prove **existence** of an **optimal transport**, i.e. existence of a way to accomplish the transport which minimizes the total cost and show **regularity properties** for this optimizer. In particular, we will be lead to analyze **widely degenerate equations** like

$$- \left[(|u_x| - 1)_+^{q-1} \frac{u_x}{|u_x|} \right]_x - \left[(|u_y| - 1)_+^{q-1} \frac{u_y}{|u_y|} \right]_y = f$$

Goals of the talk

From an overall point of view...

Prove **existence** of an **optimal transport**, i.e. existence of a way to accomplish the transport which minimizes the total cost and show **regularity properties** for this optimizer. In particular, we will be lead to analyze **widely degenerate equations** like

$$- \left[(|u_x| - 1)_+^{q-1} \frac{u_x}{|u_x|} \right]_x - \left[(|u_y| - 1)_+^{q-1} \frac{u_y}{|u_y|} \right]_y = f$$

...and from an individual one

Prove **existence** of **equilibrium** situations, i.e. existence of configurations where players have no interest in changing unilaterally their choice, in order to avoid congested routes

Introduction to the problem and goal of the talk

Some continuous models

Equilibrium issues

Regularity results

A continuous model for congested transport

We start with the overall optimization point of view

Data of the problem

- ▶ a “city” $\Omega \subset \mathbb{R}^N$
- ▶ $\rho_0, \rho_1 \in \mathcal{P}(\Omega)$ probability measures
- ▶ “admissible couplings” (transport plans)

$$\Pi \subset \Pi(\rho_0, \rho_1) = \{\gamma \in \mathcal{P}(\Omega \times \Omega) : (\pi_x)_\# \gamma = \rho_0, (\pi_y)_\# \gamma = \rho_1\}$$

- ▶ a **density-cost function** $\mathcal{H} : \mathbb{R}^N \rightarrow \mathbb{R}^+$ smooth

$$\mathcal{H}(z) = H_1(z_1) + \cdots + H_N(z_N)$$

with H_i strictly convex, $H_i(0) = 0$ and $H_i(t) \simeq |t|^p$, for $p > 1$

The cost of transportation

Unknown of the problem: traffic assignments

$Q \in \mathcal{P}(\text{Lip}([0, 1]; \Omega))$ such that $(e_0, e_1)_\# Q \in \Pi$

where $e_t(\sigma) = \sigma(t)$ for every curve σ

The cost of transportation

Unknown of the problem: traffic assignments

$Q \in \mathcal{P}(\text{Lip}([0, 1]; \Omega))$ such that $(e_0, e_1)_{\#} Q \in \Pi$

where $e_t(\sigma) = \sigma(t)$ for every curve σ

Each Q gives rise to a **traffic intensity**

$$i_Q = (i_{Q,1}, \dots, i_{Q,N})$$

positive vector measure defined on Ω by

$$\int_{\Omega} \varphi(x) di_{Q,j}(x) = \int_{\text{Lip}([0,1];\Omega)} \left(\int_0^1 \varphi(\sigma(t)) |\sigma'_j(t)| dt \right) dQ(\sigma)$$

The cost of transportation

Unknown of the problem: traffic assignments

$Q \in \mathcal{P}(\text{Lip}([0, 1]; \Omega))$ such that $(e_0, e_1) \# Q \in \Pi$

where $e_t(\sigma) = \sigma(t)$ for every curve σ

Each Q gives rise to a **traffic intensity**

$$i_Q = (i_{Q,1}, \dots, i_{Q,N})$$

positive vector measure defined on Ω by

$$\int_{\Omega} \varphi(x) di_{Q,j}(x) = \int_{\text{Lip}([0,1];\Omega)} \left(\int_0^1 \varphi(\sigma(t)) |\sigma'_j(t)| dt \right) dQ(\sigma)$$

The problem

Total cost = $\int_{\Omega} \mathcal{H}(i_Q(x)) dx$ if $i_Q \ll \mathcal{L}^N$ and $+\infty$ otherwise

A pair of (not congested) example

Anisotropic, not congested

If we take the density-cost $\mathcal{H}(z) = |z_1| + \cdots + |z_N|$ then

$$\mathbf{Total\ cost} = \int_{\Omega} d\|i_Q\|_{\ell^1} = \int \text{length}_{\ell^1}(\sigma) dQ(\sigma)$$

and the minimization is equivalent to Monge problem with cost $c(x, y) = \|x - y\|_{\ell^1}$

A pair of (not congested) example

Anisotropic, not congested

If we take the density-cost $\mathcal{H}(z) = |z_1| + \dots + |z_N|$ then

$$\text{Total cost} = \int_{\Omega} d \|i_Q\|_{\ell^1} = \int \text{length}_{\ell^1}(\sigma) dQ(\sigma)$$

and the minimization is equivalent to Monge problem with cost $c(x, y) = \|x - y\|_{\ell^1}$

Neither anisotropic, nor congested

The traffic intensity i_Q is a scalar measure, if we take $\mathcal{H}(z) = |z|$

$$\text{Total cost} = \int_{\Omega} d i_Q = \int \text{length}(\sigma) dQ(\sigma)$$

and we are back to the standard Monge problem with cost $c(x, y) = |x - y|$. The optimal i_Q is given by the **transport density**

Existence of an optimal transport

Theorem (Carlier-Jimenez-Santambrogio)

The problem

$$(\mathcal{W}) = \min \left\{ \int_{\Omega} \mathcal{H}(i_Q) dx : Q \quad \text{s.t.} \quad (e_0, e_1) \# Q \in \Pi, i_Q \in L^p \right\}$$

admits a solution \tilde{Q}

Existence of an optimal transport

Theorem (Carlier-Jimenez-Santambrogio)

The problem

$$(\mathcal{W}) = \min \left\{ \int_{\Omega} \mathcal{H}(i_Q) dx : Q \quad \text{s.t.} \quad (e_0, e_1)_{\#} Q \in \Pi, i_Q \in L^p \right\}$$

admits a solution \tilde{Q}

Sketch of the proof:

- ▶ for a minimizing sequence

$$C \geq \int_{\Omega} \mathcal{H}(i_{Q_n}) \gtrsim \int_{\Omega} |i_{Q_n}| \simeq \int \text{length}(\sigma) dQ_n(\sigma)$$

- ▶ up to a time reparametrization, $\{Q_n\}_{n \in \mathbb{N}}$ is compact and each i_{Q_n} is unchanged
- ▶ the weak L^p limit of i_{Q_n} is “greater” than i_Q and \mathcal{H} is “increasing”

**For the case $\Pi = \Pi(\rho_0, \rho_1)$
a more comfortable formulation is available...**

Beckmann's continuous model of transportation

Transportation activities are described by $\Phi : \Omega \rightarrow \mathbb{R}^N$, s.t.

- ▶ $|\Phi(x)|$ = amount of **mass** passing from x
- ▶ $\Phi(x) |\Phi(x)|^{-1}$ = **direction** of transportation in x
- ▶ $\operatorname{div} \Phi = \rho_0 - \rho_1$, i.e. the transport is ruled by the balance demand/offer
- ▶ $\mathcal{H}(\Phi) =$ cost for transporting $|\Phi|$, with direction $\Phi/|\Phi|$

Beckmann's Optimization problem

$$(\mathcal{B}) = \min_{\Phi \in L^p} \left\{ \int_{\Omega} \mathcal{H}(\Phi(x)) dx : \operatorname{div} \Phi = \rho_0 - \rho_1, \langle \Phi, \nu_{\Omega} \rangle = 0 \right\}$$

Beckmann's continuous model of transportation

Transportation activities are described by $\Phi : \Omega \rightarrow \mathbb{R}^N$, s.t.

- ▶ $|\Phi(x)|$ = amount of **mass** passing from x
- ▶ $\Phi(x) |\Phi(x)|^{-1}$ = **direction** of transportation in x
- ▶ $\operatorname{div} \Phi = \rho_0 - \rho_1$, i.e. the transport is ruled by the balance demand/offer
- ▶ $\mathcal{H}(\Phi) =$ cost for transporting $|\Phi|$, with direction $\Phi/|\Phi|$

Beckmann's Optimization problem

$$(\mathcal{B}) = \min_{\Phi \in L^p} \left\{ \int_{\Omega} \mathcal{H}(\Phi(x)) dx : \operatorname{div} \Phi = \rho_0 - \rho_1, \langle \Phi, \nu_{\Omega} \rangle = 0 \right\}$$

For $\mathcal{H}(z) = |z|$, this is the dual formulation of Kantorovich problem

$$\max_{\varphi \text{ 1-Lip}} \langle \varphi, \rho_0 - \rho_1 \rangle$$

**What is the relation between Beckmann's model
and the previous one?**

The two models are equivalent

The two models are equivalent

Restriction We consider the case $\Pi = \Pi(\rho_0, \rho_1)$

Theorem (B.-Carlier-Santambrogio)

Let $\Omega \subset \mathbb{R}^N$ bounded with smooth boundary. Assume that:

- ▶ $\rho_i = f_i \cdot \mathcal{L}^N$, with $f_i \in L^p(\Omega)$.

Then we have

$$(\mathcal{W}) = (\mathcal{B})$$

and for every optimal Q , we can construct an optimal Φ with the same cost (and viceversa)

Proof of the equivalence: $(\mathcal{B}) \leq (\mathcal{W})$

Given Q optimal, construct a vector field Φ_Q such that

$$\langle \varphi, \Phi_Q \rangle = \int_{Lip([0,1];\Omega)} \left(\int_0^1 \langle \varphi(\sigma(t)), \sigma'(t) \rangle dt \right) dQ(\sigma)$$

then

- ▶ Φ_Q is admissible for (\mathcal{B})
- ▶ $|\Phi_{Q,j}(x)| \leq i_{Q,j}(x)$ (since the traffic defined in a vectorial way allows for some “mass cancellations”)
- ▶ \mathcal{H} is increasing in each variable

so in conclusion

$$(\mathcal{B}) \leq \int_{\Omega} \mathcal{H}(\Phi_Q) \leq \int_{\Omega} \mathcal{H}(i_Q) = (\mathcal{W})$$

Proof of the equivalence: $(\mathcal{B}) \geq (\mathcal{W})$

Idea

If Φ optimal, construct Q_Φ by following the flow of $\lambda_t \Phi$ for a suitable scalar λ_t such that

$$(\star) \quad i_{Q_\Phi} = (|\Phi_1|, \dots, |\Phi_N|)$$

Proof of the equivalence: $(\mathcal{B}) \geq (\mathcal{W})$

Idea

If Φ optimal, construct Q_Φ by following the flow of $\lambda_t \Phi$ for a suitable scalar λ_t such that

$$(\star) \quad i_{Q_\Phi} = (|\Phi_1|, \dots, |\Phi_N|)$$

Heuristics

- ▶ set $\mu_t = (1 - t)\rho_0 + t\rho_1$ and take Q concentrated on the flow X_t of the field Φ/μ_t
- ▶ $(X_t)_{\#}\rho_0$ and μ_t **coincide**, since by the **method of characteristics** they both solve the same continuity equation...
- ▶ ... Q transports ρ_0 to ρ_1 , since $X_0 = \text{Id}$ and $(X_1)_{\#}\rho_0 = \rho_1$
- ▶ finally, we have (\star)

To give sense to the previous heuristics, we need the following
“**probabilistic method of characteristics**”

Theorem (Ambrosio-Crippa, Maniglia)

Let $\mu : [0, 1] \rightarrow \mathcal{P}(\Omega)$ a curve of measures and
 $\mathbf{v} : [0, 1] \times \Omega \rightarrow \mathbb{R}^N$ such that

$$\int_0^1 \int_{\Omega} |\mathbf{v}(t, x)| d\mu_t(x) dt < \infty$$

with (μ, \mathbf{v}) solving the continuity equation (in distributional sense).
Then there exists a $Q \in \mathcal{P}(C([0, 1]; \Omega))$ such that

$$\mu_t = (e_t)_\# Q \quad \text{and} \quad \sigma'(t) = \mathbf{v}(t, \sigma(t)) \text{ for } Q\text{-a.e. } \sigma$$

Remark

The choice $\mu_t = (1 - t)\rho_0 + t\rho_1$ and $\mathbf{v} = \Phi/\mu_t$ verifies the hypothesis

Some remarks on this procedure

Remark 1

Not only we have **equality of the minima**, but the two models **describe the same optimal structures** (using two complementary point of views)

Some remarks on this procedure

Remark 1

Not only we have **equality of the minima**, but the two models **describe the same optimal structures** (using two complementary point of views)

Remark 2

The deterministic flow construction becomes feasible if the optimal Φ is smooth enough (i.e. Lipschitz or Sobolev) and the data ρ_0, ρ_1 are smooth and bounded from below. In this case, we can construct an optimal traffic assignment **supported on a real flow**, not just on a probabilistic one

Introduction to the problem and goal of the talk

Some continuous models

Equilibrium issues

Regularity results

The latency functions

We have to **quantify** the effects of congestion on the routes

Latency functions

Increasing functions $h_j \geq 1$ such that

$h_j(i_{Q,j}) =$ cost (per unit length) of passing from a point
where the traffic in direction \mathbf{e}_j is $i_{Q,j}$

The latency functions

We have to **quantify** the effects of congestion on the routes

Latency functions

Increasing functions $h_j \geq 1$ such that

$$h_j(i_{Q,j}) = \text{cost (per unit length) of passing from a point where the traffic in direction } \mathbf{e}_j \text{ is } i_{Q,j}$$

Some important comments

1. the cost expressed by h_j should be thought as a **time**, i.e.

$$[h_j] = \frac{\text{time}}{\text{length}} = \frac{1}{\text{speed}}$$

in fact "the higher the congestion, the slower we can move"

The latency functions

We have to **quantify** the effects of congestion on the routes

Latency functions

Increasing functions $h_j \geq 1$ such that

$h_j(i_{Q,j}) =$ cost (per unit length) of passing from a point
where the traffic in direction \mathbf{e}_j is $i_{Q,j}$

Some important comments

1. the cost expressed by h_j should be thought as a **time**, i.e.

$$[h_j] = \frac{\text{time}}{\text{length}} = \frac{1}{\text{speed}}$$

in fact "the higher the congestion, the slower we can move"

2. why do we require $h_j \geq 1$? because

"you can not move with infinite speed on an empty road"

Equilibrium issues

Individual cost for using the road $\sigma \in C^{x,y}$

$$c_h(\sigma) := \sum_{j=1}^N \int_0^1 h_j \circ i_{Q,j}(\sigma(t)) |\sigma'_j(t)| dt$$

Finsler length, averaged according the traffic, i.e. **congestion effects compensate the difference of length**

Equilibrium issues

Individual cost for using the road $\sigma \in C^{x,y}$

$$c_h(\sigma) := \sum_{j=1}^N \int_0^1 h_j \circ i_{Q,j}(\sigma(t)) |\sigma'_j(t)| dt$$

Finsler length, averaged according the traffic, i.e. **congestion effects compensate the difference of length**

Some individuals could decide to change their path, taking a less crowded one. This change of strategy alters the traffic distribution Q and so the cost paid by the others **and so on and on...**

Goal

Does a **Nash equilibrium** exist? What does it mean here?

Wardrop equilibrium

Definition

Q is a **Wardrop equilibrium** for $h = (h_1, \dots, h_N)$ if it gives full mass to the geodesics of the *traffic-dependent metric*

$$d_Q(x, y) = \inf \left\{ \sum_{j=1}^N \int_0^1 h_j \circ i_{Q,j}(\sigma(t)) |\sigma'_j(t)| dt : \begin{array}{l} \sigma(0) = x \\ \sigma(1) = y \end{array} \right\}$$

Important remark

The metric d_Q can be defined when $h_j \circ i_{Q,j} \in L^s(\Omega)$, with $s > N$

Why? Because...

Wardrop equilibrium

Definition

Q is a **Wardrop equilibrium** for $h = (h_1, \dots, h_N)$ if it gives full mass to the geodesics of the *traffic-dependent metric*

$$d_Q(x, y) = \inf \left\{ \sum_{j=1}^N \int_0^1 h_j \circ i_{Q,j}(\sigma(t)) |\sigma'_j(t)| dt : \begin{array}{l} \sigma(0) = x \\ \sigma(1) = y \end{array} \right\}$$

Important remark

The metric d_Q can be defined when $h_j \circ i_{Q,j} \in L^s(\Omega)$, with $s > N$

Why? Because...

If $\xi \in C(\Omega; \mathbb{R}^+)$, the metric $d_\xi(x, y) = \inf \int_0^1 \xi(\sigma) |\sigma'(t)| dt$

has an Hölder estimate in terms of the L^s norm of $\xi \implies$ define d_Q as the supremum of d_{ξ_n} as $\xi_n \rightarrow h \circ i_Q$ in L^s

**Given the data ρ_0, ρ_1 and Π and the latency functions h_j ,
does a Wardrop Equilibrium exist?**

Existence via convex optimization

Theorem (Carlier-Jimenez-Santambrogio)

Let Π be **convex** and suppose that

$$\nabla \mathcal{H} = (h_1, \dots, h_N)$$

Then \tilde{Q} minimizes (\mathcal{W}) **if and only if**

1. \tilde{Q} is a Wardrop equilibrium for (h_1, \dots, h_N)
2. $\tilde{\gamma} = (e_0, e_1)_{\#} \tilde{Q} \in \Pi$ solves the MK problem

$$\min \left\{ \int_{\Omega \times \Omega} d_{\tilde{Q}}(x, y) d\gamma(x, y) : \gamma \in \Pi \right\}$$

Existence via convex optimization

Theorem (Carlier-Jimenez-Santambrogio)

Let Π be **convex** and suppose that

$$\nabla \mathcal{H} = (h_1, \dots, h_N)$$

Then \tilde{Q} minimizes (\mathcal{W}) **if and only if**

1. \tilde{Q} is a Wardrop equilibrium for (h_1, \dots, h_N)
2. $\tilde{\gamma} = (e_0, e_1)_{\#} \tilde{Q} \in \Pi$ solves the MK problem

$$\min \left\{ \int_{\Omega \times \Omega} d_{\tilde{Q}}(x, y) d\gamma(x, y) : \gamma \in \Pi \right\}$$

Proof: some hints

- ▶ Convex perturbations to derive Euler-Lagrange inequality, i.e.

$$\int_{\Omega} \langle \nabla \mathcal{H}(i_{\tilde{Q}}), i_Q \rangle \geq \int_{\Omega} \langle \nabla \mathcal{H}(i_{\tilde{Q}}), i_{\tilde{Q}} \rangle \quad \text{for every } Q$$

- ▶ necessary conditions are sufficient as well

Some comments

- ▶ A global optimum for the cost \mathcal{H} , gives a Wardrop equilibrium for the marginal costs $(\partial_{x_1} \mathcal{H}, \dots, \partial_{x_N} \mathcal{H})$

Some comments

- ▶ A global optimum for the cost \mathcal{H} , gives a Wardrop equilibrium for the marginal costs $(\partial_{x_1} \mathcal{H}, \dots, \partial_{x_N} \mathcal{H})$
- ▶ at equilibrium \tilde{Q} , the total cost $\int_{\Omega} \mathcal{H}(i_{\tilde{Q}})$ minimized **is not the total cost paid by the commuters...**

Some comments

- ▶ A global optimum for the cost \mathcal{H} , gives a Wardrop equilibrium for the marginal costs $(\partial_{x_1} \mathcal{H}, \dots, \partial_{x_N} \mathcal{H})$
- ▶ at equilibrium \tilde{Q} , the total cost $\int_{\Omega} \mathcal{H}(i_{\tilde{Q}})$ minimized **is not the total cost paid by the commuters...**
- ▶ ...the latter being given by

$$\int_{\Omega} \langle \nabla \mathcal{H}(i_{\tilde{Q}}), i_{\tilde{Q}} \rangle$$

Some comments

- ▶ A global optimum for the cost \mathcal{H} , gives a Wardrop equilibrium for the marginal costs $(\partial_{x_1} \mathcal{H}, \dots, \partial_{x_N} \mathcal{H})$
- ▶ at equilibrium \tilde{Q} , the total cost $\int_{\Omega} \mathcal{H}(i_{\tilde{Q}})$ minimized **is not the total cost paid by the commuters...**
- ▶ ...the latter being given by

$$\int_{\Omega} \langle \nabla \mathcal{H}(i_{\tilde{Q}}), i_{\tilde{Q}} \rangle$$

- ▶ Open problem: how large can be the ratio

$$\frac{\int_{\Omega} \langle \nabla \mathcal{H}(i_{\tilde{Q}}), i_{\tilde{Q}} \rangle}{\min \int_{\Omega} \langle \nabla \mathcal{H}(i_Q), i_Q \rangle} := \text{price of anarchy}$$

Introduction to the problem and goal of the talk

Some continuous models

Equilibrium issues

Regularity results

A significant choice for the cost

Basic requirement

We want costs \mathcal{H} such that

“marginal costs $\partial_{x_j} \mathcal{H}$ are latency functions, i.e. $\partial_{x_j} \mathcal{H} \geq 1$ ”

A significant choice for the cost

Basic requirement

We want costs \mathcal{H} such that

“marginal costs $\partial_{x_j} \mathcal{H}$ are latency functions, i.e. $\partial_{x_j} \mathcal{H} \geq 1$ ”

Model cost

$$\mathcal{H}(z) := \sum_{i=1}^N \frac{|z_i|^p}{p} + |z_i|, \quad z \in \mathbb{R}^N$$

A significant choice for the cost

Basic requirement

We want costs \mathcal{H} such that

“marginal costs $\partial_{x_j} \mathcal{H}$ are latency functions, i.e. $\partial_{x_j} \mathcal{H} \geq 1$ ”

Model cost

$$\mathcal{H}(z) := \sum_{i=1}^N \frac{|z_i|^p}{p} + |z|, \quad z \in \mathbb{R}^N$$

Remark

For $|z| \ll 1$, we have $\mathcal{H}(z) \simeq |z|$, i.e.

“congestion effects are negligible for small masses”

A significant choice for the cost

Basic requirement

We want costs \mathcal{H} such that

“marginal costs $\partial_{x_j} \mathcal{H}$ are latency functions, i.e. $\partial_{x_j} \mathcal{H} \geq 1$ ”

Model cost

$$\mathcal{H}(z) := \sum_{i=1}^N \frac{|z_i|^p}{p} + |z|, \quad z \in \mathbb{R}^N$$

Remark

For $|z| \ll 1$, we have $\mathcal{H}(z) \simeq |z|$, i.e.

“congestion effects are negligible for small masses”

Restriction

We require $p < N/(N-1)$, so that $\partial_{x_j} \mathcal{H} \circ i_Q \in L^s(\Omega) \quad s > N$

Optimization and optimality for (\mathcal{B})

Beckmann's dual

$$\sup \left\{ \langle \varphi, \rho_0 - \rho_1 \rangle - \int_{\Omega} \mathcal{H}^*(\nabla \varphi(x)) dx : \varphi \in W^{1,q}(\Omega) \right\}$$

Optimization and optimality for (\mathcal{B})

Beckmann's dual

$$\sup \left\{ \langle \varphi, \rho_0 - \rho_1 \rangle - \int_{\Omega} \mathcal{H}^*(\nabla \varphi(x)) dx : \varphi \in W^{1,q}(\Omega) \right\}$$

Primal-dual optimality conditions

$$\nabla \varphi_0 \in \partial \mathcal{H}(\Phi_0) \quad \text{or} \quad \Phi_0 = \nabla \mathcal{H}^*(\nabla \varphi_0)$$

Optimization and optimality for (\mathcal{B})

Beckmann's dual

$$\sup \left\{ \langle \varphi, \rho_0 - \rho_1 \rangle - \int_{\Omega} \mathcal{H}^*(\nabla \varphi(x)) dx : \varphi \in W^{1,q}(\Omega) \right\}$$

Primal-dual optimality conditions

$$\nabla \varphi_0 \in \partial \mathcal{H}(\Phi_0) \quad \text{or} \quad \Phi_0 = \nabla \mathcal{H}^*(\nabla \varphi_0)$$

Key point

Regularity of $\Phi_0 \rightsquigarrow$ regularity of solutions to

$$(BVP) \quad \operatorname{div} \nabla \mathcal{H}^*(\nabla u) = f \quad + \quad \left(\begin{array}{c} \text{homogeneous Neumann} \\ \text{conditions} \end{array} \right)$$

$$\text{Wide degeneracy} \quad \mathcal{H}^*(\xi) = \sum_{i=1}^N \frac{(|\xi_i| - 1)_+^q}{q} \quad q = p/(p-1)$$

Regularity estimates for (\mathcal{B})

Local “almost” L^∞ estimate (B.-Carlier-Santambrogio)

Let $q \geq 2$ and $f \in L^\infty(\Omega)$ with zero-mean. If $\varphi_0 \in W^{1,q}(\Omega)$ is a weak solution of (BVP) then

$$\nabla \varphi_0 \in L^r_{loc}(\Omega), \text{ for every } r \geq q$$

Regularity estimates for (\mathcal{B})

Local “almost” L^∞ estimate (B.-Carlier-Santambrogio)

Let $q \geq 2$ and $f \in L^\infty(\Omega)$ with zero-mean. If $\varphi_0 \in W^{1,q}(\Omega)$ is a weak solution of (BVP) then

$$\nabla \varphi_0 \in L^r_{loc}(\Omega), \text{ for every } r \geq q$$

Local Sobolev estimate (B.-Carlier-Santambrogio)

Let $q \geq 2$ and $f \in W^{1,p}(\Omega)$ with zero-mean. If $\varphi_0 \in W^{1,q}(\Omega)$ is a weak solution of (BVP) then

$$(|\partial_{x_j} \varphi_0| - 1)_+^{\frac{q}{2}} \frac{\partial_{x_j} \varphi_0}{|\partial_{x_j} \varphi_0|} \in W^{1,2}_{loc}(\Omega), \quad j = 1, \dots, N$$

Regularity estimates for (\mathcal{B})

Local “almost” L^∞ estimate (B.-Carlier-Santambrogio)

Let $q \geq 2$ and $f \in L^\infty(\Omega)$ with zero-mean. If $\varphi_0 \in W^{1,q}(\Omega)$ is a weak solution of (BVP) then

$$\nabla \varphi_0 \in L^r_{loc}(\Omega), \text{ for every } r \geq q$$

Local Sobolev estimate (B.-Carlier-Santambrogio)

Let $q \geq 2$ and $f \in W^{1,p}(\Omega)$ with zero-mean. If $\varphi_0 \in W^{1,q}(\Omega)$ is a weak solution of (BVP) then

$$\left(|\partial_{x_j} \varphi_0| - 1 \right)_+^{\frac{q}{2}} \frac{\partial_{x_j} \varphi_0}{|\partial_{x_j} \varphi_0|} \in W^{1,2}_{loc}(\Omega), \quad j = 1, \dots, N$$

Corollary (Regularity of Beckmann's optimizer)

$$\Phi_0 = \nabla \mathcal{H}^*(\nabla \varphi_0) \in W^{1,s}(\Omega; \mathbb{R}^N) \cap L^r(\Omega; \mathbb{R}^N)$$

for every $s < 2$ and every $r \geq q$

A sketch of the proof: higher integrability of the gradient

First of all, we try a quick review of the standard theory

- ▶ **First step:** equation for the gradient

$$\operatorname{div} (D^2 \mathcal{H}^*(\nabla \varphi_0) \nabla \partial_{x_j} \varphi_0) = \partial_{x_j} f$$

this is linear and degenerate elliptic

- ▶ **usually**, convex increasing functions $g(|\nabla \varphi_0|)$ (ex. power functions) are subsolutions and this would suffice to produce an **iterative scheme of reverse Hölder inequalities**
- ▶ **how does it work?:**

A sketch of the proof: higher integrability of the gradient

First of all, we try a quick review of the standard theory

- ▶ **First step:** equation for the gradient

$$\operatorname{div} (D^2 \mathcal{H}^*(\nabla \varphi_0) \nabla \partial_{x_j} \varphi_0) = \partial_{x_j} f$$

this is linear and degenerate elliptic

- ▶ **usually**, convex increasing functions $g(|\nabla \varphi_0|)$ (ex. power functions) are subsolutions and this would suffice to produce an **iterative scheme of reverse Hölder inequalities**
- ▶ **how does it work?**: suppose that

$$c |z|^{q-2} \operatorname{Id} \leq D^2 \mathcal{H}^*(z) \leq C |z|^{q-2} \operatorname{Id} \quad \text{for } M \leq |z|$$

then use test functions like $(|\nabla \varphi_0|^k - (2M)^k)_+$ and get the **unnatural inequality** (Caccioppoli)

$$\int_{B_\varrho} \left| \nabla \left(|\nabla \varphi_0|^{\beta_k} \right) \right|^2 \lesssim (R - \varrho)^{-2} \int_{B_R} \left(|\nabla \varphi_0|^{\beta_k} \right)^2$$

- ▶ combining with Sobolev inequality, we get the reverse Hölder inequalities

$$\|\nabla\varphi_0\|_{L^{2^*\beta_k}(B_\varrho)} \lesssim (R - \varrho)^{-\frac{1}{2^*\beta_k}} \|\nabla\varphi_0\|_{L^{2\beta_k}(B_R)}$$

- ▶ iterating, we get $\nabla\varphi_0 \in L^\infty$

...and for our \mathcal{H}^* ?

- ▶ combining with Sobolev inequality, we get the reverse Hölder inequalities

$$\|\nabla\varphi_0\|_{L^{2^*\beta_k}(B_\varrho)} \lesssim (R - \varrho)^{-\frac{1}{2^*\beta_k}} \|\nabla\varphi_0\|_{L^{2\beta_k}(B_R)}$$

- ▶ iterating, we get $\nabla\varphi_0 \in L^\infty$

...and for our \mathcal{H}^* ?

Problems

- ▶ this is **not uniformly convex**, neither globally nor “at infinity”
- ▶ ellipticity fails each time **a component** of $\nabla\varphi$ is small
- ▶ $D^2\mathcal{H}^*$ has a diagonal structure, with

$$h_i''(\partial_{x_j}\varphi_0) \simeq |\partial_{x_j}\varphi_0|^{q-2} \quad \text{on the diagonal}$$

imitating the previous proof and choosing test functions that “try to mimick the Hessian”, ex. $|\partial_{x_j}\varphi|^k$, we end up with...

- ▶ ...partial derivatives are mixed! i.e. **surrogate of Caccioppoli inequality**

$$\sum_{i=1}^N \int h_i''(\partial_{x_i} \varphi_0) \left| \partial_{x_i} (\partial_{x_j} \varphi_0)^{\beta+1} \right|^2 \lesssim \int |\nabla \varphi_0|^{q+2\beta}$$

- ▶ ...partial derivatives are mixed! i.e. **surrogate of Caccioppoli inequality**

$$\sum_{i=1}^N \int h_i''(\partial_{x_i} \varphi_0) \left| \partial_{x_i} (\partial_{x_j} \varphi_0)^{\beta+1} \right|^2 \lesssim \int |\nabla \varphi_0|^{q+2\beta}$$

- ▶ key point: a **surrogate of Sobolev inequality** for the LHS, something of the type

$$\sum_{i=1}^N \int h_i''(\partial_{x_i} \varphi_0) |\partial_{x_i} \varphi_0|^2 |\partial_{x_j} \varphi_0|^\alpha \leq \sum_{i=1}^N \int h_i''(\partial_{x_i} \varphi_0) \left| \partial_{x_i} (\partial_{x_j} \varphi_0)^{\beta+1} \right|^2 + (\text{lower order terms})$$

with $\alpha > 2\beta$

- ▶ ...partial derivatives are mixed! i.e. **surrogate of Caccioppoli inequality**

$$\sum_{i=1}^N \int h_i''(\partial_{x_i} \varphi_0) \left| \partial_{x_i} (\partial_{x_j} \varphi_0)^{\beta+1} \right|^2 \lesssim \int |\nabla \varphi_0|^{q+2\beta}$$

- ▶ key point: a **surrogate of Sobolev inequality** for the LHS, something of the type

$$\sum_{i=1}^N \int h_i''(\partial_{x_i} \varphi_0) |\partial_{x_i} \varphi_0|^2 |\partial_{x_j} \varphi_0|^\alpha \leq \sum_{i=1}^N \int h_i''(\partial_{x_i} \varphi_0) \left| \partial_{x_i} (\partial_{x_j} \varphi_0)^{\beta+1} \right|^2 + (\text{lower order terms})$$

with $\alpha > 2\beta$

- ▶ **Di Benedetto's trick**: the latter is obtained by inserting the test function $\varphi_0 |\nabla \varphi_0|^\alpha \xi^2$ in the equation (**not** in the derived equation) — for this we need to know that $\varphi_0 \in L^\infty$ (easy)

A sketch of the proof: Sobolev estimate

- ▶ **first of all:** in general $\varphi_0 \notin W^{2,q}$
- ▶ we use Nirenberg's method (i.e. the method of incremental ratios), to differentiate the equation in a discrete sense...
- ▶ ...and the monotonicity and growth properties of $\nabla\mathcal{H}^*$, i.e.

$$\langle \nabla\mathcal{H}^*(z) - \nabla\mathcal{H}^*(w), z - w \rangle \gtrsim |G(z) - G(w)|^2$$

where

$$G(z) = \sum_{i=1}^N (|z_i| - 1)_+^{\frac{q}{2}} \frac{z_i}{|z_i|} \mathbf{e}_i$$

- ▶ finally, observe that $\Phi_0 = f(G)$, with f locally Lipschitz

Regularity estimates for (\mathcal{W})

Hypothesis

Let $\rho_0, \rho_1 \in \mathcal{P}(\Omega)$ be such that $\rho_i = f_i \cdot \mathcal{L}^N$ with $f_i \in L^\infty$

Using the equivalence $(\mathcal{W}) = (\mathcal{B})$, we get:

- ▶ the optimal i_Q is in L^r_{loc} for every $r \geq p$

Regularity estimates for (\mathcal{W})

Hypothesis

Let $\rho_0, \rho_1 \in \mathcal{P}(\Omega)$ be such that $\rho_i = f_i \cdot \mathcal{L}^N$ with $f_i \in L^\infty$

Using the equivalence $(\mathcal{W}) = (\mathcal{B})$, we get:

- ▶ the optimal i_Q is in L^r_{loc} for every $r \geq p$
- ▶ $\nabla \mathcal{H}(i_Q)$ is more integrable \implies we can extend the range of p for which Wardrop equilibria are well-defined

Regularity estimates for (\mathcal{W})

Hypothesis

Let $\rho_0, \rho_1 \in \mathcal{P}(\Omega)$ be such that $\rho_i = f_i \cdot \mathcal{L}^N$ with $f_i \in L^\infty$

Using the equivalence $(\mathcal{W}) = (\mathcal{B})$, we get:

- ▶ the optimal i_Q is in L^r_{loc} for every $r \geq p$
- ▶ $\nabla \mathcal{H}(i_Q)$ is more integrable \implies we can extend the range of p for which Wardrop equilibriums are well-defined, i.e. we can pass from $p < N/(N-1)$ to $p \leq 2$

Regularity estimates for (\mathcal{W})

Hypothesis

Let $\rho_0, \rho_1 \in \mathcal{P}(\Omega)$ be such that $\rho_i = f_i \cdot \mathcal{L}^N$ with $f_i \in L^\infty$

Using the equivalence $(\mathcal{W}) = (\mathcal{B})$, we get:

- ▶ the optimal i_Q is in L^r_{loc} for every $r \geq p$
- ▶ $\nabla \mathcal{H}(i_Q)$ is more integrable \implies we can extend the range of p for which Wardrop equilibriums are well-defined, i.e. we can pass from $p < N/(N-1)$ to $p \leq 2$
- ▶ if ρ_0 and ρ_1 are bounded from below by δ , we can estimate

$$\int \text{length}(\sigma)^s dQ(\sigma) \leq C_{s,\delta} \quad \text{for every } s \geq 1$$

i.e. “optimal routes have almost uniformly bounded lengths”

Thanks for your attention

“Discipline is never an end in itself, only a means to an end”

Further readings

Discrete and continuous models

- ▶ J. G. Wardrop, *Proc. Inst. Civ. Eng.*, **2** (1952)
- ▶ M. J. Beckmann, *Econometrica*, **20** (1952)
- ▶ G. Carlier, C. Jimenez, F. Santambrogio, *SIAM J. Control Opt.* **47** (2008)

A pioneering paper on anisotropic equations

- ▶ N. Uralt'seva, N. Urdaletova, *Vest. Leningr. Univ. Math.*, **16** (1984)

The isotropic case

- ▶ L. B., *Nonlinear Anal.*, **74** (2011)
- ▶ L. B., G. Carlier, F. Santambrogio, *J. Math. Pures Appl.*, **93** (2010)