

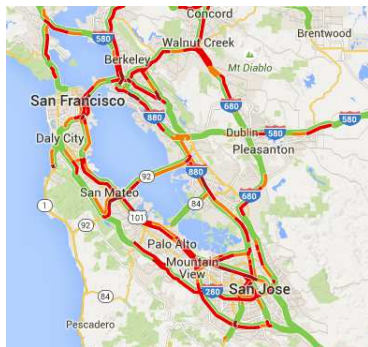
Traffic Flow Modeling on Road Networks Using Hamilton-Jacobi Equations

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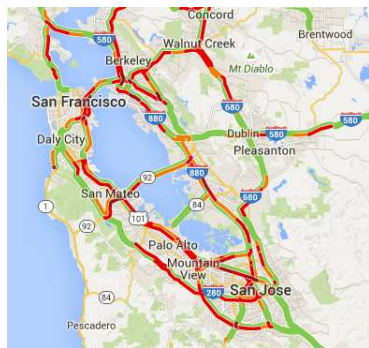
ITS seminar, UC Berkeley
October 09, 2015

Traffic flows on a network

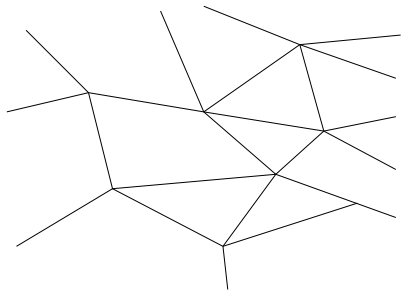


[Caltrans, Oct. 7, 2015]

Traffic flows on a network



[Caltrans, Oct. 7, 2015]



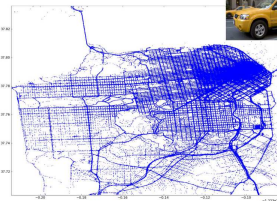
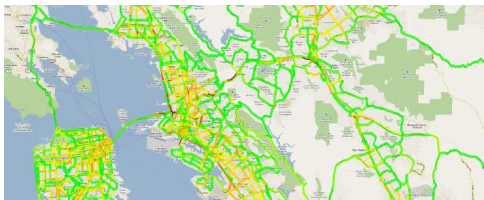
Road network \equiv graph made of edges and vertices

Breakthrough in traffic monitoring

Traffic monitoring

- “old”: **loop detectors** at **fixed** locations (Eulerian)
- “new”: **GPS** devices **moving** within the traffic (Lagrangian)

Data assimilation of Floating Car Data



[Mobile Millenium, 2008]

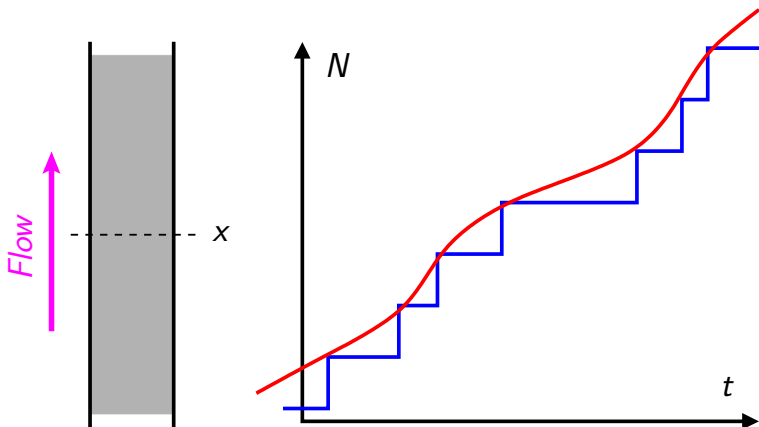
Outline

- 1 Introduction to traffic
- 2 Micro to macro in traffic models
- 3 Variational principle applied to GSOM models
- 4 HJ equations on a junction
- 5 Conclusions and perspectives

Outline

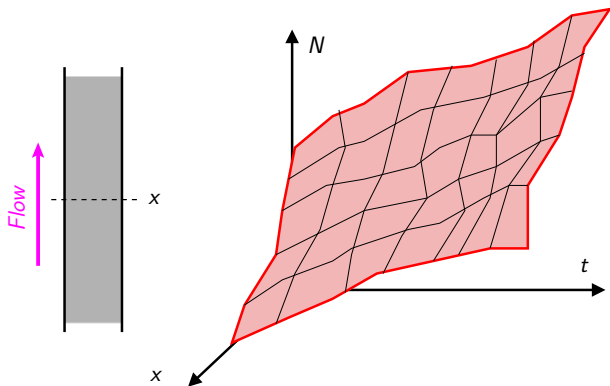
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Convention for vehicle labeling



Three representations of traffic flow

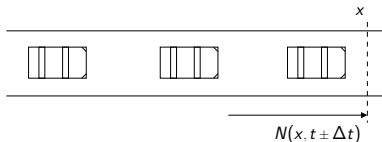
Moskowitz' surface



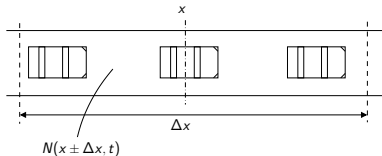
See also [Makigami et al, 1971], [Laval and Leclercq, 2013]

Notations: macroscopic

- $N(t, x)$ vehicle **label** at (t, x)
- the **flow** $Q(t, x) = \lim_{\Delta t \rightarrow 0} \frac{N(t + \Delta t, x) - N(t, x)}{\Delta t}$,



- the **density** $\rho(t, x) = \lim_{\Delta x \rightarrow 0} \frac{N(t, x) - N(t, x + \Delta x)}{\Delta x}$,

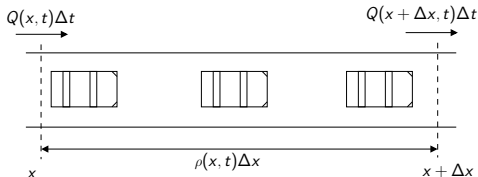


- the stream **speed** (mean spatial speed) $V(t, x)$.

Macroscopic models

- **Hydrodynamics** analogy
- Two main categories: first and second order models
- Two common equations:

$$\begin{cases} \partial_t \rho(t, x) + \partial_x Q(t, x) = 0 & \text{conservation equation} \\ Q(t, x) = \rho(t, x) V(t, x) & \text{definition of flow speed} \end{cases} \quad (1)$$



First order: the LWR model

LWR model [Lighthill and Whitham, 1955], [Richards, 1956]

Scalar one dimensional **conservation law**

$$\partial_t \rho(t, x) + \partial_x \mathfrak{F}(\rho(t, x)) = 0 \quad (2)$$

with

$$\mathfrak{F} : \rho(t, x) \mapsto Q(t, x) =: \mathfrak{F}_x(\rho(t, x))$$

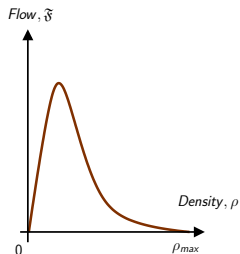
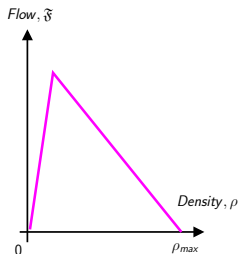
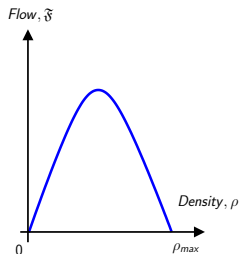
Overview: conservation laws (CL) / Hamilton-Jacobi (HJ)

		Eulerian $t - x$	Lagrangian $t - n$
CL	Variable	Density ρ	Spacing r
	Equation	$\partial_t \rho + \partial_x \mathfrak{F}(\rho) = 0$	$\partial_t r + \partial_n V(r) = 0$
HJ	Variable	Label N $N(t, x) = \int_x^{+\infty} \rho(t, \xi) d\xi$	Position \mathcal{X} $\mathcal{X}(t, n) = \int_n^{+\infty} r(t, \eta) d\eta$
	Equation	$\partial_t N + H(\partial_x N) = 0$	$\partial_t \mathcal{X} + \mathcal{V}(\partial_n \mathcal{X}) = 0$
	Hamiltonian	$H(p) = -\mathfrak{F}(-p)$	$\mathcal{V}(p) = -V(-p)$

Fundamental diagram (FD)

Flow-density fundamental diagram \mathfrak{F}

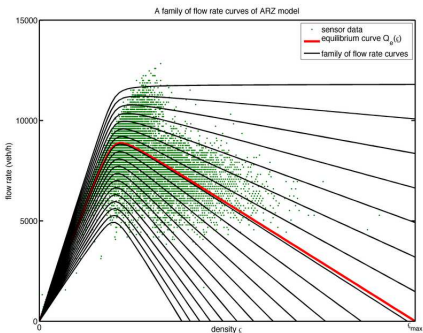
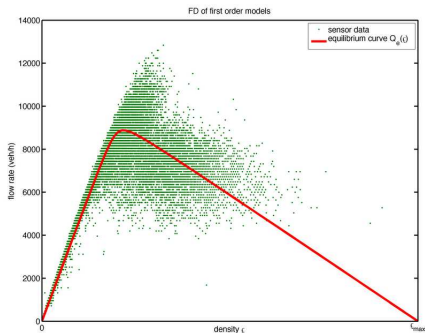
- Empirical function with
 - ρ_{max} the maximal or jam density,
 - ρ_c the critical density
- Flux is increasing for $\rho \leq \rho_c$: **free-flow** phase
- Flux is decreasing for $\rho \geq \rho_c$: **congestion** phase



[Garavello and Piccoli, 2006]

Motivation for higher order models

- Experimental evidences
 - fundamental diagram: **multi-valued** in congested case



[S. Fan, U. Illinois], NGSIM dataset

Motivation for higher order models

- **Experimental** evidences
 - fundamental diagram: **multi-valued** in congested case
 - phenomena not accounted for: bounded acceleration, capacity drop...
- Need for models able to **integrate** measurements of **different traffic quantities** (acceleration, fuel consumption, noise)

GSOM family [Lebacque, Mammari, Haj-Salem 2007]

- Generic Second Order Models (GSOM) family

$$\begin{cases} \partial_t \rho + \partial_x(\rho v) = 0 \\ \partial_t(\rho l) + \partial_x(\rho v l) = \rho \varphi(l) \\ v = \mathfrak{I}(\rho, l) \end{cases} \quad \begin{array}{l} \text{Conservation of vehicles,} \\ \text{Dynamics of the driver attribute } l, \\ \text{Fundamental diagram,} \end{array} \quad (3)$$

- Specific driver attribute l
 - the driver aggressiveness,
 - the driver origin/destination or path,
 - the vehicle class,
 - ...
- Flow-density fundamental diagram

$$\mathfrak{I} : (\rho, l) \mapsto \rho \mathfrak{I}(\rho, l).$$

GSOM family [Lebacque, Mammari, Haj-Salem 2007]

- Generic Second Order Models (GSOM) family

$$\begin{cases} \partial_t \rho + \partial_x(\rho v) = 0 & \text{Conservation of vehicles,} \\ \partial_t I + v \partial_x I = \varphi(I) & \text{Dynamics of the driver attribute } I, \\ v = \mathfrak{J}(\rho, I) & \text{Fundamental diagram,} \end{cases} \quad (3)$$

- Specific driver attribute I
 - the driver aggressiveness,
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 - ...
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GSOM family [Lebacque, Mammari, Haj-Salem 2007]

- Generic Second Order Models (GSOM) family

$$\begin{cases} \partial_t \rho + \partial_x(\rho v) = 0 & \text{Conservation of vehicles,} \\ \partial_t l + v \partial_x l = 0 & \text{Dynamics of the driver attribute } l, \\ v = \mathfrak{F}(\rho, l) & \text{Fundamental diagram,} \end{cases} \quad (3)$$

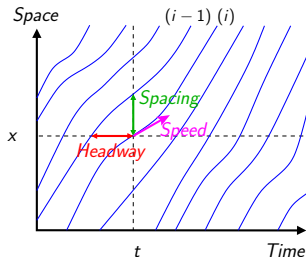
- Specific driver attribute l
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 - ...
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$$\mathfrak{F} : (\rho, l) \mapsto \rho \mathfrak{F}(\rho, l).$$

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Setting

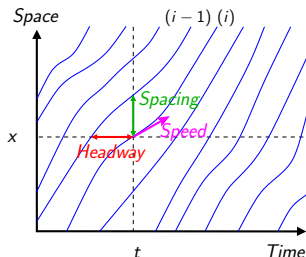


- $t \mapsto x_i(t)$ trajectory of vehicle i
- $i =$ **discrete** position index ($i \in \mathbb{Z}$)
- $n =$ continuous (Lagrangian) variable

$$n = i\varepsilon \quad \text{and} \quad t = \varepsilon s$$

- $\varepsilon > 0$ a **scale factor**

Setting



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- $\varepsilon > 0$ a **scale factor**

Proposition (Rescaled positions)

Define

$$x_i(s) = \frac{1}{\varepsilon} X^\varepsilon(\varepsilon s, i\varepsilon) \iff X^\varepsilon(t, n) = \varepsilon x_{\lfloor \frac{n}{\varepsilon} \rfloor} \left(\frac{t}{\varepsilon} \right)$$

General result

Let consider

- the simplest **microscopic** model;

$$\dot{x}_i(t) = F(x_{i-1}(t) - x_i(t)) \quad (4)$$

- the LWR **macroscopic** model (HJ equation in Lagrangian):

$$\partial_t X^0 = F(-\partial_n X^0) \quad (5)$$

General result

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- the LWR **macroscopic** model (HJ equation in Lagrangian):

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Theorem ((Monneau) Convergence to the viscosity solution)

If $X^\varepsilon(t, n) := \varepsilon x_{\lfloor \frac{n}{\varepsilon} \rfloor} \left(\frac{t}{\varepsilon} \right)$ with $(x_i)_{i \in \mathbb{Z}}$ solution of (4) and X^0 the unique solution of HJ (5), then under suitable assumptions,

$$|X^\varepsilon - X^0|_{L^\infty(\mathcal{K})} \xrightarrow{\varepsilon \rightarrow 0} 0, \quad \forall \mathcal{K} \text{ compact set.}$$

Toy model

- Vehicles consider $m \geq 1$ leaders
- First order **multi-anticipative** model

$$\dot{x}_i(t + \tau) = \max \left[0, V_{max} - \sum_{j=1}^m f(x_{i-j}(t) - x_i(t)) \right] \quad (6)$$

- f speed-spacing function
 - non-negative
 - non-increasing

Homogenization

Proposition ((Monneau) Convergence)

Assume $m \geq 1$ fixed.

If τ is small enough, if $X^\varepsilon(t, n) := \varepsilon X_{\lfloor \frac{n}{\varepsilon} \rfloor} \left(\frac{t}{\varepsilon} \right)$ with $(x_i)_{i \in \mathbb{Z}}$ solution of (6) and if $X^0(n, t)$ solves

$$\partial_t X^0 = F(-\partial_n X^0, m) \quad (7)$$

with

$$F(r, m) = \max \left[0, V_{\max} - \sum_{j=1}^m f(jr) \right],$$

then under suitable assumptions,

$$|X^\varepsilon - X^0|_{L^\infty(\mathcal{K})} \xrightarrow{\varepsilon \rightarrow 0} 0, \quad \forall \mathcal{K} \text{ compact set.}$$

Multi-anticipatory macroscopic model

- χ_j the fraction of j -anticipatory vehicles
- traffic flow \equiv mixture of traffic of j -anticipatory vehicles

$$\chi = (\chi_j)_{j=1,\dots,m}, \quad \text{with } 0 \leq \chi_j \leq 1 \quad \text{and} \quad \sum_{j=1}^m \chi_j = 1$$

- GSOM model with driver attribute $l = \chi$

$$\begin{cases} \partial_t \rho + \partial_x (\rho v) = 0, \\ \partial_t (\rho \chi) + \partial_x (\rho \chi v) = 0, \\ v := \sum_{j=1}^m \chi_j F(1/\rho, j) = W(1/\rho, \chi). \end{cases} \quad (8)$$

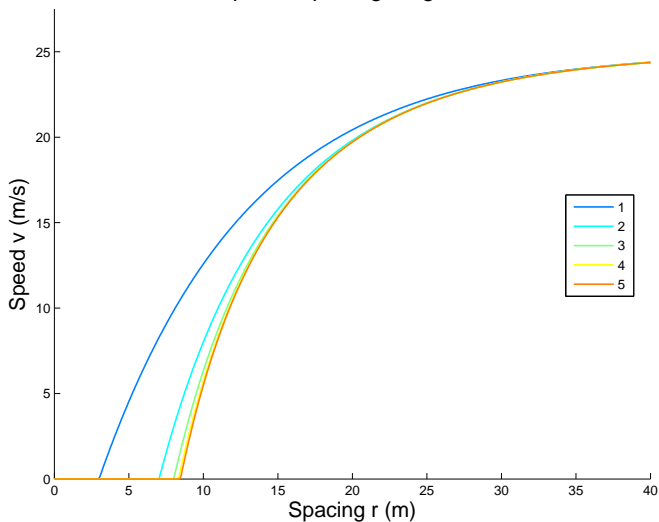
Numerical resolution

- **Godunov scheme** in Eulerian $t - x$
with $(\Delta t, \Delta x_k)$ steps \Rightarrow **CFL condition**
- **Variational formulation** and dynamic programming techniques [2]
- **Particle methods** in the Lagrangian framework $t - n$

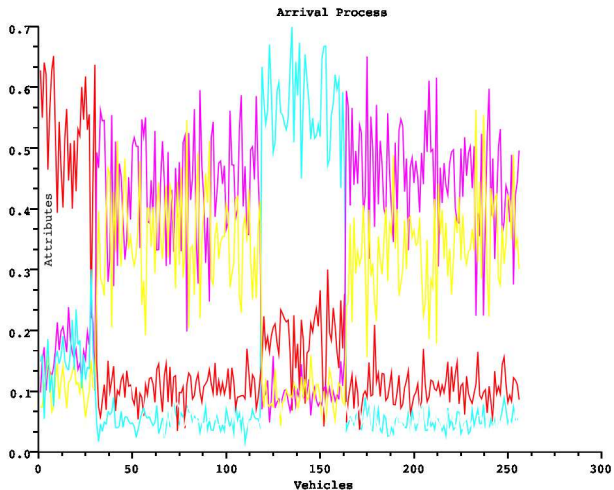
$$\begin{cases} x_n^{t+1} = x_n^t + \Delta t W \left(\frac{x_{n-1}^t - x_n^t}{\Delta n}, \chi_n^t \right) \\ \chi_n^{t+1} = \chi_n^t \end{cases} \quad (9)$$

Numerical example

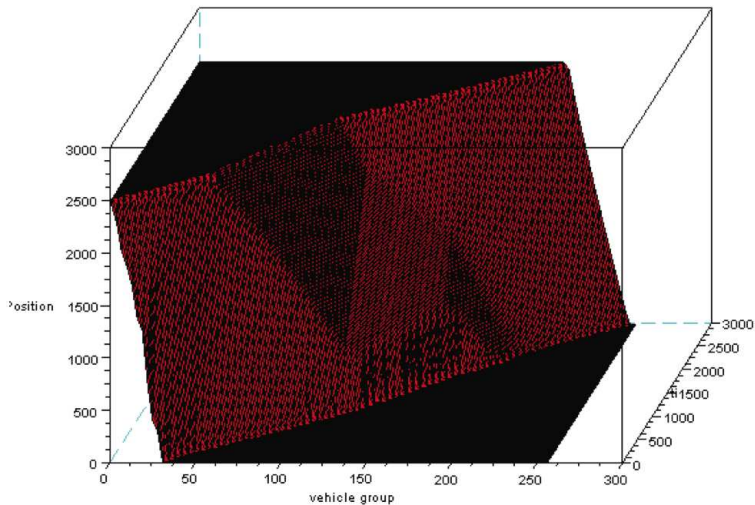
Speed–spacing diagrams



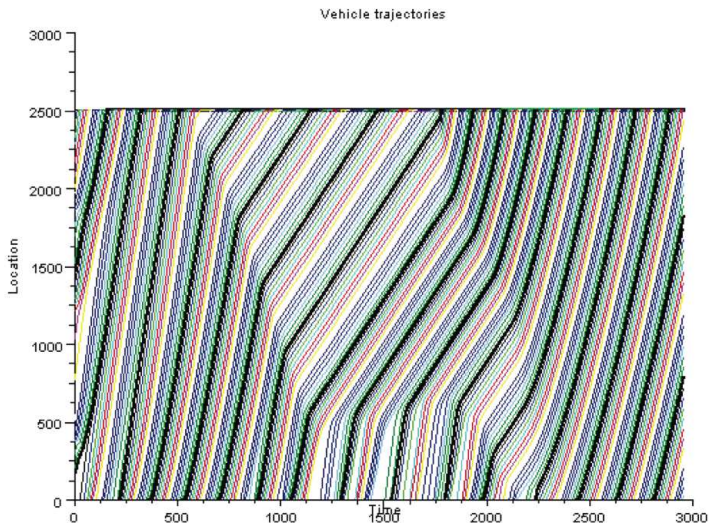
Numerical example: $(\chi_j)_j$



Numerical example: Lagrangian trajectories



Numerical example: Eulerian trajectories



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LWR in Eulerian (t, x)

- Cumulative vehicles count (CVC) or Moskowitz surface $N(t, x)$

$$Q = \partial_t N \quad \text{and} \quad \rho = -\partial_x N$$

- If density ρ satisfies the scalar (LWR) conservation law

$$\partial_t \rho + \partial_x \mathfrak{F}(\rho) = 0$$

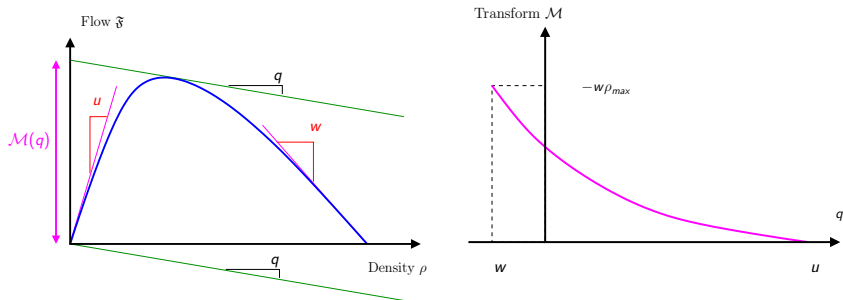
- Then N satisfies the first order Hamilton-Jacobi equation

$$\partial_t N - \mathfrak{F}(-\partial_x N) = 0 \tag{10}$$

LWR in Eulerian (t, x)

- Legendre-Fenchel transform with \mathfrak{F} **concave** (*relative capacity*)

$$\mathcal{M}(q) = \sup_{\rho} [\mathfrak{F}(\rho) - \rho q]$$



LWR in Eulerian (t, x)

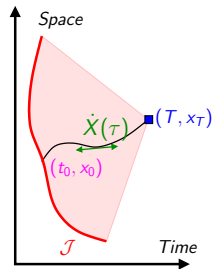
(continued)

- **Lax-Hopf formula** (representation formula) [Daganzo, 2006]

$$N(T, x_T) = \min_{u(\cdot), (t_0, x_0)} \int_{t_0}^T \mathcal{M}(u(\tau)) d\tau + N(t_0, x_0),$$

$$\left\{ \begin{array}{l} \dot{X} = u \\ u \in \mathcal{U} \\ X(t_0) = x_0, \quad X(T) = x_T \\ (t_0, x_0) \in \mathcal{J} \end{array} \right.$$

(11)

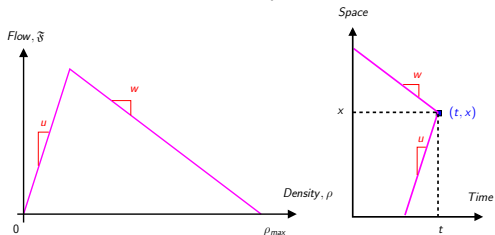


- **Viability theory** [Claudel and Bayen, 2010]

LWR in Eulerian (t, x)

(Historical note)

- **Dynamic programming** [Daganzo, 2006] for **triangular FD** (u and w free and congested speeds)



- Minimum principle [Newell, 1993]

$$N(t, x) = \min \left[N \left(t - \frac{x - x_u}{u}, x_u \right), \right. \\ \left. N \left(t - \frac{x - x_w}{w}, x_w \right) + \rho_{max}(x_w - x) \right], \quad (12)$$

LWR in Lagrangian (n, t)

- Consider $X(t, n)$ the location of vehicle n at time $t \geq 0$

$$v = \partial_t X \quad \text{and} \quad r = -\partial_n X$$

- If the spacing $r := 1/\rho$ satisfies the LWR model (Lagrangian coord.)

$$\partial_t r + \partial_n \mathcal{V}(r) = 0$$

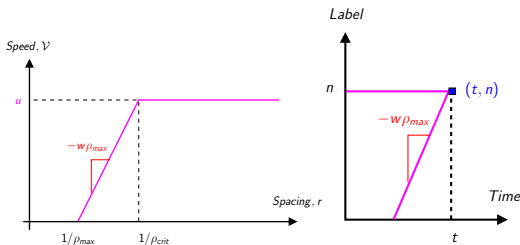
- Then X satisfies the first order Hamilton-Jacobi equation

$$\partial_t X - \mathcal{V}(-\partial_n X) = 0. \tag{13}$$

LWR in Lagrangian (n, t)

(continued)

- Dynamic programming for triangular FD



- Minimum principle \Rightarrow car following model [Newell, 2002]

$$X(t, n) = \min \left[X(t_0, n) + u(t - t_0), \right. \\ \left. X(t_0, n + w\rho_{max}(t - t_0)) + w(t - t_0) \right]. \quad (14)$$

GSOM in Lagrangian (n, t)

- From [Lebacque and Khoshyaran, 2013], GSOM in Lagrangian

$$\begin{cases} \partial_t r + \partial_N v = 0 & \text{Conservation of vehicles,} \\ \partial_t I = 0 & \text{Dynamics of } I, \\ v = \mathcal{W}(N, r, t) := \mathcal{V}(r, I(N, t)) & \text{Fundamental diagram.} \end{cases} \quad (15)$$

- Position $\mathcal{X}(N, t) := \int_{-\infty}^t v(N, \tau) d\tau$ satisfies the **HJ equation**

$$\partial_t \mathcal{X} - \mathcal{W}(N, -\partial_N \mathcal{X}, t) = 0, \quad (16)$$

- And $I(N, t)$ solves the **ODE**

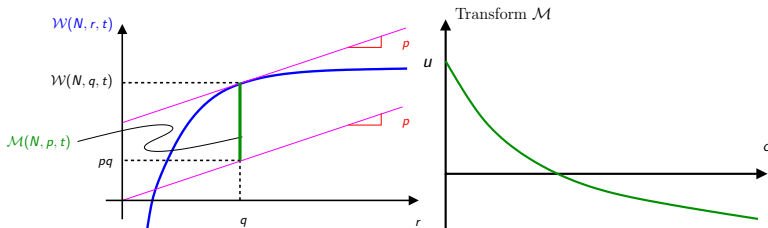
$$\begin{cases} \partial_t I(N, t) = 0, \\ I(N, 0) = i_0(N), \end{cases} \quad \text{for any } N.$$

GSOM in Lagrangian (n, t)

(continued)

- Legendre-Fenchel transform of \mathcal{W} according to r

$$\mathcal{M}(N, c, t) = \sup_{r \in \mathbb{R}} \{ \mathcal{W}(N, r, t) - cr \}$$



GSOM in Lagrangian (n, t)

(continued)

- **Lax-Hopf** formula

$$\mathcal{X}(N_T, T) = \min_{u(\cdot), (N_0, t_0)} \int_{t_0}^T \mathcal{M}(N, u, t) dt + \mathbf{c}(N_0, t_0),$$

$$\left| \begin{array}{l} \dot{N} = u \\ u \in \mathcal{U} \\ N(t_0) = N_0, \quad N(T) = N_T \\ (N_0, t_0) \in \mathcal{K} \end{array} \right. \quad (17)$$

GSOM in Lagrangian (n, t)

(continued)

- Optimal trajectories = **characteristics**

$$\begin{cases} \dot{N} = \partial_r \mathcal{W}(N, r, t), \\ \dot{r} = -\partial_N \mathcal{W}(N, r, t), \end{cases} \quad (18)$$

- System of ODEs to solve
- Difficulty: **not straight lines** in the general case

General ideas

First key element: **Lax-Hopf formula**

- Computations only for the **characteristics**

$$\mathcal{X}(N_T, T) = \min_{(N_0, r_0, t_0)} \int_{t_0}^T \mathcal{M}(N, \partial_r \mathcal{W}(N, r, t), t) dt + \mathbf{c}(N_0, r_0, t_0),$$

$$\left| \begin{array}{l} \dot{N}(t) = \partial_r \mathcal{W}(N, r, t) \\ \dot{r}(t) = -\partial_N \mathcal{W}(N, r, t) \\ N(t_0) = N_0, \quad r(t_0) = r_0, \quad N(T) = N_T \\ (N_0, r_0, t_0) \in \mathcal{K} \end{array} \right.$$
(19)

- $\mathcal{K} := \text{Dom}(\mathbf{c})$ is the set of initial/boundary values

General ideas

(continued)

Second key element: **inf-morphism** prop. [Aubin et al, 2011]

- Consider a union of sets (initial and boundary conditions)

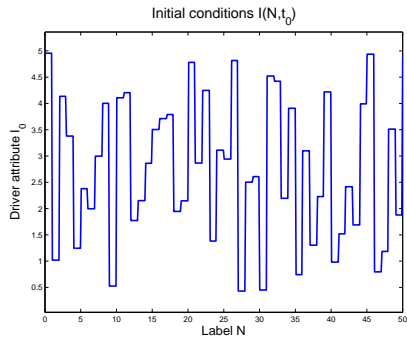
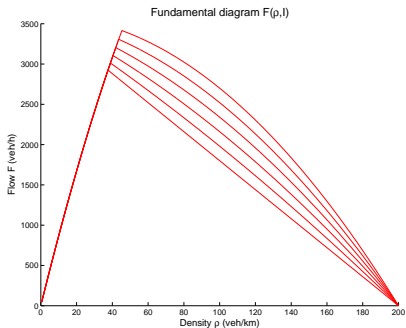
$$\mathcal{K} = \bigcup_I \mathcal{K}_I,$$

- then the global minimum is

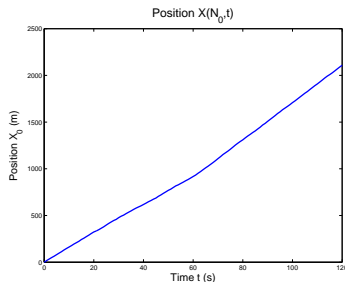
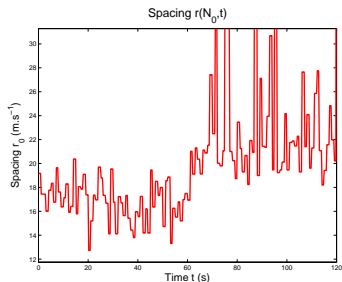
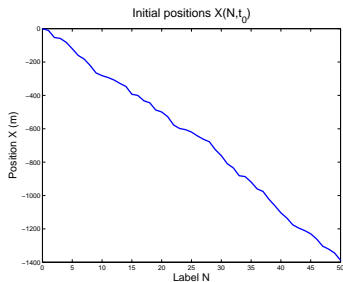
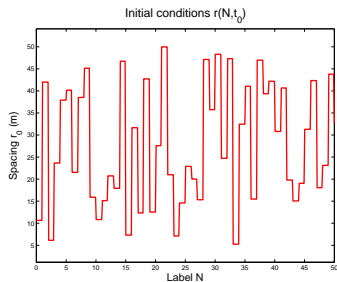
$$\mathcal{X}(N_T, T) = \min_I \mathcal{X}_I(N_T, T), \quad (20)$$

- with \mathcal{X}_I **partial solution** to sub-problem \mathcal{K}_I .

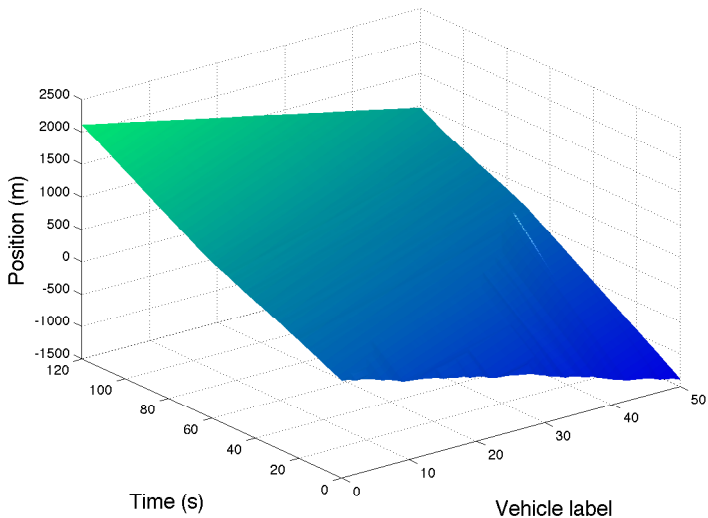
Fundamental Diagram and Driver Attribute



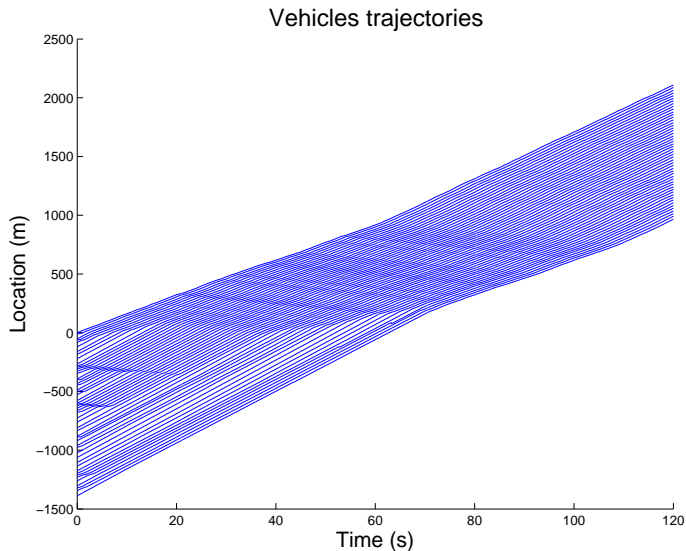
Initial and Boundaries Conditions



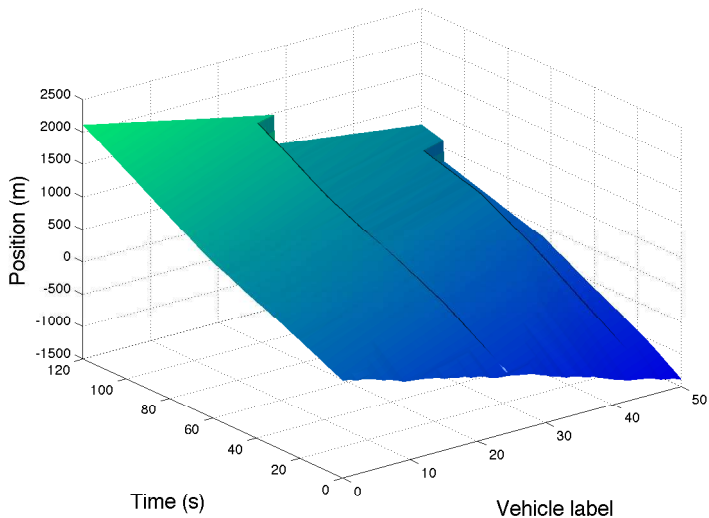
Numerical result (Initial cond. + first traj.)



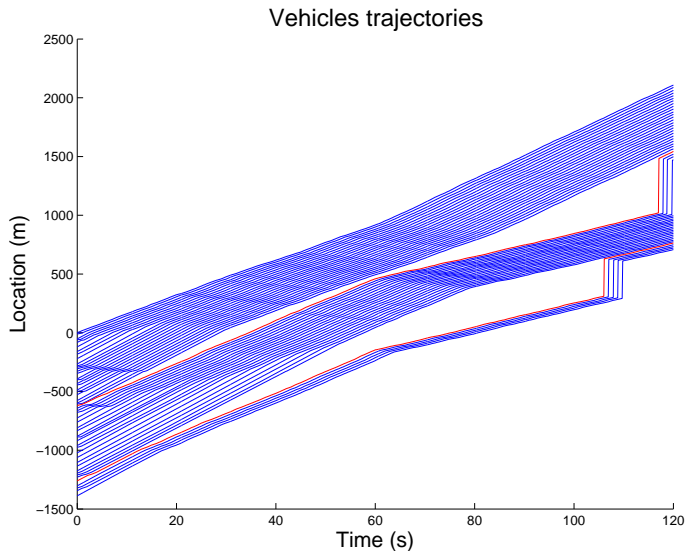
Numerical result (Initial cond. + first traj.)



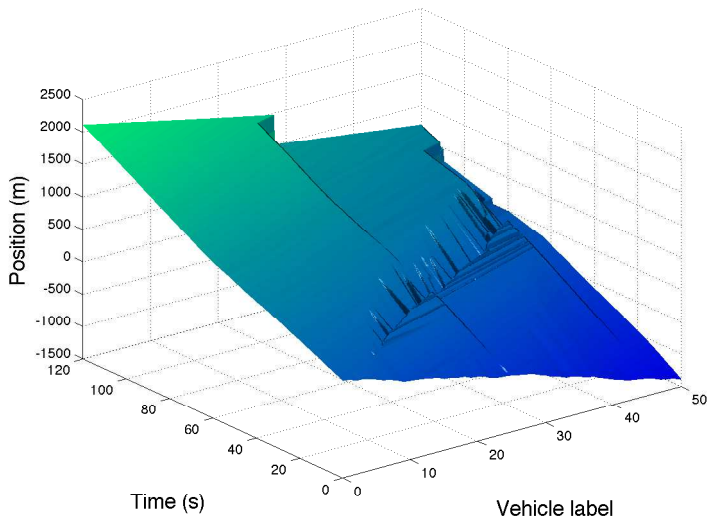
Numerical result (Initial cond.+ 3 traj.)



Numerical result (Initial cond. + 3 traj.)



Numerical result (Initial cond. + 3 traj. + Eulerian data)



Outline

- 1 Introduction to traffic
- 2 Micro to macro in traffic models
- 3 Variational principle applied to GSOM models
- 4 HJ equations on a junction**
- 5 Conclusions and perspectives

Motivation

Classical approaches:

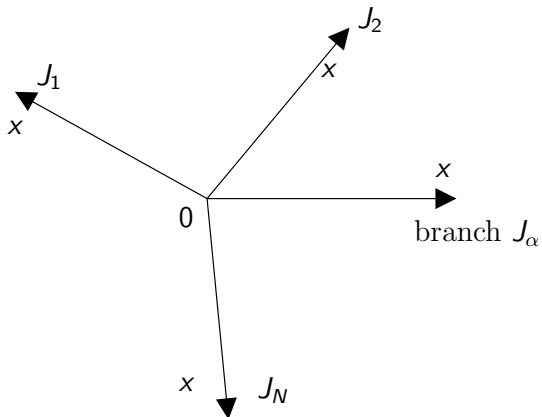
- Macroscopic modeling on (homogeneous) **sections**
- **Coupling conditions** at (pointwise) **junction**

For instance, consider

$$\left\{ \begin{array}{l} \partial_t \rho + \partial_x Q(\rho) = 0, \\ \rho(\cdot, t = 0) = \rho_0(\cdot), \\ \underbrace{\psi(\rho(x = 0^-, t))}_{\text{upstream}}, \underbrace{\rho(x = 0^+, t)}_{\text{downstream}} = 0, \end{array} \right. \quad \begin{array}{l} \text{scalar conservation law,} \\ \text{initial conditions,} \\ \text{coupling condition.} \end{array} \quad (21)$$

See Garavello, Piccoli [3], Lebacque, Khoshyaran [6] and Bressan et al. [1]

Star-shaped junction



Junction model

Proposition (Junction model [IMZ, '13])

That leads to the following junction model (see [5])

$$\begin{cases} \partial_t u^\alpha + H_\alpha(\partial_x u^\alpha) = 0, & x > 0, \alpha = 1, \dots, N \\ u^\alpha = u^\beta =: u, & x = 0, \\ \partial_t u + \mathcal{H}(\partial_x u^1, \dots, \partial_x u^N) = 0, & x = 0 \end{cases} \quad (22)$$

with initial condition $u^\alpha(0, x) = u_0^\alpha(x)$ and

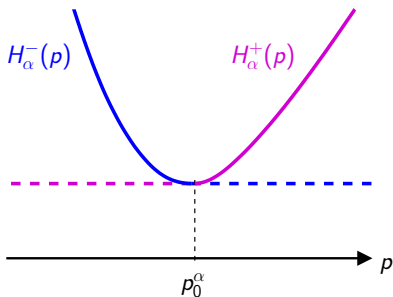
$$\mathcal{H}(\partial_x u^1, \dots, \partial_x u^N) = \underbrace{\max_{\alpha=1, \dots, N} \{H_\alpha^-(\partial_x u^\alpha)\}}_{\text{from optimal control}}.$$

Basic assumptions

For all $\alpha = 1, \dots, N$,

(A0) The initial condition u_0^α is Lipschitz continuous.

(A1) The Hamiltonians H_α are $C^1(\mathbb{R})$ and convex such that:



Presentation of the scheme

Proposition (Numerical Scheme)

Let us consider the discrete space and time derivatives:

$$p_i^{\alpha,n} := \frac{U_{i+1}^{\alpha,n} - U_i^{\alpha,n}}{\Delta x} \quad \text{and} \quad (D_t U)_i^{\alpha,n} := \frac{U_i^{\alpha,n+1} - U_i^{\alpha,n}}{\Delta t}$$

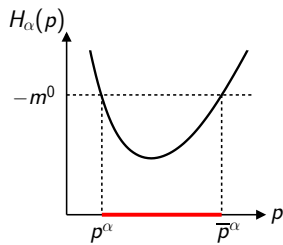
Then we have the following numerical scheme:

$$\begin{cases} (D_t U)_i^{\alpha,n} + \max\{H_\alpha^+(p_{i-1}^{\alpha,n}), H_\alpha^-(p_i^{\alpha,n})\} = 0, & i \geq 1 \\ U_0^n := U_0^{\alpha,n}, & i = 0, \quad \alpha = 1, \dots, N \\ (D_t U)_0^n + \max_{\alpha=1, \dots, N} H_\alpha^-(p_0^{\alpha,n}) = 0, & i = 0 \end{cases} \quad (23)$$

With the initial condition $U_i^{\alpha,0} := u_0^\alpha(i\Delta x)$.

Δx and $\Delta t =$ **space and time steps** satisfying a **CFL condition**

Stronger CFL condition



As for any $\alpha = 1, \dots, N$, we have
(gradient estimates)

$$\underline{p}_\alpha \leq p_i^{\alpha, n} \leq \bar{p}_\alpha \quad \text{for all } i, n \geq 0$$

Then the CFL condition becomes:

$$\frac{\Delta x}{\Delta t} \geq \sup_{\substack{\alpha=1, \dots, N \\ p_\alpha \in [\underline{p}_\alpha, \bar{p}_\alpha]}} |H'_\alpha(p_\alpha)| \quad (24)$$

Existence and uniqueness

Theorem (Existence and uniqueness [IMZ, '13])

Under (A0)-(A1), there exists a *unique viscosity solution* u of (22) on the junction, satisfying for some constant $C_T > 0$

$$|u(t, y) - u_0(y)| \leq C_T \quad \text{for all } (t, y) \in J_T.$$

Moreover the function u is Lipschitz continuous with respect to (t, y) .

Convergence

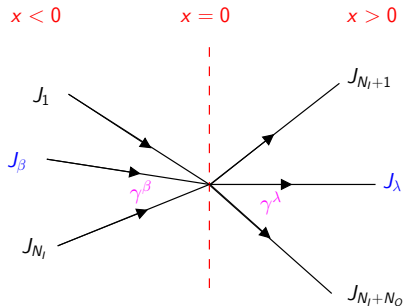
Theorem (Convergence from discrete to continuous [CML, '13])

Assume that (A0)-(A1) and the CFL condition (24) are satisfied. Then the numerical solution *converges* uniformly to u the unique viscosity solution of the junction model (22) when $\varepsilon := (\Delta t, \Delta x) \rightarrow 0$

$$\limsup_{\varepsilon \rightarrow 0} \sup_{(n\Delta t, i\Delta x) \in \mathcal{K}} |u^\alpha(n\Delta t, i\Delta x) - U_i^{\alpha, n}| = 0$$

► Proof

Setting



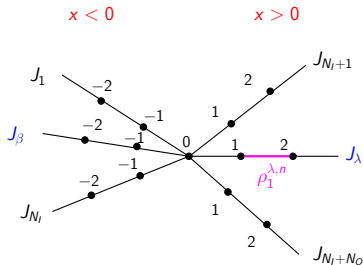
N_I incoming and N_O outgoing roads

Links with “classical” approach

Definition (Discrete car density)

The discrete vehicle density $\rho_i^{\alpha,n}$ with $n \geq 0$ and $i \in \mathbb{Z}$ is given by:

$$\rho_i^{\alpha,n} := \begin{cases} \gamma^\alpha p_{|i|-1}^{\alpha,n} & \text{for } \alpha = 1, \dots, N_I, \quad i \leq -1 \\ -\gamma^\alpha p_i^{\alpha,n} & \text{for } \alpha = N_I + 1, \dots, N_I + N_O, \quad i \geq 0 \end{cases} \quad (25)$$



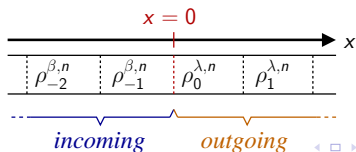
Traffic interpretation

Proposition (Scheme for vehicles densities)

The scheme deduced from (23) for the discrete densities is given by:

$$\frac{\Delta x}{\Delta t} \{\rho_i^{\alpha, n+1} - \rho_i^{\alpha, n}\} = \begin{cases} F^\alpha(\rho_{i-1}^{\alpha, n}, \rho_i^{\alpha, n}) - F^\alpha(\rho_i^{\alpha, n}, \rho_{i+1}^{\alpha, n}) & \text{for } i \neq 0, -1 \\ F_0^\alpha(\rho_0^{\alpha, n}) - F^\alpha(\rho_i^{\alpha, n}, \rho_{i+1}^{\alpha, n}) & \text{for } i = 0 \\ F^\alpha(\rho_{i-1}^{\alpha, n}, \rho_i^{\alpha, n}) - F_0^\alpha(\rho_0^{\alpha, n}) & \text{for } i = -1 \end{cases}$$

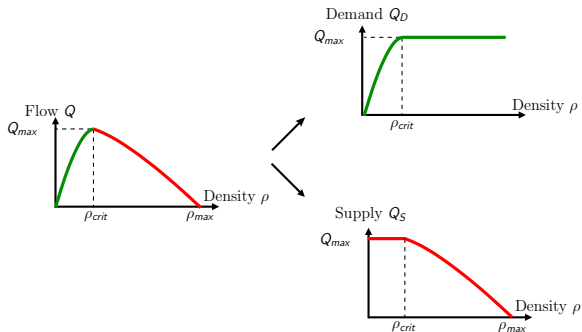
With
$$\begin{cases} F^\alpha(\rho_{i-1}^{\alpha, n}, \rho_i^{\alpha, n}) := \min \{ Q_D^\alpha(\rho_{i-1}^{\alpha, n}), Q_S^\alpha(\rho_i^{\alpha, n}) \} \\ F_0^\alpha(\rho_0^{\alpha, n}) := \gamma^\alpha \min \left\{ \min_{\beta \leq N_I} \frac{1}{\gamma^\beta} Q_D^\beta(\rho_0^{\beta, n}), \min_{\lambda > N_I} \frac{1}{\gamma^\lambda} Q_S^\lambda(\rho_0^{\lambda, n}) \right\} \end{cases}$$



Supply and demand functions

Remark

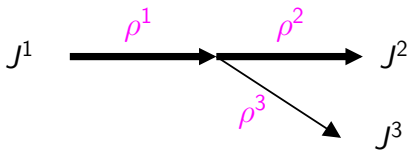
It recovers the seminal *Godunov scheme* with passing flow = minimum between *upstream demand* Q_D and *downstream supply* Q_S .



From [Lebacque '93, '96] and [Daganzo '95]

Example of a Diverge

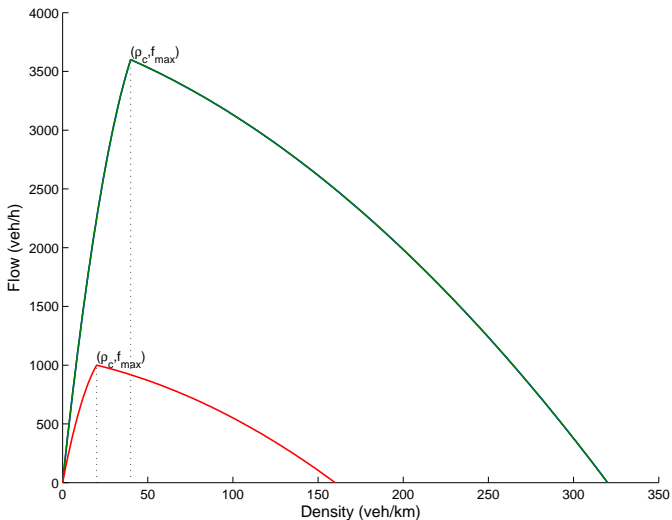
An **off-ramp**:



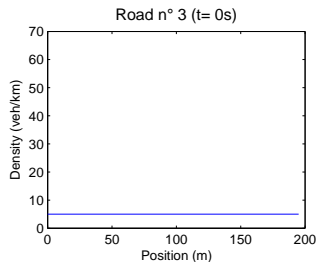
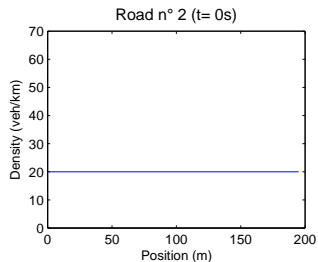
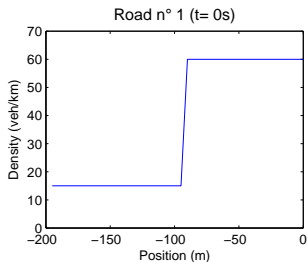
with

$$\begin{cases} \gamma^e = 1, \\ \gamma^l = 0.75, \\ \gamma^r = 0.25 \end{cases}$$

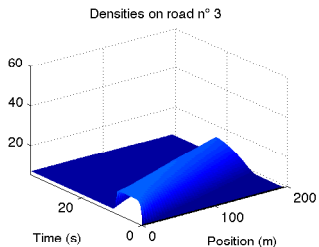
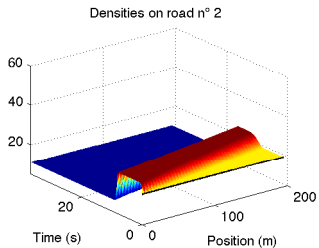
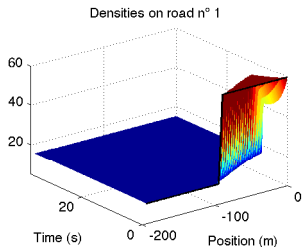
Fundamental Diagrams



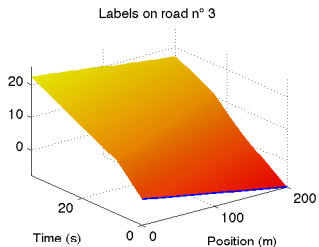
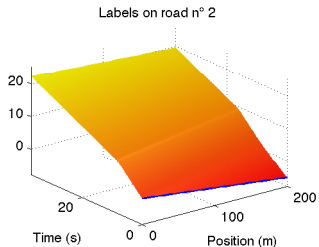
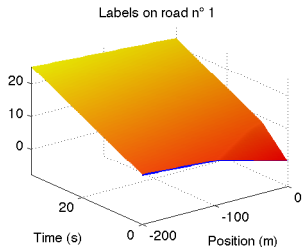
Initial conditions ($t=0s$)



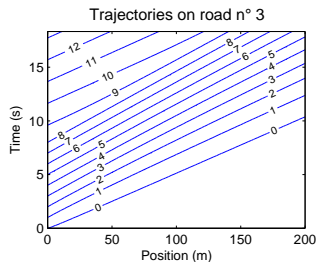
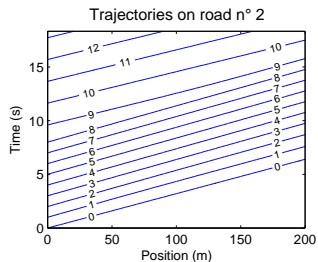
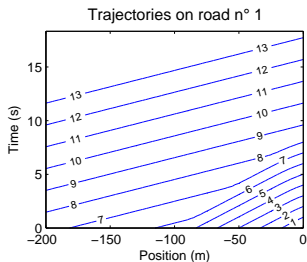
Numerical solution: densities



Numerical solution: Hamilton-Jacobi



Trajectories



New junction model

Proposition (Junction model [IM, '14])

From [4], we have

$$\begin{cases} \partial_t u^\alpha + H_\alpha(\partial_x u^\alpha) = 0, & x > 0, \alpha = 1, \dots, N \\ u^\alpha = u^\beta =: u, & x = 0, \\ \partial_t u + \mathcal{H}(\partial_x u^1, \dots, \partial_x u^N) = 0, & x = 0 \end{cases} \quad (26)$$

with initial condition $u^\alpha(0, x) = u_0^\alpha(x)$ and

$$\mathcal{H}(\partial_x u^1, \dots, \partial_x u^N) = \max \left[\overbrace{\mathcal{L}}^{\text{flux limiter}}, \underbrace{\max_{\alpha=1, \dots, N} \{H_\alpha^-(\partial_x u^\alpha)\}}_{\text{minimum between demand and supply}} \right].$$

Weaker assumptions on the Hamiltonians

For all $\alpha = 1, \dots, N$,

(A0) The initial condition u_0^α is Lipschitz continuous.

(A1) The Hamiltonians H_α are continuous and **quasi-convex** i.e.

there exists points p_0^α such that

$$\begin{cases} H_\alpha & \text{is non-increasing on } (-\infty, p_0^\alpha], \\ H_\alpha & \text{is non-decreasing on } [p_0^\alpha, +\infty). \end{cases}$$

Homogenization on a network

Proposition (Homogenization on a periodic network [IM'14])

Assume (A0)-(A1). Consider a *periodic* network.

If $u^\varepsilon \in \mathbb{R}^d$ satisfies HJ equation on network,

then u^ε converges uniformly towards u^0 when $\varepsilon \rightarrow 0$,

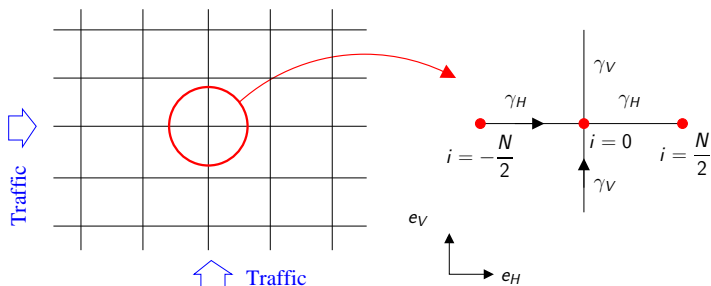
with $u^0 \in \mathbb{R}^d$ solution of

$$\partial_t u^0 + \bar{H}(Du^0) = 0, \quad t > 0, \quad x \in \mathbb{R}^d \quad (27)$$

See [Imbert, Monneau '14] [4]

Numerical homogenization on a network

Numerical **scheme** adapted to the **cell problem** ($d = 2$)



First example

Proposition (Effective Hamiltonian for fixed coefficients [IM'14])

If (γ^H, γ^V) are fixed, then the

- (Hamiltonian) *effective Hamiltonian* \bar{H} is given by

$$\bar{H}(\partial_x u_H, \partial_x u_V) = \max \left\{ \mathcal{L}, \max_{i=\{H,V\}} H(\partial_x u_i) \right\},$$

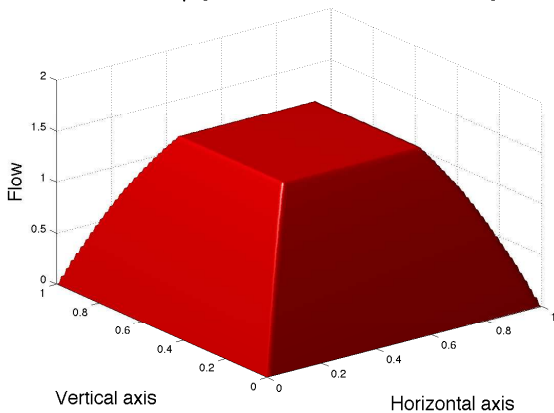
- (traffic flow) *effective flow* \bar{Q} is given by

$$\bar{\mathfrak{F}}(\rho_H, \rho_V) = \min \left\{ -\mathcal{L}, \frac{\mathfrak{F}(\rho_H)}{\gamma^H}, \frac{\mathfrak{F}(\rho_V)}{\gamma^V} \right\}.$$

First example

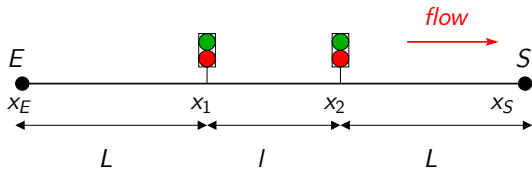
Numerics: assume $\mathfrak{F}(\rho) = 4\rho(1 - \rho)$ and $\mathcal{L} = -1.5$,

Results for $\gamma=[0.5 \quad 0.5 \quad 0.5 \quad 0.5]$



Second example

Two consecutive traffic signals on a 1D road

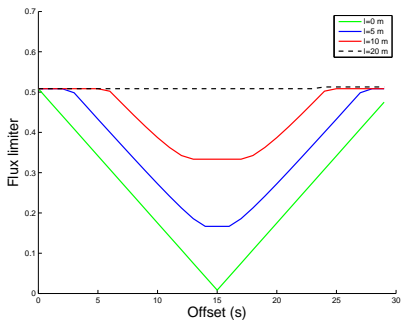
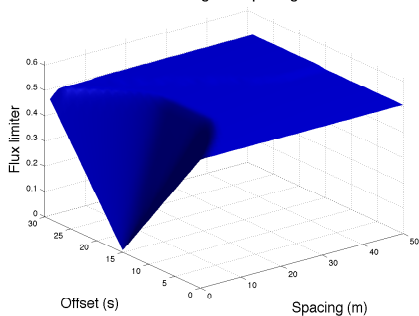


Homogenization theory by [Galise, Imbert, Monneau, '14]

Second example

Effective flux limiter $-\bar{\mathcal{L}}$ (numerics only)

Flux limiter w.r.t. signals spacing and offset



Outline

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Personal conclusions






	Advantages	Drawbacks
Homogeneous link	Micro-macro link Explicit solutions Data assimilation	Limited time delay Concavity of the FD Exactness (2nd order) Multilane
Junction	Uniqueness of the solution Homogenization result	Fixed proportions Multilane

Perspectives

Some **open** questions:

- Micro-macro: higher **time delay**?
- Confront the results with **real data** (micro datasets)
- Explicit **Lax-Hopf formula** for time/space dependent Hamiltonians?

Some references I

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-  M. GARAVELLO AND B. PICCOLI, *Traffic flow on networks*, American institute of mathematical sciences Springfield, MO, USA, 2006.
-  C. IMBERT AND R. MONNEAU, *Level-set convex Hamilton–Jacobi equations on networks*, (2014).
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J.-P. LEBACQUE AND M. M. KHOSHYARAN, *First-order macroscopic traffic flow models: Intersection modeling, network modeling*, in Transportation and Traffic Theory. Flow, Dynamics and Human Interaction. 16th International Symposium on Transportation and Traffic Theory, 2005.

THANKS FOR YOUR ATTENTION

Any question?

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