



AUTOMATING MOBILITY IN SMART CITIES

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OUTLINE

- What is a “Smart City” ?

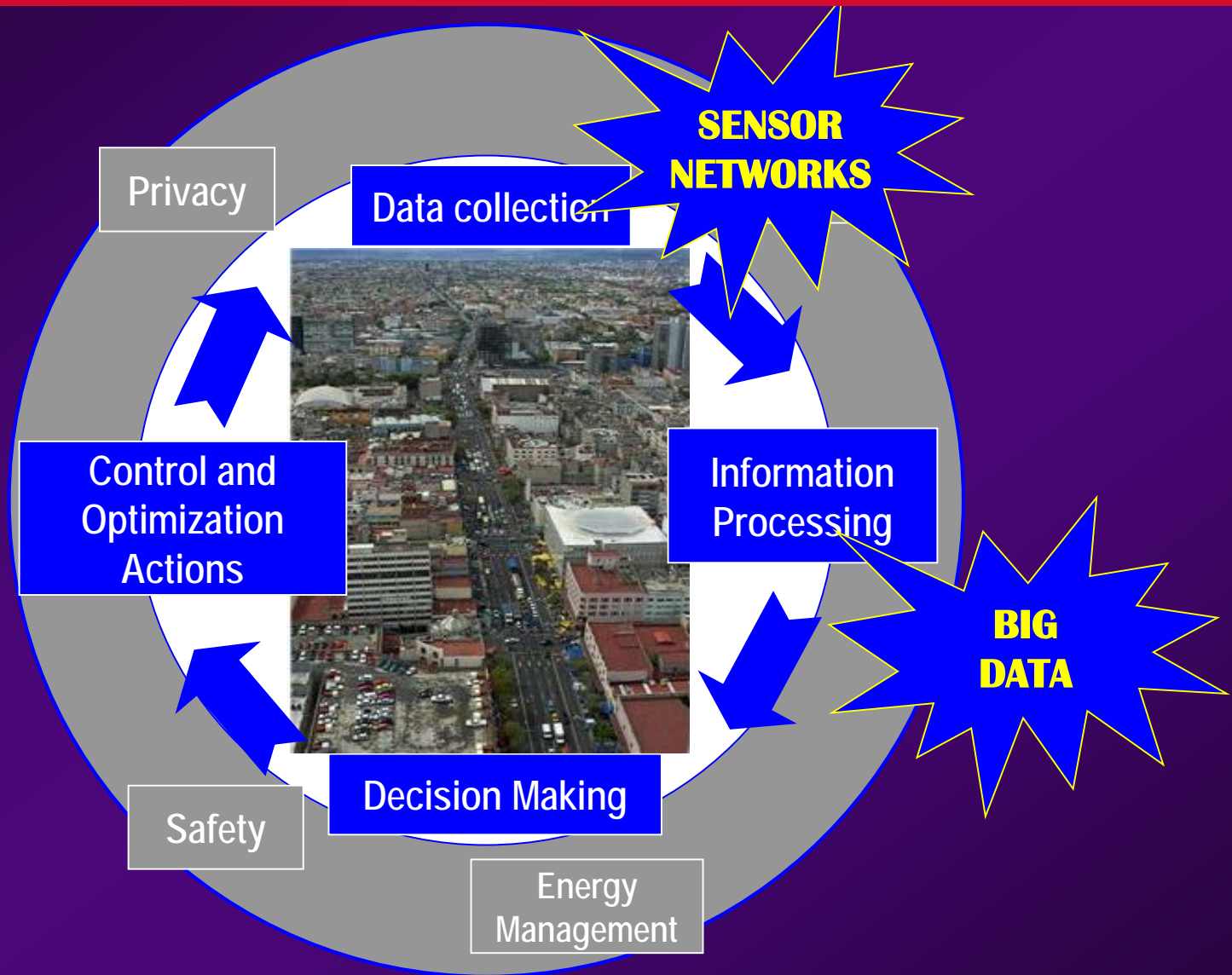
- Mobility as a resource contention game:

Selfish v Social optimality \Rightarrow PRICE OF ANARCHY (PoA)

Two takeaways (proposed research directions) from this talk:

1. Use “Big Data” to estimate the PoA
2. Use Connected Autonomous Vehicles (CAVs) + control to reduce/eliminate the PoA

“SMART CITY” AS A CYBER-PHYSICAL SYSTEM



“SMART CITY” AS A CYBER-PHYSICAL SYSTEM

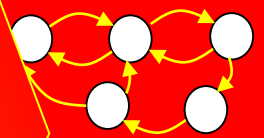
PHYSICAL

CYBER

CYBER

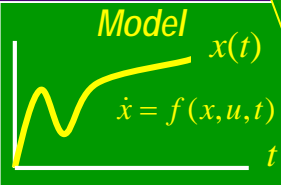
This is a
HYBRID SYSTEM

Model



Decision Making

Model



PHYSICAL

WHAT IS A “SMART CITY” ?

“A city well performing in a forward-looking way in [economy, people, governance, mobility, environment, and living] built on the smart combination of endowments and activities of self-decisive, independent and aware citizens.” *Giffinger et al, 2007*

Hitachi's vision for the Smart Sustainable City seeks to achieve concern for the **global environment and lifestyle safety** and convenience through the **coordination of infrastructure**. Smart Sustainable Cities realized through the coordination of infrastructures consist of two infrastructure layers that support consumers' lifestyles together with the urban management infrastructure that links these together using IT *Hitachi Web, 2014*

Smart Sustainable Cities **use information and communication technologies (ICT)** to be more intelligent and efficient in the use of resources, resulting in cost and energy savings, improved service delivery and quality of life, and reduced environmental footprint--all **supporting innovation and the low-carbon economy**. *Cohen, 2014*

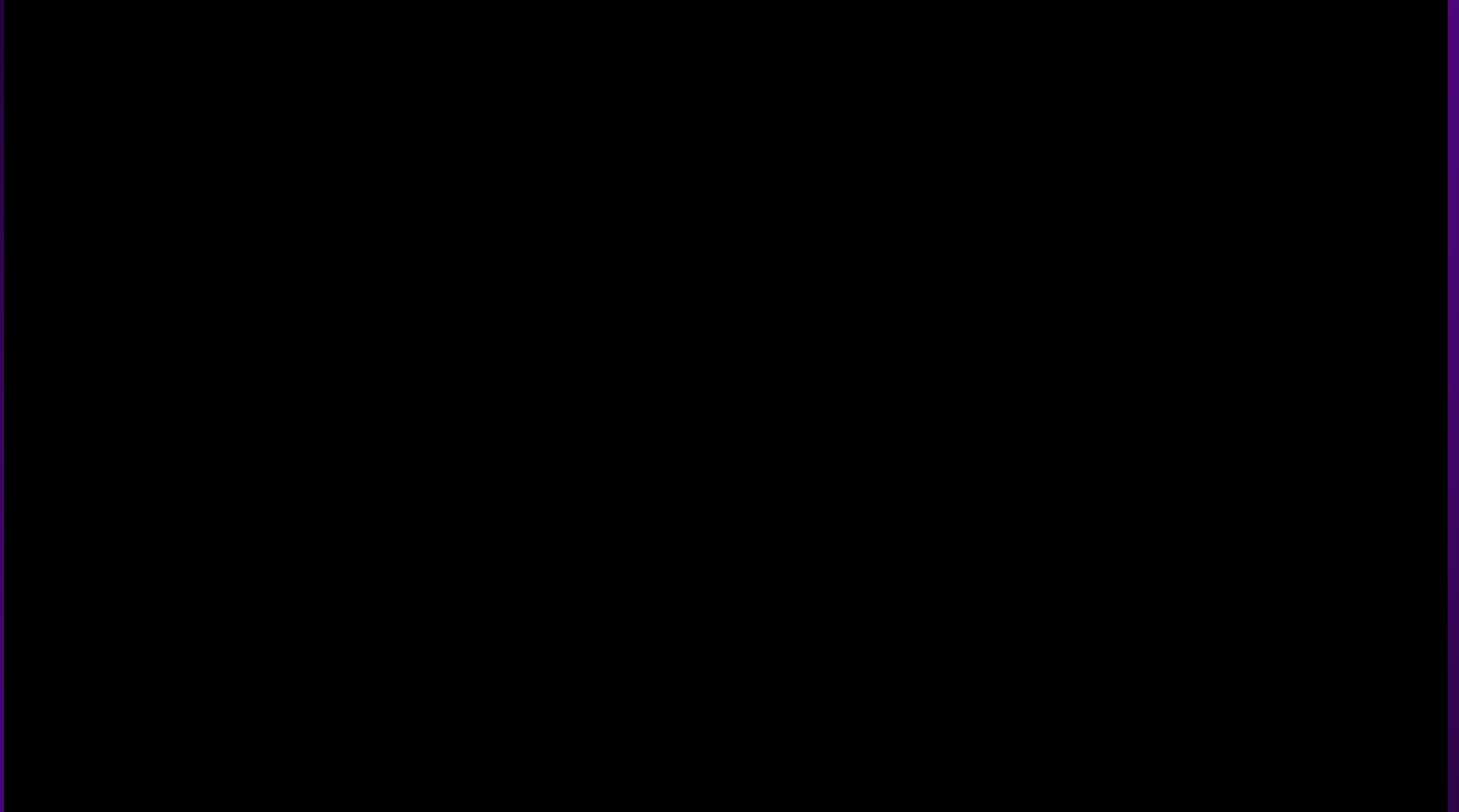
“We believe a city to be smart when investments in human and social capital and traditional (transport) and **modern (ICT) communication infrastructure** fuel sustainable economic growth and a high quality of life, with a **wise management of natural resources**, through participatory governance.” *Meijer and Bolívar, 2013*

WHAT IS A “SMART CITY” ?

Smart Sustainable Cities use information and communication technologies (ICT) to be more intelligent and efficient in the use of resources, resulting in cost and energy savings, improved service delivery and quality of life, and reduced environmental footprint--all supporting innovation and the low-carbon economy.

Cohen, 2014

WHAT IS A “SMART CITY” ?



CREDIT: Fernando Livschitz

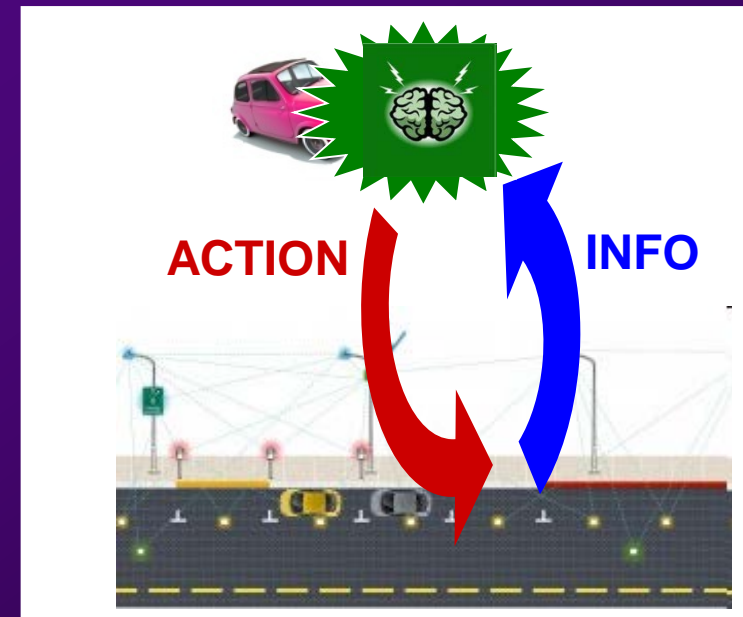
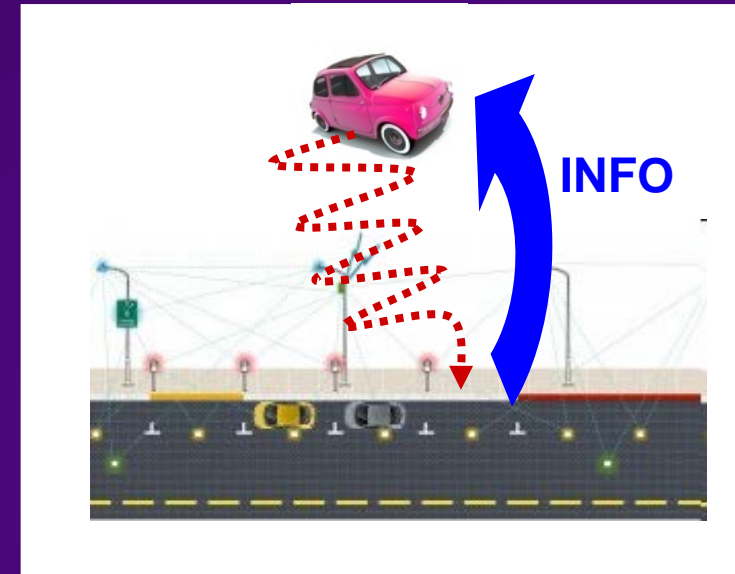
<http://www.fastcodesign.com/3035870/filmmaker-creates-worlds-most-terrifying-traffic-intersection>

WHAT IS REALLY “SMART” ?

COLLECTING DATA IS NOT “SMART”

- JUST A NECESSARY STEP TO BEING “SMART”

PROCESSING DATA TO MAKE GOOD DECISIONS IS “SMART”



TRAFFIC CONTROL



100-km Chinese traffic jam enters Day 9



The BU Bridge mess, Boston, MA (simulation using VISSIM)

WHY CAN'T WE IMPROVE TRAFFIC...

... EVEN IF WE KNOW THE ACHIEVABLE OPTIMUM
IN A TRAFFIC NETWORK ???

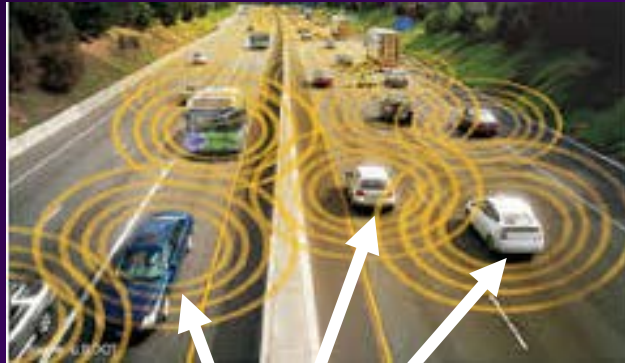
Because:

- **Not enough controls** (traffic lights, tolls, speed fines)
→ No chance to unleash the power of feedback!
- **Not knowing other drivers' behavior** leads to poor decisions
(a simple game-theoretic fact)
→ Drivers seek individual (**selfish**) optimum,
not system-wide (**social**) optimum



PRICE OF ANARCHY
(POA)

GAME-CHANGING OPPORTUNITY: CONNECTED AUTONOMOUS VEHICLES (CAVs)



FROM (SELFISH) "DRIVER OPTIMAL"
TO (SOCIAL) "SYSTEM OPTIMAL"
TRAFFIC CONTROL

CAVs



THE "INTERNET OF CARS"

NO TRAFFIC LIGHTS, NEVER STOP...

THE CASE FOR “SELF-DRIVING” CARS

- Humans are bad drivers
(94% of accidents are due to human error)
- Computers do not get distracted (humans do)
- Computers can process vast amounts of data (humans cannot)
- Computers can maintain steady cruising speeds
(leading to improved energy efficiency)
- Computers react quickly (humans do not)
- Computer can make fast and accurate driving adjustments
- Computers do not blink, do not drink, and do not sleep

OBJECTIONS TO “SELF-DRIVING” CARS

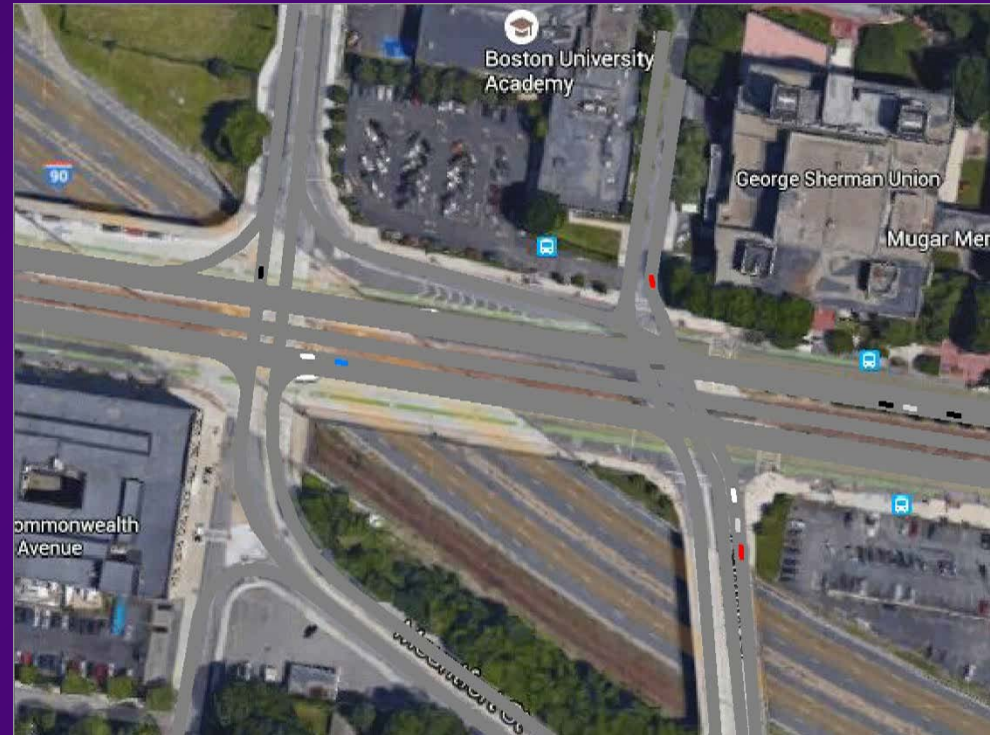
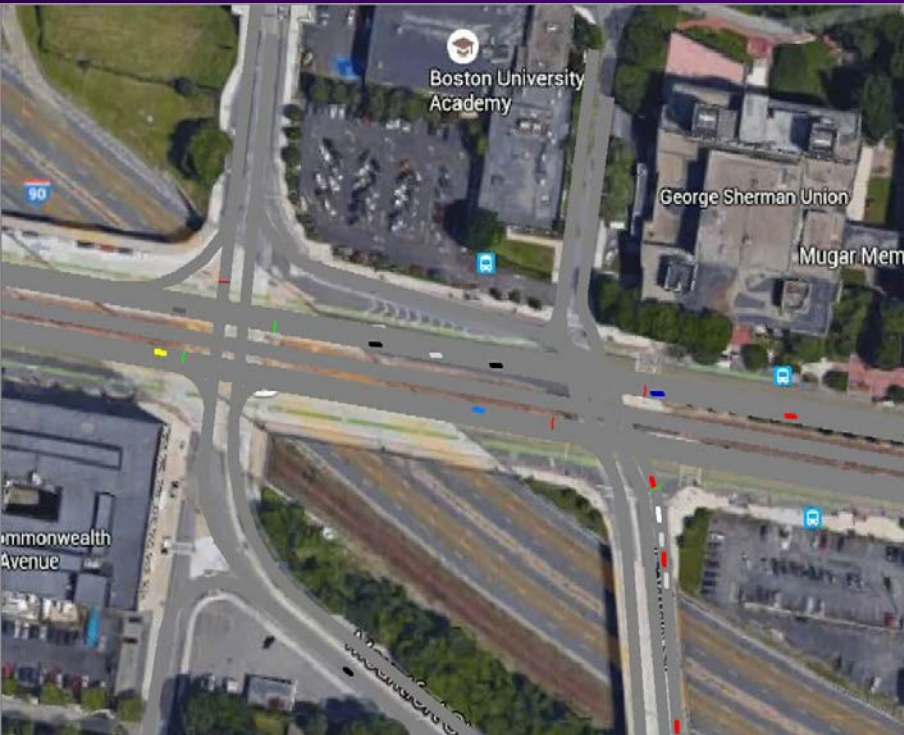
- Legal issues: who is to blame for a fault ?
- How to integrate with normal cars ?
- Security and Privacy (due to connectivity)
- Accidents may be rare, but when they occur they are likely to be serious
- Technical challenges...

HOW TO QUANTIFY BENEFITS OF AUTOMATED MOBILITY ?

BEFORE (traffic lights)

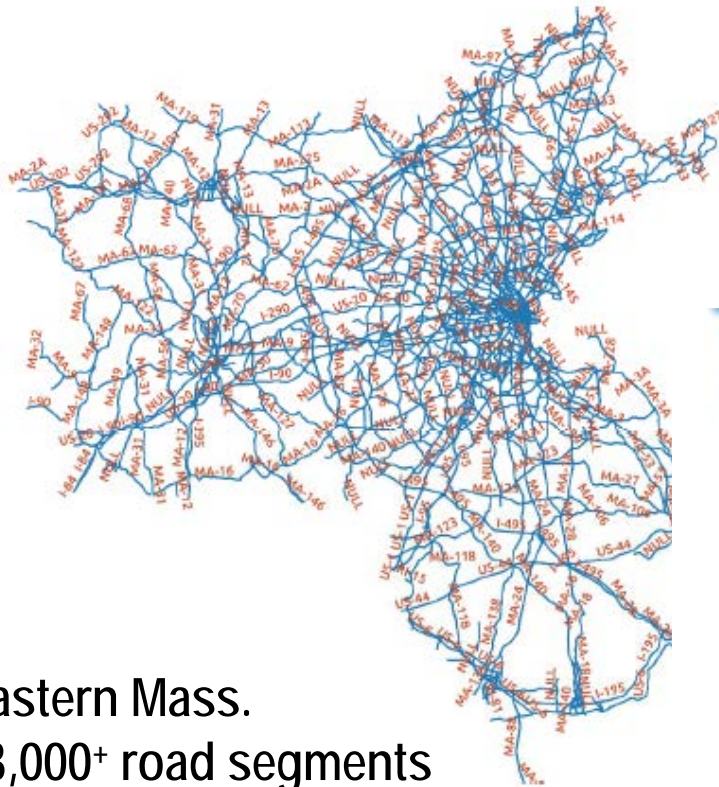


AFTER (no traffic lights, CAVs)



One of the worst-designed double intersections ever...
(BU Bridge – Commonwealth Ave, Boston, MA)

HOW TO MEASURE THE PRICE OF ANARCHY ?

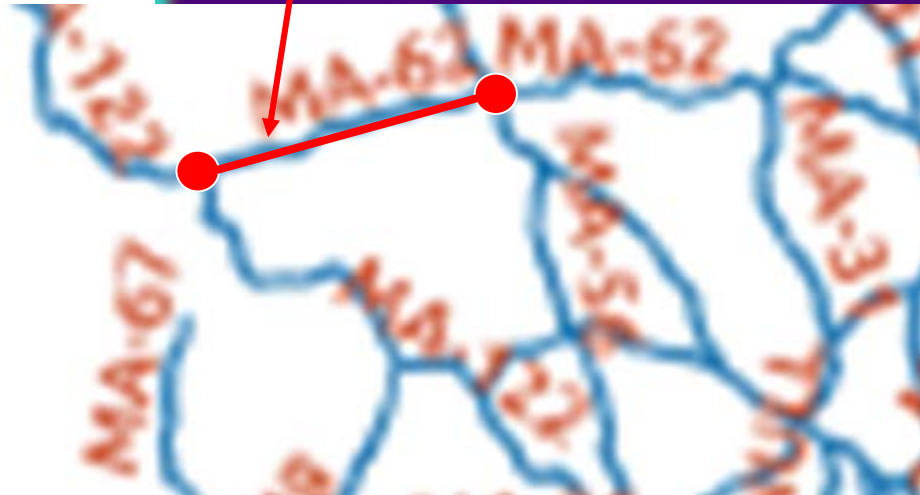


Eastern Mass.
13,000+ road segments

LINK a

FLOW x_a

COST FUNCTION $t_a(x_a)$



Under USER-CENTRIC (selfish) control: x_a^{user} is the equilibrium flow
Under SYSTEM-CENTRIC (social) control: x_a^{social} is the equilibrium flow

HOW TO MEASURE THE PRICE OF ANARCHY ?

$$\text{PoA} = \frac{\sum_{\text{all } a} x_a^{\text{user}} t(x_a^{\text{user}})}{\sum_{\text{all } a} x_a^{\text{social}} t(x_a^{\text{social}})} \geq 1$$

← BEFORE

← AFTER

Two takeaways (proposed research directions) from this talk:

1. Measure/estimate the PoA ?



Inverse Optimization

2. Reduce/eliminate the PoA ?



Optimal Control Framework

ESTIMATING THE PRICE OF ANARCHY

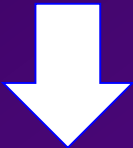


CHALLENGES AS THINGS NOW STAND...

- We don't know user COST FUNCTIONS
- We don't know user ORIGIN-DESTINATION pairs (no DEMAND model)



We can't solve the SYSTEM OPTIMALITY problem



We can't exploit CAVs



We can't assess the value of investing in CAV-based technologies, since we can't evaluate the PRICE OF ANARCHY

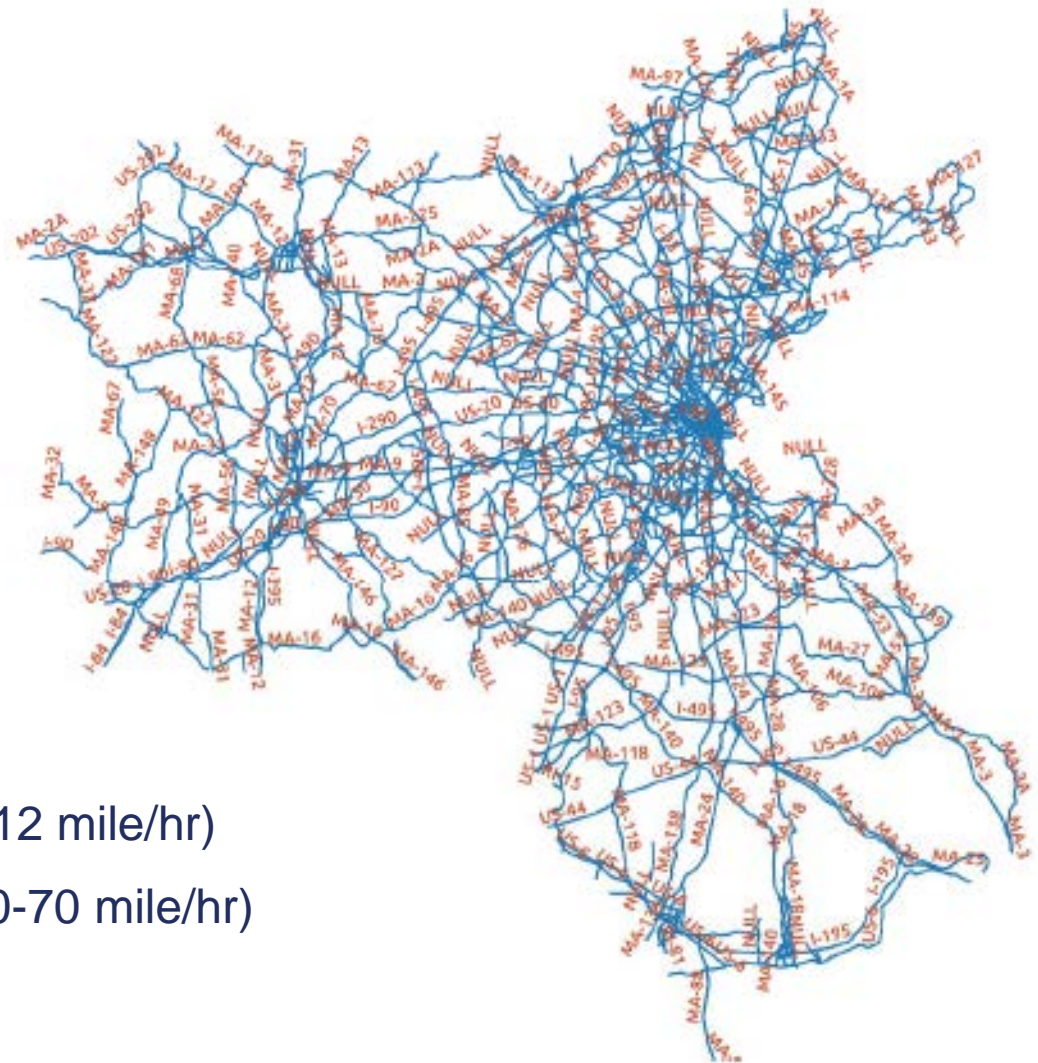
BUT WE DO HAVE PLENTY OF DATA...

THE **BIG DATA** SET

Data Set provided by City of Boston
and Mass. Planning Organization

Average and real-time speed data in
Eastern Mass. for every minute of 2012

- 13000+ road segments
(avg. distance 0.7 mile)
- 50+ GB of data

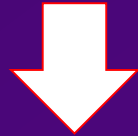


- Lowest Speed (6-12 mile/hr)
- Highest Speed (60-70 mile/hr)

INVERSE OPTIMIZATION – KEY IDEA

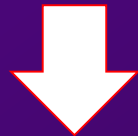
BACKWARD optimization:

- Data reveal a (**selfish**) equilibrium (Wardrop/Nash equilibrium)
- What are the (virtual) cost functions which best fit the data that lead to this equilibrium?



FORWARD optimization:

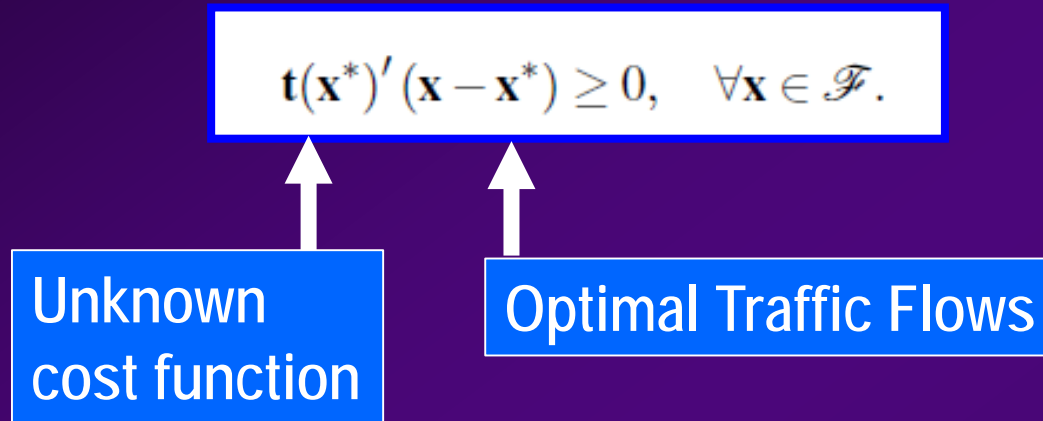
- Use these cost functions to find (**social**) optimal traffic flows



- Estimate the PRICE OF ANARCHY

INVERSE OPTIMIZATION PROBLEM

Optimal Traffic Flow allocation as a Variational Inequality (VI) problem:



Assumption 1: $t(\cdot)$ is strongly monotone and continuously differentiable.
 \mathcal{F} is nonempty and contains an interior point (Slater's condition)

THEOREM: Suppose Assumption 1 holds. Then, there exists a Wardrop (Nash) equilibrium of the single-class transportation network which is the unique solution of the VI problem.

Patriksson, 2015

INVERSE OPTIMIZATION PROBLEM

Inverse Variational inequality problem

$$\begin{array}{ll} \min_{\mathbf{t}, \boldsymbol{\varepsilon}} & \|\boldsymbol{\varepsilon}\| \\ \text{s.t.} & \mathbf{t}(\mathbf{x}_k)'(\mathbf{x} - \mathbf{x}_k) \geq -\varepsilon_k, \quad \forall \mathbf{x} \in \mathcal{F}_k, \quad \forall k. \end{array}$$

Cost functions
that fit data

Given Data

Solve for cost functions $\mathbf{t}(\cdot)$ in a *Reproducing Kernel Hilbert Space*

INVERSE OPTIMIZATION PROBLEM

Data reconciliation

Generalization

$$\begin{aligned} & \min_{f, \mathbf{y}, \boldsymbol{\epsilon}} \quad \|\boldsymbol{\epsilon}\| + \gamma \|f\|_{\mathcal{H}}^2 \\ \text{s.t.} \quad & \mathbf{e}'_a \mathbf{N}'_k \mathbf{y}^{\mathbf{w}} \leq t_a^0 f\left(\frac{x_a}{m_a}\right), \\ & \forall \mathbf{w} \in \mathcal{W}^{(k)}, a \in \mathcal{A}^{(k)}, k \in \llbracket \mathcal{K} \rrbracket, \\ & \sum_{a \in \mathcal{A}^{(k)}} t_a^0 x_a f\left(\frac{x_a}{m_a}\right) - \sum_{\mathbf{w} \in \mathcal{W}^{(k)}} (\mathbf{d}^{\mathbf{w}})' \mathbf{y}^{\mathbf{w}} \leq \epsilon_k, \\ & \forall k \in \llbracket \mathcal{K} \rrbracket, \\ & f\left(\frac{x_a}{m_a}\right) \leq f\left(\frac{x_{\tilde{a}}}{m_{\tilde{a}}}\right), \\ & \forall a, \tilde{a} \in \bigcup_{k=1}^{|\mathcal{K}|} \mathcal{A}^{(k)} \text{ s.t. } \frac{x_a}{m_a} \leq \frac{x_{\tilde{a}}}{m_{\tilde{a}}}, \\ & \boldsymbol{\epsilon} \geq \mathbf{0}, \quad f \in \mathcal{H}, \\ & f(0) = 1, \end{aligned}$$

INVERSE OPTIMIZATION PROBLEM

Reproducing Kernel:

$$\phi(x, y) = (c + xy)^n = \sum_{i=0}^n \binom{n}{i} c^{n-i} x^i y^i$$

$$\begin{aligned} & \min_{\beta, \mathbf{y}, \epsilon} \quad \|\epsilon\| + \gamma \sum_{i=0}^n \frac{\beta_i^2}{\binom{n}{i} c^{n-i}} \\ \text{s.t.} \quad & \mathbf{e}'_a \mathbf{N}'_k \mathbf{y}^{\mathbf{w}} \leq t_a^0 \sum_{i=0}^n \beta_i \left(\frac{x_a}{m_a} \right)^i, \\ & \forall \mathbf{w} \in \mathcal{W}^{(k)}, a \in \mathcal{A}^{(k)}, k \in [\mathcal{K}], \\ & \sum_{a \in \mathcal{A}_k} t_a^0 x_a \sum_{i=0}^n \beta_i \left(\frac{x_a}{m_a} \right)^i - \sum_{\mathbf{w} \in \mathcal{W}_k} (\mathbf{d}^{\mathbf{w}})' \mathbf{y}^{\mathbf{w}} \leq \epsilon_k, \\ & \forall k \in [\mathcal{K}], \\ & \sum_{i=0}^n \beta_i \left(\frac{x_a}{m_a} \right)^i \leq \sum_{i=0}^n \beta_i \left(\frac{x_{\tilde{a}}}{m_{\tilde{a}}} \right)^i, \\ & \forall a, \tilde{a} \in \bigcup_{k=1}^{|\mathcal{K}|} \mathcal{A}^{(k)} \text{ s.t. } \frac{x_a}{m_a} \leq \frac{x_{\tilde{a}}}{m_{\tilde{a}}}, \\ & \epsilon \geq \mathbf{0}, \quad \beta_0 = 1, \end{aligned}$$

Link Cost Function Estimates

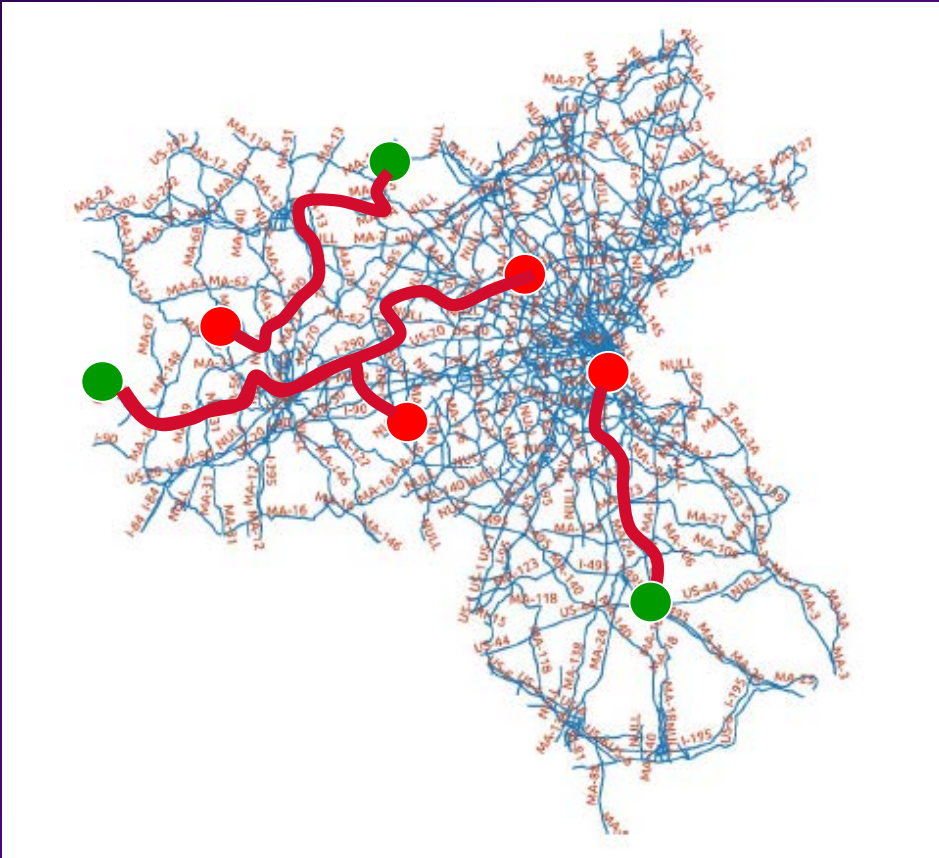
$$\hat{f}(x) = 1 + \sum_{i=1}^n \beta_i^* x^i$$

O-D MATRIX ESTIMATION

That's a separate challenging problem!

We solve it using *Generalized Least Squares* (GLS) methods

Zhang et al, IFAC 2017 – WeP13.1



*Typically,
hundreds/thousands
of O-D pairs...*

FORWARD OPTIMIZATION PROBLEM

Nonlinear Programming Problem (NLP):

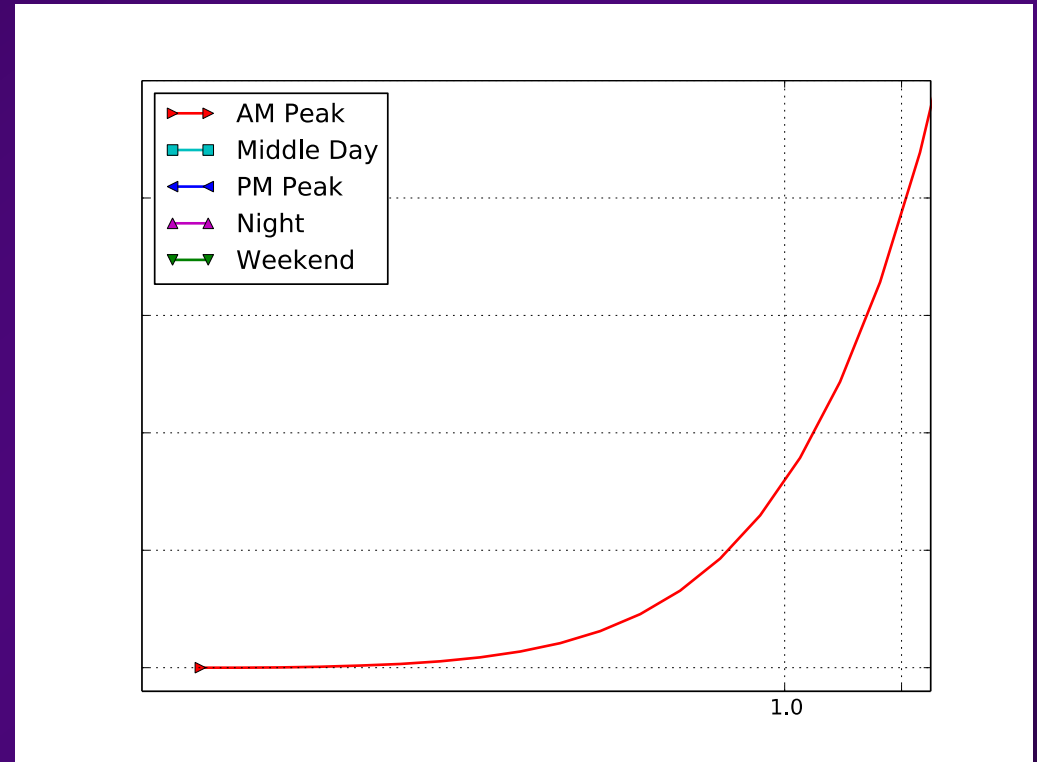
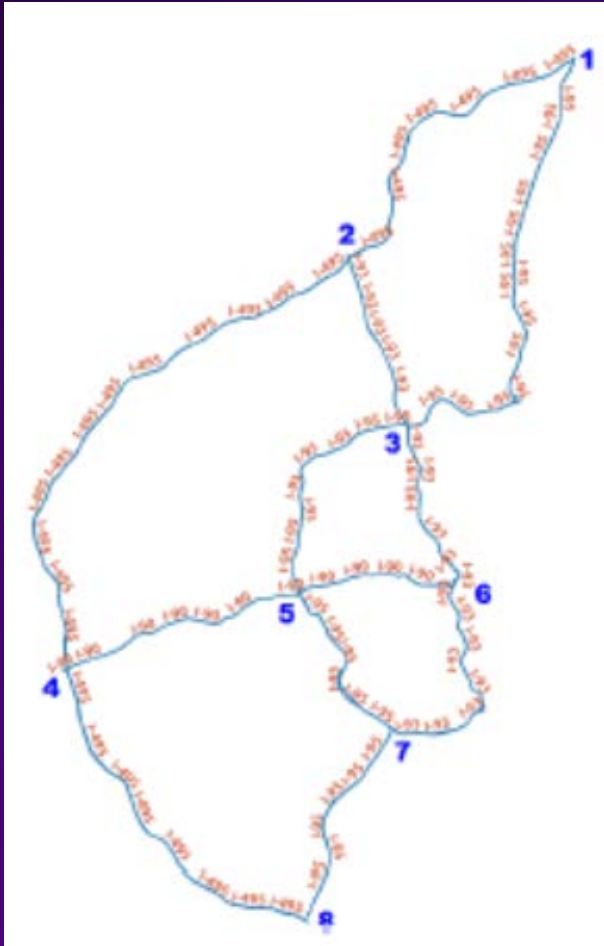
Estimated Cost Functions

$$\min_{\mathbf{x} \in F} \sum_{a \in A} x_a t_a(x_a)$$

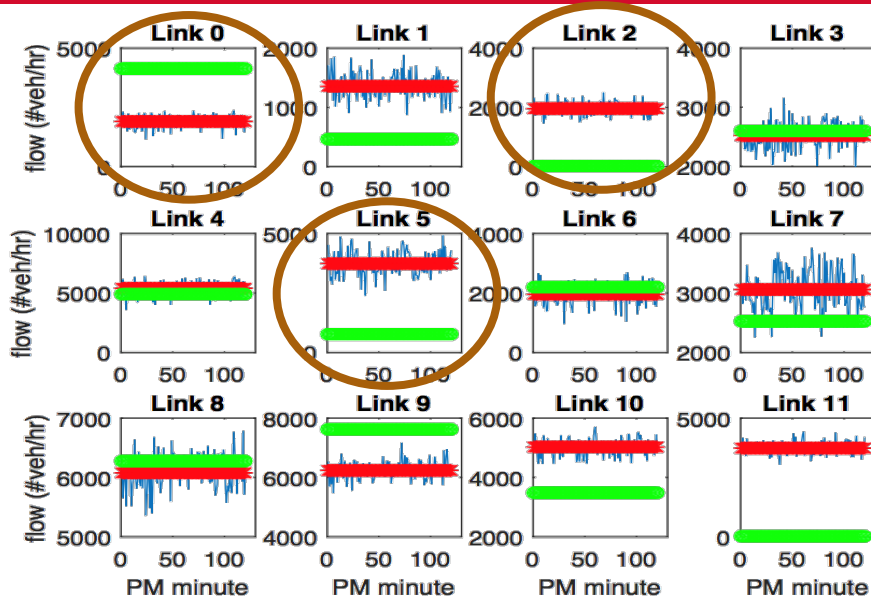
Feasible Flows
from O-D demand matrix

*Optimal
System-centric (social)
Flows \mathbf{x}^**

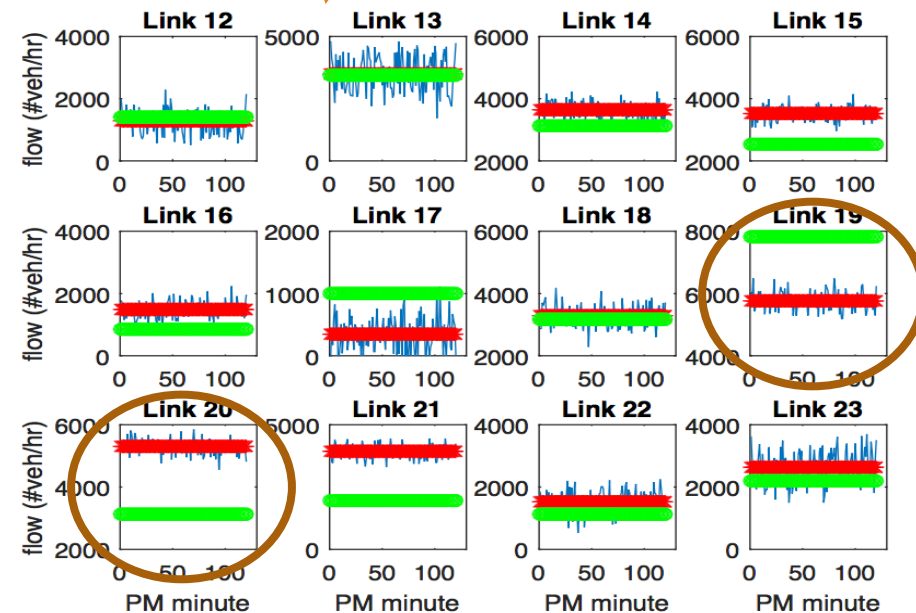
COST FUNCTION ESTIMATES: *BOSTON AREA 2012*



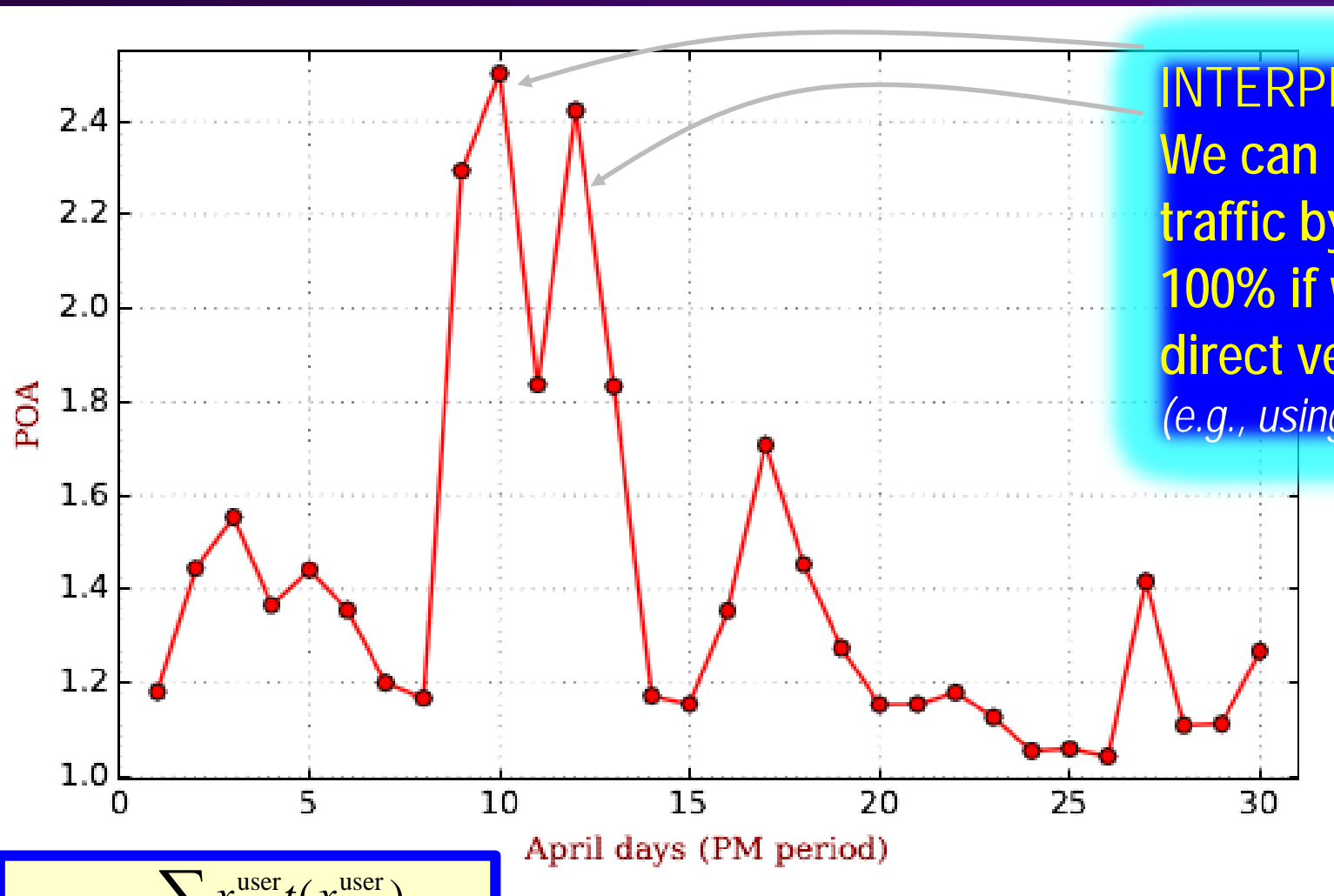
PRICE OF ANARCHY – BOSTON AREA 2012



Link flows:
Social-opt. (green)
User-opt. (red)



PRICE OF ANARCHY – BOSTON AREA 2012



INTERPRETATION:
We can improve
traffic by more than
100% if we can
direct vehicles
(e.g., using CAVs)

$$\text{PoA} = \frac{\sum_{\text{all } a} x_a^{\text{user}} t(x_a^{\text{user}})}{\sum_{\text{all } a} x_a^{\text{social}} t(x_a^{\text{social}})} \geq 1$$

Zhang et al, IEEE CDC 2016

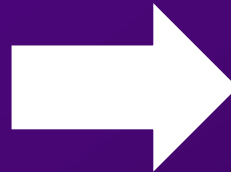
NEXT STEPS...

Goal 1 accomplished:

PoA is HIGH

⇒ Evidence to support investing in CAVs to achieve System-Centric (Social) Optimality

⇒ *How do we do it ?*



NEXT STEPS - *ROUTING*

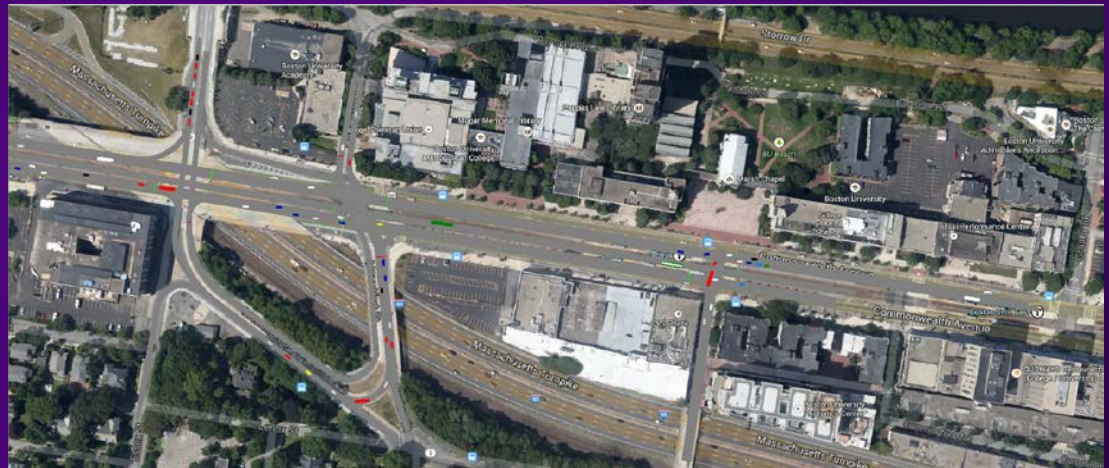
Relatively easy:

- Recommendations/Suggestions (e.g., through apps)
- Incentives, Pricing Schemes
- Automated Enforcement
(CAV selects route, driver can override)

NEXT STEPS – *TRAFFIC NETWORK BOTTLENECKS*

Need to automatically control velocity/acceleration in urban environments:

- Merging points
- Intersections



A DECENTRALIZED OPTIMAL CONTROL FRAMEWORK FOR CAVs



NO TRAFFIC LIGHTS, NEVER STOP...

VEHICLE COORDINATION

- Centralized approaches:

■ Reservation schemes:

Dresner and Stone (2004), Huang et al (2012), Zhang et al (2013), Kim and Kumar (2014), Zhu and Ukkusuri(2015)

■ Control and Optimization:

Levine and Athans (1966), Varaiya (1993), Lu and Hedrick (2000), Kotsialos and Papageorgiou (2004), Li and Wang (2006), Lee and Park (2013), Kamal et al (2013), Pasquale et al (2015)

■ Queueing models: Miculescu and Karaman (2014)

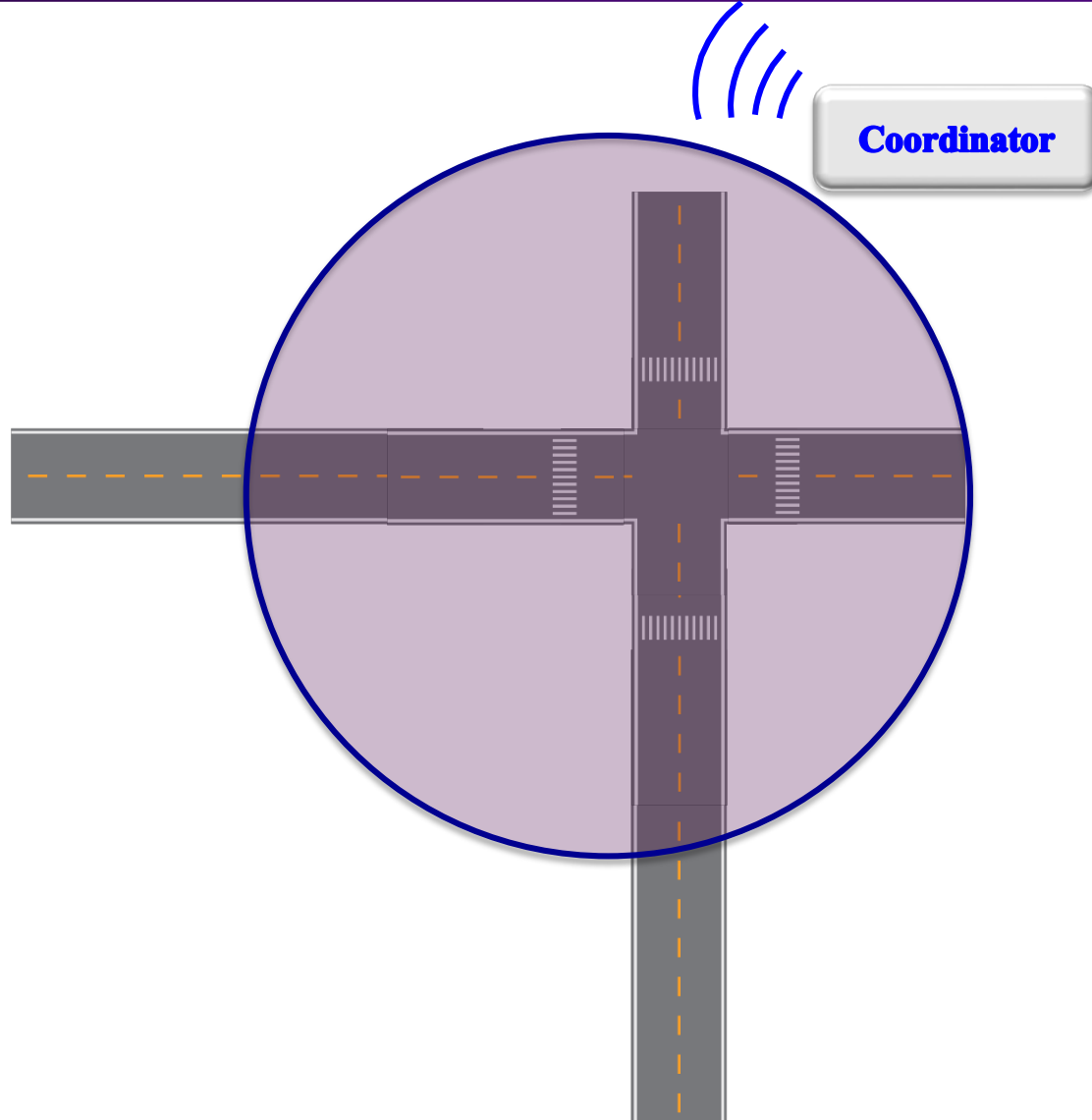
- Decentralized approaches:

- Heuristics: Milanes et al (2011), Onieva et al (2012)
- Critical set: Hafner et al (2013), Colombo and Del Vecchio (2014)
- Optimization: Makarem et al (2013), Campos et al (2014)

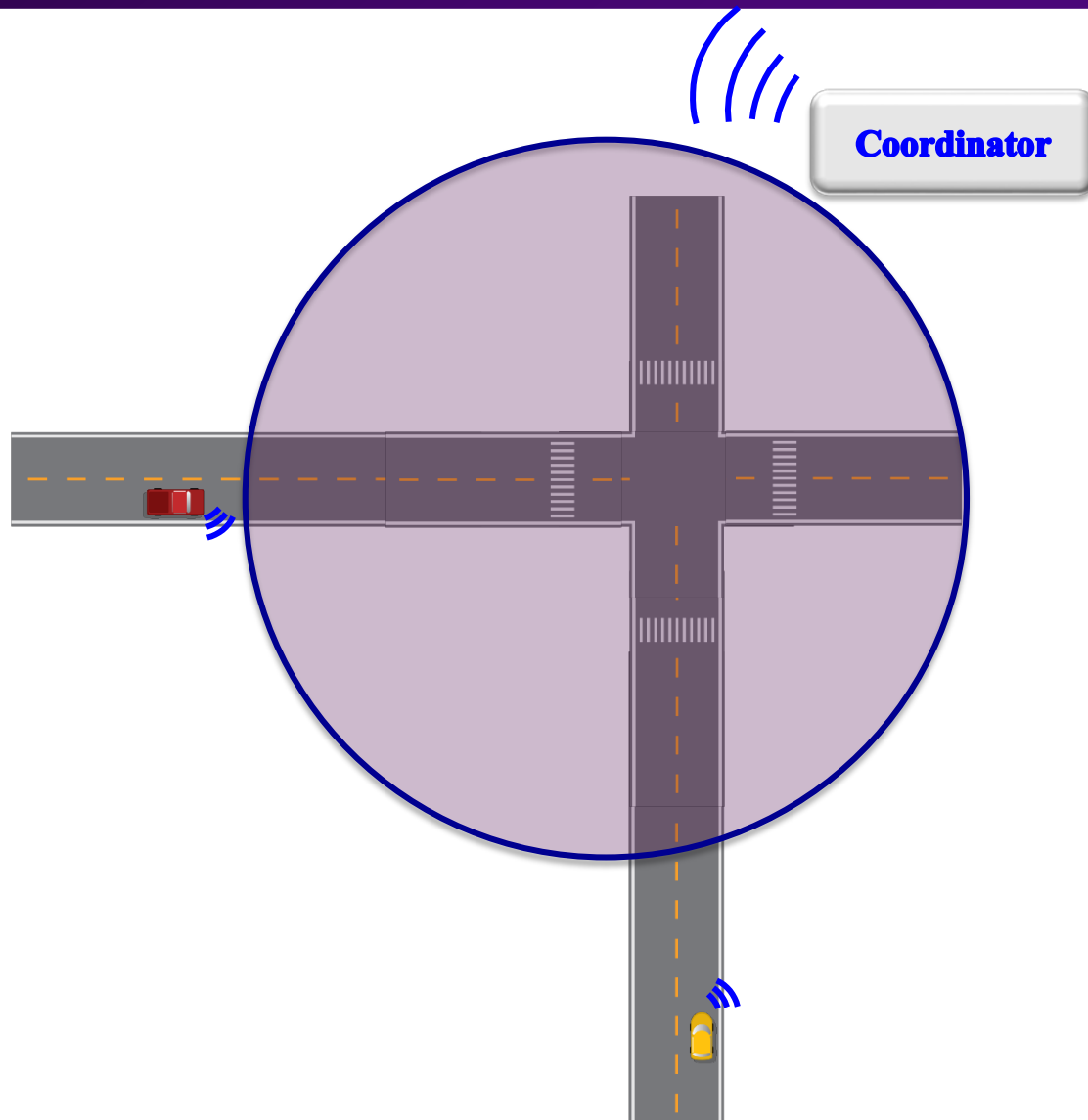
RELATED RESEARCH

- KTH Royal Inst. of Tech., Sweden (K. Johansson et al)
- GIPSA-Lab, Grenoble, France (C. Canudas de Wit)
- U. of Genova, U. of Pavia (S. Sacone, S. Siri, A. Ferrara et al)
- Nanyang Technological University, Singapore (R. Su et al)
- Tsinghua U., China (Y. Zhang)
- MIT (A. Annaswamy, S. Karaman et al)
- UC Berkeley (A. Bayen et al)
- U. Michigan/Mcity (H. Peng et al)
- ...

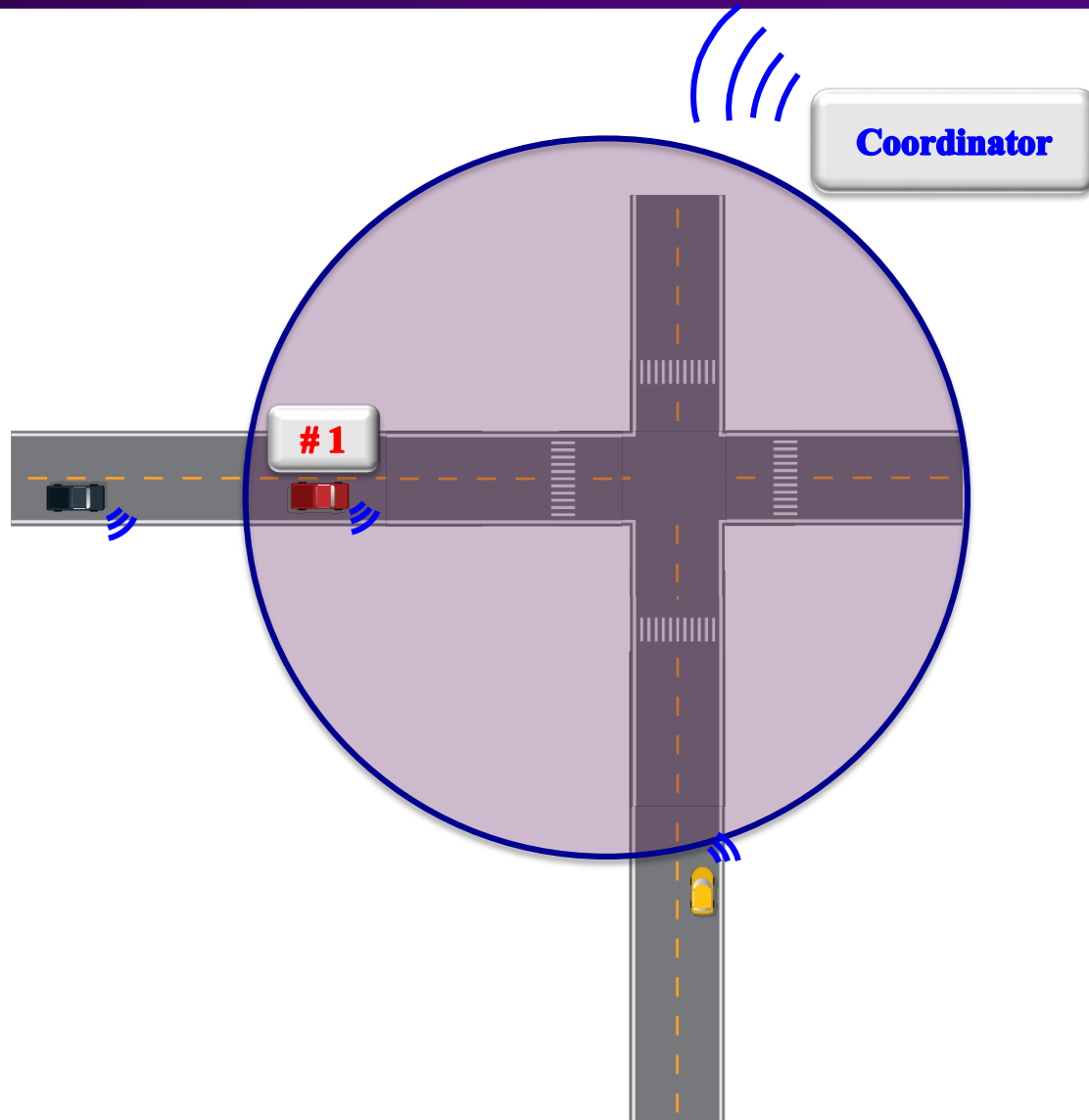
NO TRAFFIC LIGHTS - CAVs



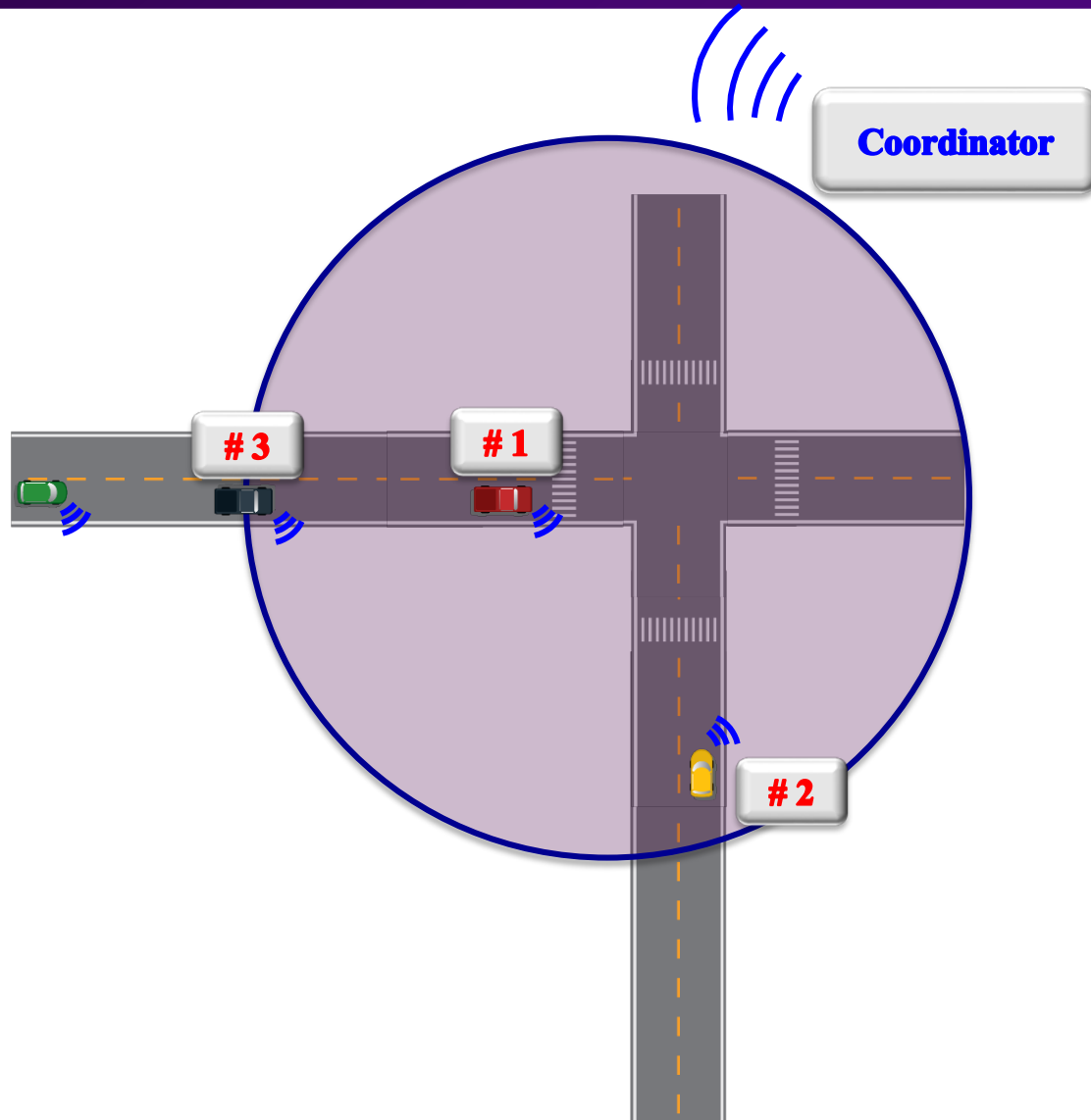
NO TRAFFIC LIGHTS - CAVs



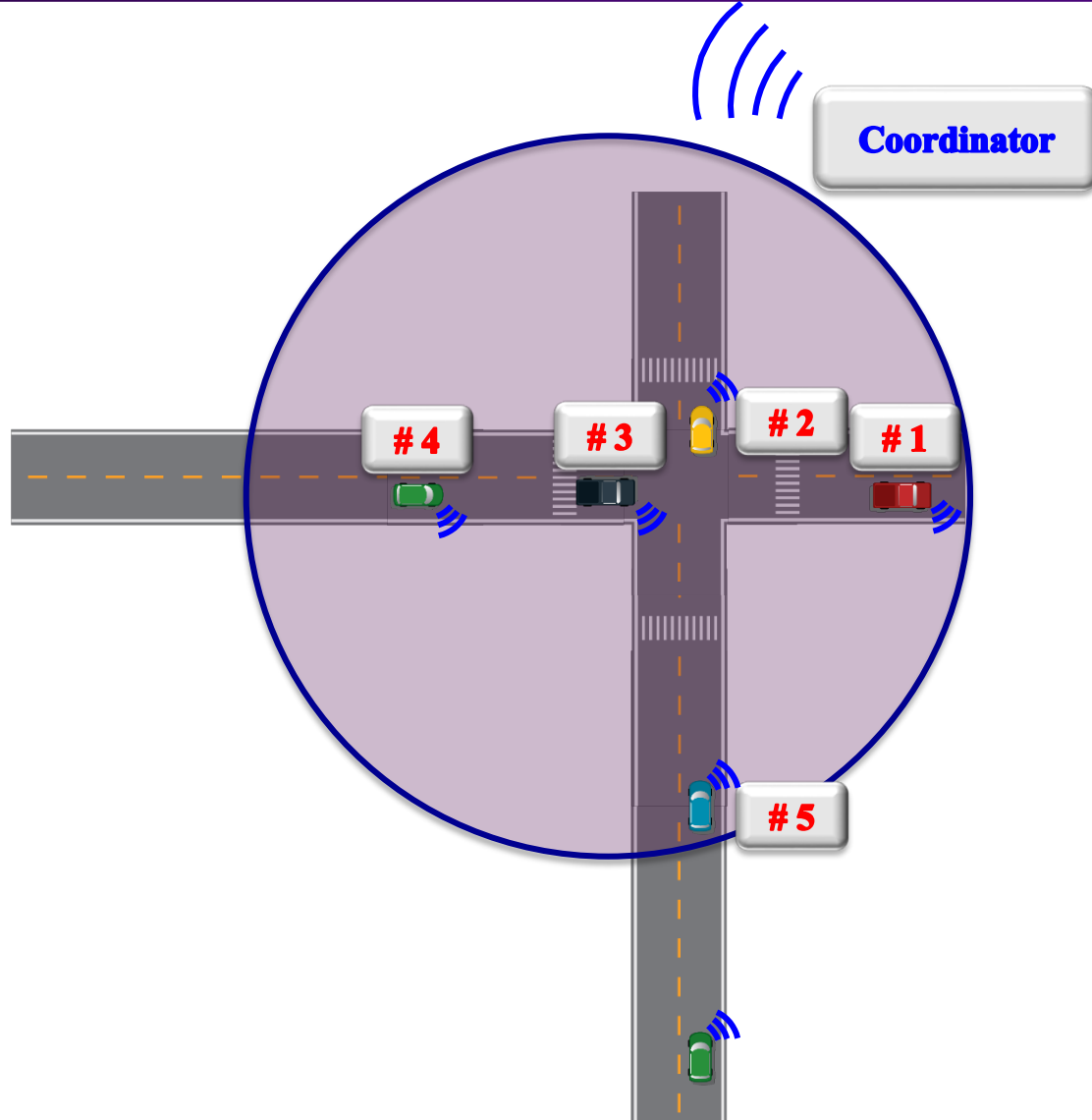
NO TRAFFIC LIGHTS - CAVs



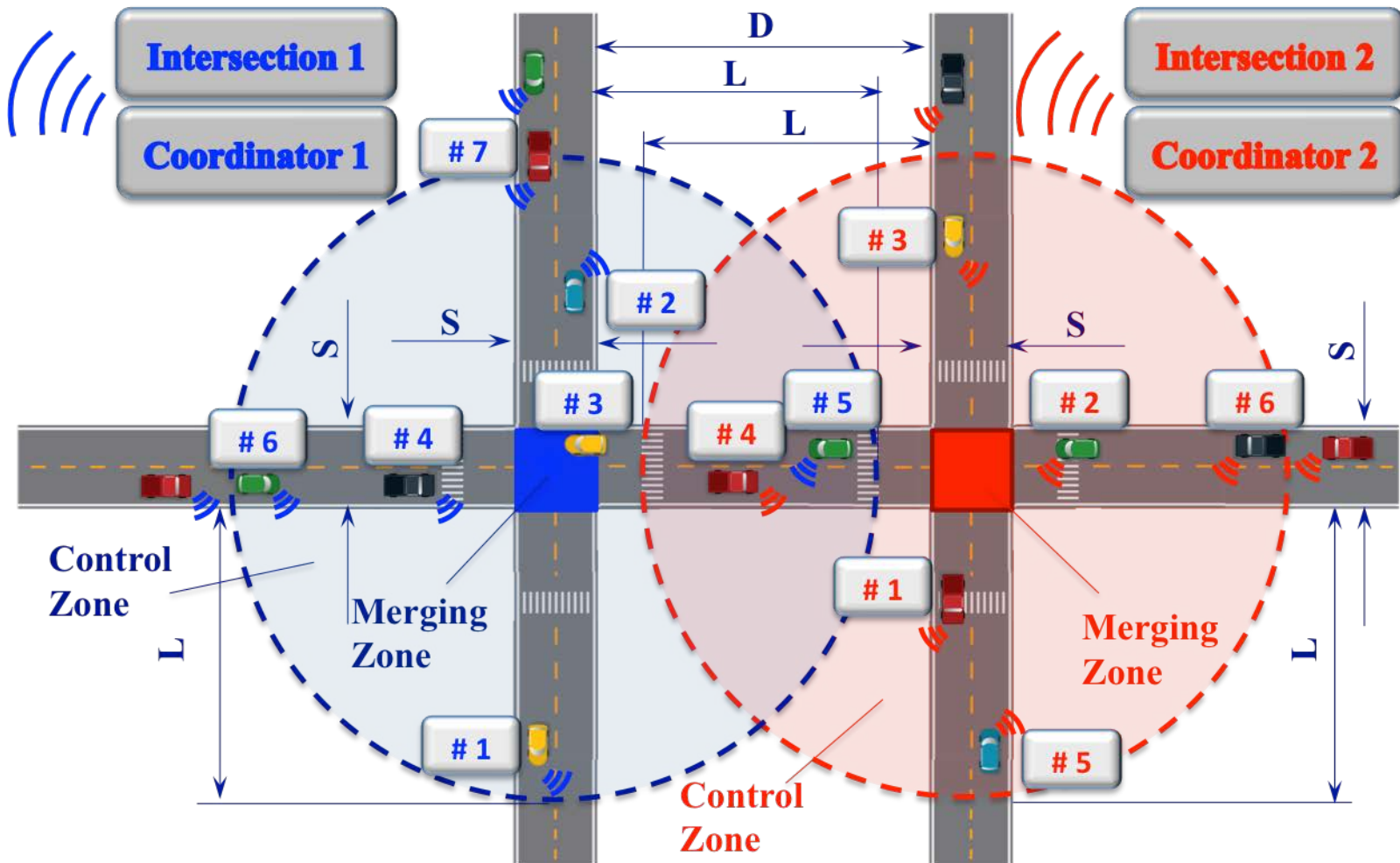
NO TRAFFIC LIGHTS - CAVs



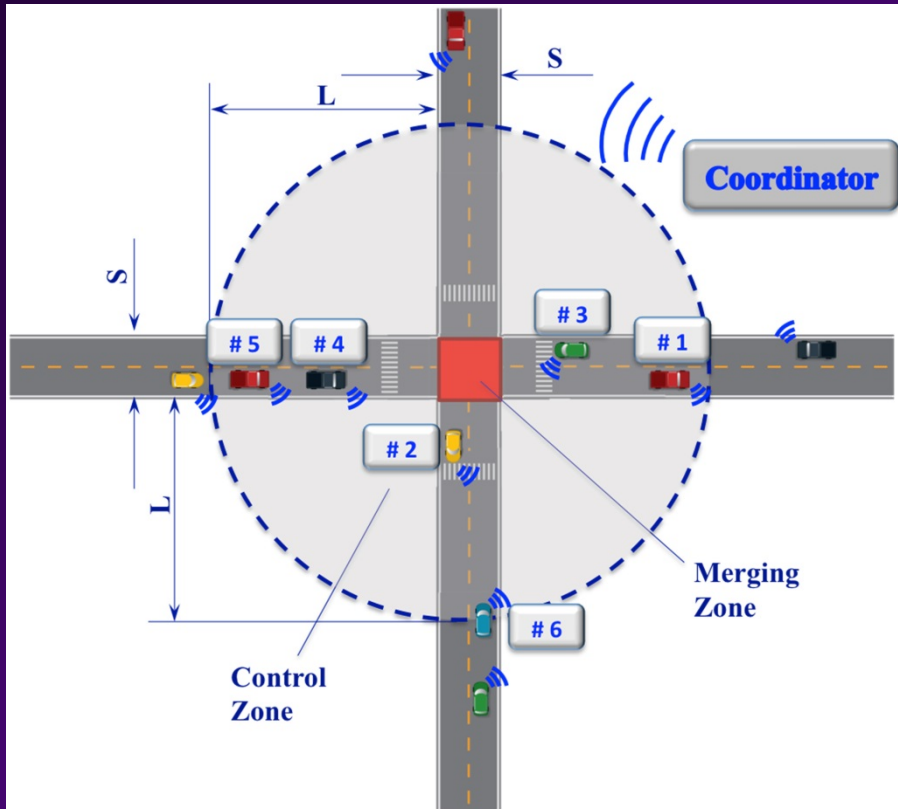
NO TRAFFIC LIGHTS - CAVs



NO TRAFFIC LIGHTS - CAVs



THE MODEL



CAV dynamics:

$$\dot{p}_i = v_i(t)$$

$$\dot{v}_i = u_i(t)$$

$$t \in [t_i^0, t_i^f]$$

t_i^0 : Enters Control Zone (CZ)

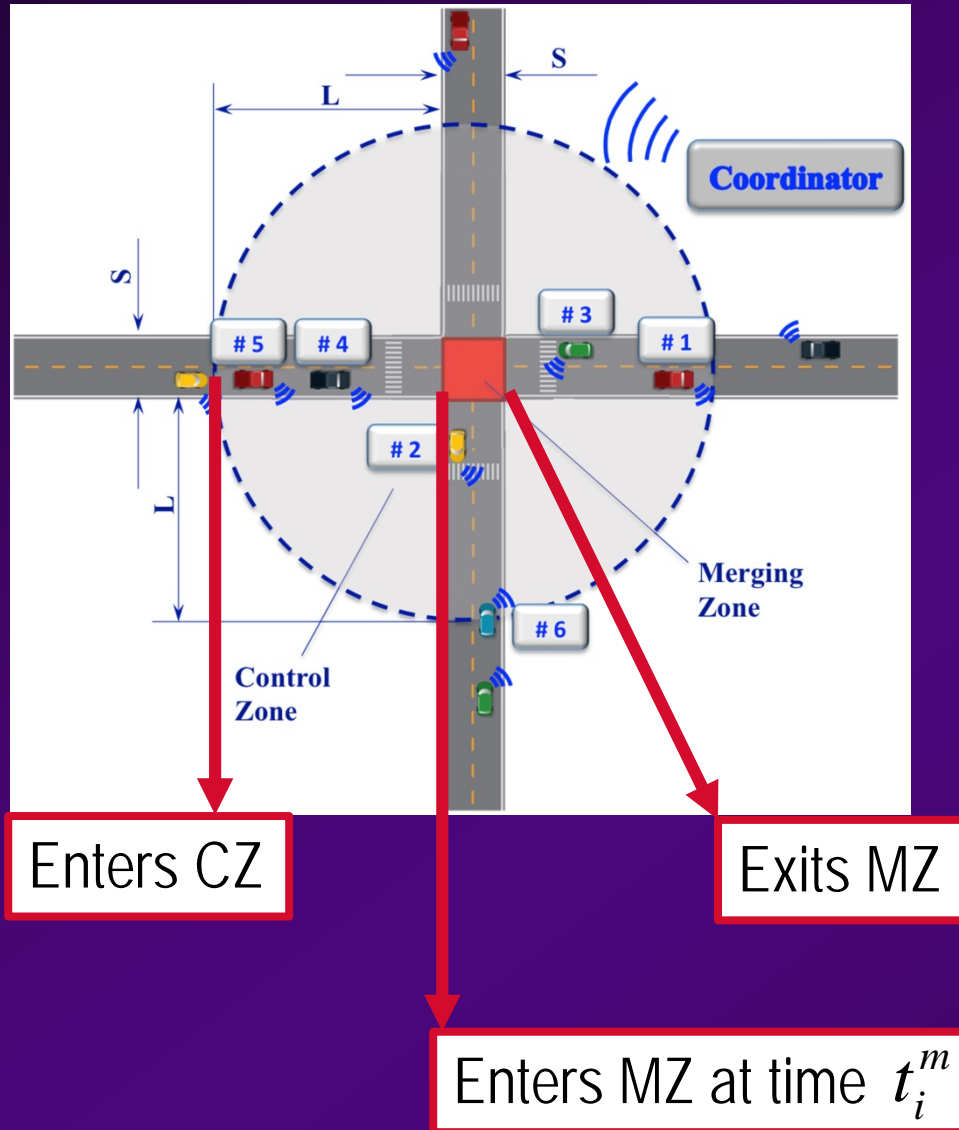
t_i^f : Exits Merging Zone (MZ)

Speed, Acceleration constraints:

$$u_{\min} \leq u_i(t) \leq u_{\max}$$

$$0 \leq v_{\min} \leq v_i(t) \leq v_{\max}$$

THE MODEL



Control Zone queue:

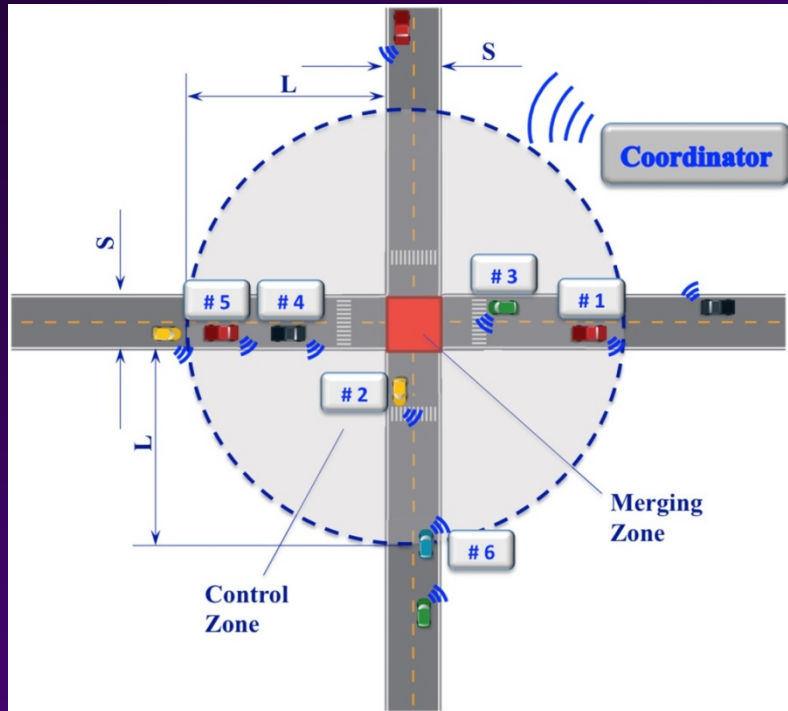
$$\mathcal{N}(t) = \{1, \dots, N(t)\}$$

Order constraint:

$$t_i^m \geq t_i^{m-1}, \quad i \in \mathcal{N}(t), i > 1$$

*Not necessarily FIFO
– can change order at CAV
arrival events*

THE MODEL



Depending on physical location of i relative to $i-1$,
 $i-1$ belongs to one of the four subsets:

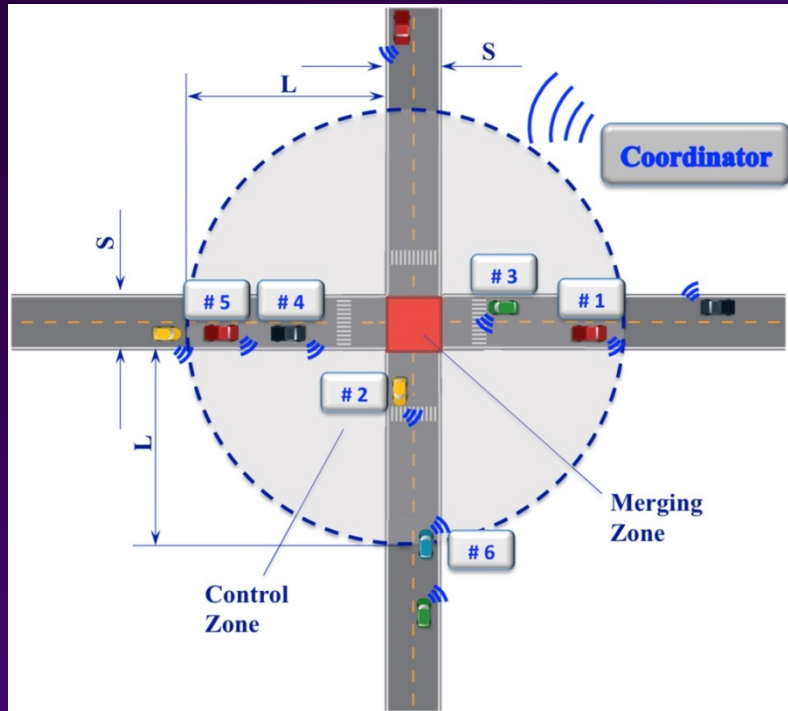
1. $R_i(t)$: same road, same direction as i ,
different lanes

2. $L_i(t)$: same road, same lane as i

3. $C_i(t)$: different road from i ,
possible collision at MZ

4. $O_i(t)$: same road as i , opposite direction,
no collision at MZ

THE MODEL - ASSUMPTIONS



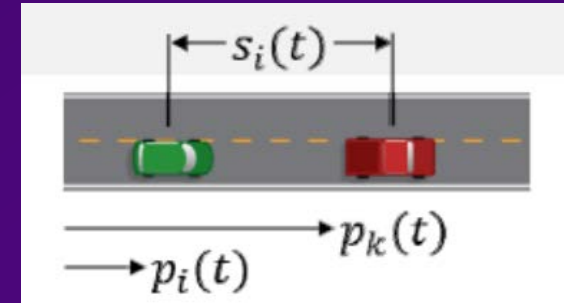
- No turn or lane change
- Constant speed in MZ:

$$t_i^f = t_i^m + \frac{S}{v_i(t_i^m)}$$

SAFETY CONSTRAINTS

- Rear end safety constraint:

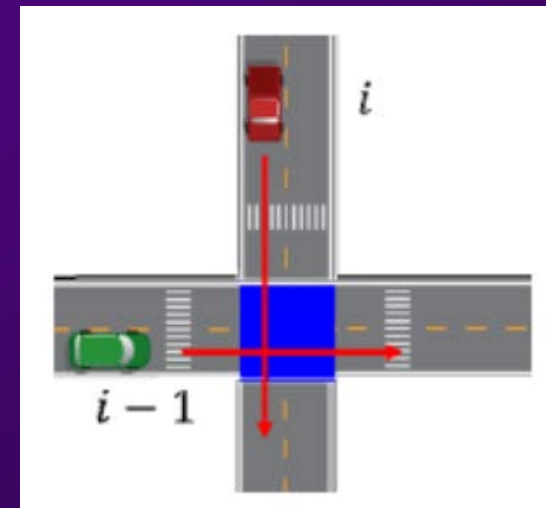
$$s_i(t) = p_k(t) - p_i(t) \geq \delta, \quad t \in [t_i^0, t_i^f]$$



- Lateral collision avoidance constraint:

$$\Gamma_i = \{t : t \in [t_i^m, t_i^f]\}$$

$$\Gamma_i \cap \Gamma_j = \emptyset, \quad t \in [t_i^m, t_i^f], \quad j \in C_i(t)$$



ENERGY MINIMIZATION PROBLEM: *E-MIN*

$$\min_{u_i(t)} J_i(u_i(t), t_i^m) = \frac{1}{2} \int_{t_i^0}^{t_i^m} u_i^2(t) dt$$

- subject to :
1. CAV dynamics
 2. Speed/Acceleration constraints
 3. Order constraints: $t_i^m \geq t_i^{m-1}$
 4. Rear-end safety constraint
 5. Lateral collision avoidance constraint

$$p_i(t_i^0) = 0, \quad p_i(t_i^m) = L$$

Given t_i^0 , $v_i(t_i^0)$, t_i^m  *How is this determined?*

Each CAV minimizes ENERGY COST FUNCTIONAL

ENERGY MINIMIZATION PROBLEM: *E-MIN*

Feasible control set for *E-MIN*:

$\mathcal{A}_i = \{u_i(t) \in U_i \text{ subject to :}$

1. CAV dynamics
2. Speed/Acceleration constraints
3. Order constraints: $t_i^m \geq t_i^{m-1}$
4. Rear-end safety constraint
5. Lateral collision avoidance constraint

$$p_i(t_i^0) = 0, \quad p_i(t_i^m) = L$$

$$\text{Given } t_i^0, \quad v_i(t_i^0), \quad t_i^m \}$$

HOW IS i^{th} MERGING TIME DETERMINED ?

Maximize THROUGHPUT – Problem TP-MAX

$$\min_{\mathbf{t}_{(2:N(t))}} \sum_{i=2}^{N(t)} \left(t_i^m(\mathbf{u}_{(1:i)}(t)) - t_{i-1}^m(\mathbf{u}_{(1:i-1)}(t)) \right)$$

$$= \min_{\mathbf{t}_{N(t)}} \left(t_{N(t)}^m(\mathbf{u}_{(1:i)}(t)) - t_1^m(\mathbf{u}_{(1)}(t)) \right)$$

$$\text{subject to : } u_i(t; t_i^m) \in \mathcal{A}_i, i \in \mathcal{N}(t)$$

$$s_i(t) = p_k(t) - p_i(t) \geq \delta, t \in [t_i^0, t_i^m]$$

$$t_i^m \geq t_{i-1}^m, i \in \mathcal{N}(t), i > 1$$

HOW IS i^{th} MERGING TIME DETERMINED ?

THEOREM:


The solution of TP-MAX is recursively determined by each i :

$$t_i^{m*} = \begin{cases} t_1^{m*} & \text{if } i = 1 \\ \max\{t_{i-1}^{m*}, t_k^{m*} + \frac{\delta}{v_k^m}, t_i^c\} & \text{if } i-1 \in R_i(t) \cup O_i(t) \\ \max\{t_{i-1}^{m*} + \frac{\delta}{v_{i-1}^m}, t_i^c\} & \text{if } i-1 \in L_i(t) \\ \max\{t_{i-1}^{m*} + \frac{S}{v_{i-1}^m}, t_i^c\} & \text{if } i-1 \in C_i(t) \end{cases}$$

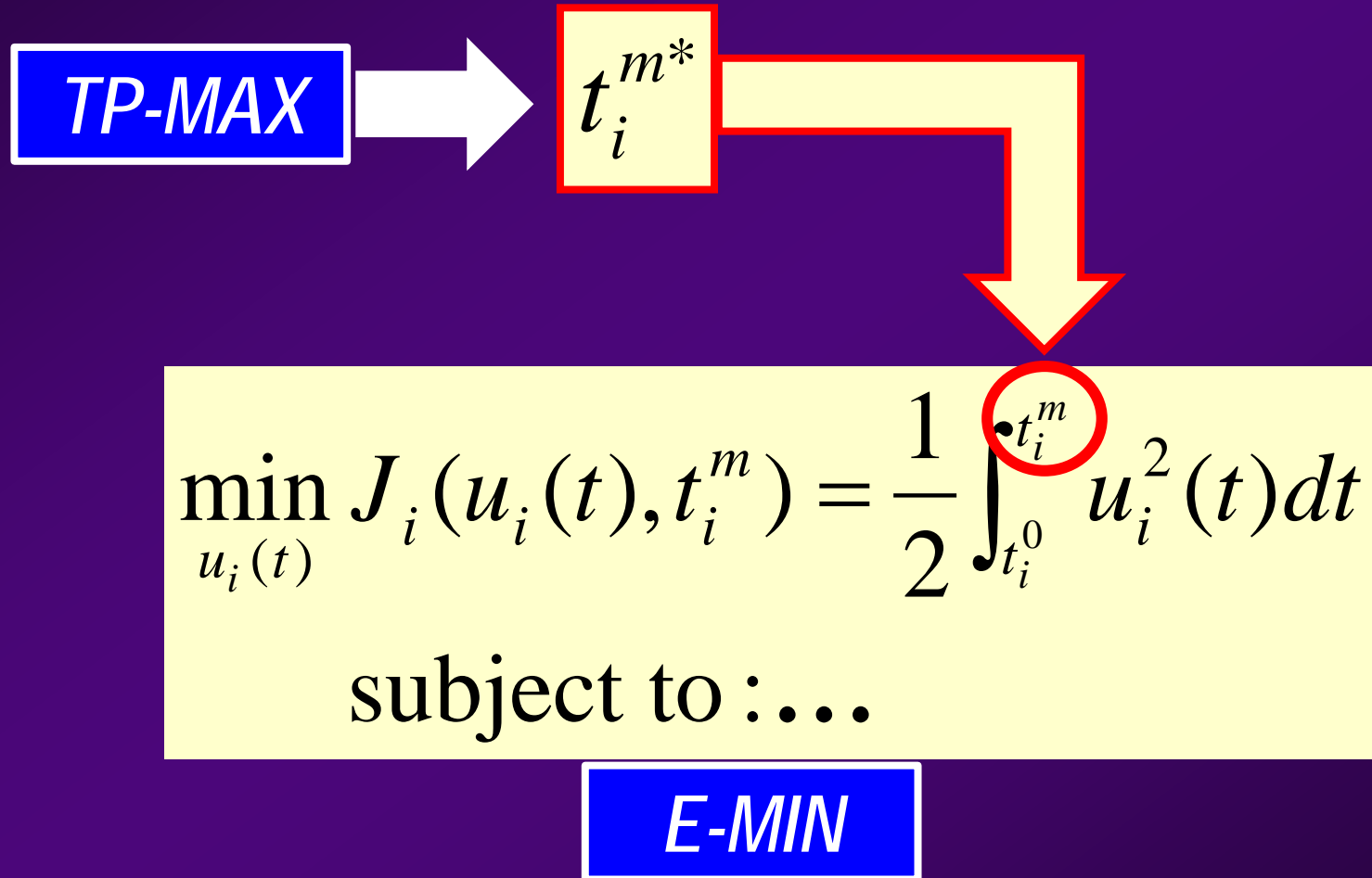
where: $t_i^c = t_i^1 \mathbf{1}_{v_i^m = v_{\max}} + t_i^2 (1 - \mathbf{1}_{v_i^m = v_{\max}})$

$$t_i^1 = t_i^0 + \frac{L}{v_{\max}} + \frac{(v_{\max} - v_i^0)^2}{2u_{i,\max} v_{\max}}$$

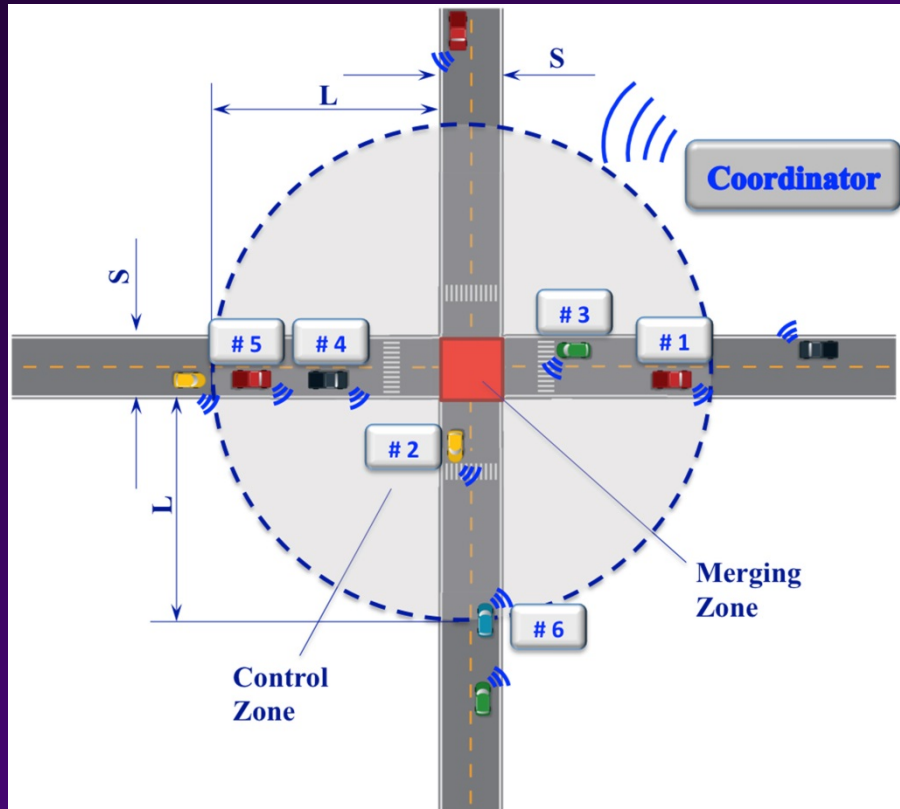
$$t_i^2 = t_i^0 + \frac{[2Lu_{i,\max} + (v_i^0)^2]^{1/2} - v_i^0}{2u_{i,\max}}$$

 **Known constant**

HOW IS i^{th} MERGING TIME DETERMINED ?



DECENTRALIZED FRAMEWORK



CAV INFORMATION SET upon entering a CZ:

$$Y_i(t) = \left\{ \overset{\checkmark}{p_i(t)}, \overset{\checkmark}{v_i(t)}, \overset{\checkmark}{w}, Q_i, s_i(t), t_i^{m*} \right\}$$

w : unique CAV ID

Q_i : one of the four sets R_i , L_i , C_i , O_i

t_i^{m*} : solution of TP-MAX obtained by i

- INFORMATION SET available to i and COORDINATOR upon entering CZ
- Communication needed (e.g., DSRC)

DECENTRALIZED PROBLEM FOR EACH CAV i

$$\min_{u_i(t)} \frac{1}{2} \int_{t_i^0}^{t_i^{m*}} u_i^2(t) dt$$

- subject to :
1. CAV dynamics
 2. Speed/Acceleration constraints
 3. t_i^{m*} **from TP-MAX solution**

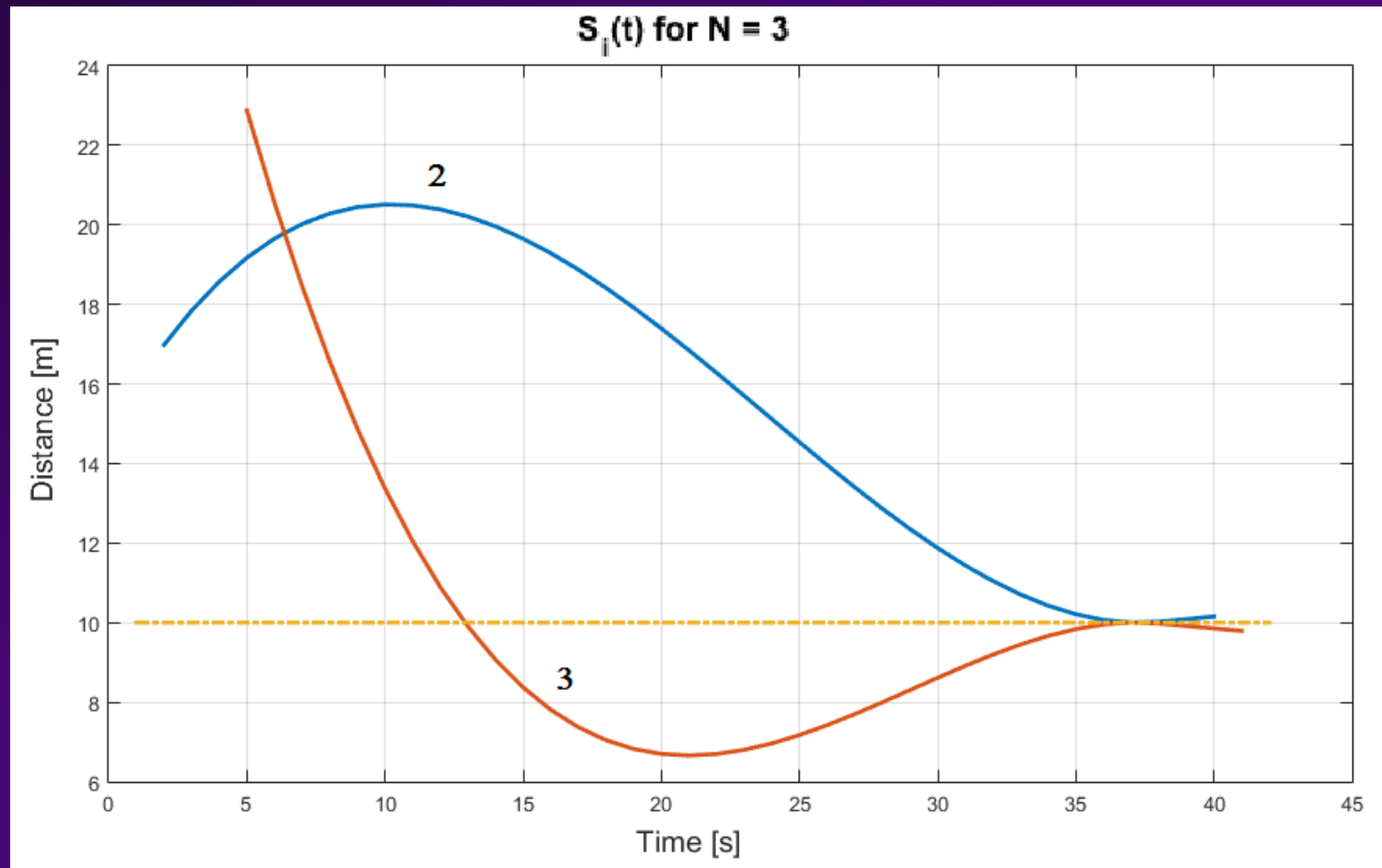
$$p_i(t_i^0) = 0, \quad p_i(t_i^{m*}) = L$$

Given t_i^0, v_i^0

NOT INCLUDED:

- Lateral collision avoidance constraint \rightarrow Implicitly handled by t_i^{m*}
- Rear-end safety constraint \rightarrow Only guaranteed at t_i^{m*} ???

SAFETY CONSTRAINT NOT GUARANTEED...



Safety constraint violation by CAV 3 when $\delta = 10$.

DECENTRALIZED PROBLEM SOLUTION

When constraints are not active:

$$u_i^*(t) = a_i t + b_i$$

$$v_i^*(t) = \frac{1}{2} a_i t^2 + b_i t + c_i$$

$$p_i^*(t) = \frac{1}{6} a_i t^3 + \frac{1}{2} b_i t^2 + c_i t + d_i$$

Coefficients obtained from:

$$\begin{bmatrix} \frac{1}{6}(t_i^0)^3 & \frac{1}{2}(t_i^0)^2 & t_i^0 & 1 \\ \frac{1}{2}(t_i^0)^2 & t_i^0 & 1 & 0 \\ \frac{1}{6}(t_i^m)^3 & \frac{1}{2}(t_i^m)^2 & t_i^m & 1 \\ -t_i^m & -1 & 0 & 0 \end{bmatrix} \cdot \begin{bmatrix} a_i \\ b_i \\ c_i \\ d_i \end{bmatrix} = \begin{bmatrix} p_i(t_i^0) \\ v_i(t_i^0) \\ p_i(t_i^m) \\ 0 \end{bmatrix}$$

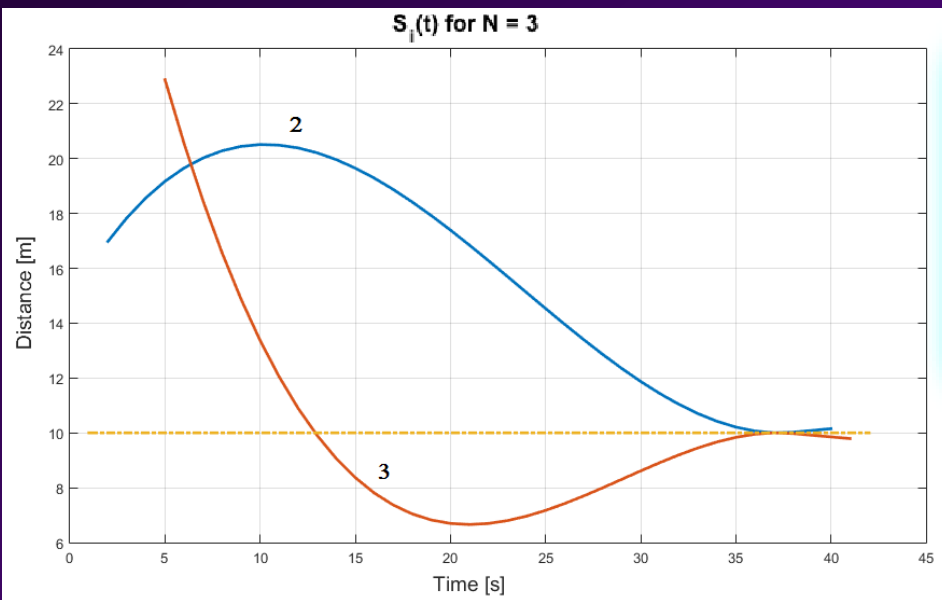
DECENTRALIZED PROBLEM SOLUTION

When one or more constraints are active:

Solution is of the same form and still analytically tractable

Malikopoulos, Cassandras, and Zhang, 2017

FEASIBILITY ANALYSIS



Under what conditions can we guarantee safety throughout the CZ ?

THEOREM:

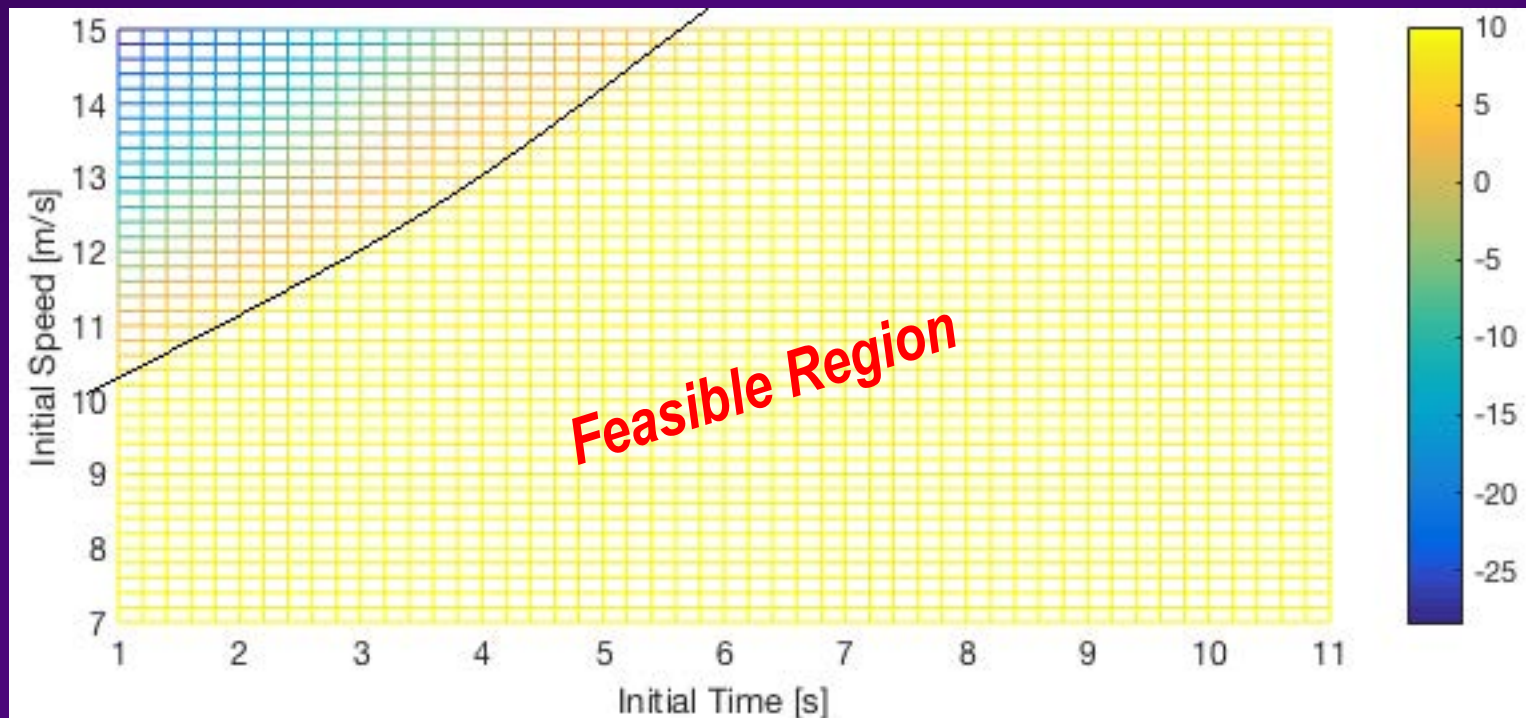
There exists a nonempty feasible region of initial conditions (t_i^0, v_i^0) for each i such that, under the decentralized optimal control, $s_i(t) = p_k(t) - p_i(t) \geq \delta$ holds for all $t \in [t_i^0, t_i^m]$ given initial conditions $t_k^0, v_k^0, t_k^m, v_k^0$ for k

Zhang, Cassandras, and Malikopoulos, ACC 2017

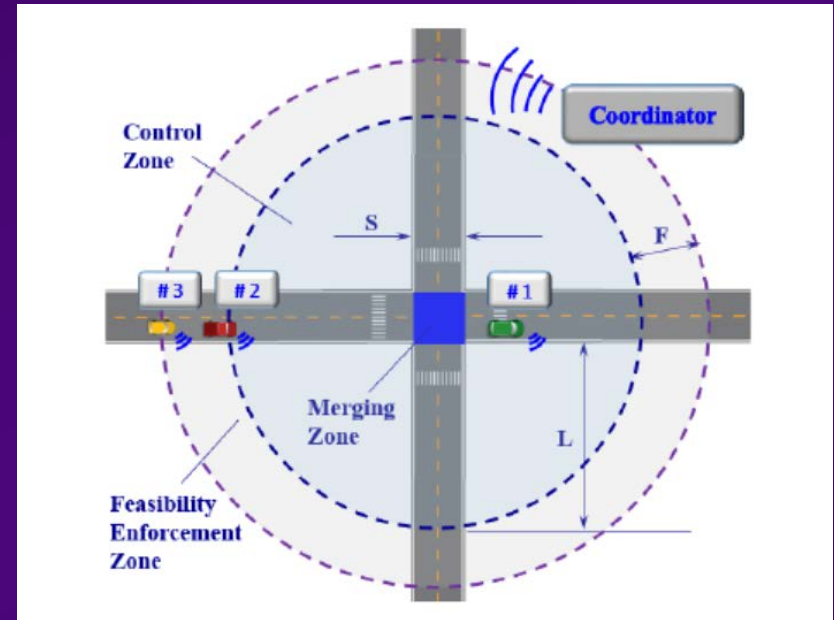
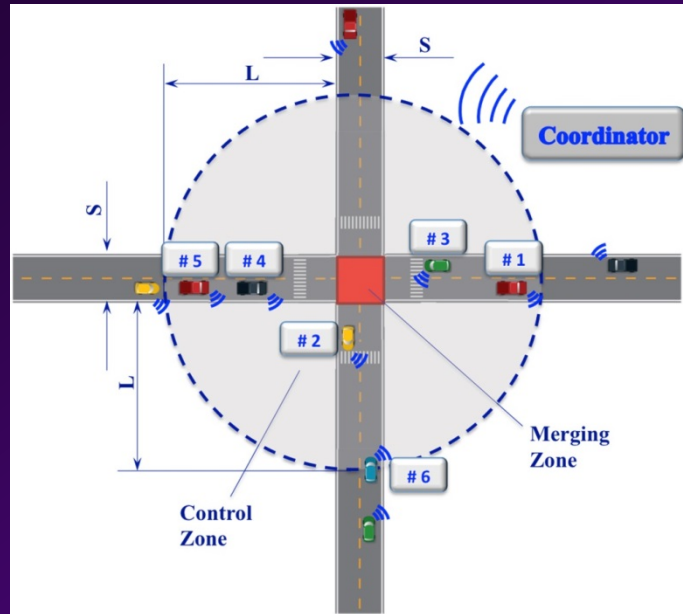
FEASIBILITY ANALYSIS

THEOREM:

There exists a nonempty feasible region of initial conditions (t_i^0, v_i^0) for each i such that, under the decentralized optimal control, $s_i(t) = p_k(t) - p_i(t) \geq \delta$ holds for all $t \in [t_i^0, t_i^m]$ given initial conditions $t_k^0, v_k^0, t_k^m, v_k^0$ for k



FEASIBILITY ENFORCEMENT ZONE



What is the length of the Feasibility Enforcement Zone (FEZ) ?

Worst case analysis:

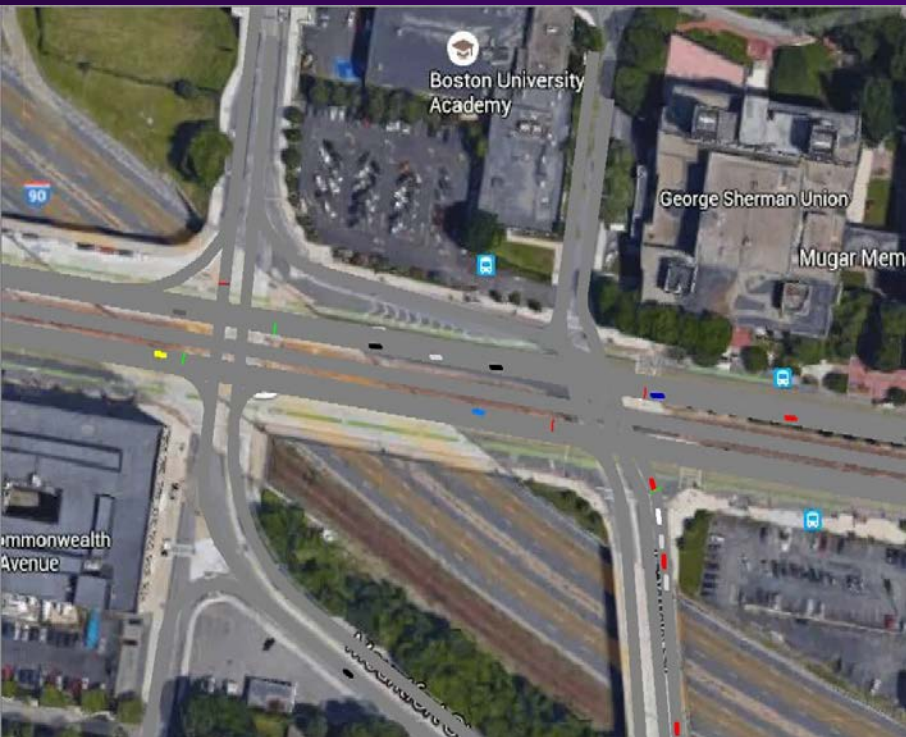
When CAV i enters FEZ with v_{\max} and needs to reach CZ with v_{\min}



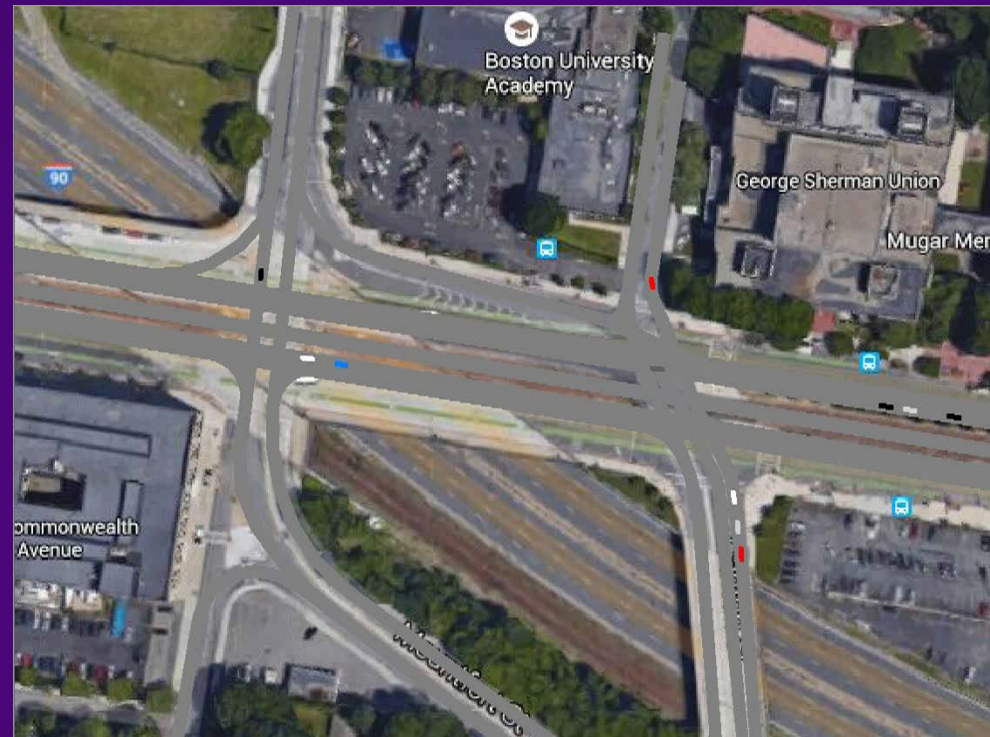
$$\bar{F} = \frac{v_{\min}^2 - v_{\max}^2}{2u_B}, \quad u_B : \text{min. acceleration s.t. } u_{\min} < u_B < 0$$

WHO NEEDS TRAFFIC LIGHTS?

With **traffic lights**



With **decentralized control of CAVs**



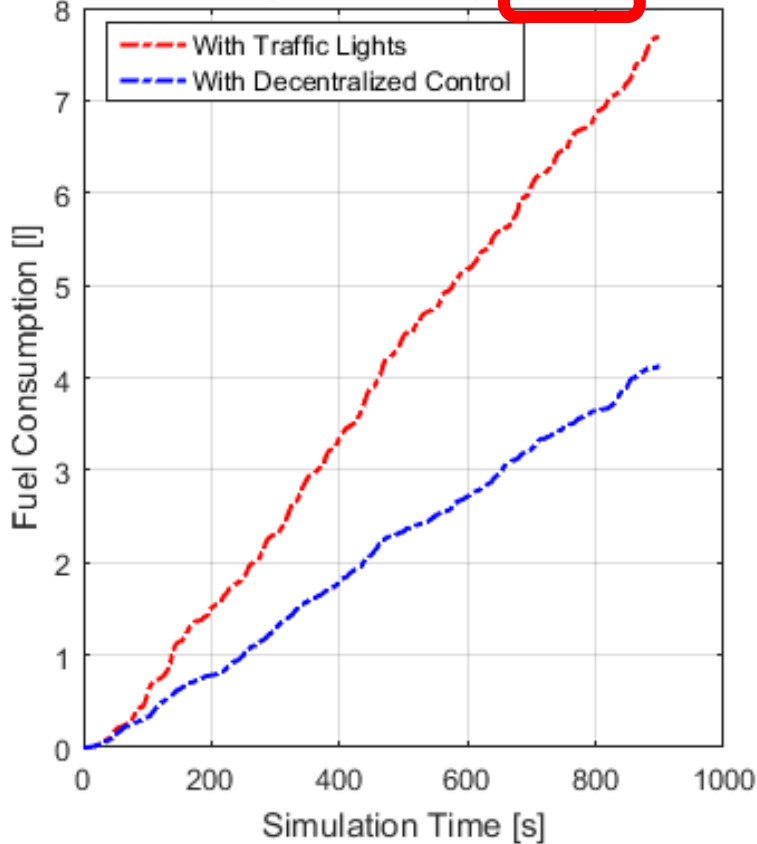
One of the worst-designed double intersections ever...
(BU Bridge – Commonwealth Ave, Boston, MA)

EXAMPLE

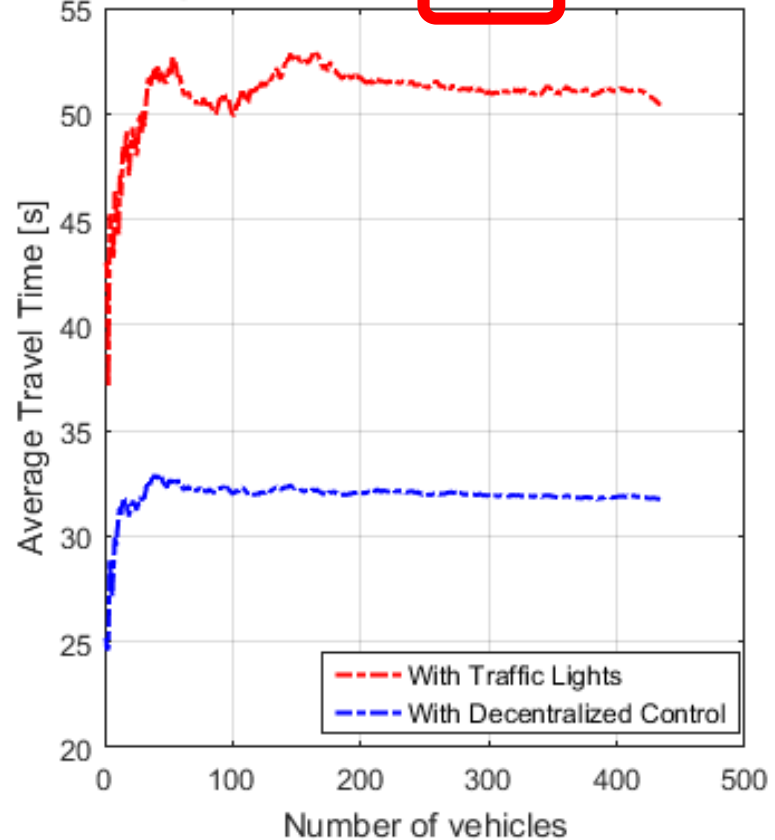
WIN-WIN!

+ fewer harmful emissions

Fuel Consumption (434 vehicles) **46.63%** improvement



Average Travel Time **30.89%** improvement



TESTING AUTOMATED MOBILITY

BU Robotics Lab

Mcity test bed,
U. Michigan



OPTIMAL CONTROL FRAMEWORK – ISSUES

- Computational complexity for on-line implementation
- Incorporating turns and extending to multiple intersections
- Alternative formulations: travel time + fuel efficiency
- How about pedestrians and non-CAV traffic?

CONCLUSIONS

Two takeaways (proposed research directions) from this talk:

1. Use real data to infer user behavior and solve system-centric problems, estimate **Price of Anarchy (PoA)**
 2. Use **Connected Autonomous Vehicles (CAVs)** + control to reduce/eliminate the PoA
-

Interesting OPEN QUESTIONS regarding **Automated Mobility**:

- What fraction of CAVs does it take to realize benefits ?
- How do we integrate CAVs with pedestrians, bicycles, etc ?
- Is **Shared Mobility On-Demand** the long-term answer ?
(typical car utilization is 4%...)

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WHERE DISCOVERIES BEGIN



City of Boston.gov



Thank you
Merci...