SMART CITIES AS CYBER ^ PHYSICAL SYSTEMS

SOCIAL

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OUTLINE

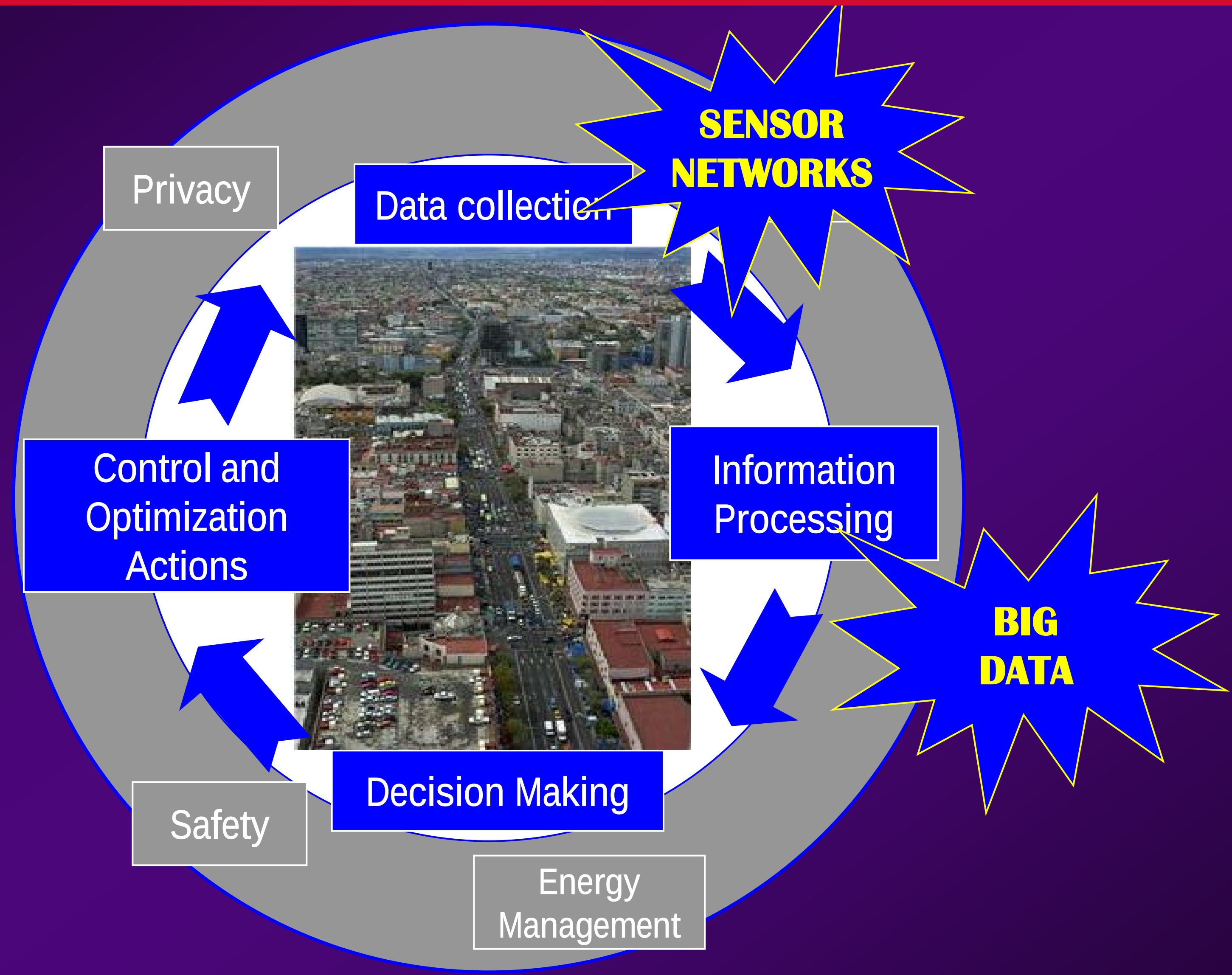
- What is a “Smart City” ?

- A Data-Driven Dynamic Resource Allocation Framework

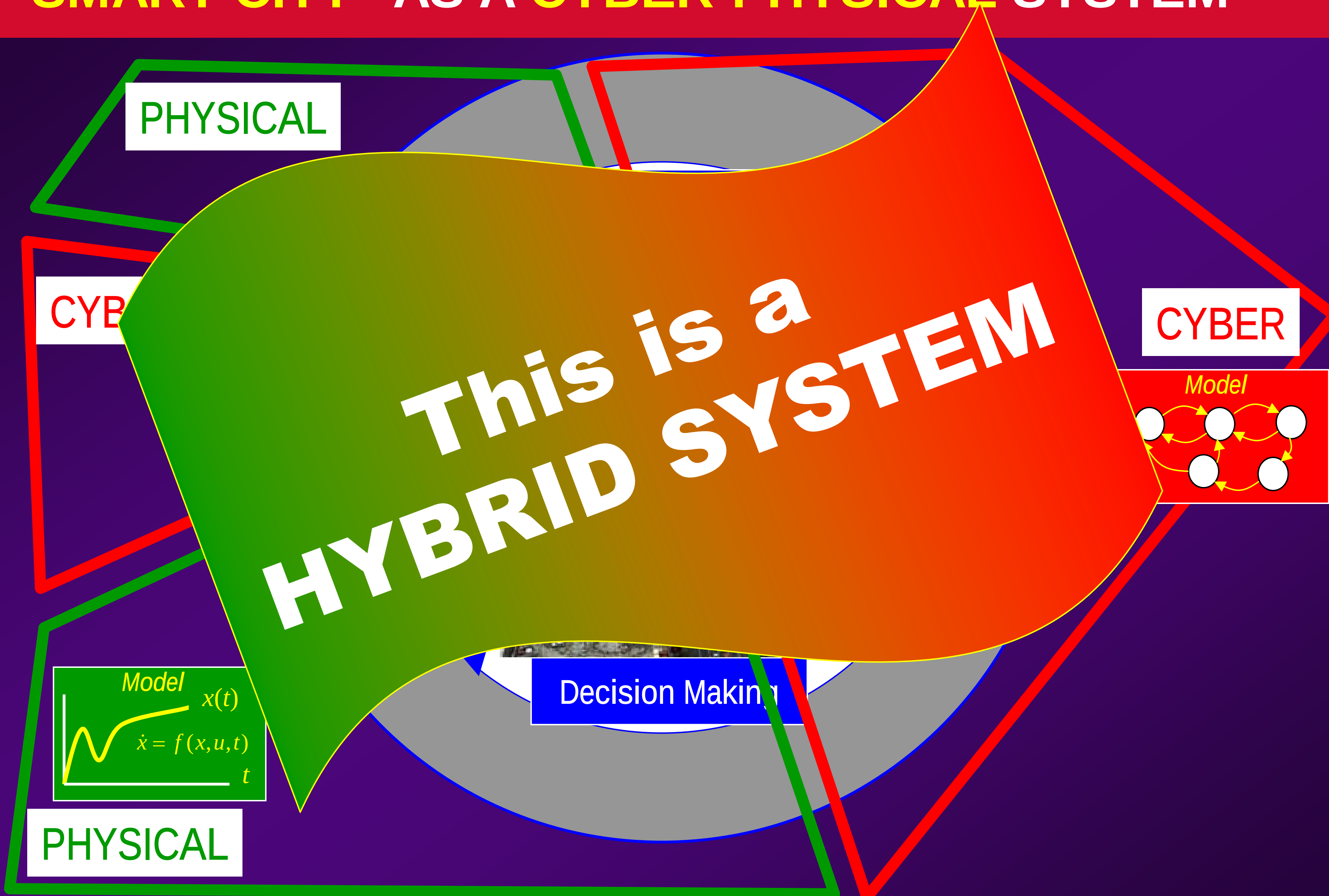
- Examples of Smart City problems and solutions:

  - Adaptive Traffic Light Control
  - Smart Parking
  - Street Bump
  - Traffic control: eliminating the Price of Anarchy (PoA)

"SMART CITY" AS A CYBER-PHYSICAL SYSTEM



“SMART CITY” AS A CYBER-PHYSICAL SYSTEM



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*

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*

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*

"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” ?

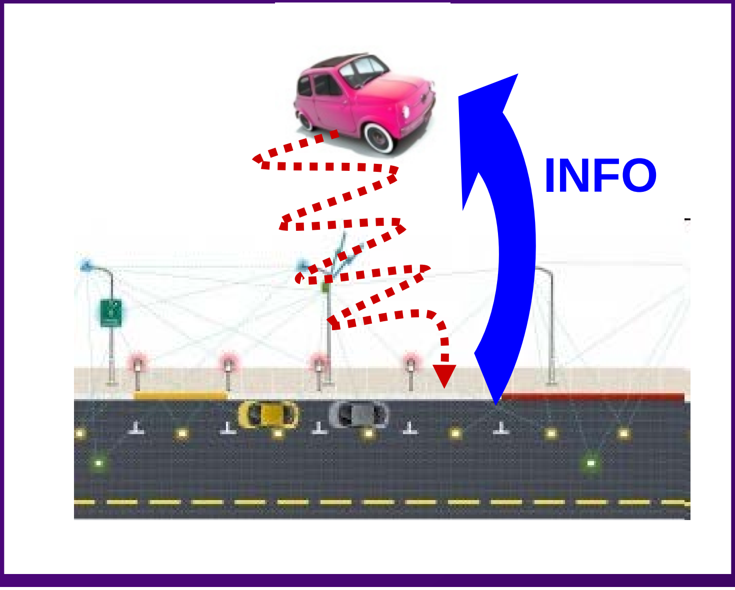
CREDIT: Fernando Livschitz

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

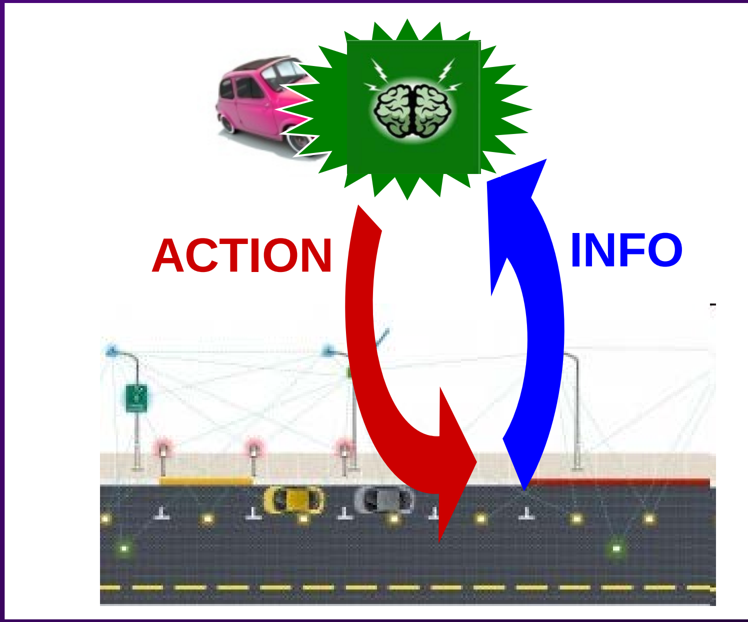
WHAT IS *REALLY* "SMART" ?

COLLECTING DATA IS NOT "SMART"

- JUST A NECESSARY STEP TO BEING "SMART"



PROCESSING DATA TO MAKE GOOD DECISIONS IS "SMART"



WHAT IS A "SMART CITY" ?

- Ubiquitous wireless connectivity of *users* and *resources*
- Abundance of real-time data shared among *users* and *resources*

⇩ *Some SMART things we can do*

- Bring in feedback control mechanisms
- Reduce/eliminate much of the infrastructure
  (e.g., *Connected Automated Vehicles*)
- Achieve system-centric (social) optimality rather than user-centric (selfish) optimality - *the SOCIAL component in CPS*

DATA-DRIVEN DYNAMIC RESOURCE ALLOCATION

DYNAMIC RESOURCE ALLOCATION

CHARGING STATIONS

TRAFFIC LIGHTS

ZIPCARS

STATE $\mathbf{x}(t)$

TIME

$$\mathbf{x}(t') = f[\mathbf{x}(t), \mathbf{u}(t), e(t)], \quad t' > t$$

CONTROL

- Reserve resource
- De-assign resource
- Change resource price
- Steer vehicle
- …

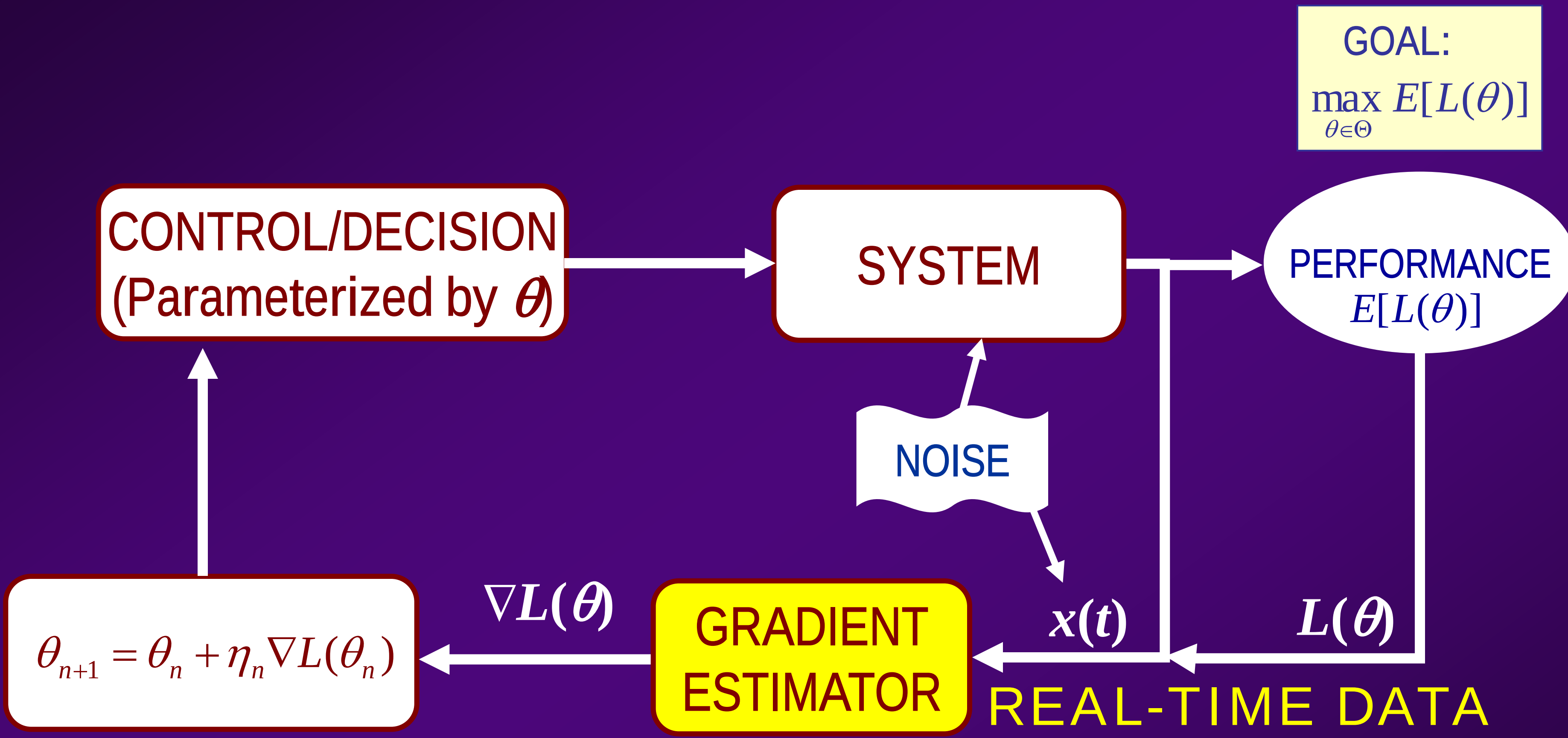
$$\min_{\mathbf{u}(t)} J(x(t), \mathbf{u}(t), t)$$

$$\text{s.t.} \begin{cases} \text{user constraints} \\ \text{resource constraints} \end{cases}$$

EVENTS

- New request
- Cancel request
- Resource freed
- …

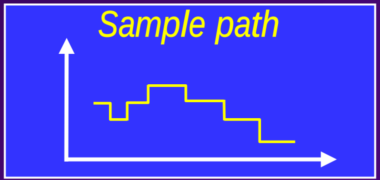
DATA-DRIVEN STOCHASTIC OPTIMIZATION

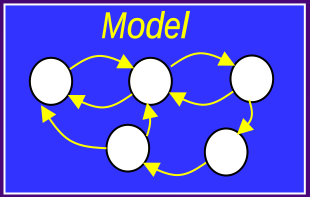


DIFFICULTIES: - $E[L(\theta)]$ NOT available in closed form

- $\nabla L(\theta)$ not easy to evaluate
- $\nabla L(\theta)$ may not be a good estimate of $\nabla E[L(\theta)]$

DATA-DRIVEN STOCHASTIC OPTIMIZATION IN *DES*: INFINITESIMAL PERTURBATION ANALYSIS (IPA)





CONTROL/DECISION (Parameterized by θ)

Discrete Event System (DES)

PERFORMANCE $E[L(\theta)]$

NOISE

$x(t)$

$L(\theta)$

IPA

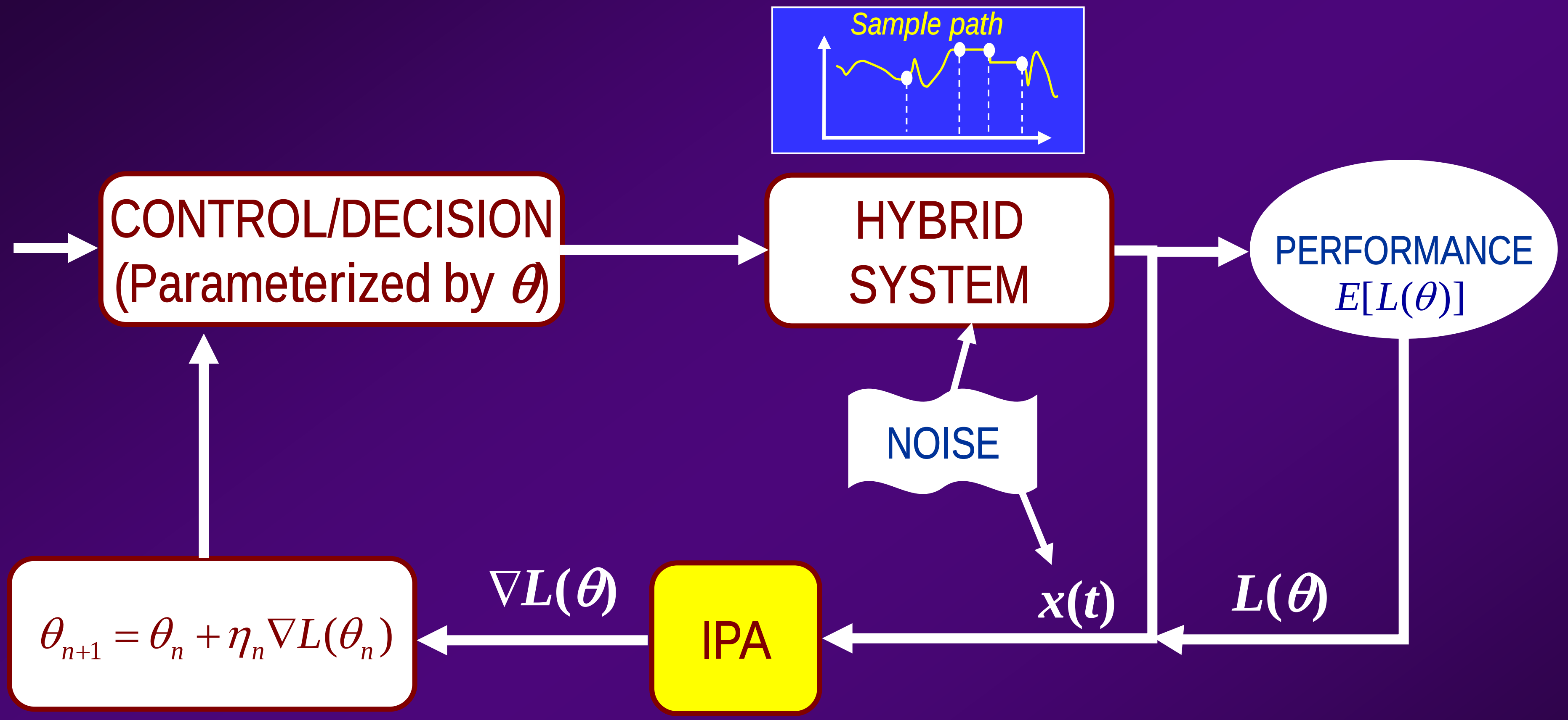
$\nabla L(\theta)$

$$\theta_{n+1} = \theta_n + \eta_n \nabla L(\theta_n)$$

For many (but NOT all) DES:
- Unbiased estimators
- General noise distributions
- Simple on-line implementation

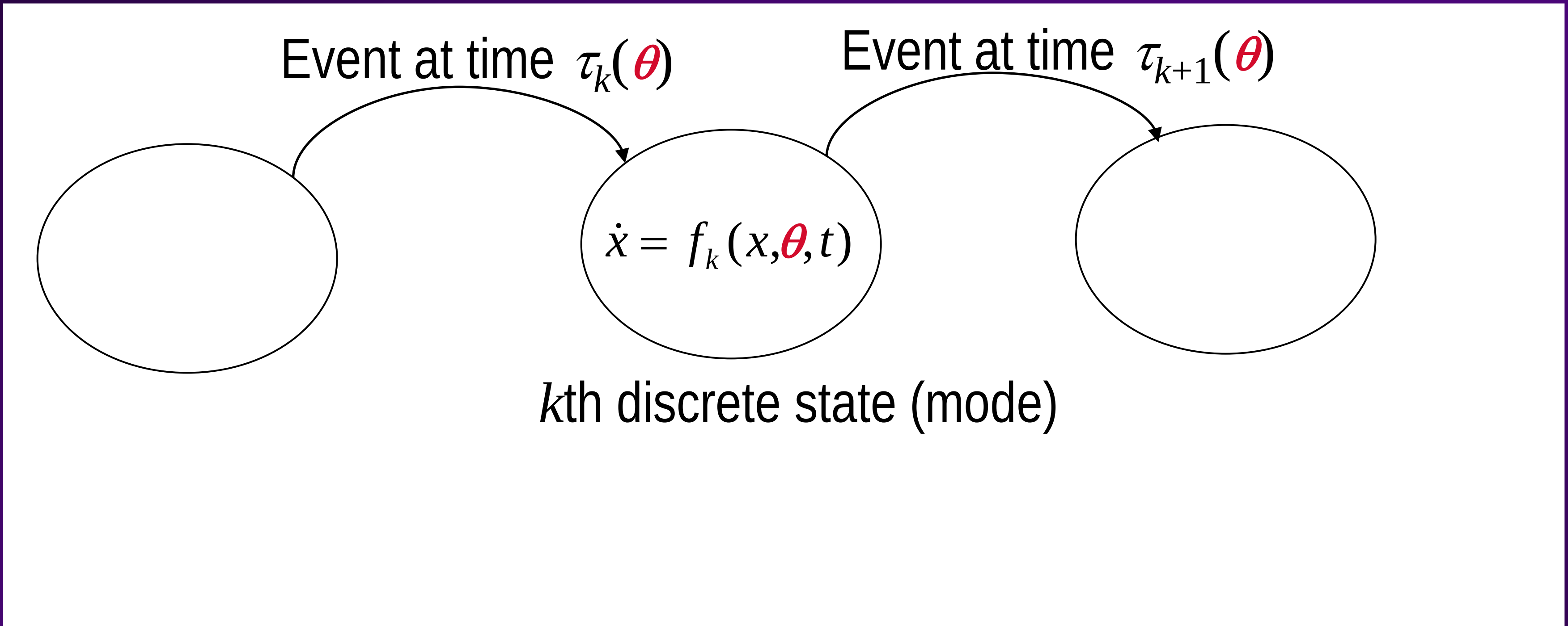
[*Ho and Cao, 1991*, *Glasserman, 1991*, *Cassandras, 1993, 2008*]

REAL-TIME STOCHASTIC OPTIMIZATION: *CPS (HYBRID) SYSTEMS*



A general framework for an IPA theory in Hybrid Systems

STOCHASTIC HYBRID AUTOMATA



θ: control parameter, $\theta \in \Theta$ (system design parameter,
parameter of an input process,
or parameter that characterizes a control policy)

THE IPA CALCULUS

NOTATION: $$x'(t) = \frac{\partial x(\theta, t)}{\partial \theta}, \quad \tau_k' = \frac{d\tau_k(\theta)}{d\theta}$$

[*Wardi et al, IEEE TAC*, 2010; *Cassandras et al, Europ. J. Control, 2010*]

IPA: *THREE FUNDAMENTAL EQUATIONS* *

System dynamics over $(\tau_k(\theta),\ \tau_{k+1}(\theta)]$: $\dot{x} = f_k(x,\theta,t)$

1. $x'(\tau_k^+) = x'(\tau_k^-) + [f_{k-1}(\tau_k^-) - f_k(\tau_k^+)]\cdot\tau'_k$

2. $$x'(t) = e^{\int_{\tau_k}^{t} \frac{\partial f_k(u)}{\partial x} du}\left[\int_{\tau_k}^{t} \frac{\partial f_k(v)}{\partial \theta} e^{-\int_{\tau_k}^{v} \frac{\partial f_k(u)}{\partial x} du} dv + x'(\tau_k^+)\right]$$

3. $\tau'_k = 0$ or $\tau'_k = -\left[\frac{\partial g}{\partial x} f_k(\tau_k^-)\right]^{-1}\left(\frac{\partial g}{\partial \theta} + \frac{\partial g}{\partial x} x'(\tau_k^-)\right)$

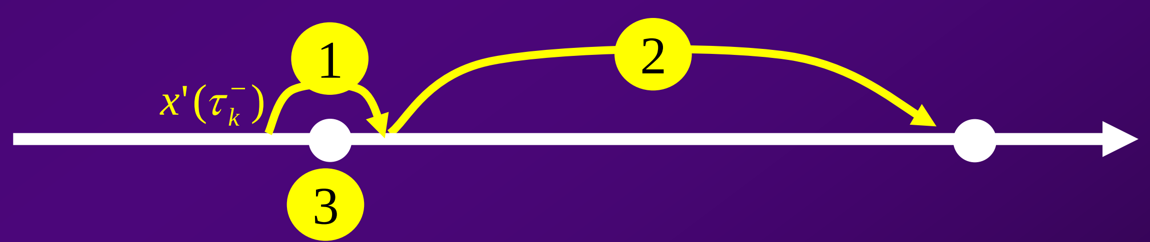
Recall:

$$x'(t) = \frac{\partial x(\theta,t)}{\partial \theta}$$

$$\tau'_k = \frac{d\tau_k(\theta)}{d\theta}$$

$g(x(\theta,\tau_k),\theta) = 0$

Switching function



*Some more complicated cases omitted

IPA PROPERTIES

1. *ROBUSTNESS*
2. *DECOMPOSABILITY*
3. *SCALABILITY*

Yao and Cassandras, J. DEDS, 2011

IPA PROPERTIES

Back to performance metric:

$$L(\theta) = \sum_{k=0}^{N} \int_{\tau_k}^{\tau_{k+1}} L_k(x,\theta,t)dt$$

NOTATION:

$$L_k'(x,\theta,t) = \frac{\partial L_k(x,\theta,t)}{\partial \theta}$$

Then:

$$\frac{dL(\theta)}{d\theta} = \sum_{k=0}^{N} \Bigg[\underbrace{\tau_{k+1}' \cdot L_k(\tau_{k+1}) - \tau_k' \cdot L_k(\tau_k)}_{\text{What happens at event times}} + \underbrace{\int_{\tau_k}^{\tau_{k+1}} L_k'(x,\theta,t)dt}_{\text{What happens between event times}} \Bigg]$$

1. ROBUSTNESS

THEOREM 1: If either 1,2 holds, then $dL(\theta)/d\theta$ depends only on information available at event times τ_k:

1. $L(x,\theta,t)$ is independent of t over $[\tau_k(\theta),\ \tau_{k+1}(\theta))$ for all k

2. $L(x,\theta,t)$ is only a function of x and for all t over $[\tau_k(\theta),\ \tau_{k+1}(\theta))$:

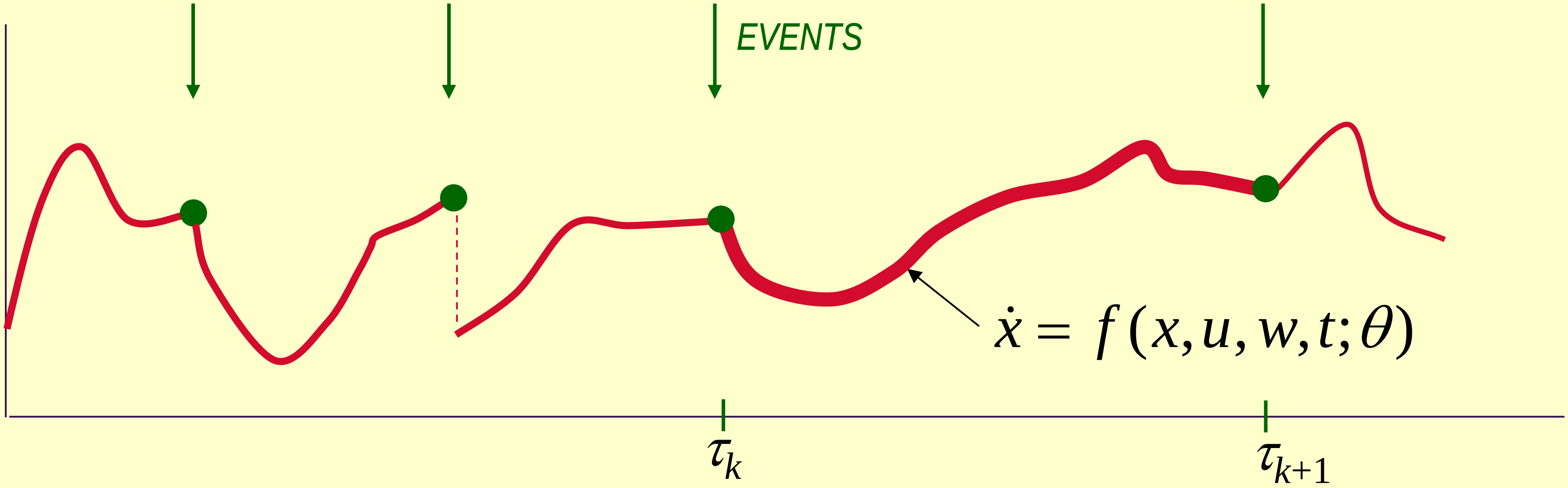
$$\frac{d}{dt}\frac{\partial L_k}{\partial x} = \frac{d}{dt}\frac{\partial f_k}{\partial x} = \frac{d}{dt}\frac{\partial f_k}{\partial \theta} = 0$$

$$\frac{dL(\theta)}{d\theta} = \sum_{k=0}^{N}\left[\tau'_{k+1}\cdot L_k(\tau_{k+1}) - \tau'_k \cdot L_k(\tau_k) + \cancel{\int_{\tau_k}^{\tau_{k+1}} L'_k(x,\theta,t)dt}\right]$$

IMPLICATION: - Performance sensitivities can be obtained from information limited to event times, which is easily observed

- *No need to track system in between events !*

1. ROBUSTNESS



OBVIOUS: Evaluating $x(t;\theta)$ requires full knowledge of w and f

NOT OBVIOUS: $\dfrac{dx(t;\theta)}{d\theta}$ may be *independent* of w and f

It often depends only on: - event times τ_k

- possibly $f(\tau_{k+1}^-)$

2. DECOMPOSABILITY

THEOREM 2: Suppose an endogenous event occurs at τ_k with switching function $g(x,\theta)$.

If $f_k(\tau_k^+) = 0$, then $x'(\tau_k^+)$ is independent of f_{k-1}.

If, in addition, $\dfrac{dg}{d\theta} = 0$ then $x'(\tau_k^+) = 0$

IMPLICATION: Performance sensitivities are often reset to 0

$\Rightarrow$ sample path can be conveniently decomposed

3. SCALABILITY

OBSERVATION: IPA is entirely *event-driven*

$\Rightarrow$ scales with event set size, not state space!

1. $x'(\tau_k^+) = x'(\tau_k^-) + [\, f_{k-1}(\tau_k^-) - f_k(\tau_k^+)] \cdot \tau'_k$

2. $x'(\tau_{k+1}^-) = e^{\int_{\tau_k}^{\tau_{k+1}} \frac{\partial f_k(u)}{\partial x} du} \left[\int_{\tau_k}^{\tau_{k+1}} \frac{\partial f_k(v)}{\partial \theta} e^{-\int_{\tau_k}^{v} \frac{\partial f_k(u)}{\partial x} du} dv + x'(\tau_k^+) \right]$

3. $\tau'_k = 0$ or $\tau'_k = -\left[\frac{\partial g}{\partial x} f_k(\tau_k^-) \right]^{-1} \left(\frac{\partial g}{\partial \theta} + \frac{\partial g}{\partial x} x'(\tau_k^-) \right)$

IPA PROPERTIES

In many cases:

- *No need for a detailed model* (captured by f_k) to describe state behavior in between events

- This explains why *simple abstractions of a complex stochastic system* can be adequate to perform sensitivity analysis and optimization, as long as event times are accurately observed and local system behavior at these event times can also be measured

A SMART CITY APPLICATION:

ADAPTIVE

TRAFFIC LIGHT CONTROL

TRAFFIC LIGHT CONTROL - BACKGROUND

A basic binary switching control (GREEN – RED) problem with a long history…

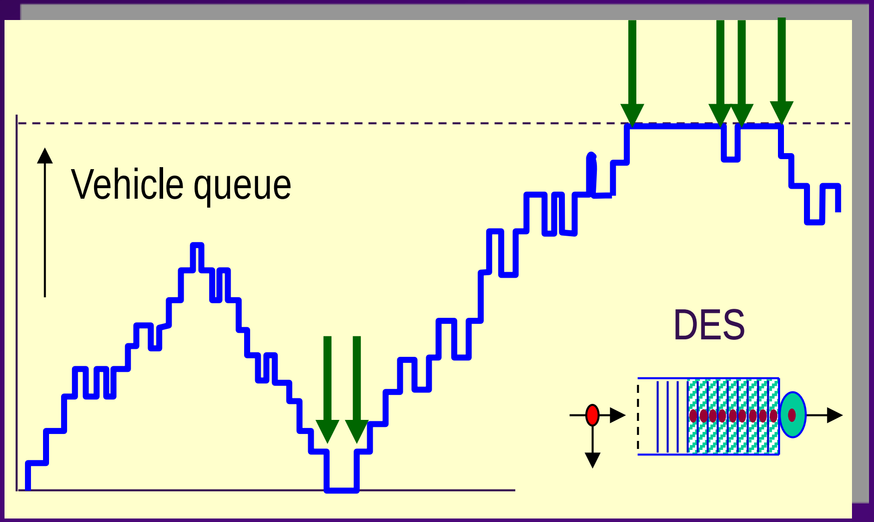
- Mixed Integer Linear Programming (MILP) [*Dujardin et al, 2011*]
- Extended Linear Complementarity Problem (ELCP) [*DeSchutter, 1999*]
- MDP and Reinforcement Learning [*Yu et al., 2006*]
- Game Theory [*Alvarez et al., 2010*]
- Evolutionary algorithms [*Taale et al., 1998*]
- Fuzzy Logic [*Murat et al., 2005*]
- Expert Systems [*Findler and Stapp, 1992*]
- *Perturbation Analysis*

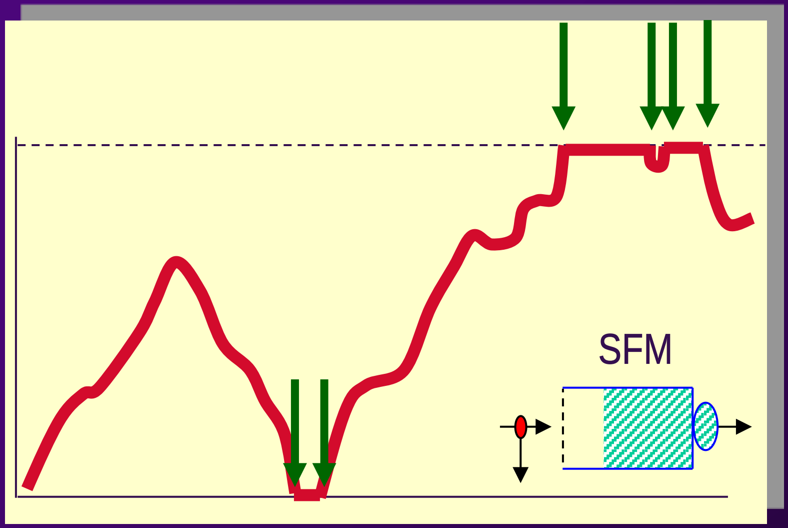
TRAFFIC LIGHT CONTROL - BACKGROUND

- *Perturbation Analysis* [*Panayiotou et al., 2005*]
  [*Geng and Cassandras, 2012*]

Single Intersection

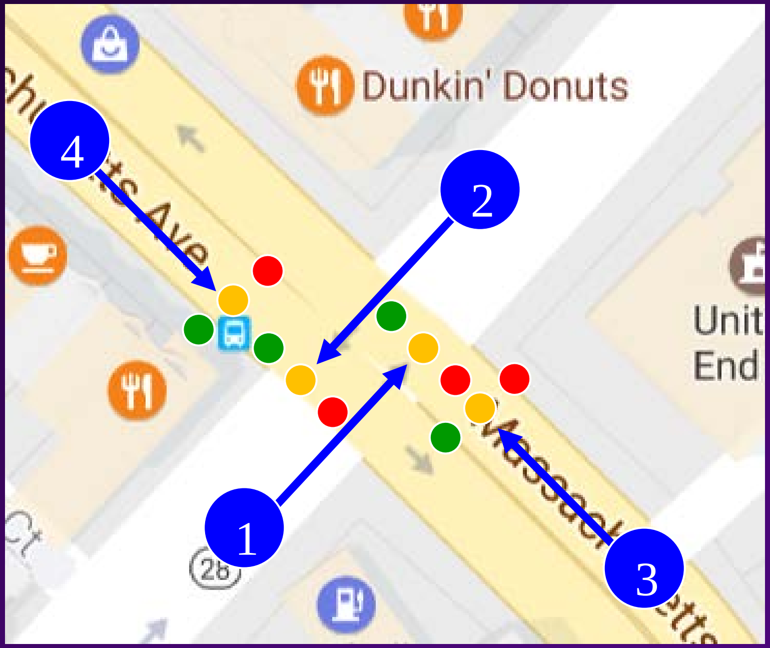
Use a Hybrid System Model: Stochastic Flow Model (SFM)





Aggregate states into *modes* and keep only events causing mode transitions

SINGLE-INTERSECTION MODEL



Traffic light control:

$$\theta = [\theta_1, \theta_2, \theta_3, \theta_4]$$

GREEN light cycle
at queue n = **1,2,3,4**

OBLECTIVE:

Determine θ to minimize
total weighted vehicle queues

$$\min_{\theta} J_T(\theta) = \frac{1}{T} E\left[\sum_{n=1}^{4} \int_0^T w_n x_n(\theta, t) dt\right]$$

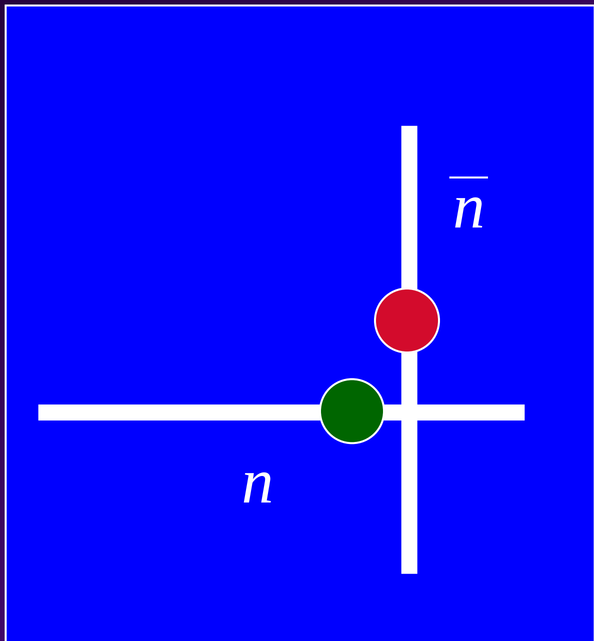
SINGLE-INTERSECTION MODEL

$$\min_{\theta} J_T(\theta) = \frac{1}{T} E\left[\sum_{n=1}^{4} \int_0^T w_n x_n(\theta, t) dt\right] = \frac{1}{T} E\left[L_T(\theta)\right]$$

IPA APPROACH:

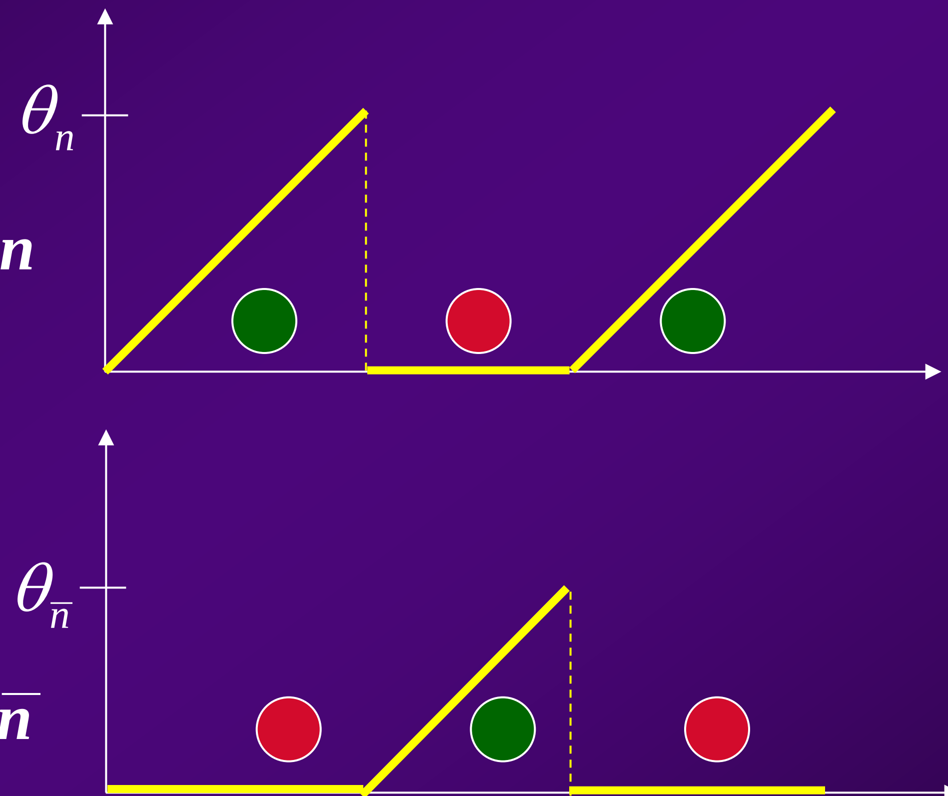
- Observe events and event times, estimate $\frac{dJ_T(\theta)}{d\theta}$ through $\frac{dL_T(\theta)}{d\theta}$
- Then, $\theta_{n+1} = \theta_n + \eta_n \frac{dL_T(\theta_n)}{d\theta}$

HYBRID SYSTEM STATE DYNAMICS



GREEN $\boldsymbol{n}$

GREEN $\boldsymbol{\bar{n}}$



$$\dot{z}_n(t) = \begin{cases} 1 & if \;\; 0 < z_n(t) < \theta_n \;\; or \;\; z_{\bar{n}}(t) = \theta_{\bar{n}} \\ 0 & otherwise \end{cases}$$

GREEN light "clock"

$$z_n(t^+) = 0 \; if \;\; z_n(t) = \boxed{\theta_n}$$

$\rightarrow$ Control: GREEN light cycle

HYBRID SYSTEM STATE DYNAMICS

$$\dot{z}_n(t) = \begin{cases} 1 & if \;\; 0 < z_n(t) < \theta_n \;\; or \;\; z_{\bar{n}}(t) = \theta_{\bar{n}} \\ 0 & otherwise \end{cases}$$

$$z_n(t^+) = 0 \; if \;\; z_n(t) = \theta_n$$

[RESOURCE DYNAMICS]

Define:

$$G_n(t) = \begin{cases} 1 & if \;\; 0 < z_n(t) < \theta_n \;\; or \;\; z_{\bar{n}}(t) = \theta_{\bar{n}} \\ 0 & otherwise \end{cases}$$

GREEN ... ueue ***n***

$$\dot{x}_n(t) = \begin{cases} \alpha_n(t) \\ 0 \\ \alpha_n(t) - \beta_n(t) & \ldots wise \end{cases}$$

...tent

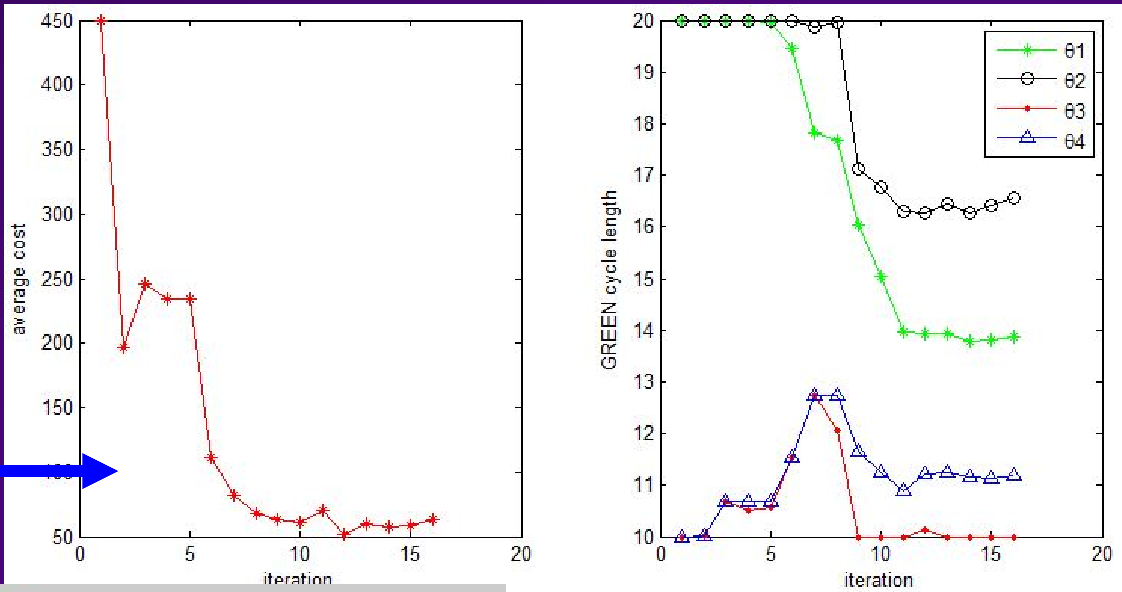
[USER DYNAMICS]

IPA ROBUSTNESS:
$\alpha_n(t)$, $\beta_n(t)$ DO NOT HAVE TO BE KNOWN!

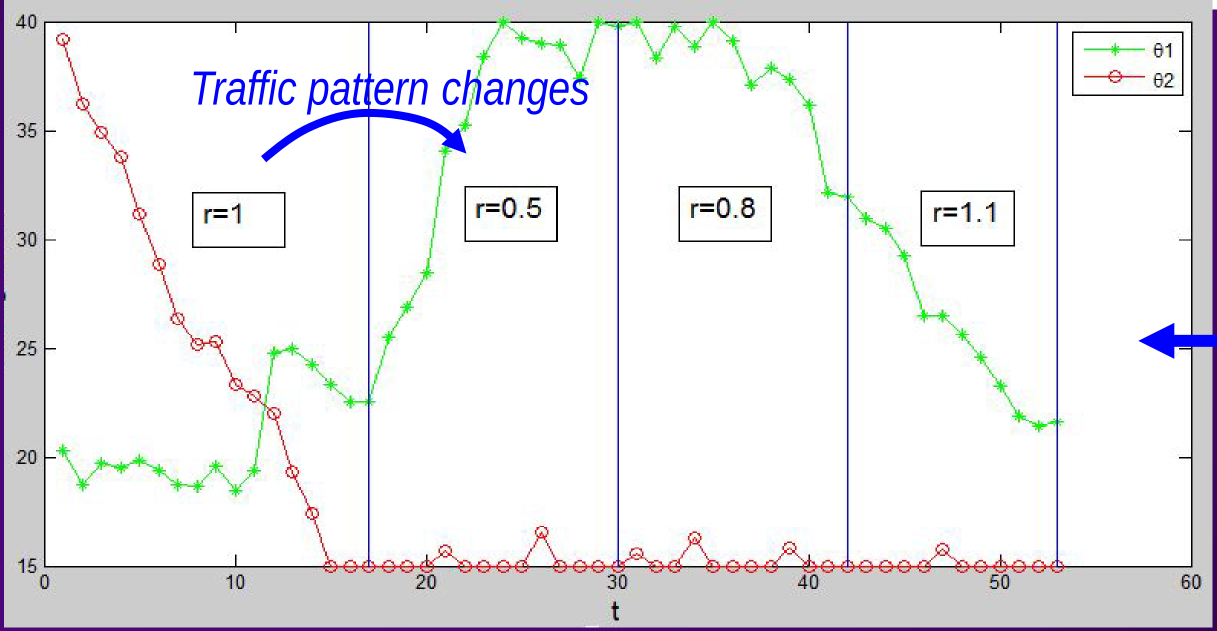
Vehicle departure rate process

Vehicle arrival rate process

TYPICAL SIMULATION RESULTS



9-fold cost reduction



Adaptivity

EXTENSIONS

- Two intersections with blocking

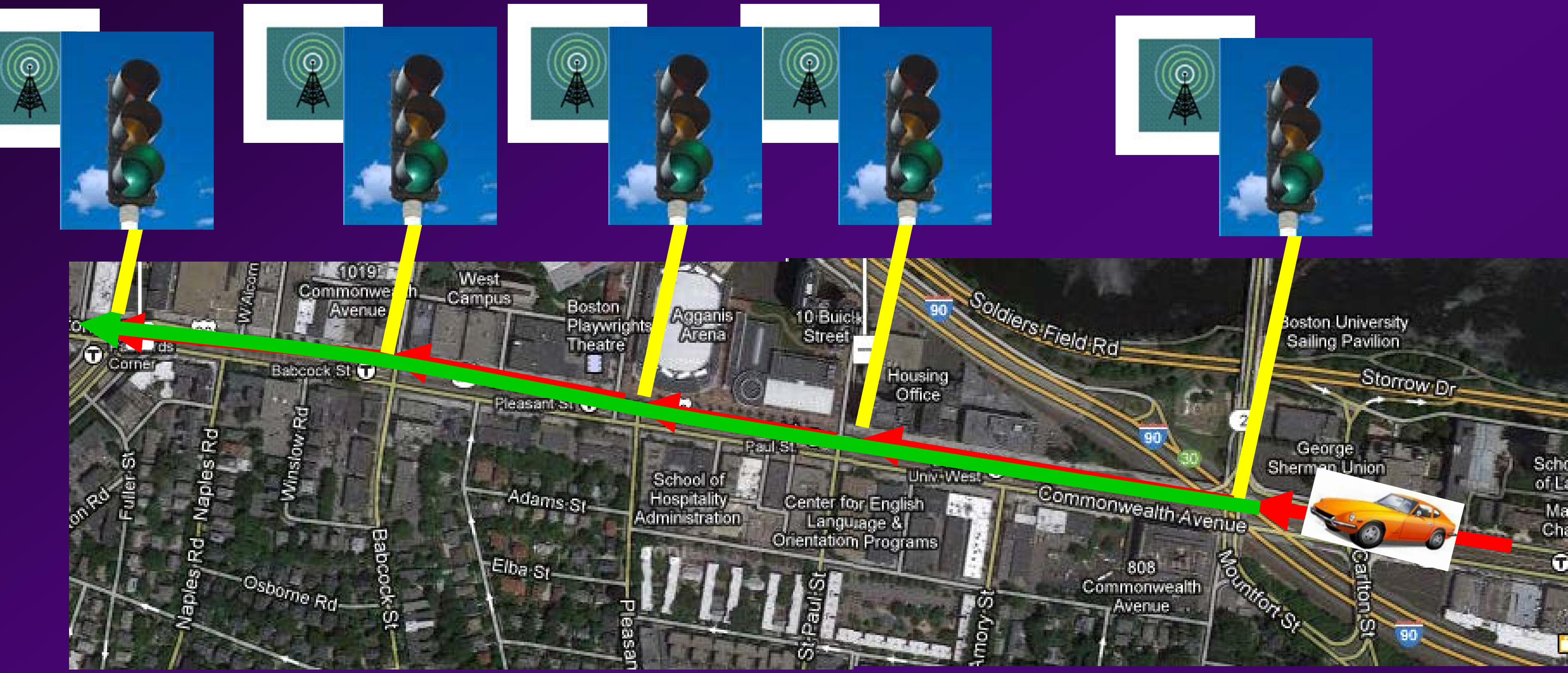
  [*Geng and Cassandras, J. DEDS, 2015*]

- Quasi-Dynamic TLC: assume partially observable queues

  [*Fleck, Cassandras and Geng, IEEE TCST, 2016*]

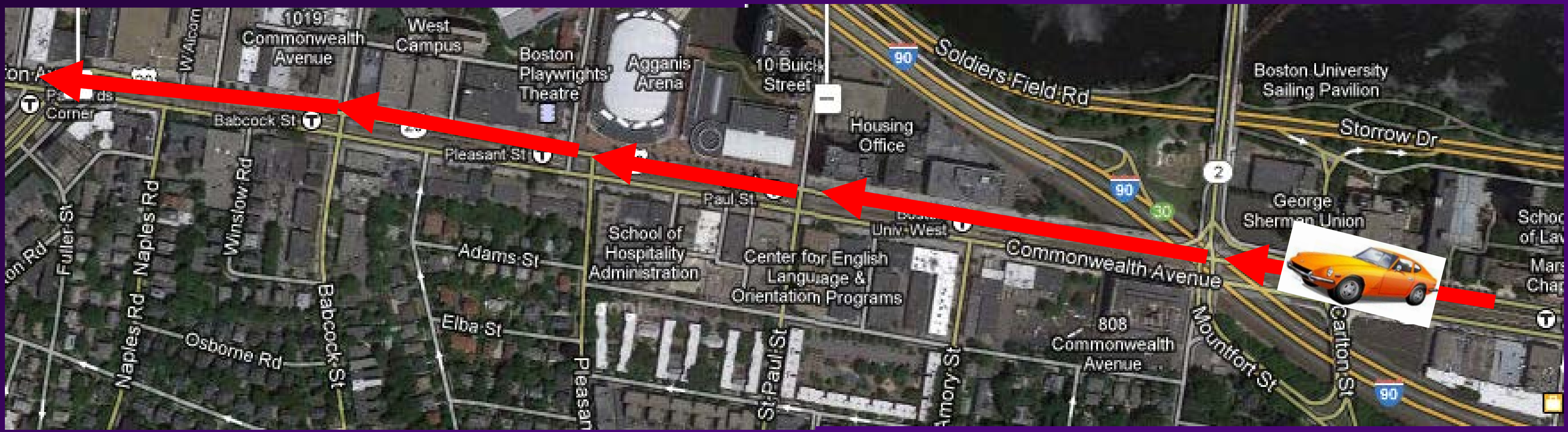
- Network of intersections: exploit IPA SCALABILITY property

NETWORK-WIDE TRAFFIC LIGHT CONTROL



- Automatically adapt RED/GREEN light cycles based on observed data
- Predict and alleviate congestion over entire urban network
- Reduce waiting times, congestion
- Reduce pollution and fuel waste

NETWORK-WIDE TRAFFIC LIGHT CONTROL

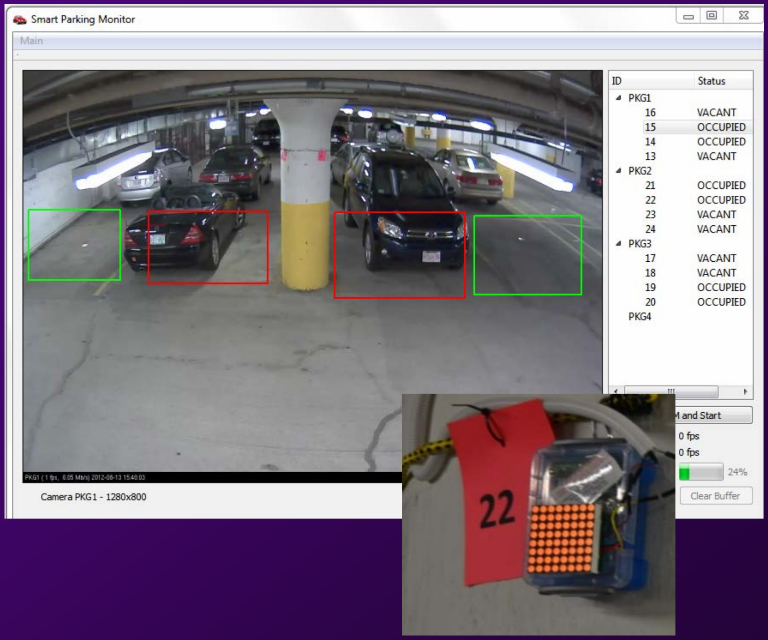


Two ways of looking at this problem:

1. Control Traffic Lights (infrastructure intensive)
2. Control speed/acceleration of vehicle assuming connectivity between vehicles (V2V) and traffic lights (V2I)
   (e.g., *adjust speed to make a GREEN just in time*)

SMART PARKING

iPhone app



SMART PARKING

***30%** of vehicles on the road in the downtowns of major cities are cruising for a parking spot. It takes the average driver **7.8** minutes to find a parking spot in the downtown core of a major city.*

R. Arnott, T.Rave, R.Schob, *Alleviating Urban Traffic Congestion.* 2005

GUIDANCE-BASED PARKING – DRAWBACKS…

Drivers:

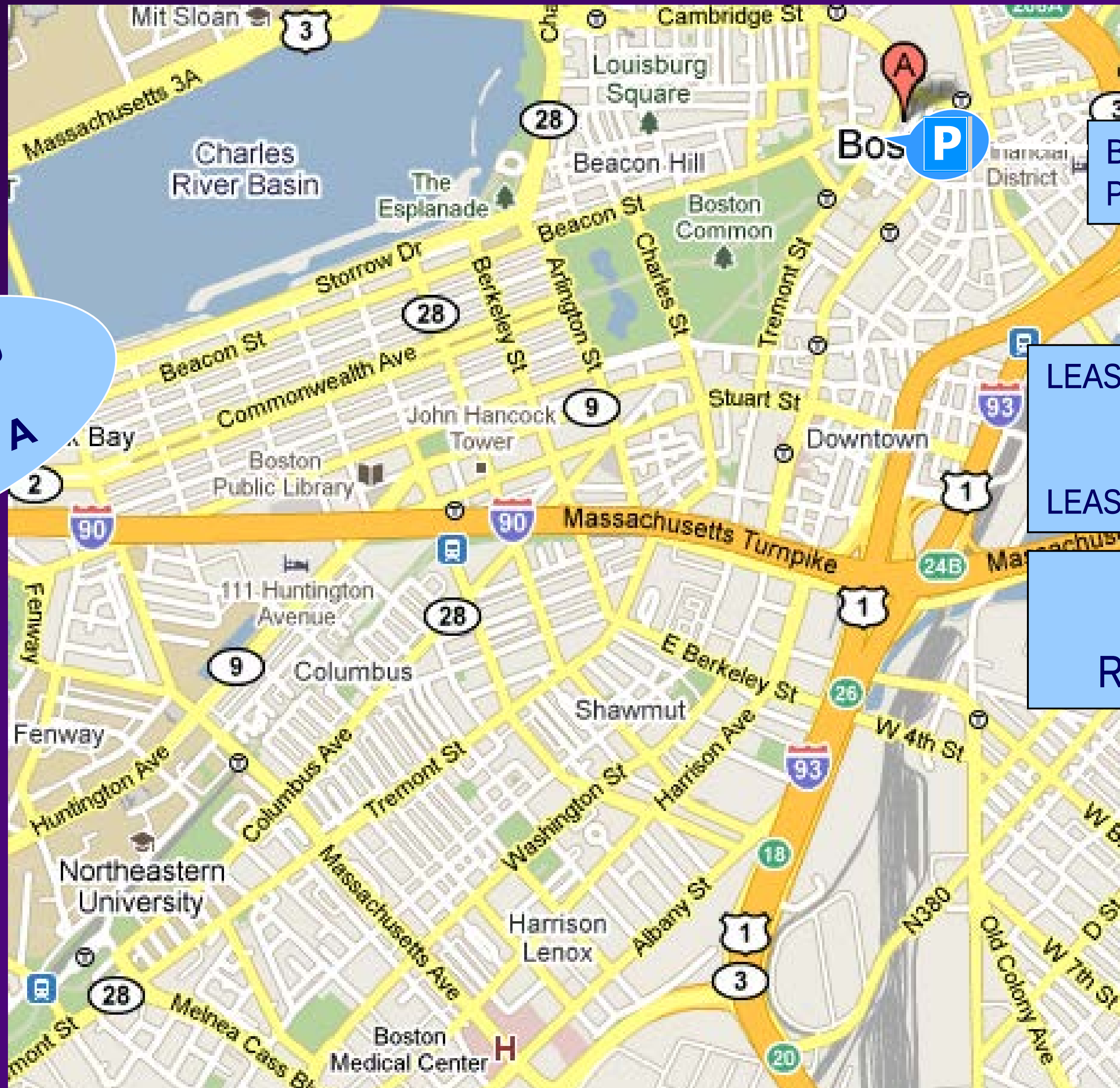
- May not find a vacant space
- May miss better space
- Processing info while driving

City:

- Imbalanced parking utilization
- May create ADDED CONGESTION (as multiple drivers converge to where a space exists)

Searching for parking $\Rightarrow$ Competing for parking

SMART PARKING



BEST PARKING SPOT

LEAST DISTANCE from A

+

LEAST COST

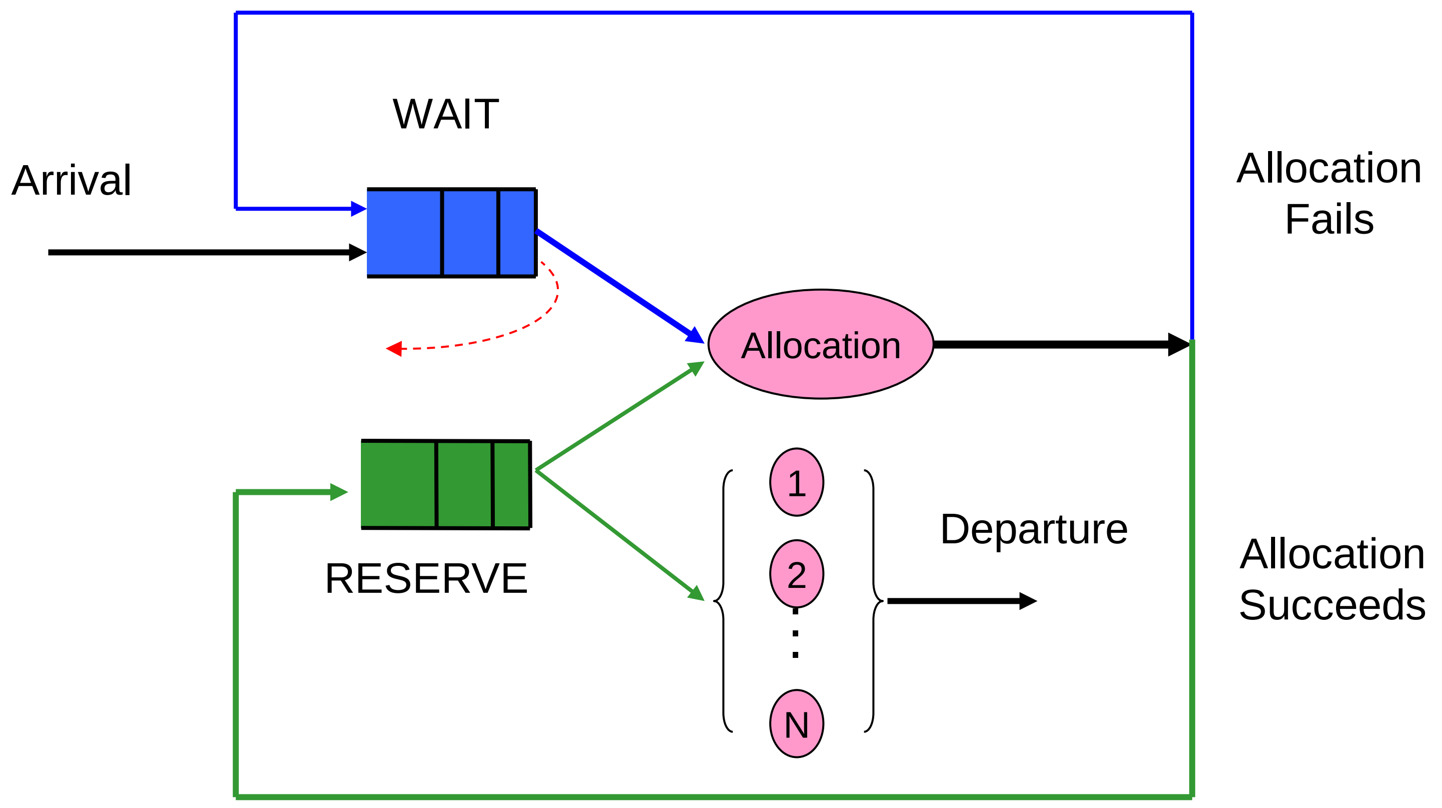
+

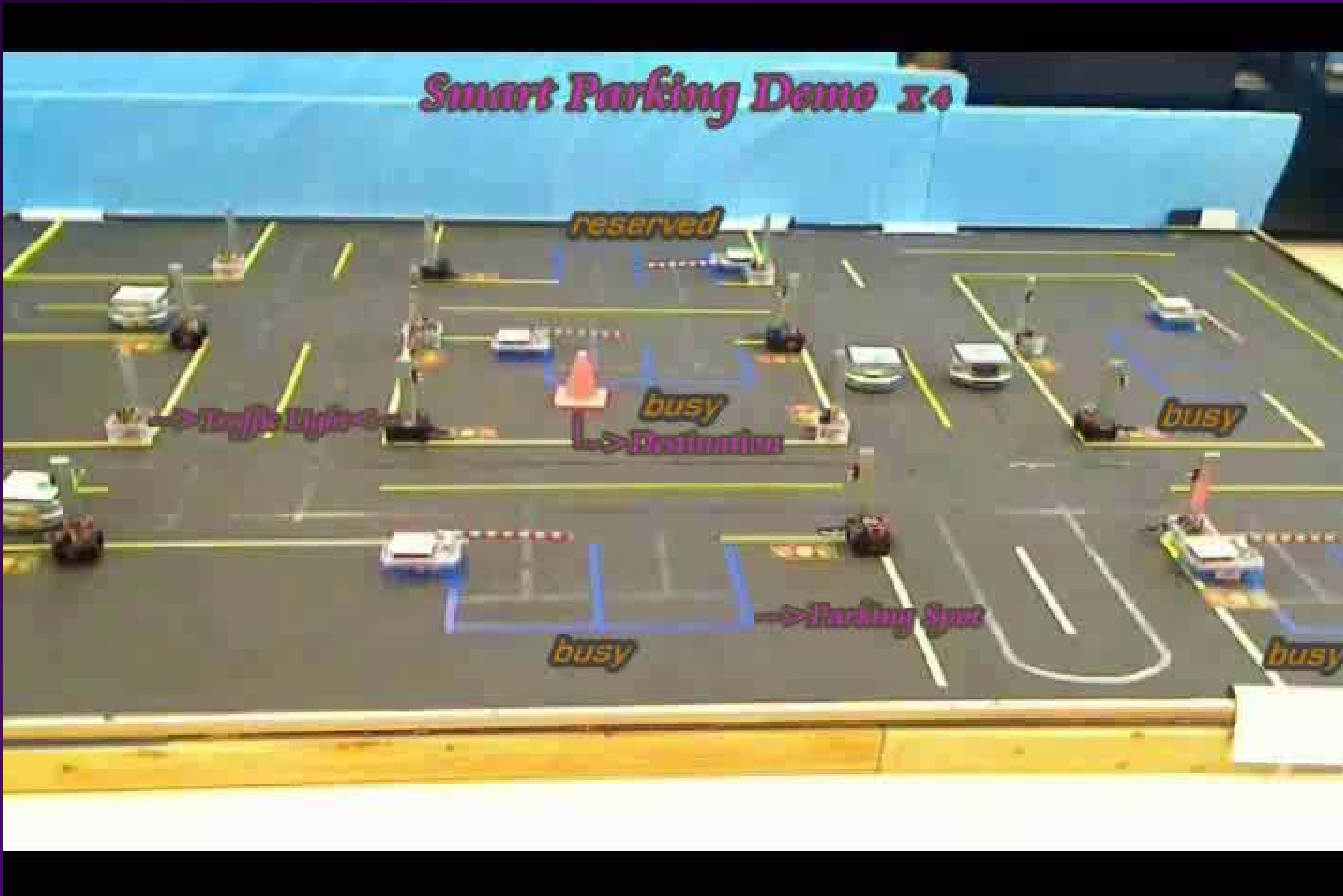
RESERVE IT

Find best parking spot for DESTINATION A

[Geng and Cassandras, *IEEE Trans. on Intelligent Transportation Systems*, 2013]

DYNAMIC RESOURCE ALLOCATION PROBLEM FORMULATION




Smart Parking Demo x4
reserved
busy
busy
busy
busy

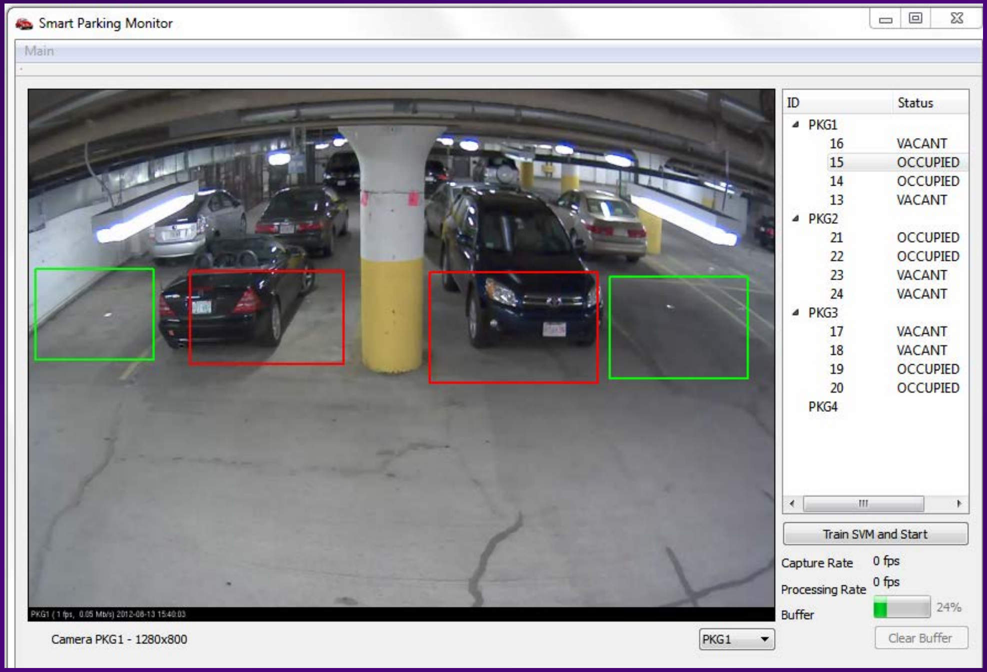
SMART PARKING – IMPLEMENTATION

- Parking space availability detection
  - Standard sensors (e.g., magnetic, cameras)
  - Wireless sensor networking
- Vehicle localization
  - GPS
- System-Driver communication
  - Smartphone
  - Vehicle navigation system
- Parking reservation
  - Red/Green/Yellow light system

SMART PARKING - IMPLEMENTATION

2011 IBM/IEEE Smarter Planet Challenge prize

http://smartpark.bu.edu/smartparking_ios6/login.php



Currently in operation at BU garage
(with Smartphone app:
BU Smart Parking)

STREET BUMP: DETECTING "BUMPS" THROUGH SMARTPHONES + DATA ANALYTICS

iPhone app

2014 IBM/IEEE Smarter Planet Challenge prize

STREET BUMP – PROCESSING "BIG DATA"

- Detect obstacles using iPhone accelerometer and GPS
  ⇒ no infrastructure needed

- Send to central server through Street Bump app

- Process data to classify obstacles:

  Anomaly detection and clustering algorithms, similar to cybersecurity problems

- Detect "actionable" obstacles

- Prioritize and dispatch Smart City crews to fix problems:

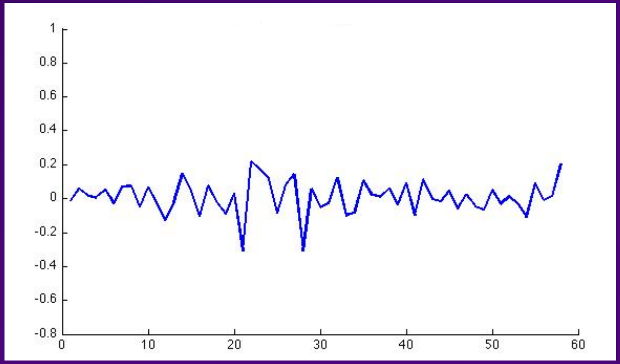
  DATA-DRIVEN DYNAMIC RESOURCE ALLOCATION

[Brisimi et al, *IEEE Access*, 2016]

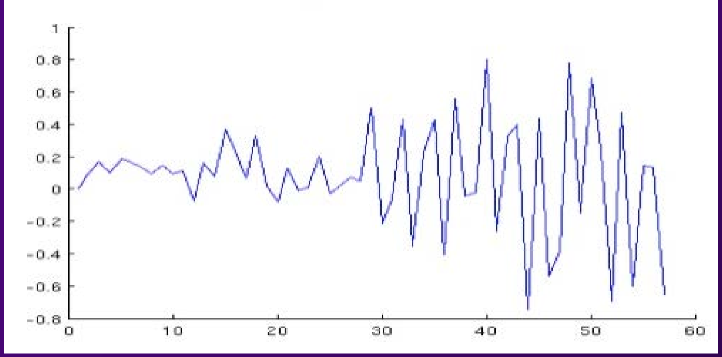
STREET BUMP – PROCESSING "BIG DATA"

Methodologies used:

- Anomaly detection, Machine Learning algorithms
- Bump signal signature analysis: REGULARITY METRIC
- Bump signal randomness content: ENTROPY METRIC



NON-ACTIONABLE
(Flat Casting)



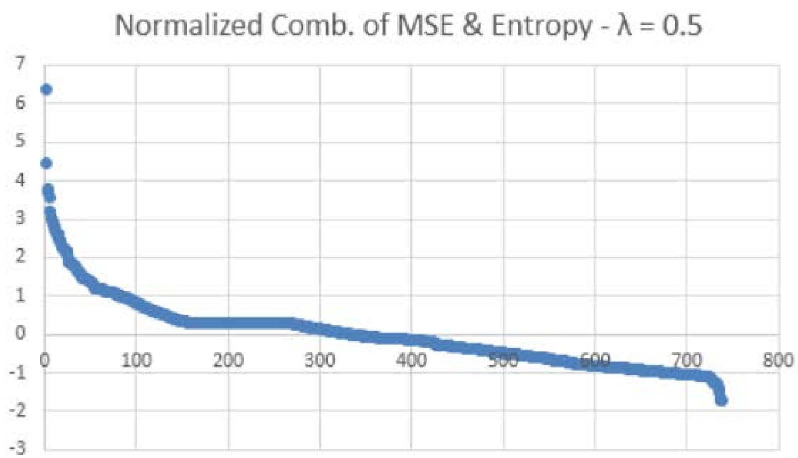
ACTIONABLE
(Pothole)

STREET BUMP – ANOMALY INDEX RANKED LIST

$$AI = 0.5MSE + 0.5H(x)$$

TOP-10 ACTIONABLE OBSTACLES

- $\lambda = 0.5$
- Truly actionable (T): 88/100 (88%)
- False Alarm (F): 12%



Categories	1 = Non-actionable	Comb. of MSE&Entropy
'Pot Hole'	2	6.358133291
'Sunk Casting (Immediate repair)'	2	4.458249603
'Pothole'	2	3.781396384
'Cracking Around Casting (Pothole)'	2	3.696543324
'Bad Utility Patch (permanent)'	2	3.553264957
'Pothole'	2	3.209940023
'Pothole'	2	3.035801435
'Bad Utility Patch (permanent)'	2	2.963345039
'Flat Casting'	1	2.928413599
'Pothole'	2	2.83604503
'Bad Utility Patch (permanent)'	2	2.783582864
'Sunk Casting (immediate repair)'	2	2.726196475
'Catch Basin (repair)'	2	2.626632962
'Pothole'	2	2.626487835
'Sunk Casting (repair)'	2	2.496122077
'Bad Utility Patch (permanent)'	2	2.441951962
'Pothole'	2	2.393910452
'Sunk Casting (immediate repair)'	2	2.302992173
'Sunk Casting (repair)'	2	2.271229115
'Pot Hole'	2	2.253794862
'Sunk Casting (repair)'	2	2.225175587
'Sunk Casting (immediate repair)'	2	2.204039646
'Cracking Around Casting (pothole)'	2	2.186933029
'Pothole'	2	2.169196119
'Bad Utility Patch (temporary)'	2	2.096893702
'Pothole'	2	1.961382389
'Sunk Casting (repair)'	2	1.876441708
'Flat Casting'	1	1.855250669
'Pot Hole (no repair)'	1	1.83324128
'Bad Utility Patch (permanent)'	2	1.825949708
'Sunk Casting (Repair)'	2	1.815833626
'Pothole'	2	1.772191028
'Sunk Casting (repair)'	2	1.766306302
'Flat Casting'	1	1.747079501
'Sunk Casting (repair)'	2	1.681360281
'Sunk Casting (immediate repair)'	2	1.651942764
'Raised Casting (repair)'	2	1.618505807
'Pothole'	2	1.574023242
'Sunk Casting (immediate repair)'	2	1.574015672
'Pothole'	2	1.497205598
'Pot Hole'	2	1.484528469
'Pothole'	2	1.469825022
'Catch Basin (repair)'	2	1.462558728
'Sunk Casting (repair)'	2	1.454257109
'Pothole'	2	1.453174152
'Flat Casting'	1	1.422754809
'Sunk Casting (repair)'	2	1.417971776
'Pothole'	2	1.402428087
'Catch Basin (repair)'	2	1.37466431

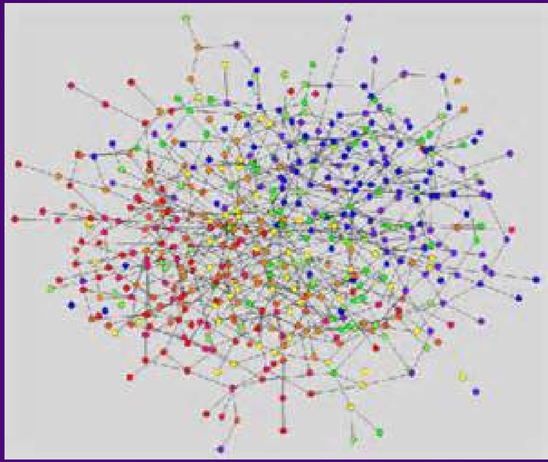
SHARING RESOURCES: THE "PRICE OF ANARCHY"

TRAFFIC CONTROL

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:

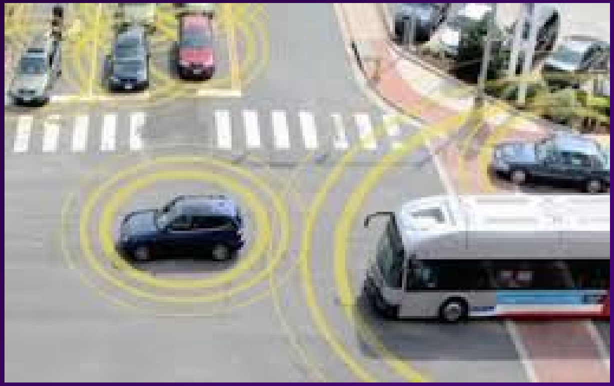
- Not enough controls (traffic lights, tolls, speed fines)

  → No chance to unleash the power of feedback!

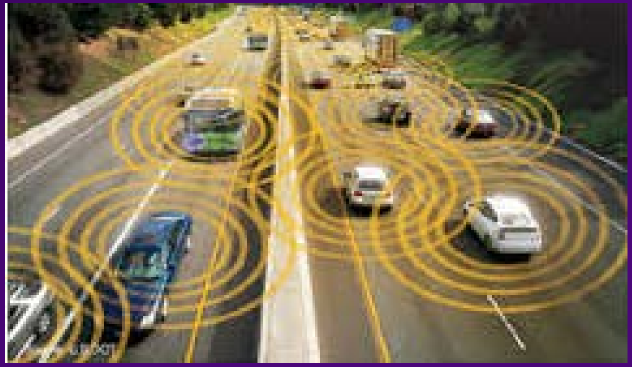
- Not knowing other drivers' behavior leads to poor decisions (a simple game-theoretic fact)

  → Drivers seek individual (selfish) optimum, not system-wide (social) optimum } *PRICE OF ANARCHY* (POA)

GAME-CHANGING OPPORTUNITY: CONNECTED AUTOMATED VEHICLES (CAVs)

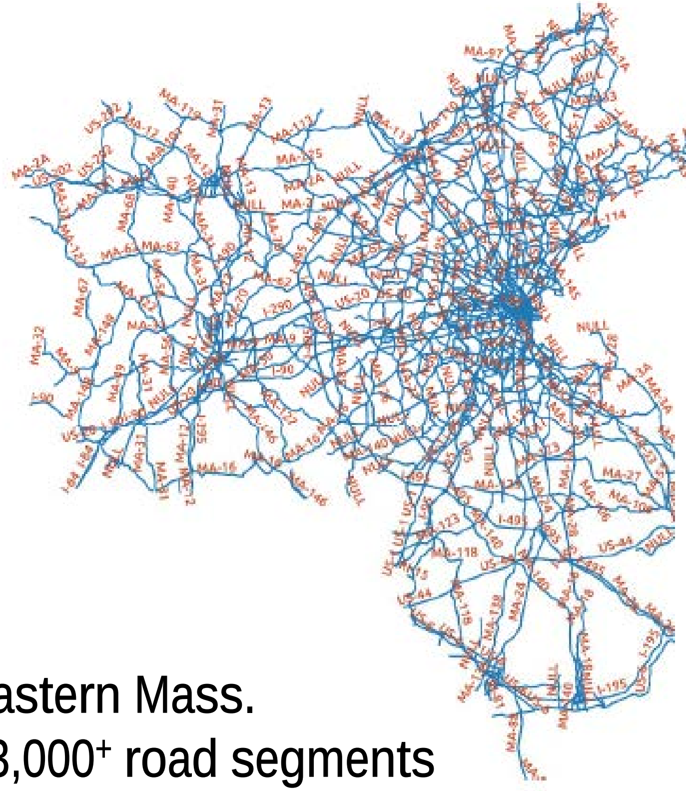


NO TRAFFIC LIGHTS, NEVER STOP…



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

HOW TO MEASURE THE PoA ?

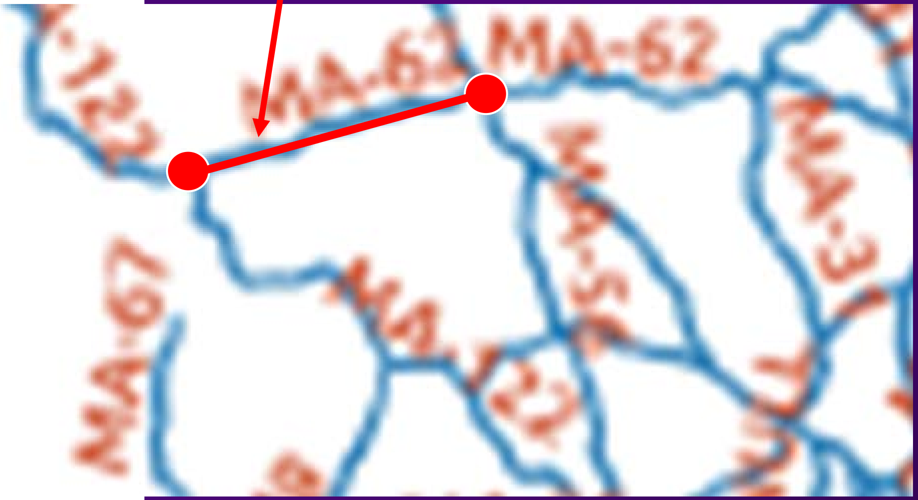


Eastern Mass.
13,000^{+} road segments

LINK a

FLOW x_a

COST FUNCTION $t_a(x_a)$



Under USER-CENTRIC control, x_a^{user} is the equilibrium flow

Under SYSTEM-CENTRIC control, x_a^{social} is the equilibrium flow

HOW TO MEASURE THE PoA ?

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

Can we measure/estimate the PoA ?

DIFFICULTIES 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….

INVERSE OPTIMIZATION PROBLEM

KEY IDEA:

BACKWARD optimization:

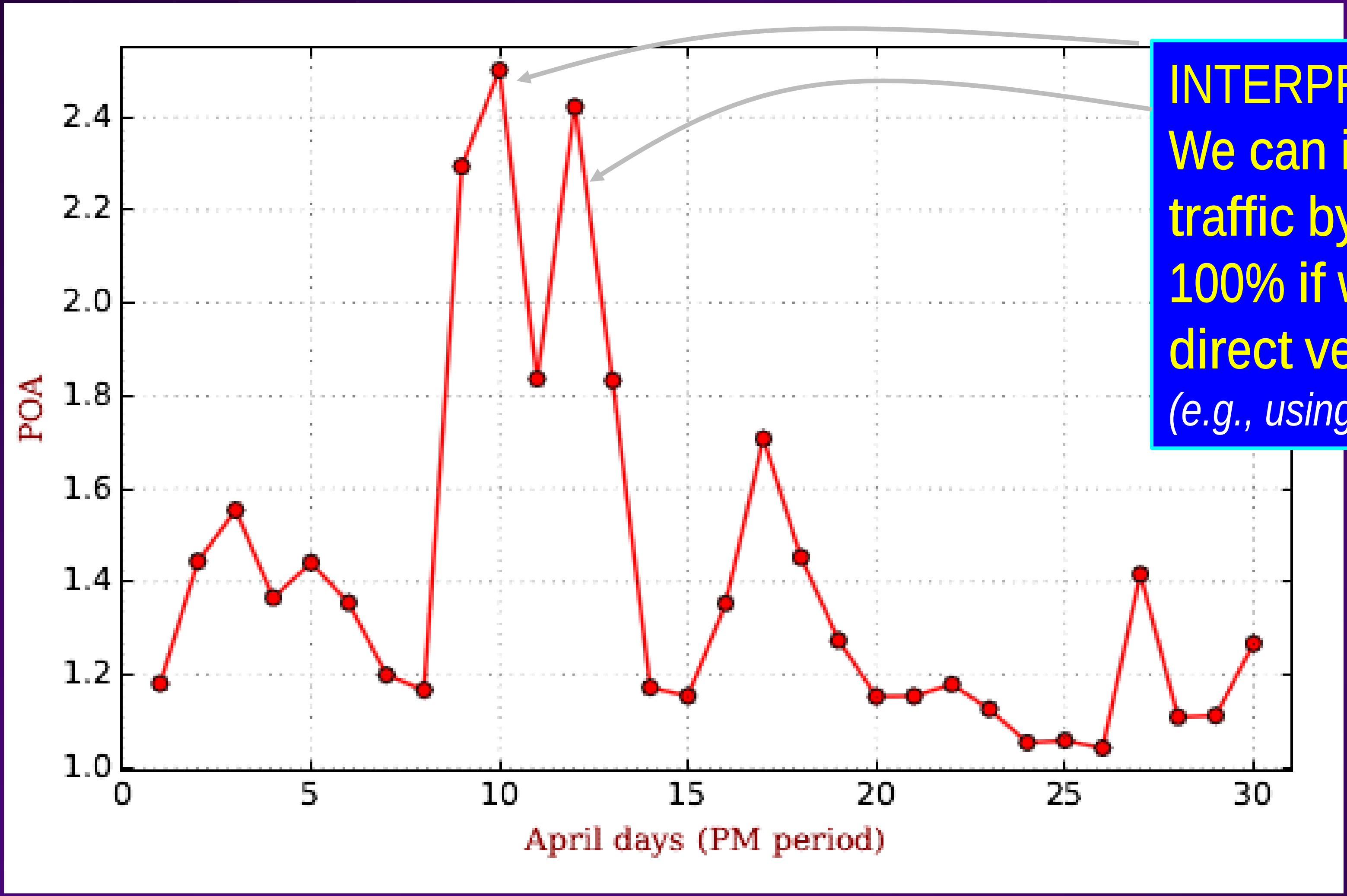
- **Data reveal a (selfish) equilibrium (Wardrop/Nash equilibrium)**
- **What are the (virtual) cost functions that best fit the data and lead to this equilibrium?**

FORWARD optimization:

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

- Estimate the PRICE OF ANARCHY

PRICE OF ANARCHY – *BOSTON AREA 2012*



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

Zhang et al, IEEE CDC, 2016 - MoA22

A DECENTRALIZED OPTIMAL CONTROL FRAMEWORK FOR CAVs

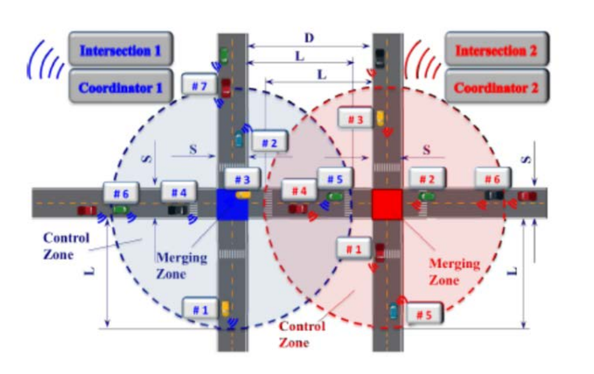


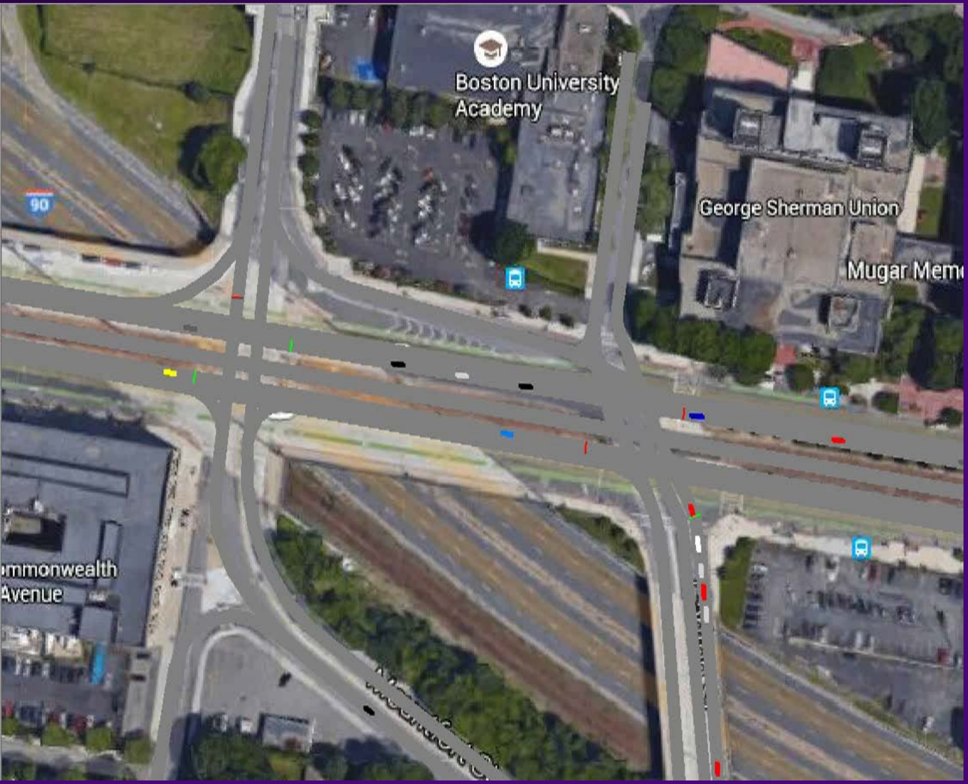
Fig. 1. Two intersections with connected and automated vehicles.

A story for another time, but here is what the end of its first chapter looks like…

[Zhang et al, *ACC*, 2016]

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)

WHO NEEDS TRAFFIC LIGHTS?

How about pedestrians?

CONCLUSIONS

- "Smart Cities" are complex CYBER-PHYSICAL systems that can be studied in a stochastic hybrid system setting

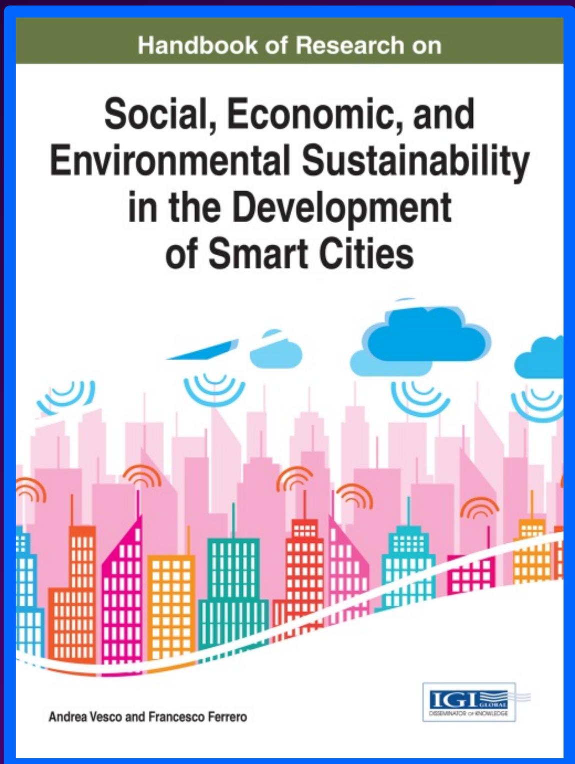
- Capitalize on WIRELESS NETWORKING + BIG DATA

  + DATA-DRIVEN CONTROL and OPTIMIZATION METHODS

- "CONNECTED VEHICLES" provide a tremendous opportunity for feedback methods,
  game theoretic approaches, no infrastructure

- What about HUMANS? Need to expand to

  CYBER - *SOCIAL* - PHYSICAL systems



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Thank you