[*News Gazette*, '12]

Traffic Monitoring with Smartphones

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Who cares about traffic?

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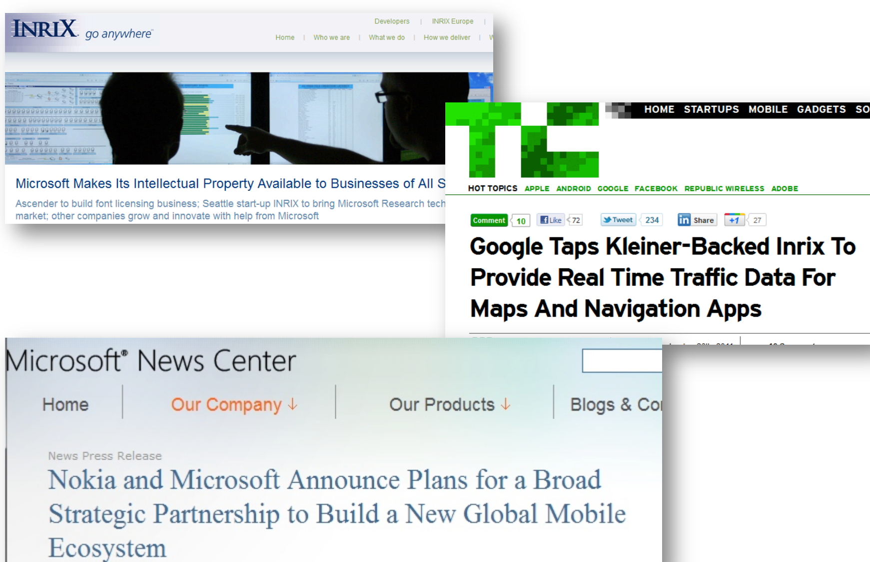

Understanding human – infrastructure interaction

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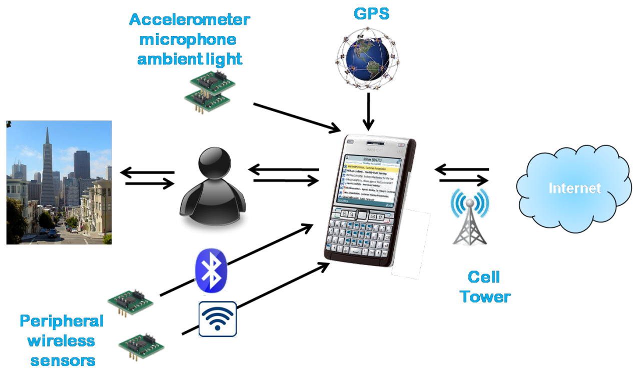
- Cell phones are the world's <u>largest</u> sensor network:
  - > 3 billion devices
  - Global coverage, human centric
  - Increasingly connected, programmable
- Wikipedia for the physical world
  - "First draft" of our interaction with the environment, in real-time
  - Crowd-sourced data
  - Participatory sensing
  - Information distribution



Outline of this talk

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- Parameter calibration with GPS smartphone data
  - Velocity traffic dynamics
  - MCMC for traffic parameter estimation
  - Numerical examples
- Traffic sensing for extreme congestion events
  - TrafficTurk smartphone app
  - Experimental deployments

Governing equation: *Lighthill Whitham Richards* PDE

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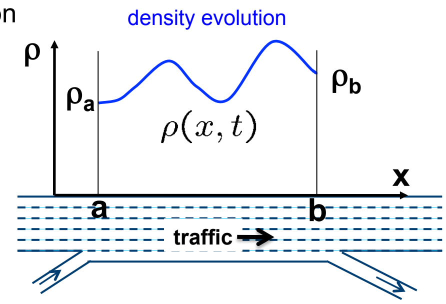
- LWR PDE – first order hyperbolic conservation law
  - $\rho(x,t) \in [0, \rho_{\max}]$ is the density
  - $q(\rho) \in [0, q_{\max}]$ is the flux function

$$\boxed{\frac{\partial \rho}{\partial t} + \frac{\partial q(\rho)}{\partial x} = 0}$$



  - initial condition:

$$\rho(x,0) = \rho_0(x)$$

  - boundary conditions (weak sense)

$$\rho(a,t) = \rho_a(t)$$
$$\rho(b,t) = \rho_b(t)$$

[Lighthill and Whitham, 1955; Richards 1956]

Governing equation: *Lighthill Whitham Richards* PDE

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- example fundamental diagram – Greenshields
  - flux is given by:

$$q(\rho) = \rho v(\rho)$$

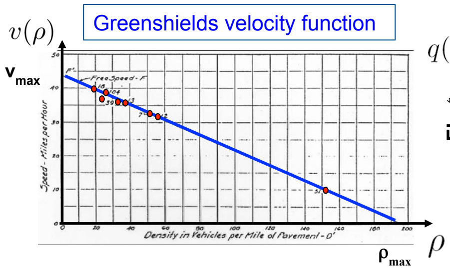
  - express velocity as a function of density:

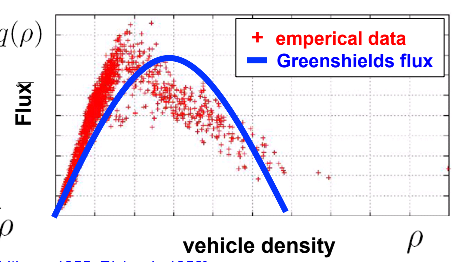
$$v(\rho) = v_{\max}\left(1 - \frac{\rho}{\rho_{\max}}\right)$$

LWR PDE (last slide)

$$\frac{\partial \rho}{\partial t} + \frac{\partial q(\rho)}{\partial x} = 0$$

Greenshields velocity function





[Greenshields, 1935; Lighthill and Whitham, 1955; Richards 1956]

Time and space discretization

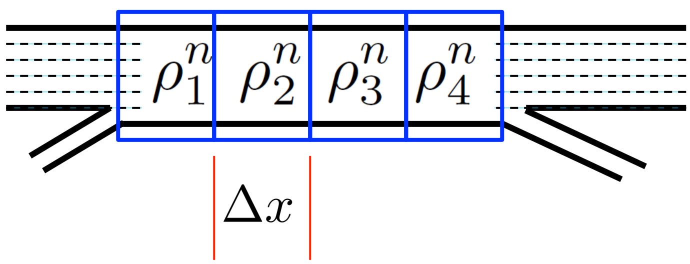
discrete space Δx indexed by $i \in \{0, \cdots, i_{\max}\}$

discrete time ΔT indexed by $n \in \{0, \cdots, n_{\max}\}$

ρ_i^n density in cell i at time n :

$$\rho^n = \left[\rho_1^n, \cdots, \rho_{i_{\max}}^n\right]$$

at timestep n :



Discretized LWR equation

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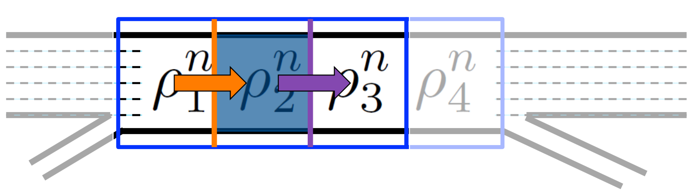
- Cell Transmission Model

$$\rho_i^{n+1} = \rho_i^n + \frac{\Delta T}{\Delta x}\left(q\left(\rho_{i-1}^n, \rho_i^n\right) - q\left(\rho_i^n, \rho_{i+1}^n\right)\right)$$

Cars in cell i at n+1 = cars in cell i at n + Flow entering cell i - Flow exiting cell i

$$q\left(\rho_1, \rho_2\right) = \min\left\{S\left(\rho_1\right), R\left(\rho_2\right)\right\}$$



[Godunov 59; Daganzo 94; Lebacque 96]

Sending and receiving functions

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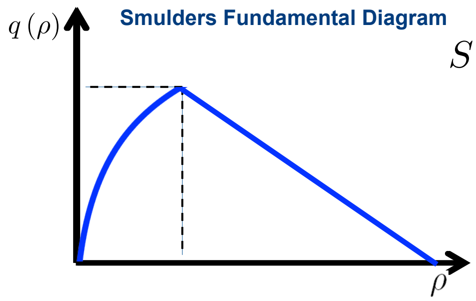
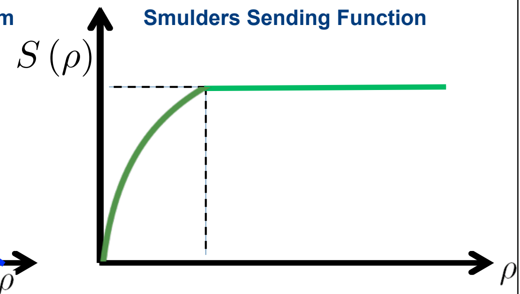
- Cell Transmission Model

$$\rho_i^{n+1} = \rho_i^n + \frac{\Delta T}{\Delta x}\left(q\left(\rho_{i-1}^n, \rho_i^n\right) - q\left(\rho_i^n, \rho_{i+1}^n\right)\right)$$

$$q\left(\rho_1, \rho_2\right) = \min\left\{\underline{S\left(\rho_1\right)}, R\left(\rho_2\right)\right\}$$





[Smulders '90]

Sending and receiving functions

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- Cell Transmission Model

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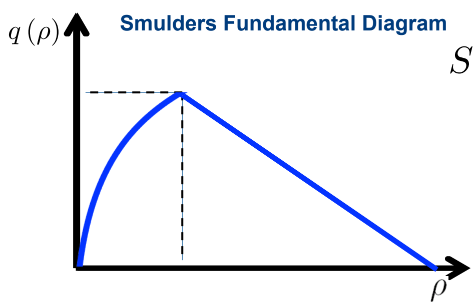

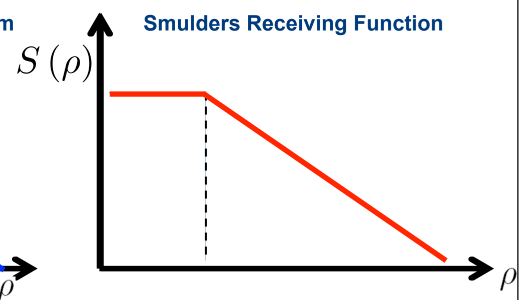

[Smulders '90]

Discrete velocity evolution

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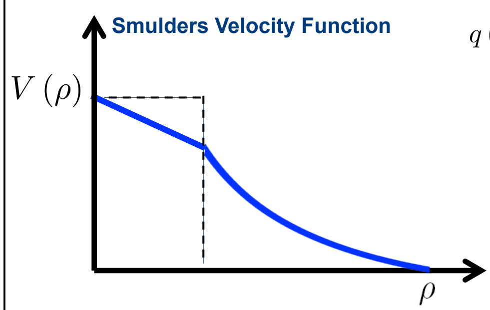
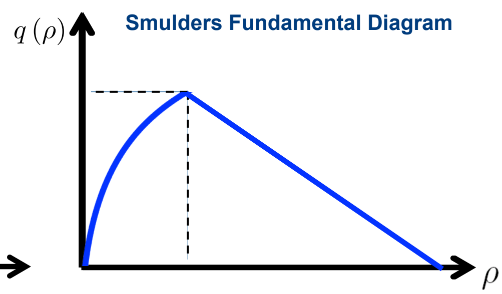
- Recall the velocity function and its inverse:

$$v = V(\rho)$$

$$\rho = V^{-1}(v)$$





[Smulders '90]

Discrete velocity evolution

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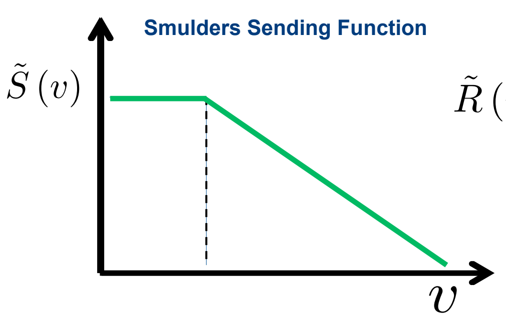
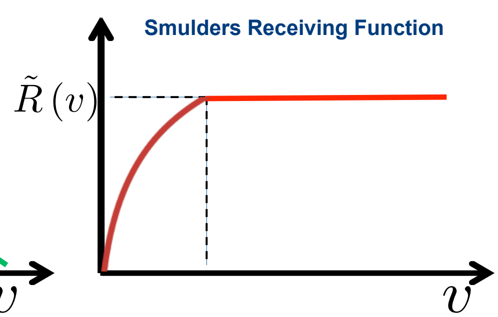
- Cell Transmission Model for velocity

$$v_i^{n+1} = V\left(V^{-1}(v_i^n) + \frac{\Delta T}{\Delta x}\left(\tilde{q}(v_{i-1}^n, v_i^n) - \tilde{q}(v_i^n, v_{i+1}^n)\right)\right)$$

$$\tilde{q}(v_1, v_2) = \min\left\{\tilde{S}(v_1), \tilde{R}(v_2)\right\}$$





[Work, Blandin, Tossavainen, Piccoli, and Bayen '10]

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  - Numerical examples

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  - Experimental deployments

Flow model calibration vs direct state estimation

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- Mobile Millennium Network (Northern CA)
  - 4,000 links
  - 3,000 junctions

Using historic data to calibrate a flow model:

- For each edge:
  - 3 fundamental diagram parameters

- For each junction
  - 1 allocation parameter / yielding parameter
  - 7 boundary condition hyper-parameters

Direct approach: 12,000+ 24,000 = 36,000 parameters!!!

Flow model calibration vs direct state estimation

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- Mobile Millennium Network (Northern CA)
  - 4,000 links
  - 3,000 junctions

Using historic data to directly estimate the traffic state

- For each edge:
  - One traffic speed every 15 minutes
  - 96 fifteen minute time intervals in one day
  - (7 days a week)

Flow model calibration vs direct state estimation

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- Mobile Millennium Network (Northern CA)
  - 4,000 links
  - 3,000 junctions

Using historic data to directly estimate the traffic state

- For each edge:
  - One traffic speed every 15 minutes
  - 96 fifteen minute time intervals in one day
  - (7 days a week)

Direct approach: 96 x 4,000 = 386,000 parameters (for one day) (Order of magnitude larger than flow model)

Problem setup

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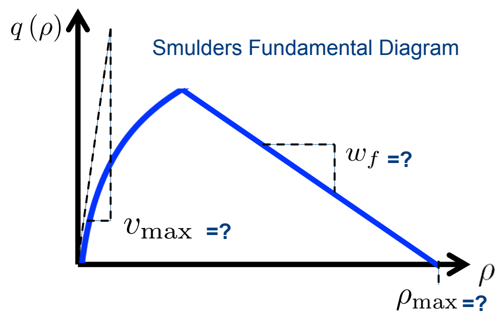
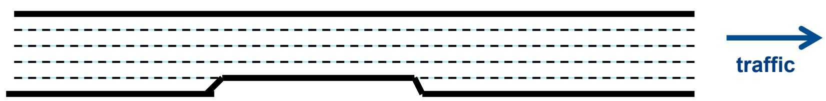
Given: GPS speed data
+ Traffic flow model

Find: Fundamental diagram parameters (for each link)





Observation equation

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- Given by:

$$y = h(\theta) + \varepsilon$$

- Where $h(\theta)$ requires:
  - Forward simulation of the velocity field using the CTM-v under the parameters theta.
  - Knowledge of where the measurements y are obtained.

- The noise $\varepsilon \sim \mathcal{N}(0, \Gamma_\varepsilon)$

Posterior density on model parameters

- Posterior density on the model parameters (via Bayes rule)

$$p(\theta|y) \propto p_{\mathrm{pr}}(\theta)p(y|\theta)$$

where $p_{\mathrm{pr}}(\theta)$ is the prior on the model parameters

- Likelihood function: (requires forward traffic sim)

$$p(y|\theta) \propto \exp\left(-\frac{1}{2}\left(y - h(\theta)\right)^{\mathrm{T}} \Gamma_{\varepsilon}^{-1} \left(y - h(\theta)\right)\right)$$

Random walk Metropolis - Hastings

Algorithm 1 Random walk Metropolis–Hastings

```
Pick initial value θ_1
Set θ = θ_1
for k = 2 : K do
    Calculate p(θ|y)
    Draw w ~ N(0, Γ_w) and set z = θ + w (proposal step)
    Calculate p(z|y)
    Calculate λ(θ, z) = min(1, p(z|y)/p(θ|y))
    Draw u ~ U[0, 1]
    if u ≤ λ(θ, z) then
        Accept: Set θ = z, θ_k = θ
    else
        Reject: Set θ_k = θ
    end if
end for
```

- Initialization of the chain

Random walk Metropolis - Hastings

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Algorithm 1 Random walk Metropolis–Hastings

Pick initial value θ_1
Set $\theta = \theta_1$
for $k = 2 : K$ **do**
  Calculate $p(\theta|y)$
  Draw $w \sim \mathcal{N}(0, \Gamma_w)$ and set $z = \theta + w$ (proposal step)
  Calculate $p(z|y)$
  Calculate $\lambda(\theta, z) = \min(1, p(z|y)/p(\theta|y))$
  Draw $u \sim \mathcal{U}[0, 1]$
  if $u \leq \lambda(\theta, z)$ **then**
    Accept: Set $\theta = z$, $\theta_k = \theta$
  else
    Reject: Set $\theta_k = \theta$
  end if
end for

- Compute the probability of theta given the data

Random walk Metropolis - Hastings

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  else
    Reject: Set $\theta_k = \theta$
  end if
end for

- Compute the probability of z (the proposal parameters) given the data

Random walk Metropolis - Hastings

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  else
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  end if
end for

- Compute the acceptance ratio

Random walk Metropolis - Hastings

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Algorithm 1 Random walk Metropolis–Hastings

Pick initial value θ_1
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  if $u \leq \lambda(\theta, z)$ **then**
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  end if
end for

- Accept or reject the proposal

Random walk Metropolis - Hastings

Algorithm 1 Random walk Metropolis–Hastings

Pick initial value θ_1
Set $\theta = \theta_1$
for $k = 2 : K$ **do**
  Calculate $p(\theta|y)$
  Draw $w \sim \mathcal{N}(0, \Gamma_w)$ and set $z = \theta + w$ (proposal step)
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  Draw $u \sim \mathcal{U}[0, 1]$
  if $u \leq \lambda(\theta, z)$ **then**
    Accept: Set $\theta = z$, $\theta_k = \theta$
  else
    Reject: Set $\theta_k = \theta$
  end if
end for

- Repeat

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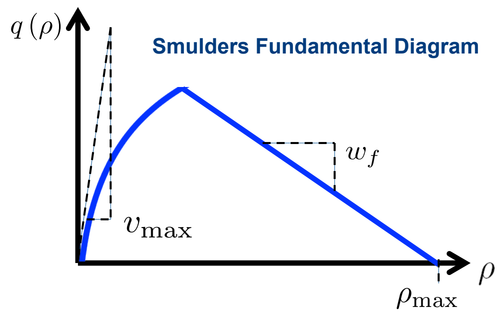
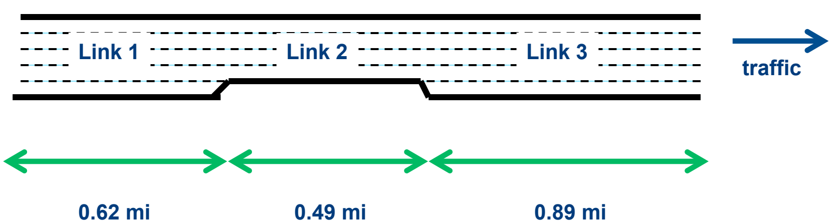
Problem setup



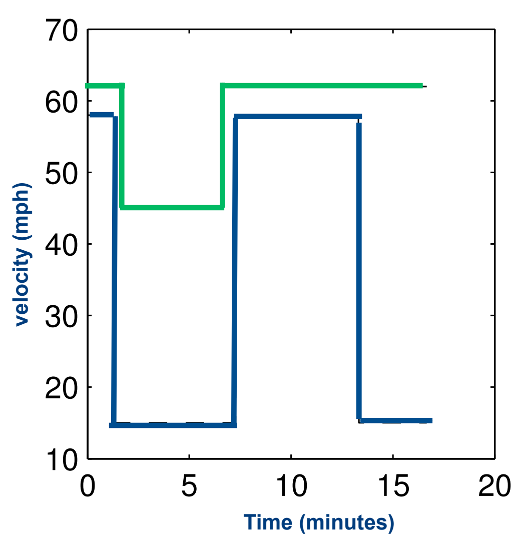
True Parameters

parameter	link 1	link 2	link 3
lanes	5	4	5
$v_{\max}$ (mph)	77	77	77
$\rho_{\max}$ (veh/mi)	5×180	4×170	5×160
w_f (mph)	16	16	16



True velocity boundary conditions

- Upstream
- downstream



[Tossavainen & Work (submitted) 2013]

True velocity field

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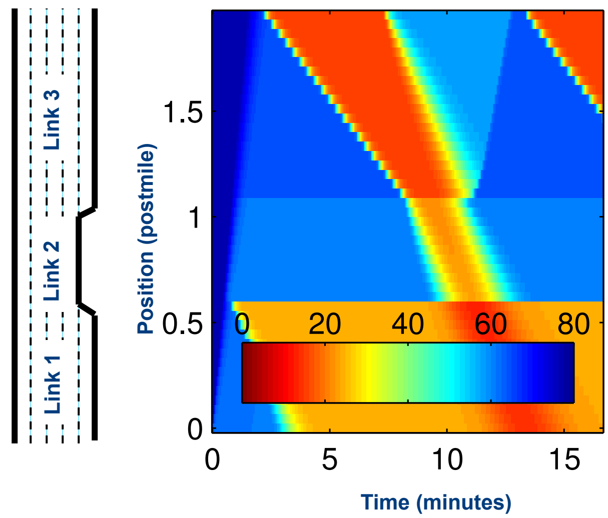

[Tossavainen & Work (submitted) 2013]

Synthetic GPS measurements

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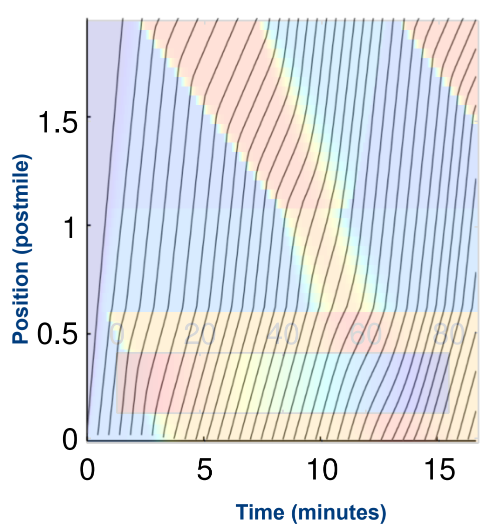
- Obtained via numerical integration of *true* velocity field
- Probe vehicle flow rate:
  ~120 probe veh/hr
- Measurement errors on the true velocity field: ~ $\mathcal{N}(0, 4)$



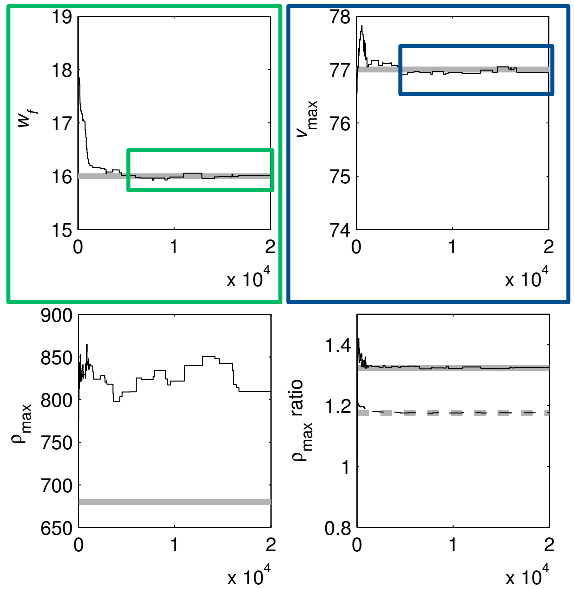
[Tossavainen & Work (submitted) 2013]

Numerical performance

- True parameters (grey):

parameter	link 1	link 2	link 3
lanes	5	4	5
$v_{\max}$ (mph)		77	
w_f (mph)		16	
$\rho_{\max}$ (veh/mi)	900	680	800
$\frac{\rho_{\max,i}}{\rho_{\max,2}}$	1.32	1	1.18

$$\theta = \begin{pmatrix} \rho_{\max,1} \\ \rho_{\max,2} \\ \rho_{\max,3} \\ v_{\max} \\ w_f \end{pmatrix}$$



[Tossavainen & Work (submitted) 2013]

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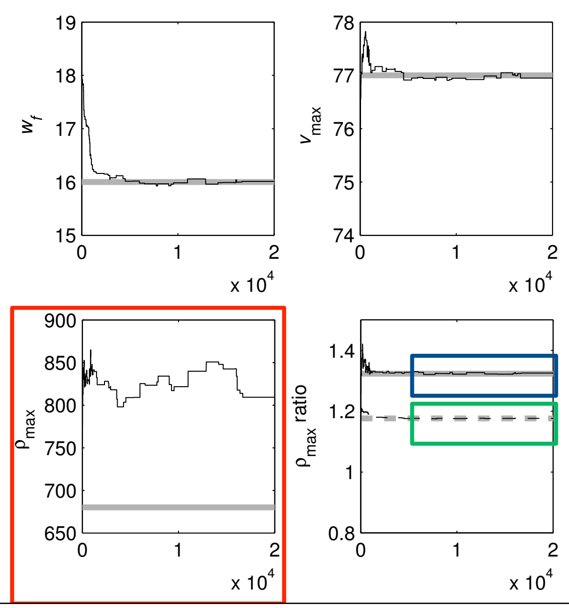


[Tossavainen & Work (submitted) 2013]

Shock speeds

- Shock speed: $$s = \frac{V_\theta^{-1}(v_1)v_1 - V_\theta^{-1}(v_2)v_2}{V_\theta^{-1}(v_1) - V_\theta^{-1}(v_2)}$$

where $\rho = V_\theta^{-1}(v) = \begin{cases} \rho_{\max}\left(1 - \frac{v}{v_{\max}}\right) & \text{if } v \geq v_c \\ \rho_{\max}\left(\frac{1}{1+\frac{v}{w_f}}\right) & \text{otherwise} \end{cases}$. (Smulders)

Let $V_\theta^{-1}(v) = \rho_{\max} Z(v)$,

then $$s = \frac{\alpha Z(v_1)v_1 - Z(v_2)v_2}{\alpha Z(v_1) - Z(v_2)} \;,$$

where $\alpha = \frac{\rho_{\max,1}}{\rho_{\max,2}}$.

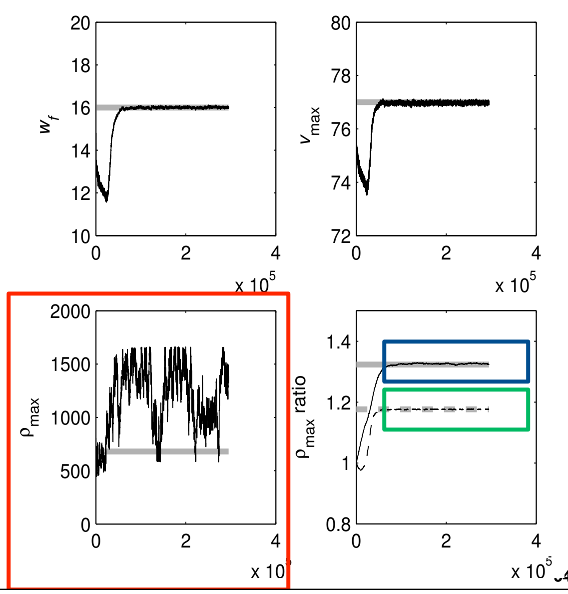
[Tossavainen & Work (submitted) 2013]

Numerical performance – jam density ratios

- True parameters (grey):

parameter	link 1	link 2	link 3
lanes	5	4	5
$v_{\max}$ (mph)		77	
w_f (mph)		16	
$\rho_{\max}$ (veh/mi)	900	680	800
$\frac{\rho_{\max,i}}{\rho_{\max,2}}$	1.32	1	1.18

$$\theta = \begin{pmatrix} \alpha_{1,2} \\ \rho_{\max,2} \\ \alpha_{3,2} \\ v_{\max} \\ w_f \end{pmatrix}$$



[Tossavainen & Work (submitted) 2013]

Prediction error with estimated parameters

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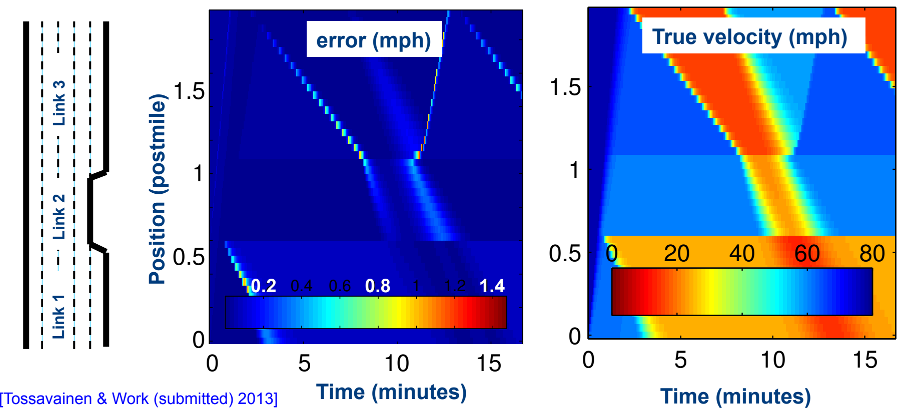
Parameter	True value	Mean value	Standard deviation
$\alpha_{1,2}$	1.32	1.32	0.01
$\rho_{\max,2}$	680	944	200
$\alpha_{3,2}$	1.18	1.18	0.002
$v_{\max}$	77.0	77.0	0.06
w_f	16.0	15.9	0.1



[Tossavainen & Work (submitted) 2013]

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Another app for traffic monitoring?

[trafficturk.com]

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Extreme congestion events

- Event driven congestion
  - Sporting events
  - Political rallies
  - Natural disasters

- Impact on transportation infrastructure
  - Network topology changes
  - Damage to physical components
  - Loss of cyber components

Limitations of current systems

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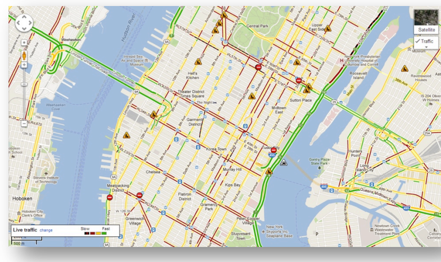
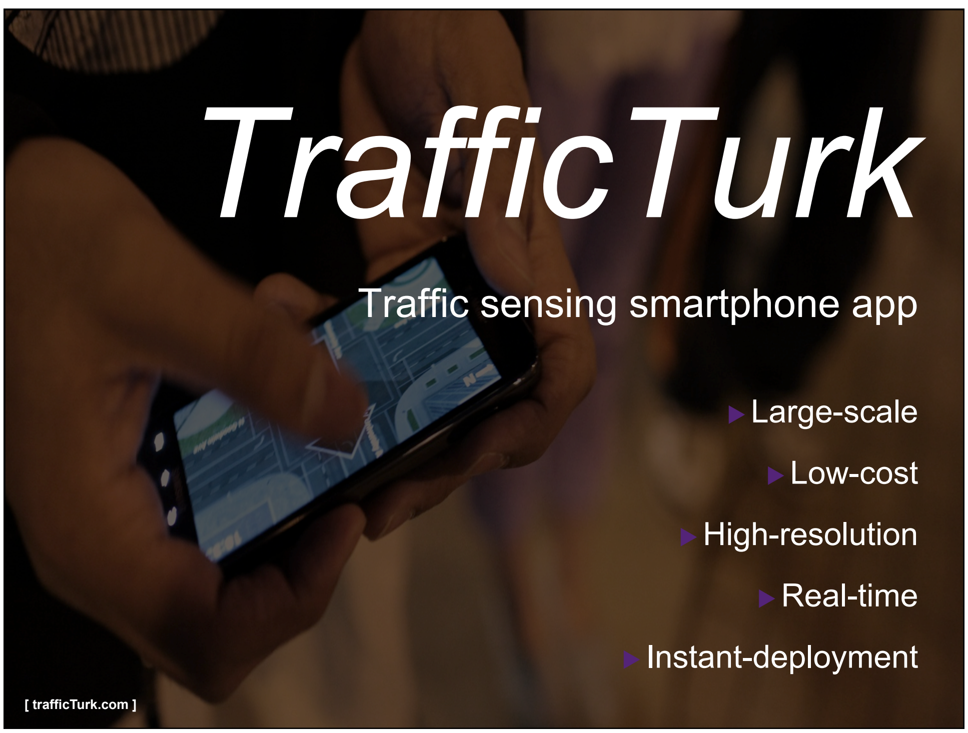
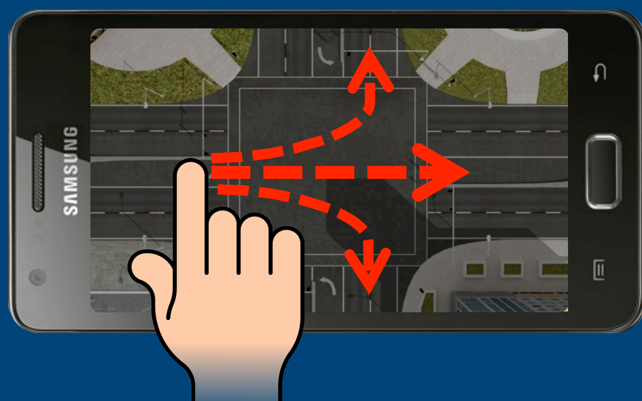
- Surface streets
  - Sparsity of sensing
  - Limited gps data



- machine learning based algorithms:
  - Heavily influenced by historical priors
- Flow models:
  - Unknown boundary controllers (traffic signals)

Need for cheap, instantly deployable (temporary) sensing





When a vehicle passes the intersection,
swipe its movement on the screen.

Inspiration

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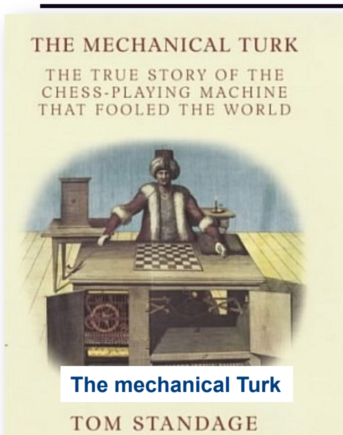

The mechanical Turk

Amazon's Mechanical Turk

Turning movement counters
(Transportation's Mechanical Turk)


TrafficTurk in Urbana-Champaign
100+ sensors deployed to monitor football traffic
220,000+ vehicles swiped


6 am
10 am
ILLINOIS

11 training sessions

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PLAY WITH AN ANDROID APP AND EARN

$50

GO TO

WWW.TRAFFICTURK.COM

Apply before October 24, 2012

Traffic Turk is a research project at the University of Illinois at Urbana-Champaign

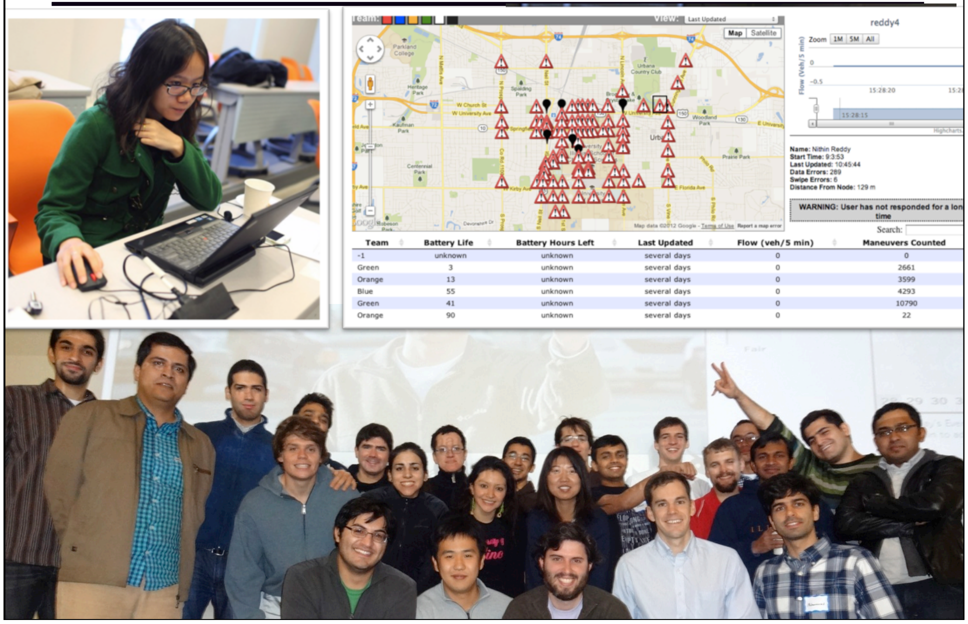
Also get a free pair of smartphone gloves!

135 student volunteers

illinois.edu

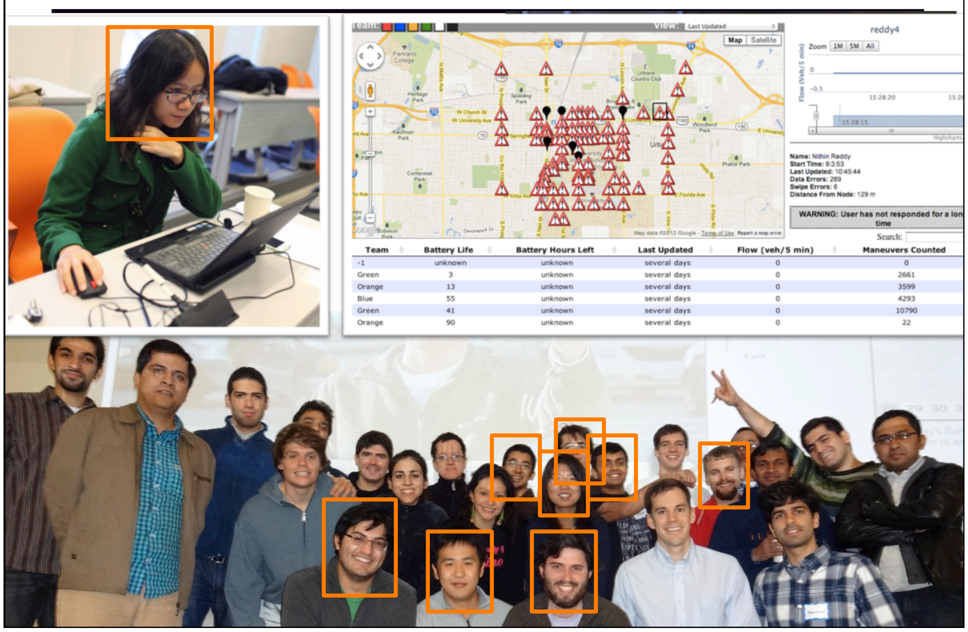
Streaming data to Mission Control

illinois.edu



[research team]

illinois.edu



TrafficTurk Experiment - NYC

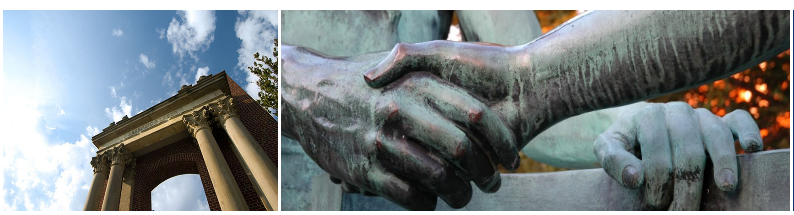
- Hurricane Sandy – November 3 and 4, 2012
- Garment District, Manhattan
- Overnight map deployment
- Recruitment at Columbia University

- Real disaster response experience

= 10+ hours monitoring

[NSF RAPID # 1308842]

[*Scientific American* Citizen Science featured project '12]



Traffic Monitoring with Smartphones

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