Data, Predictions, and Decisions in Support of People and Society

Eric Horvitz

Microsoft

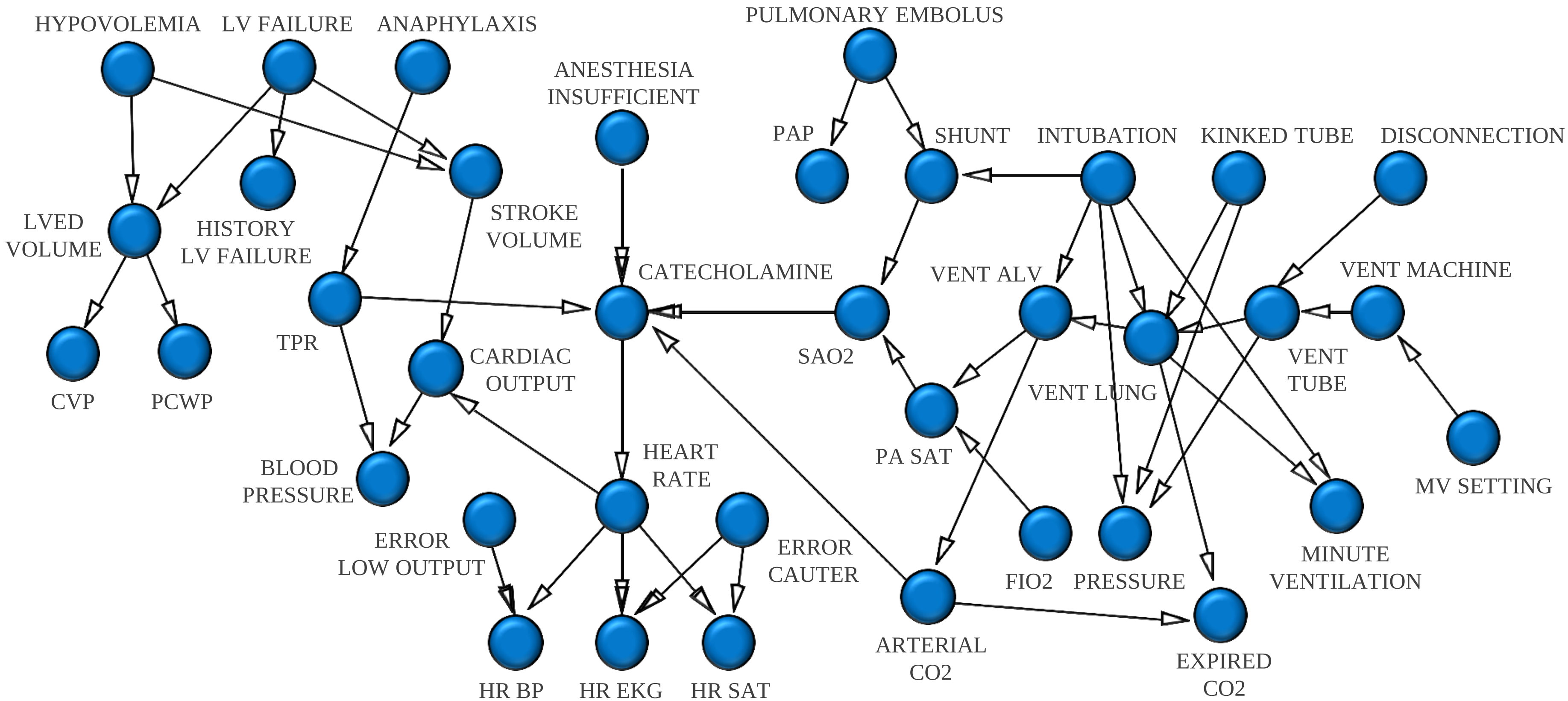
#KDD2014

Data Science for Social Good

Critical contributions to humanity

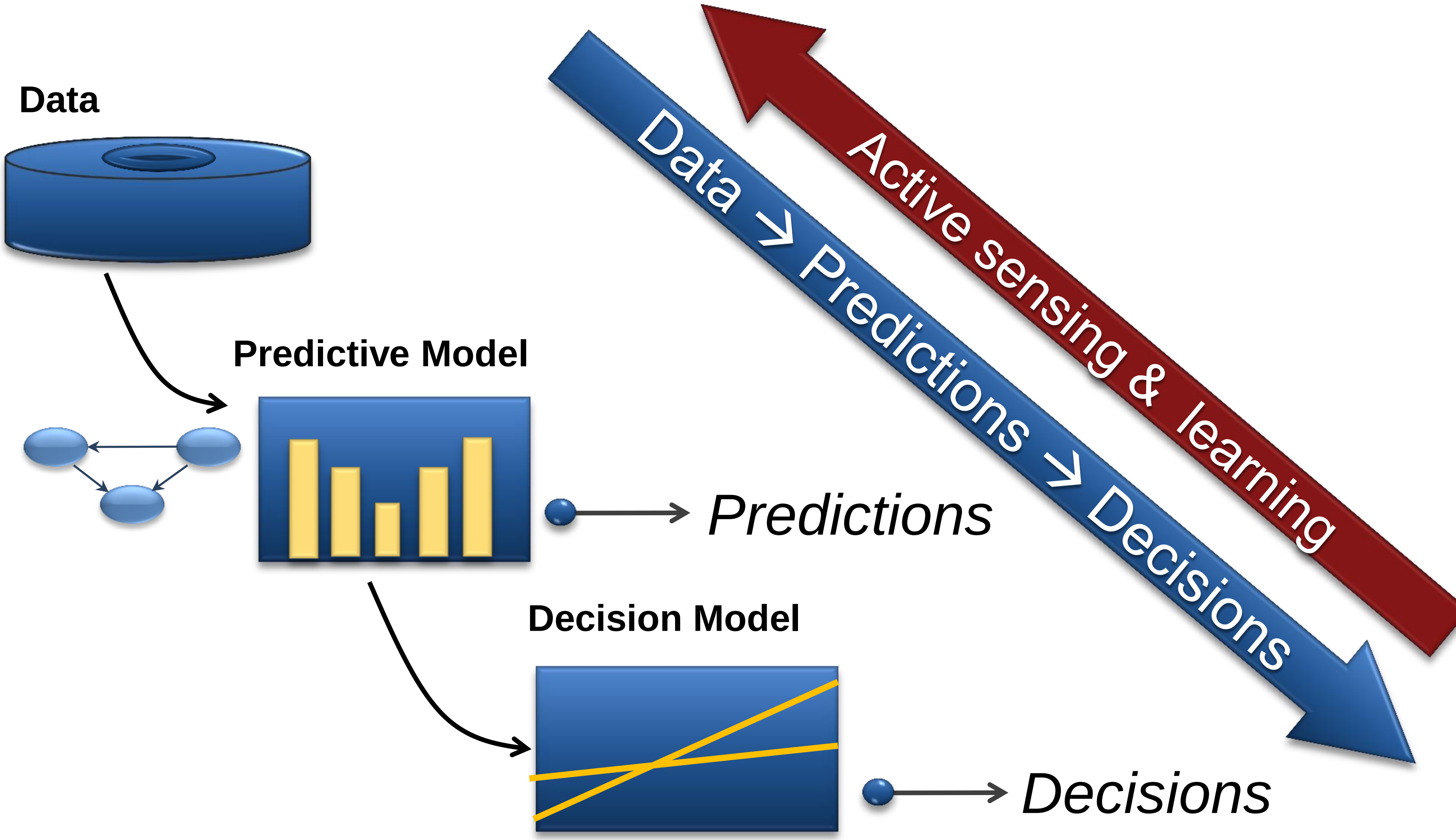
Learning, inference, and decision making

Inference for high-stakes challenges



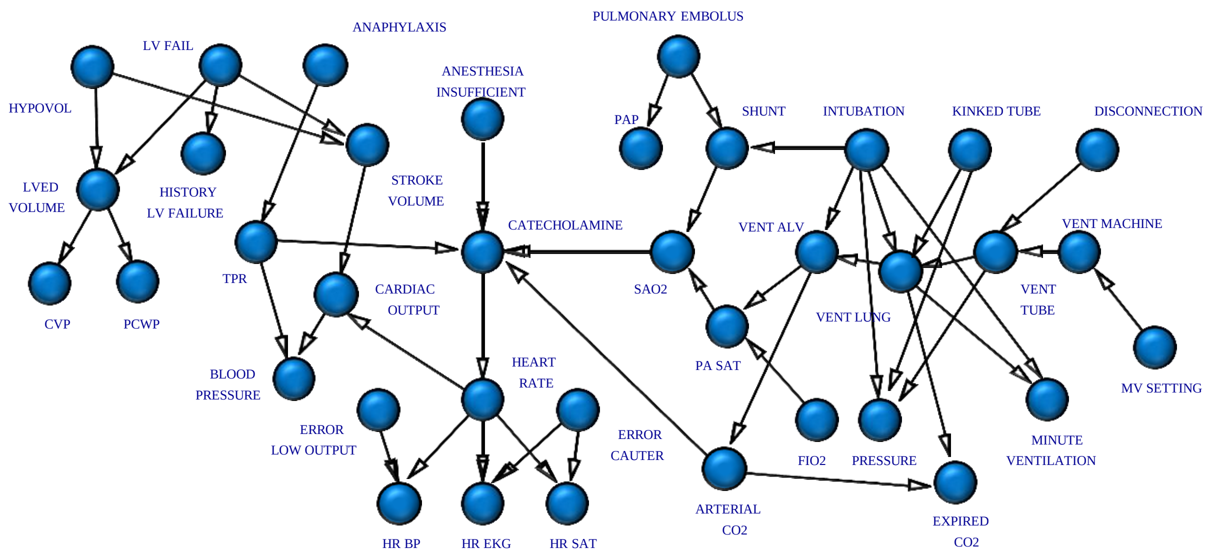
H. & A. Seiver, UAI 1997

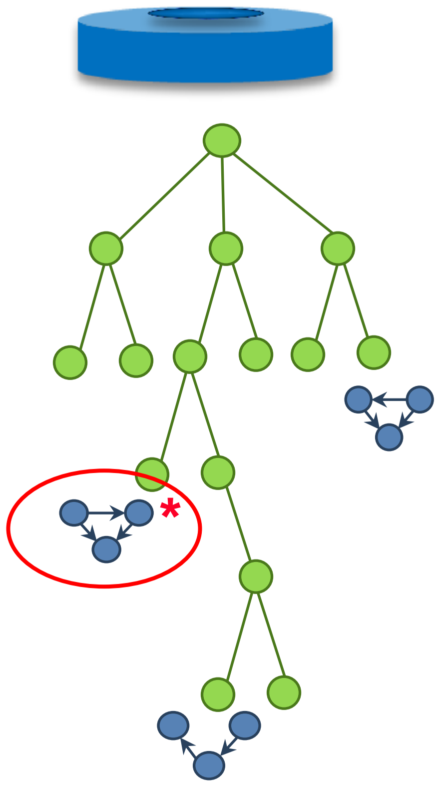
Predictions to Decisions



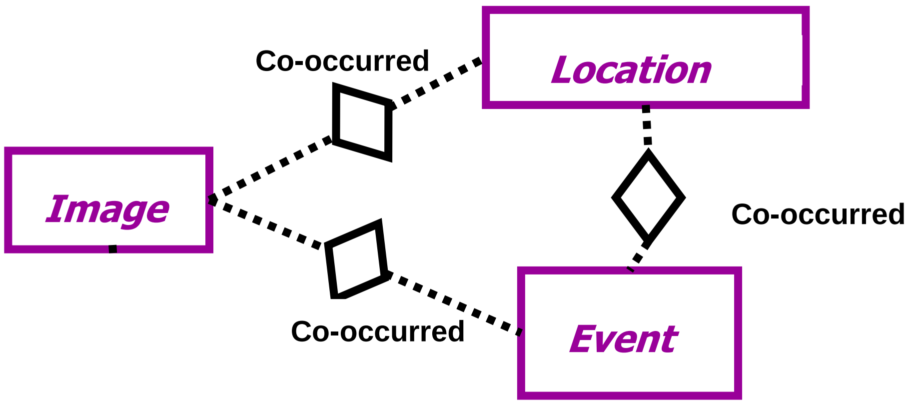
Exciting Times

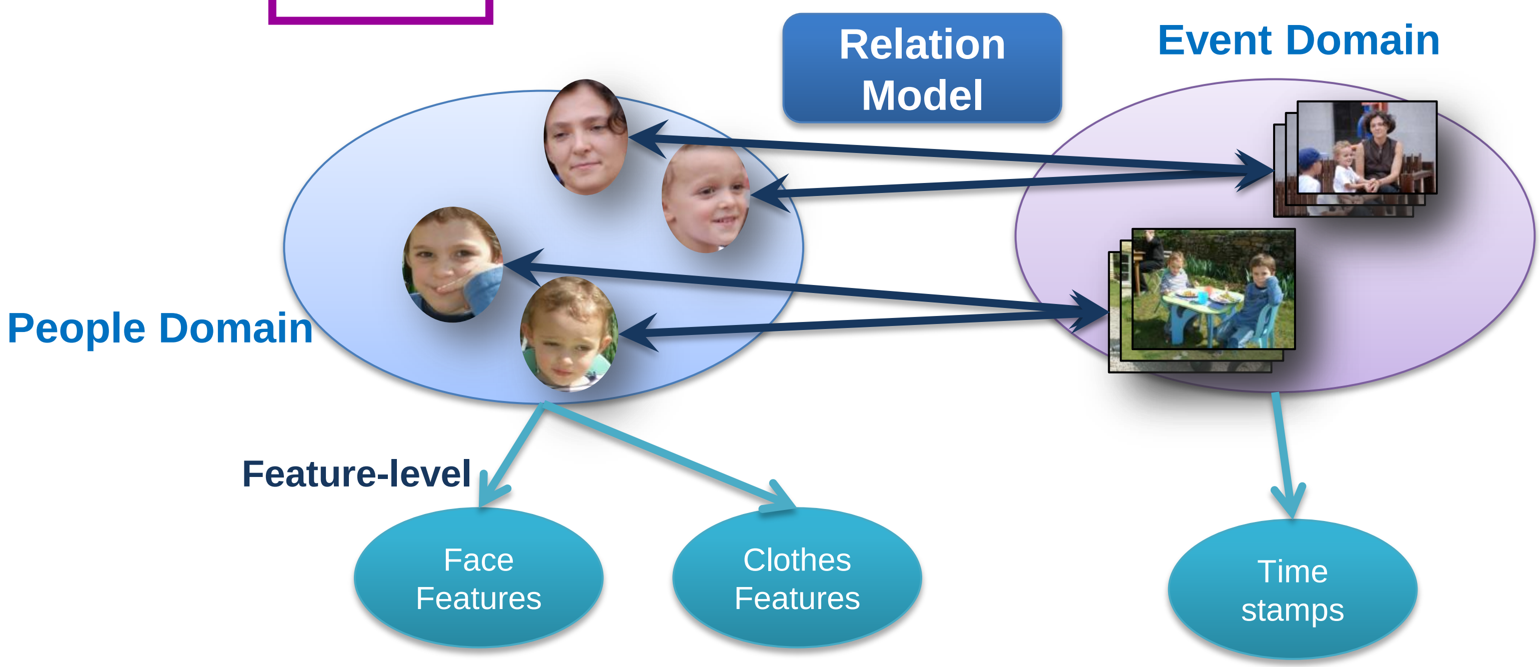
Learning procedures keeping pace with data





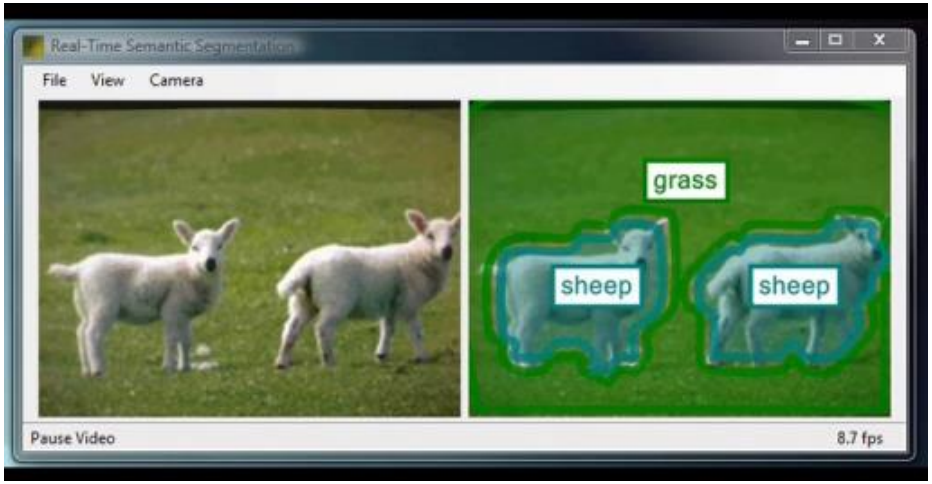
Rise of Rich Representations





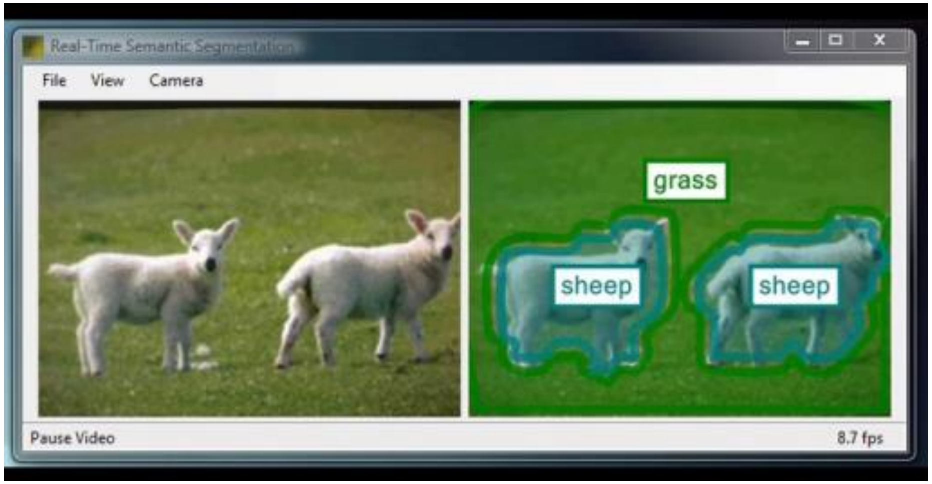
D. Lin, A. Kapoor, G. Hua, S. Baker, ECCV 2010

Rise of Rich Representations



J. Shotton, J. Winn, C. Rother, A. Criminisi

Rise of Rich Representations



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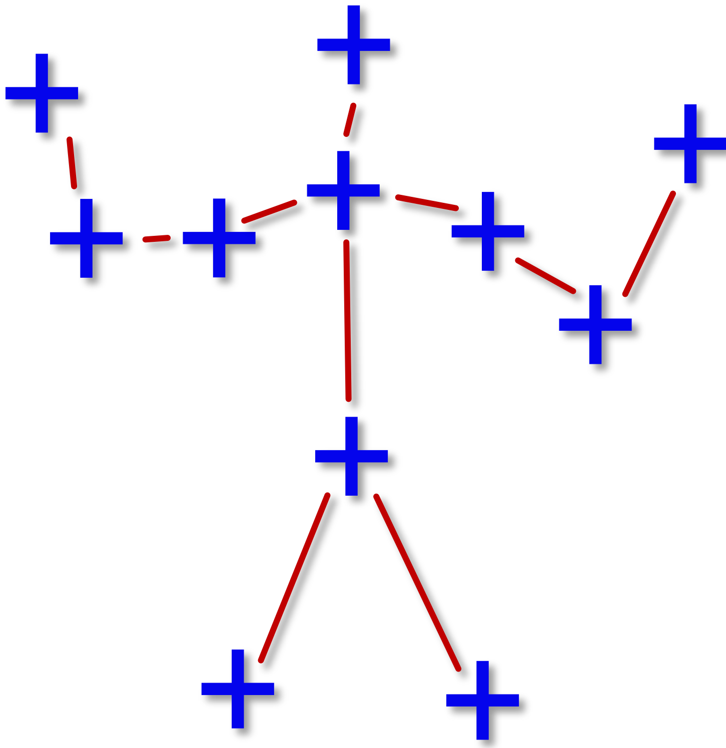
Rise of Rich Representations



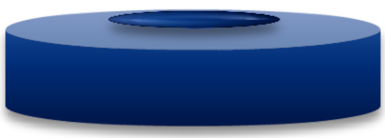
J. Shotton, J. Winn, C. Rother, A. Criminisi

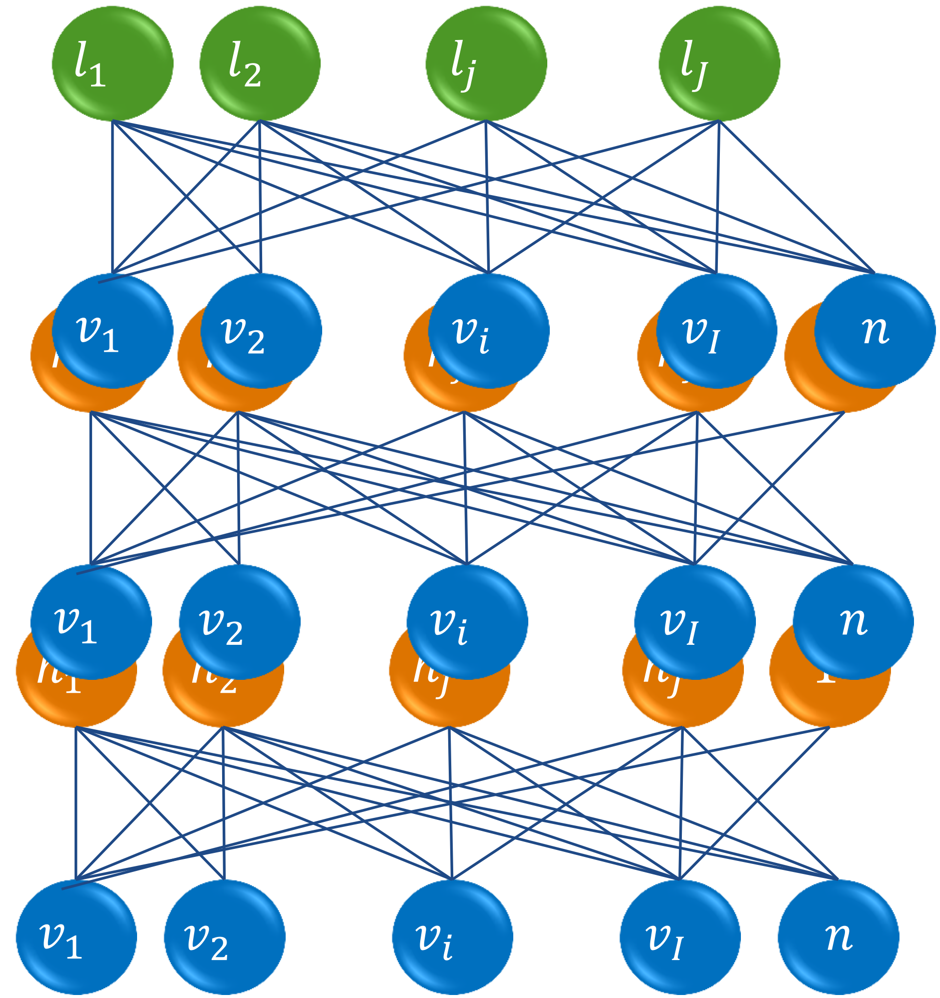
Rise of Rich Representations

KINECT
for XBOX 360.

Renaissance of Familiar Methods

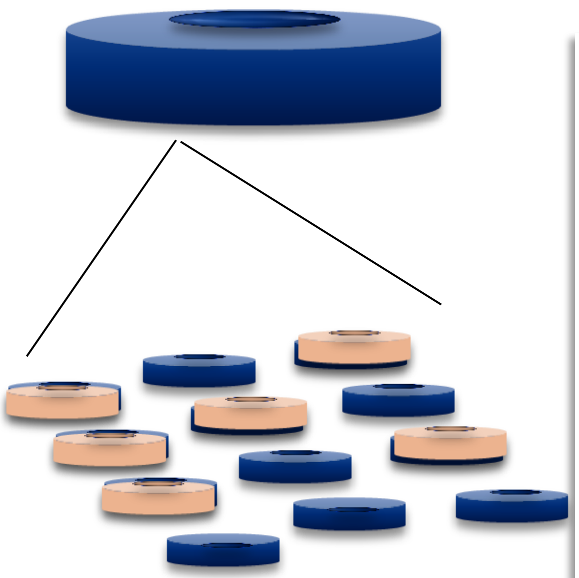
Pursuit of speech, vision with stacked representations



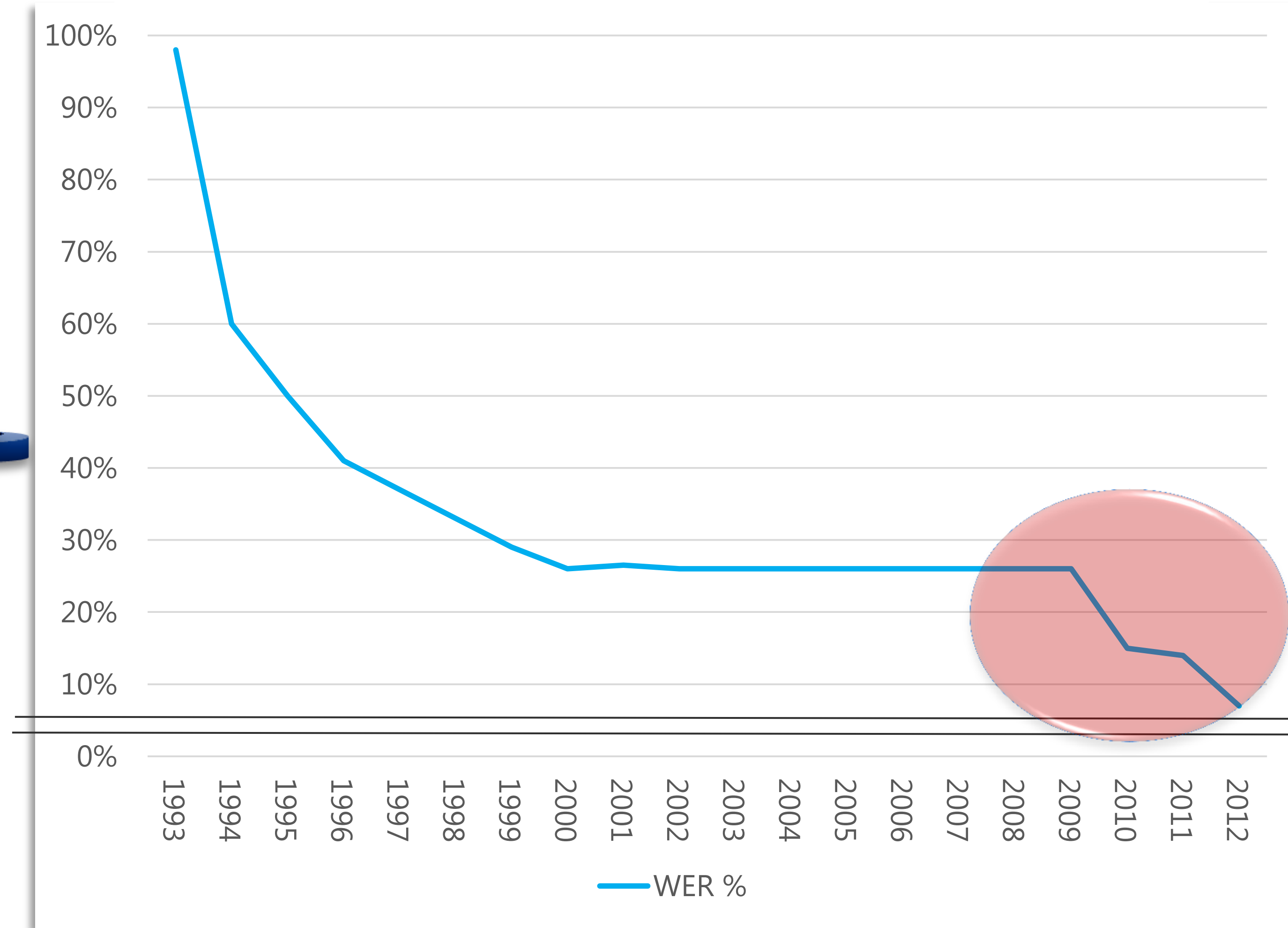


Renaissance of Familiar Methods

Pursuit of speech, vision with stacked representations



Conversational Speech: *Switchboard* challenge



Renaissance of Familiar Methods

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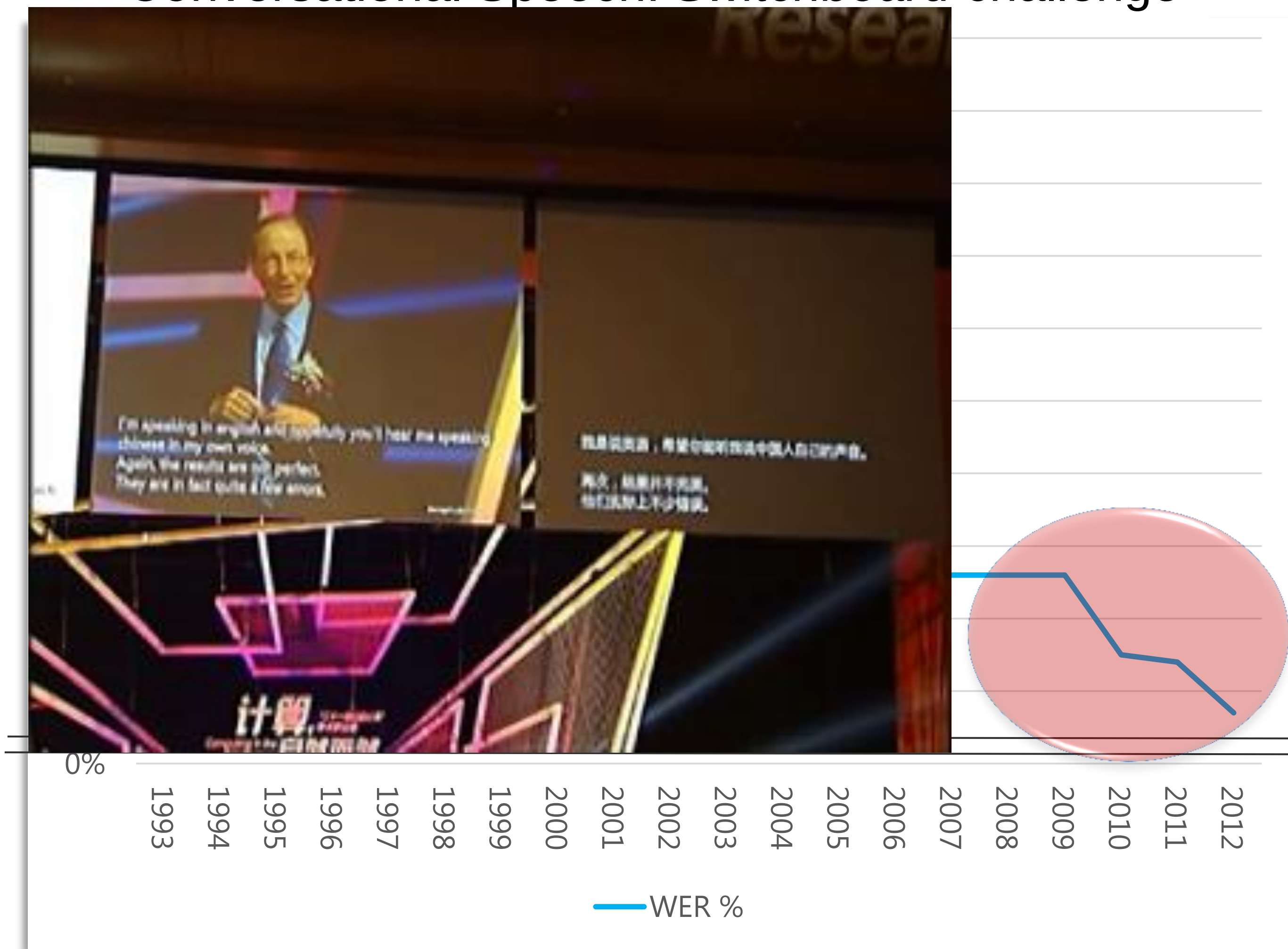
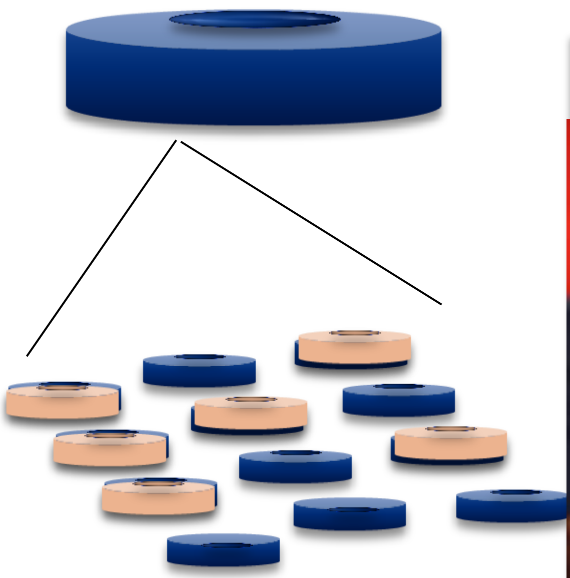
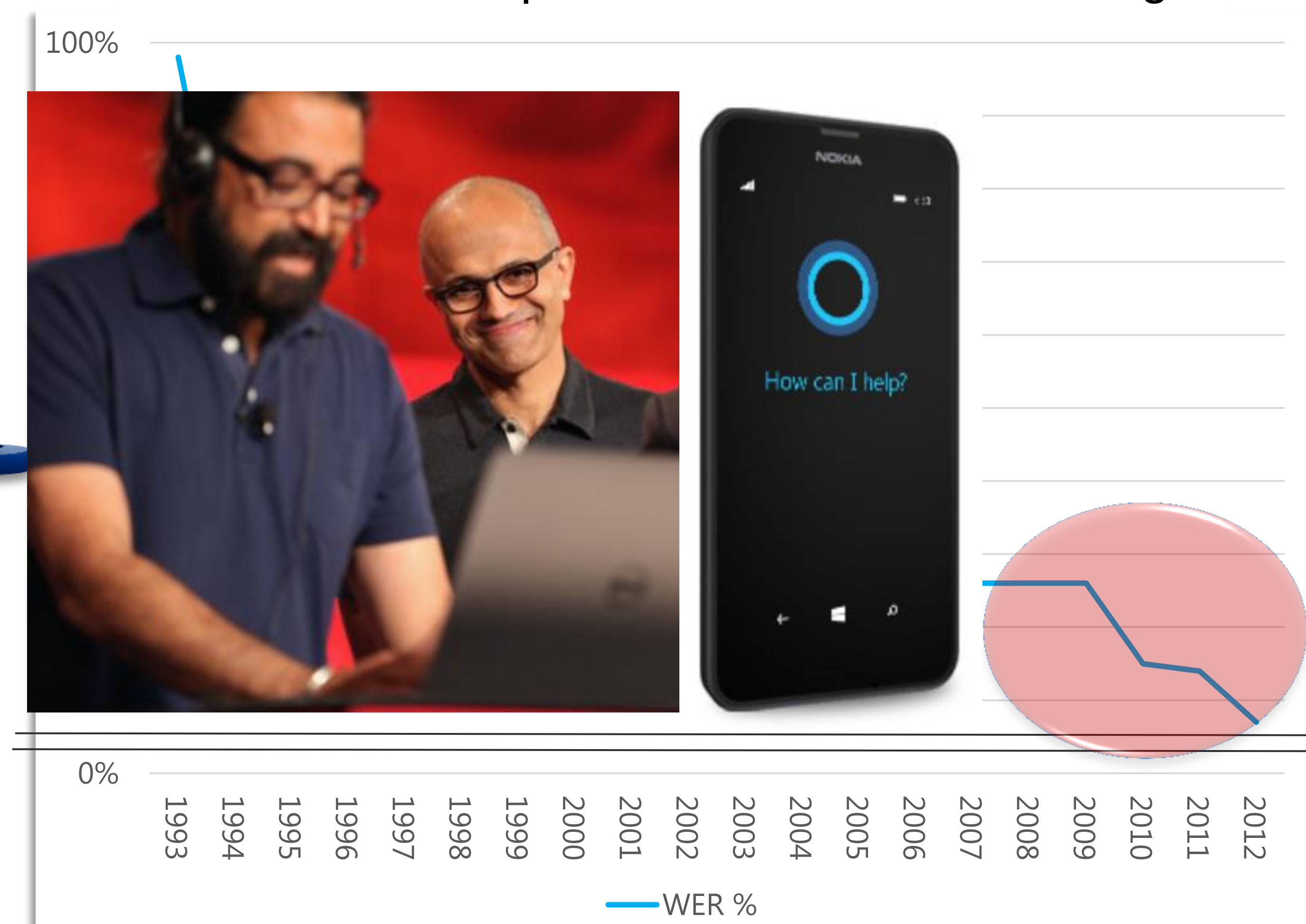


Renaissance of Familiar Methods

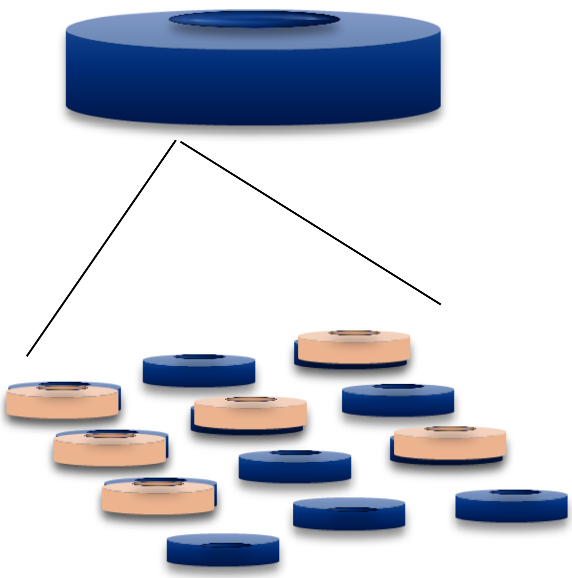
Pursuit of speech, vision with stacked representations

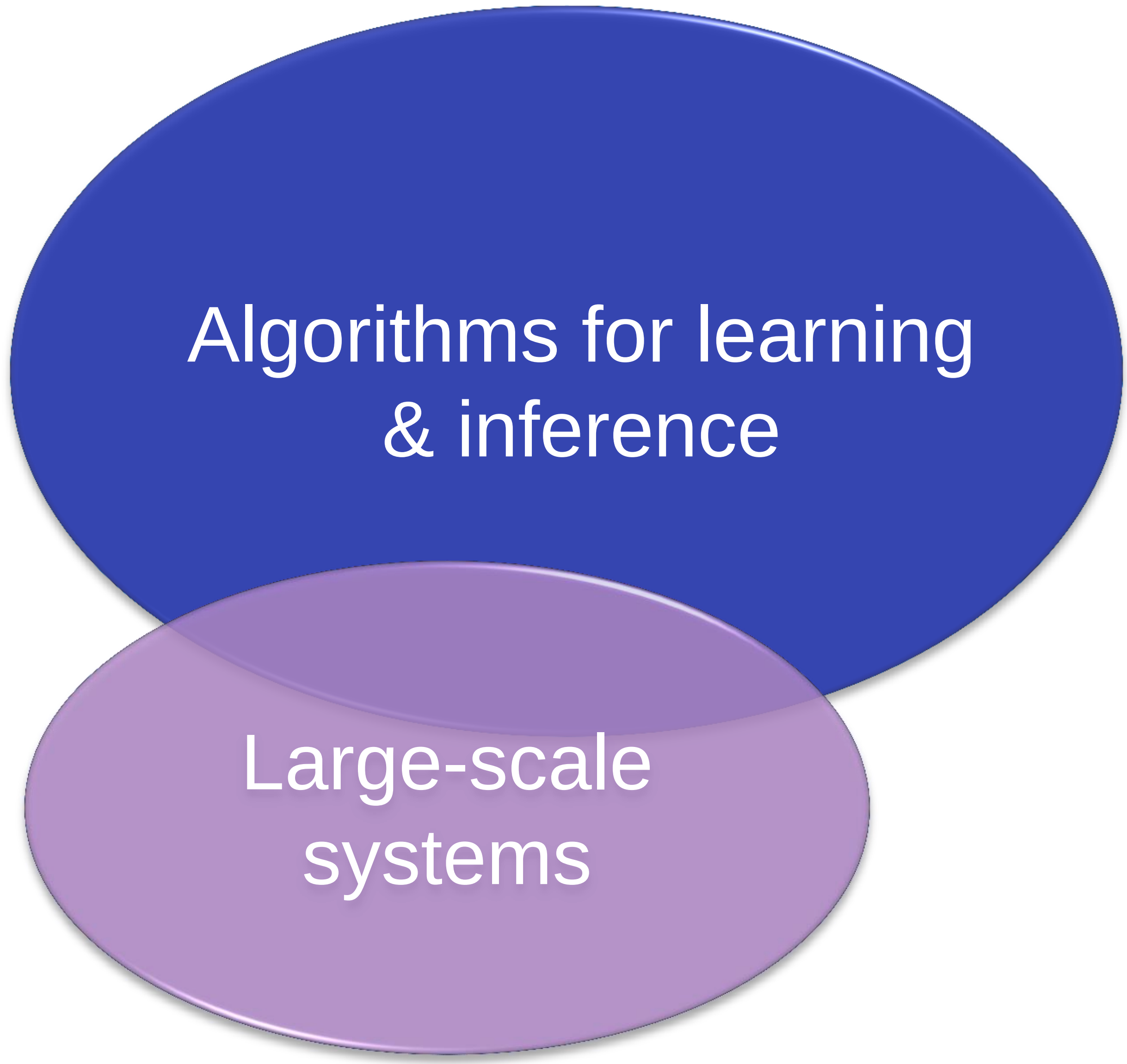


Conversational Speech: *Switchboard* challenge



Data, Learning, and Systems





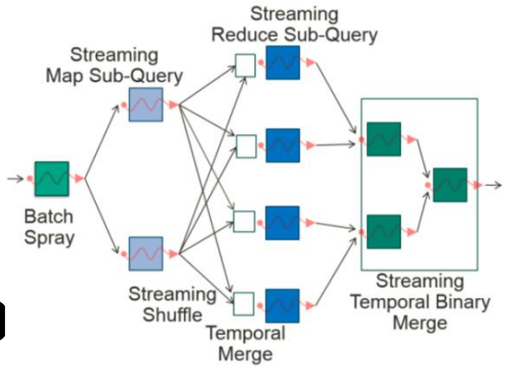
Beauty and the Bottleneck

Hekaton: Database service

In-memory, manycore, latch-free:

30x speed-up

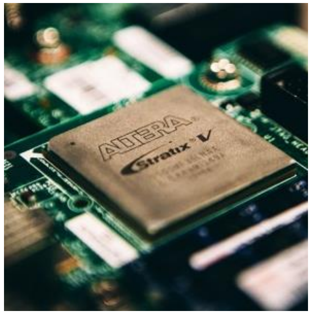
Trill: Streaming analytics



Column-oriented batches, P3 sort:

2-4 orders of magnitude speed-up

Catapult: Data center search perf.



Speed-ups via FPGA

40x speed-up

Data Science for Social Good

Transportation

Clinical medicine

Public health

Inferences about Traffic

Smartflow, UAI 2005

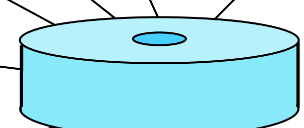
Multiple views on traffic

Weather

Major events

Incident reports

Operator ID: Nick
Heading: INCIDENT
Message: INCIDENT
INFORMATION
Cleared 1637: I-405 SB
JS I-90 ACC BLK RL CCTV
1623 - WSP, FIR ON SCENE



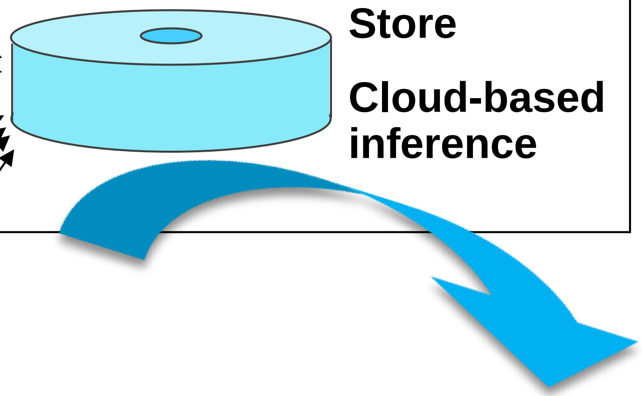
- **Event store**
- **Learning**
- **Reasoning**

H., J. Apacible, R. Sarin, L. Liao, UAI 2005

Forecasting Future Traffic

- System-wide status & dynamics
- Incident reports
- Sporting events
- Weather
- Time of day
- Day of week
- Season
- Holiday status

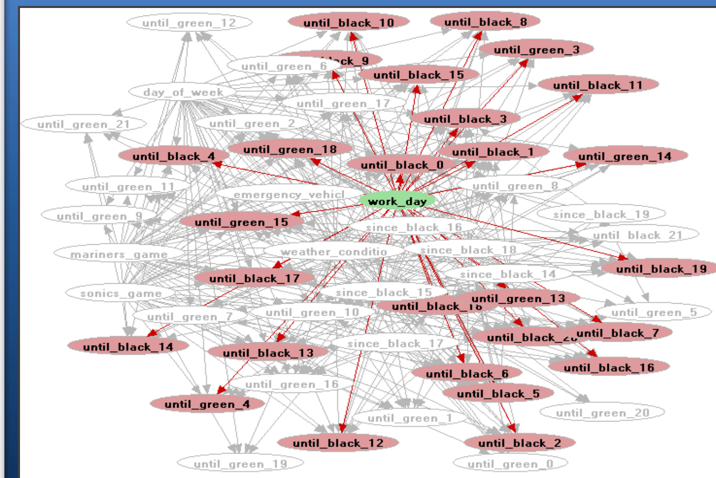
Traffic forecasting service

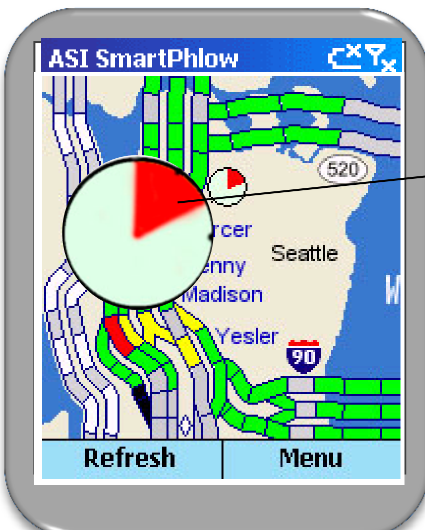


Store

Cloud-based inference

Base-level predictions





Max likely duration

[H., J. Apacible, R. Sarin, L. Liao, UAI 2005]()

Forecasting Future Traffic

- System-wide status & dynamics
- Incident reports
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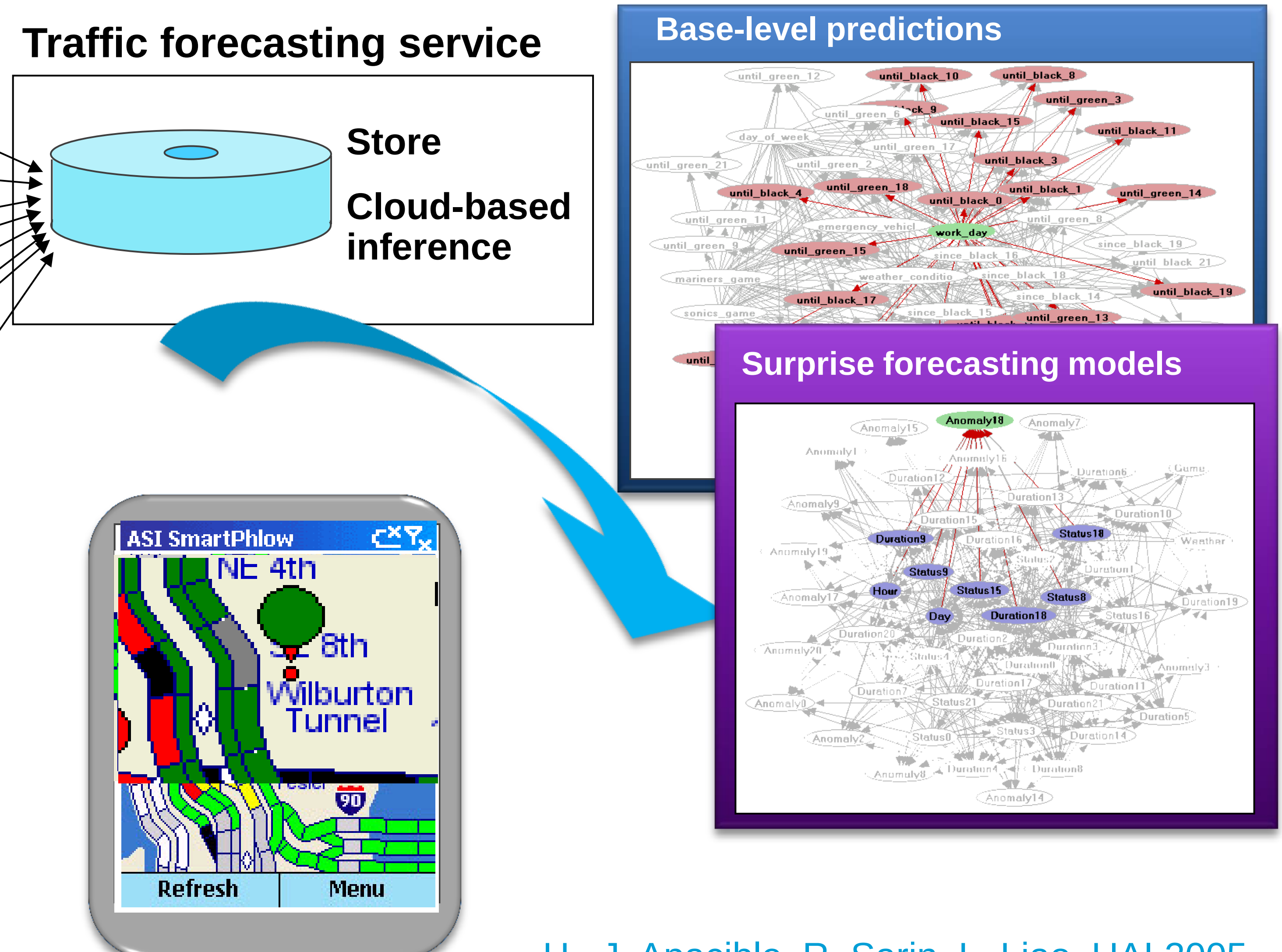
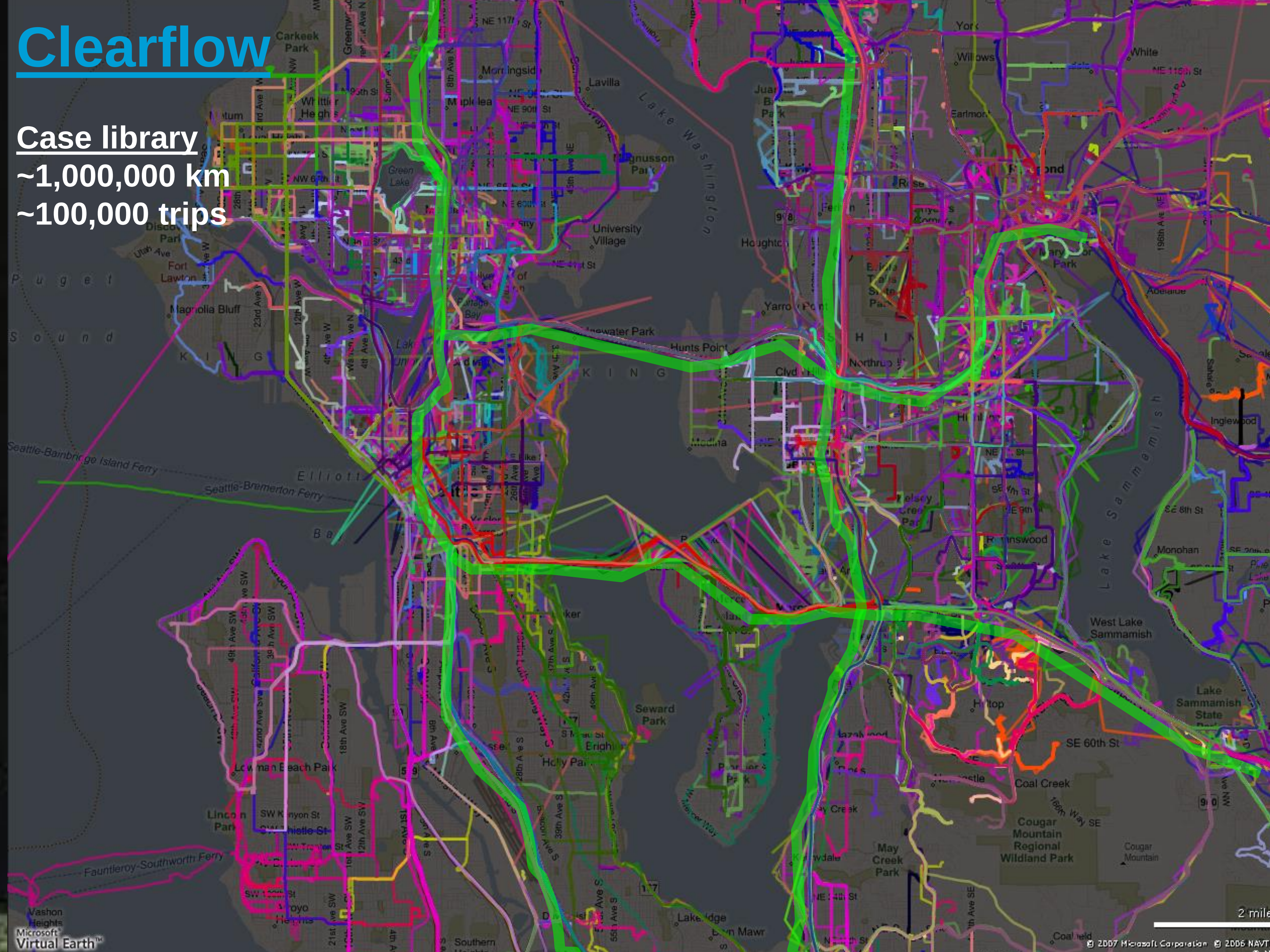
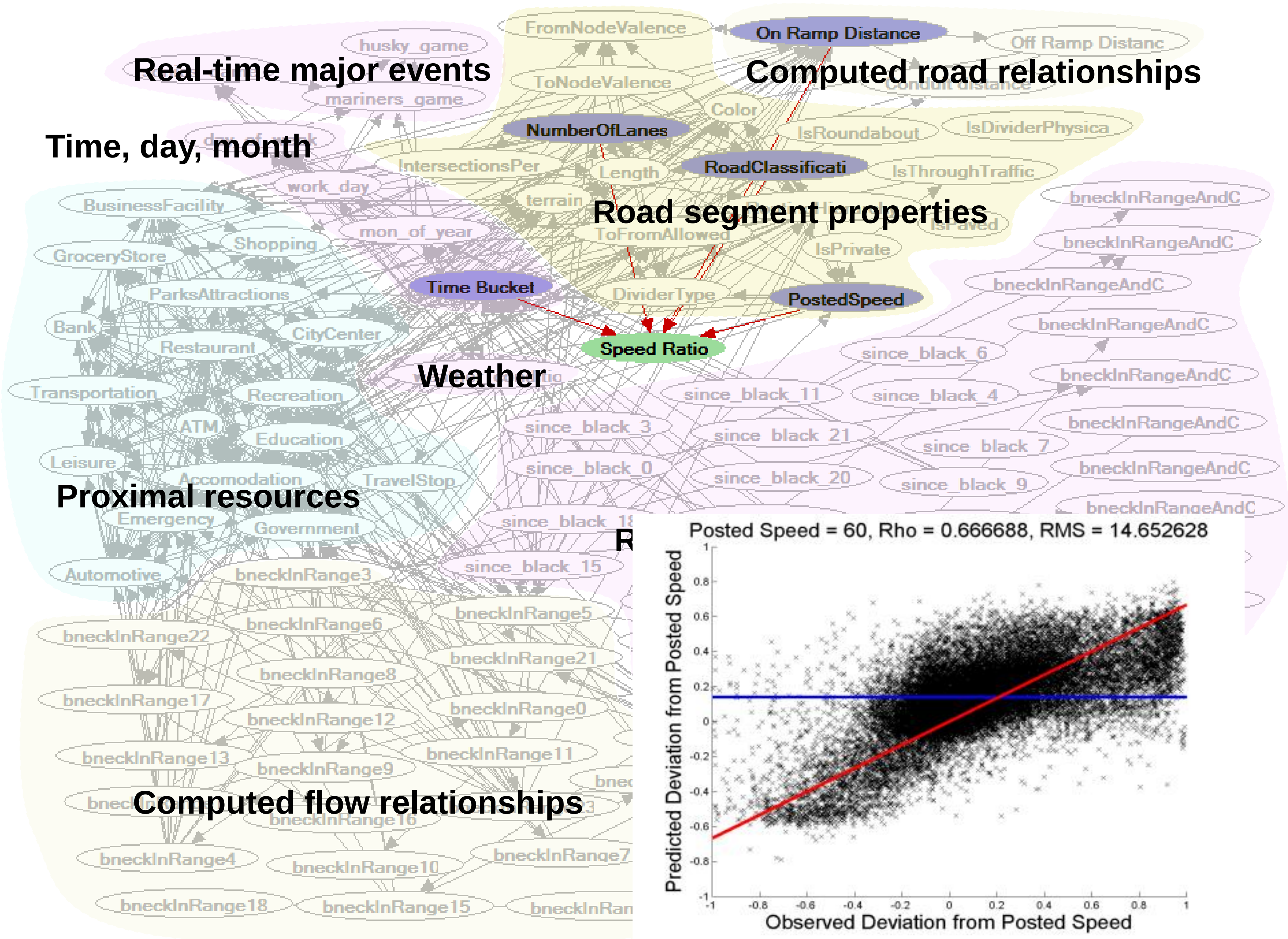


H., J. Apacible, R. Sarin, L. Liao, UAI 2005

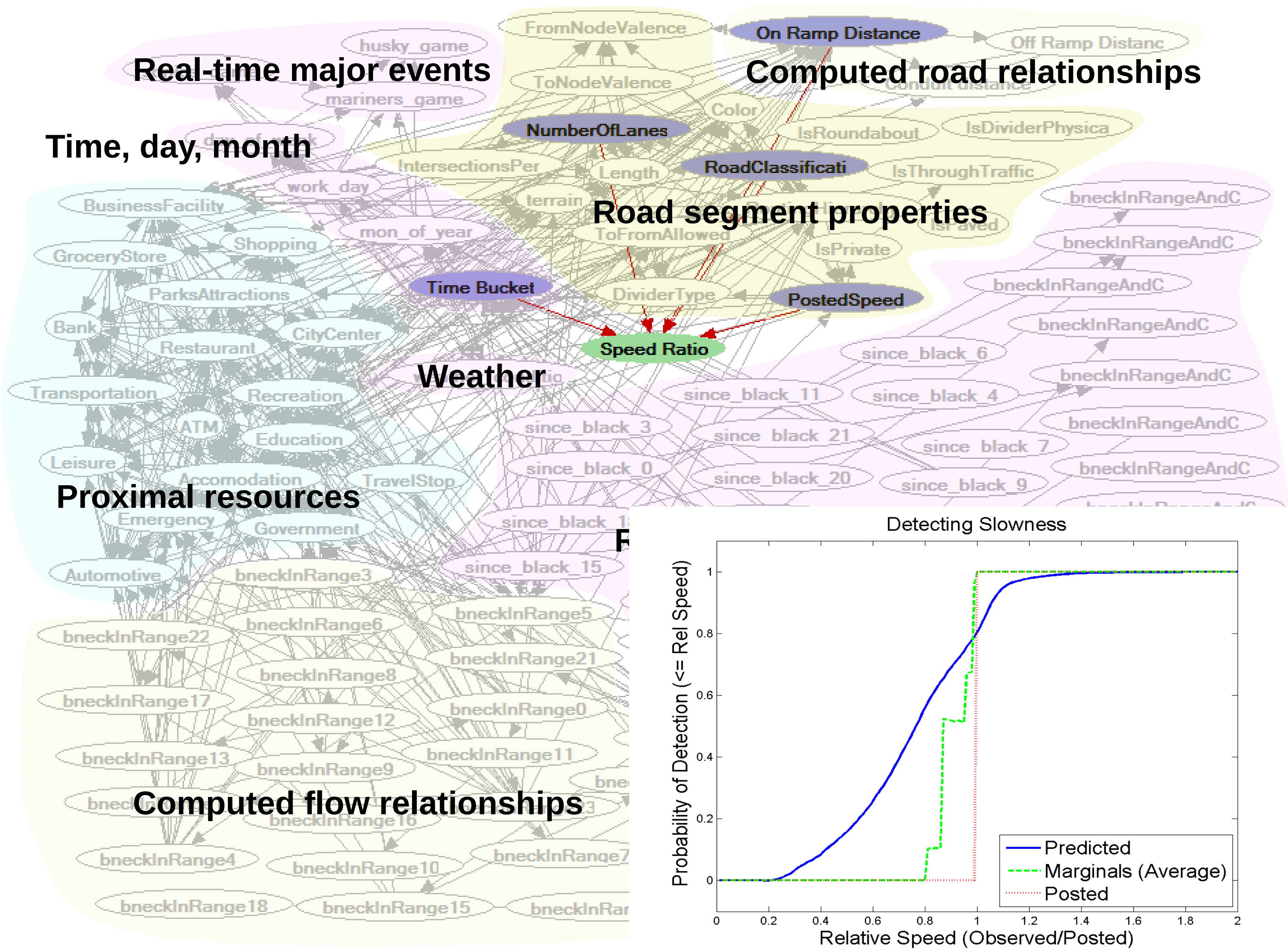
Clearflow

Case library
~1,000,000 km
~100,000 trips





Real-time major events
Computed road relationships
Time, day, month
Road segment properties
Weather
Proximal resources
Computed flow relationships
On Ramp Distance
NumberOfLanes
RoadClassificati
Time Bucket
PostedSpeed
Speed Ratio
Posted Speed = 60, Rho = 0.666688, RMS = 14.652628
Predicted Deviation from Posted Speed
Observed Deviation from Posted Speed



Real-time major events
Computed road relationships
Time, day, month
Road segment properties
Weather
Proximal resources
Computed flow relationships
husky_game
mariners_game
FromNodeValence
On Ramp Distance
Off Ramp Distanc
ToNodeValence
Color
NumberOfLanes
IsRoundabout
IsDividerPhysica
IntersectionsPer
Length
RoadClassificati
IsThroughTraffic
work_day
terrain
mon_of_year
ToFromAllowed
IsPrivate
Time Bucket
DividerType
PostedSpeed
Speed Ratio
BusinessFacility
Shopping
GroceryStore
ParksAttractions
Bank
CityCenter
Restaurant
Transportation
Recreation
ATM
Education
Leisure
Accomodation
TravelStop
Emergency
Government
Automotive
bneckInRangeAndC
since_black_6
since_black_11
since_black_4
since_black_3
since_black_21
since_black_7
since_black_0
since_black_20
since_black_9
since_black_15
bneckInRange3
bneckInRange5
bneckInRange22
bneckInRange6
bneckInRange21
bneckInRange8
bneckInRange17
bneckInRange0
bneckInRange12
bneckInRange13
bneckInRange11
bneckInRange9
bneckInRange16
bneckInRange4
bneckInRange10
bneckInRange18
bneckInRange15
Detecting Slowness
Probability of Detection (<= Rel Speed)
Relative Speed (Observed/Posted)
0
0.2
0.4
0.6
0.8
1
1.2
1.4
1.6
1.8
2
Predicted
Marginals (Average)
Posted

The New York Times

Technology

Microsoft Introduces Tool for Avoiding Traffic Jams

By JOHN MARKOFF
Published: April 10, 2008

Microsoft now considers surface street traffic as well as freeway speeds in its routing.

SAN FRANCISCO — Microsoft on Thursday plans to introduce a Web-based service for driving directions that incorporates complex software models to help users avoid traffic jams.

Related

Times Topics: Microsoft Corporation

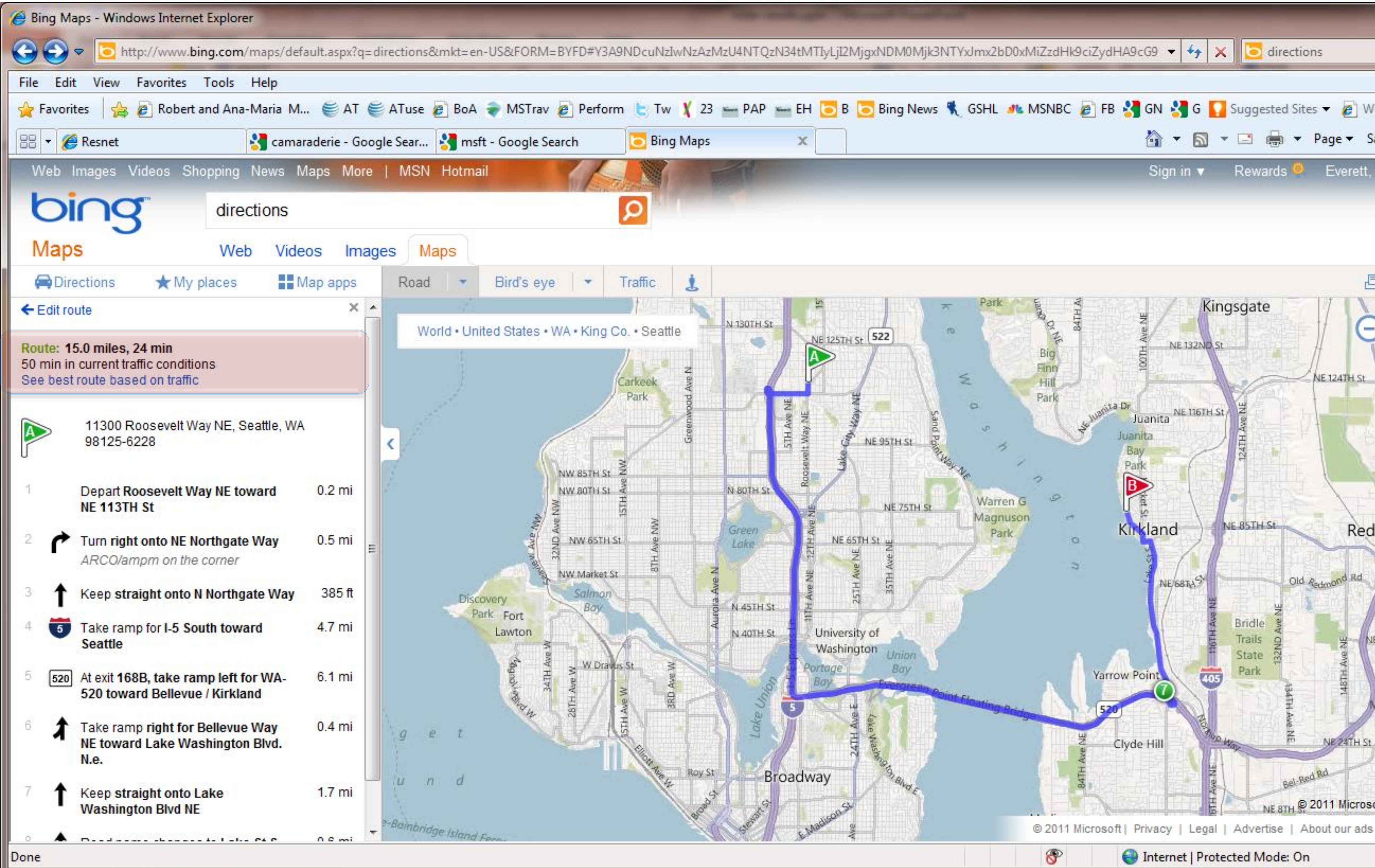
The new service's software technology, called Clearflow, was developed over the last five years by a group of artificial-intelligence researchers at the company's Microsoft Research laboratories. It is an ambitious attempt to apply machine-learning techniques to the problem of traffic congestion. The system is intended to reflect the complex traffic interactions that occu traffic backs up on freeways and spills over onto city streets.

The Clearflow system will be freely available as part of the company's Live.com site (maps.live.com) for 72 cities in the United States. Microsoft says it will give drivers alternative route information that is more accurate and attuned to current traffic pa on both freeways and side streets.

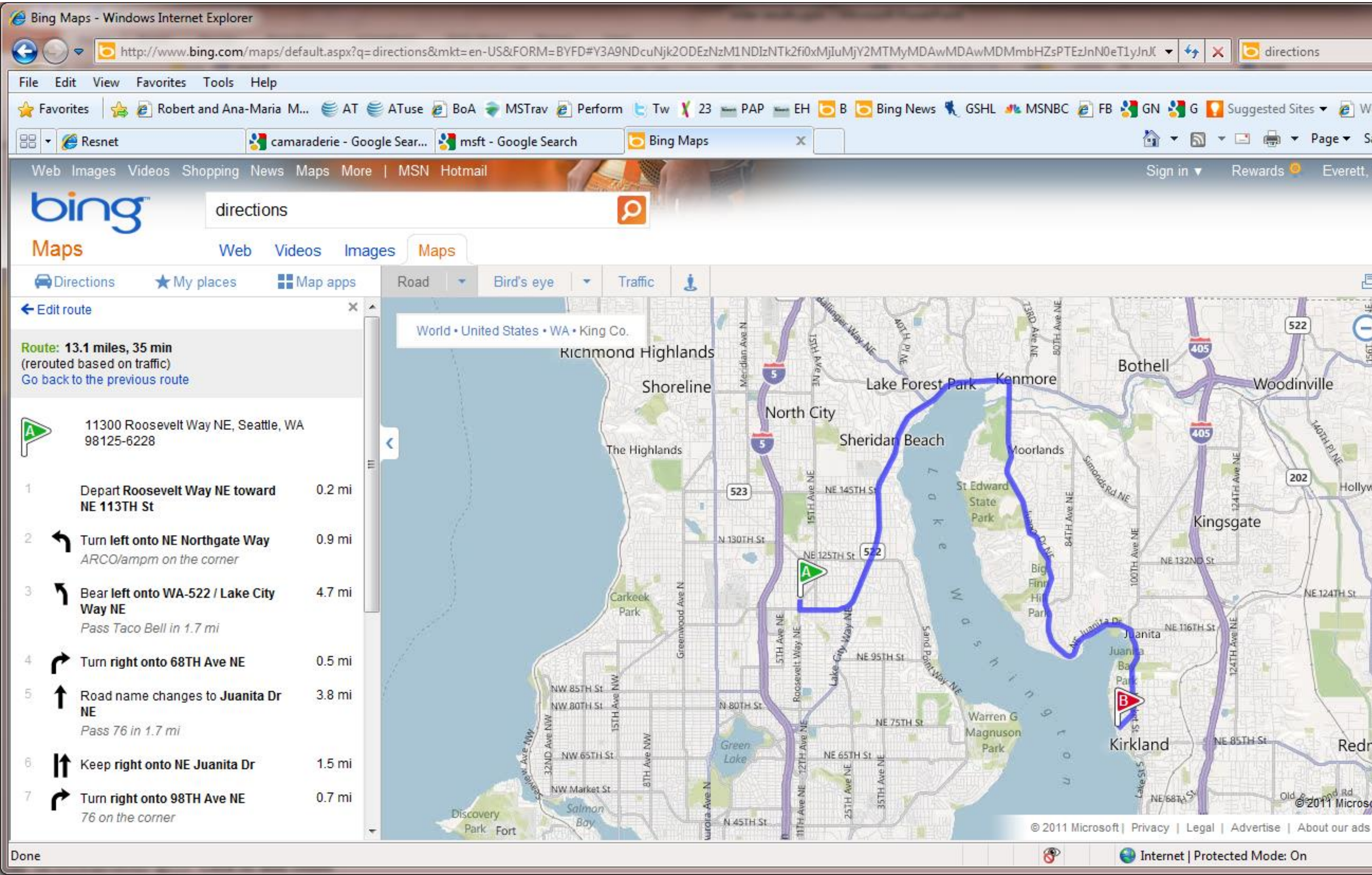
Traffic-Sensitive Routing

72 cities across North America
Flows assigned to ~60 million streets every few minutes

Traffic-Sensitive Routing

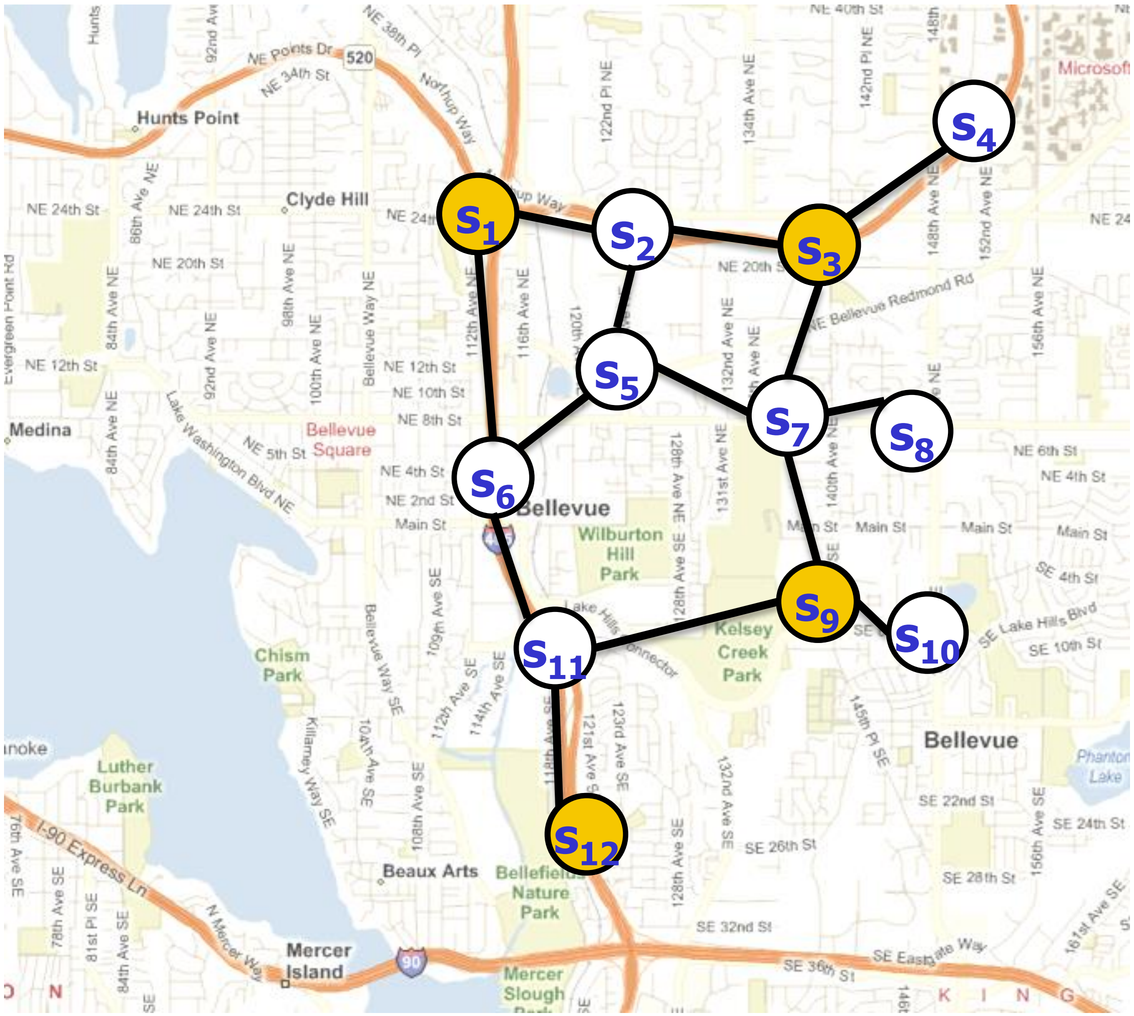


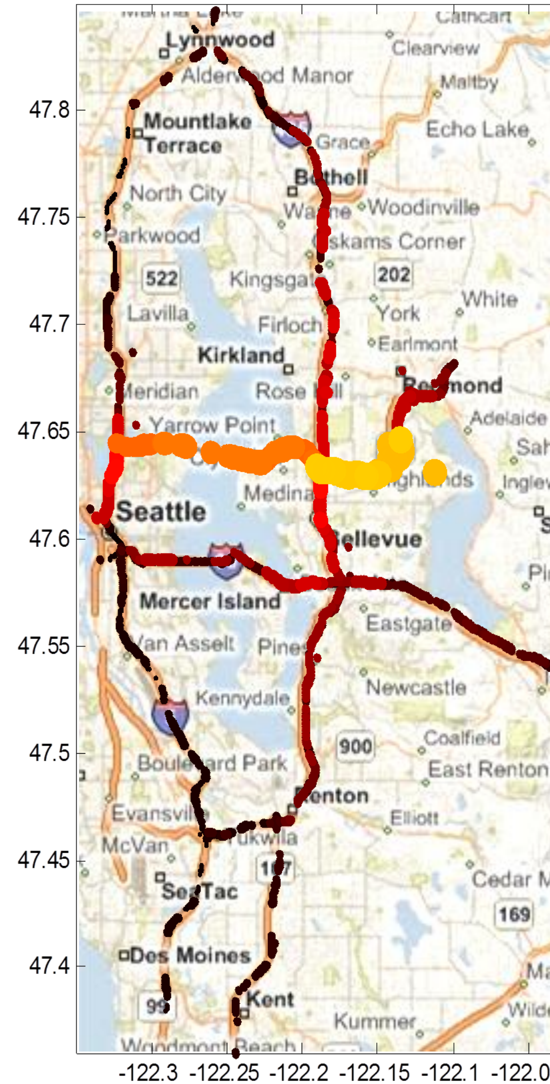
Traffic-Sensitive Routing



Community Sensing

Utilitarian: Demand-weighted value

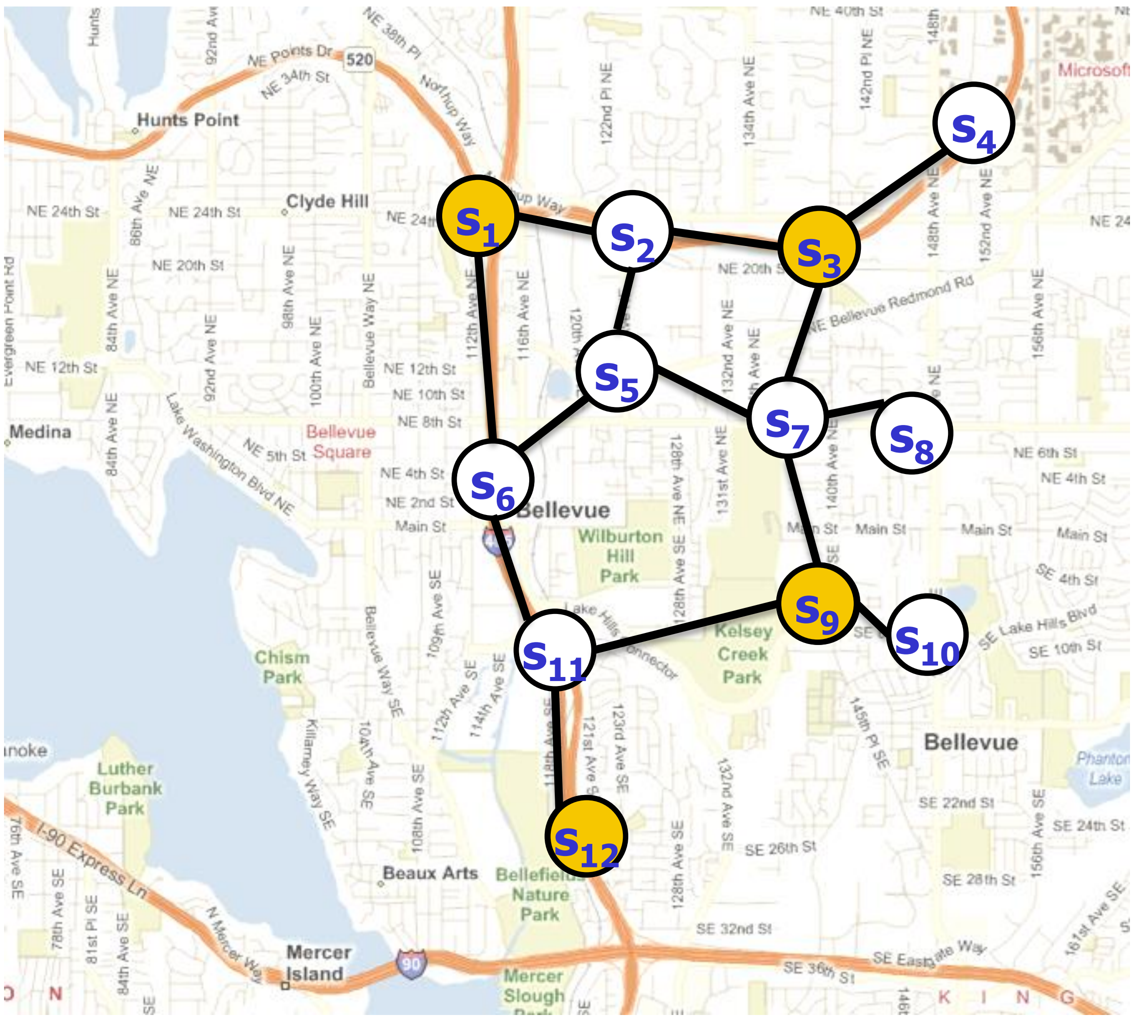


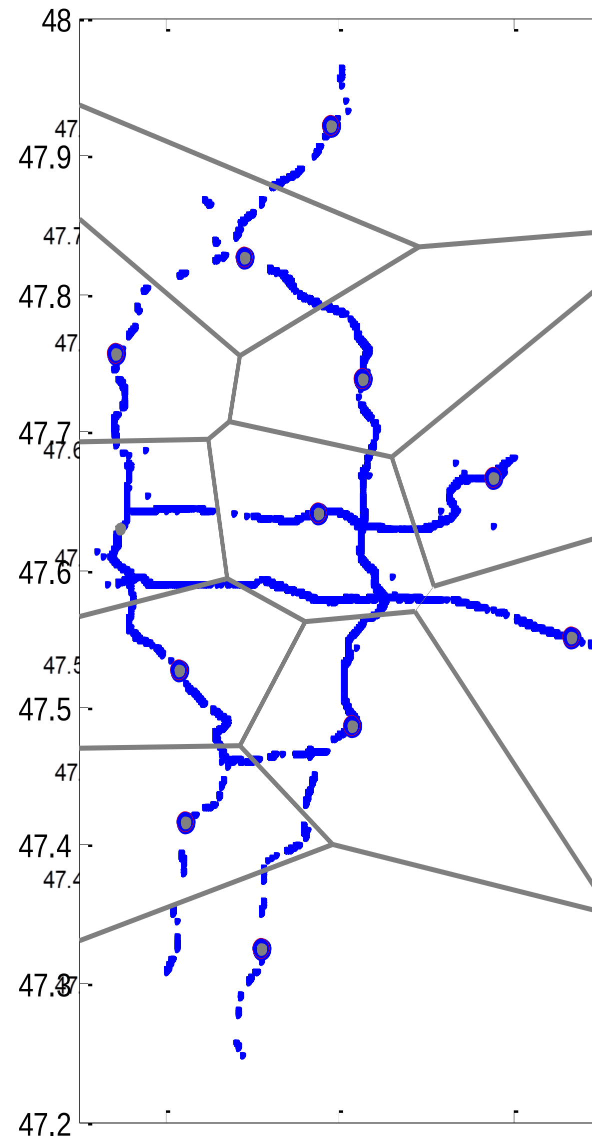


Krause, H., et al., IPSN 2008

Community Sensing

Utilitarian: Demand-weighted value





Krause, H., et al., IPSN 2008

Community Sensing

Utilitarian: Demand-weighted value

Phenomenon

Variables of spatiotemporal process

$\mathrm{Var}(\mathcal{X}_s \mid \mathcal{X}_\mathcal{A} = \mathbf{x}_\mathcal{A})$ $\quad \mathrm{Var}(\mathcal{X}_s) - \mathrm{Var}(\mathcal{X}_s \mid \mathcal{X}_\mathcal{A} = \mathbf{x}_\mathcal{A})$

Demand Model

Population needs

$$R(\mathcal{A}) = \sum_{s \in \mathcal{V}} \mathbb{E}\left[\mathcal{D}_s(\mathrm{Var}(\mathcal{X}_s) - \mathrm{Var}(\mathcal{X}_s \mid \mathcal{X}_\mathcal{A}))\right]$$

Sensor Availability

Sharing Preferences

Avail. of observations B at locations A

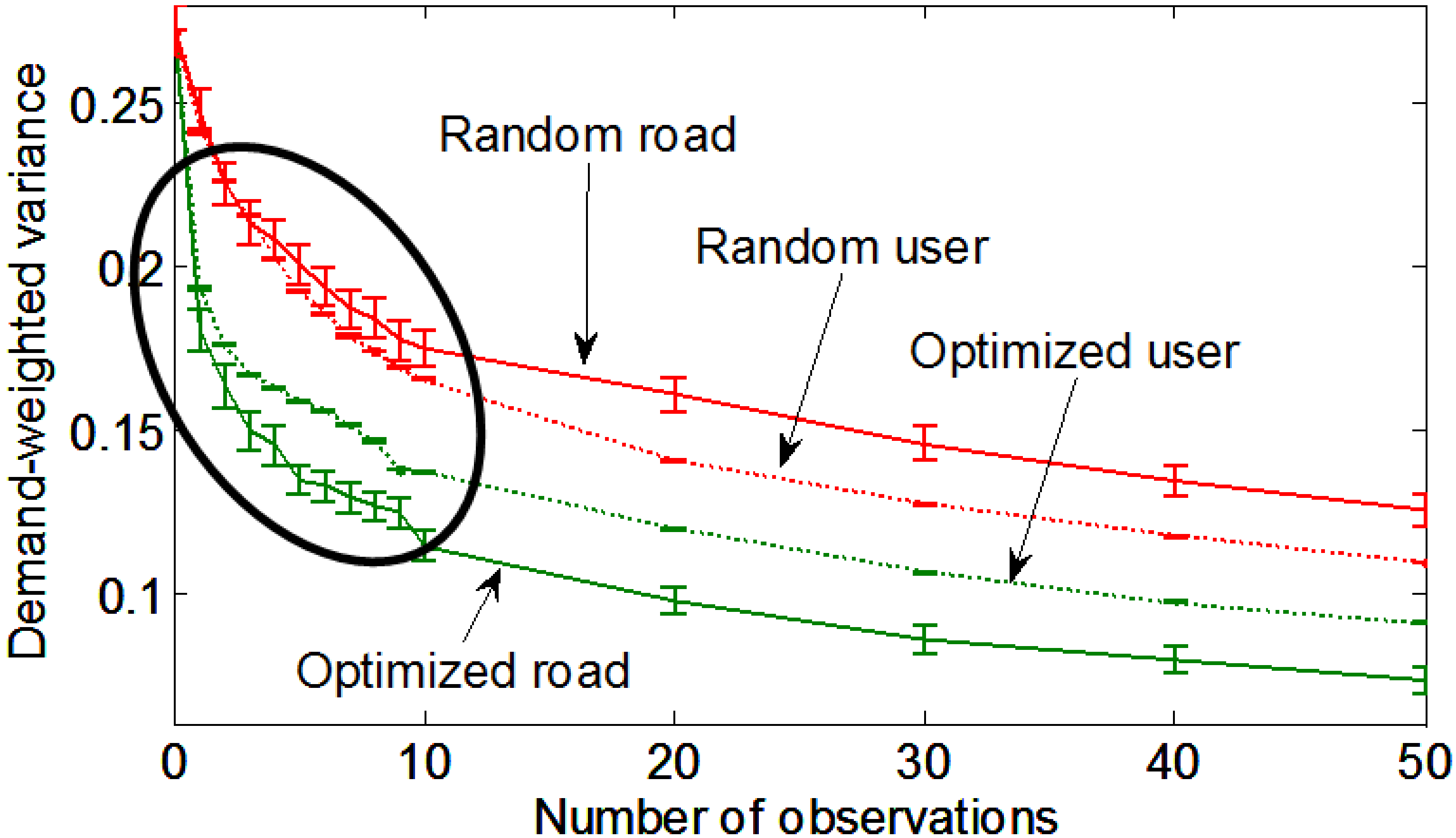
$$P(\mathcal{A} \mid \mathcal{B})$$

$$F(\mathcal{B}) = \mathbb{E}_{\mathcal{A}|\mathcal{B}}[R(\mathcal{A})] = \sum_{\mathcal{A}} P(\mathcal{A} \mid \mathcal{B}) R(\mathcal{A})$$

Krause, H., et al., IPSN 2008

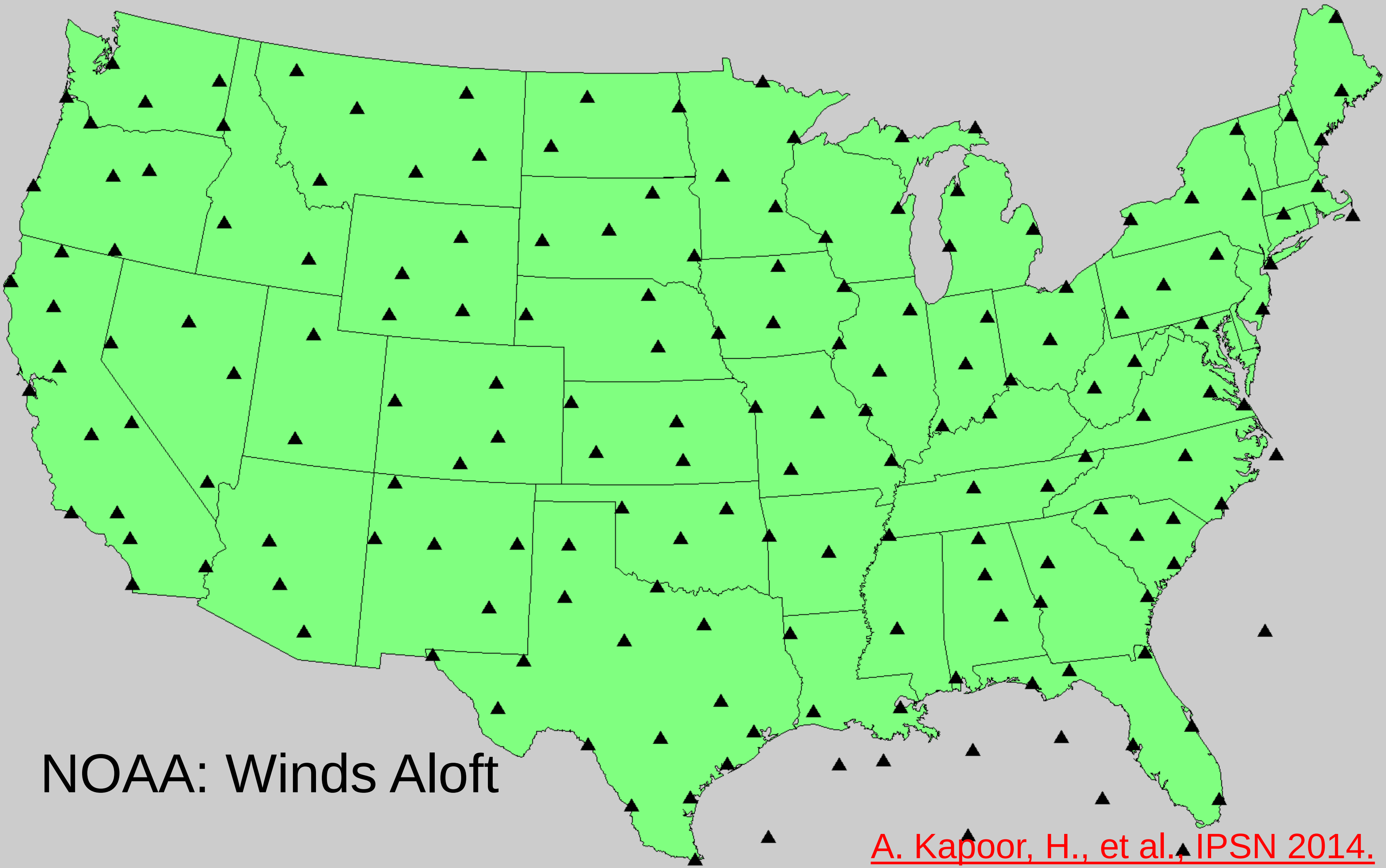
Community Sensing

Utilitarian: Demand-weighted value



Krause, H., et al., IPSN 2008

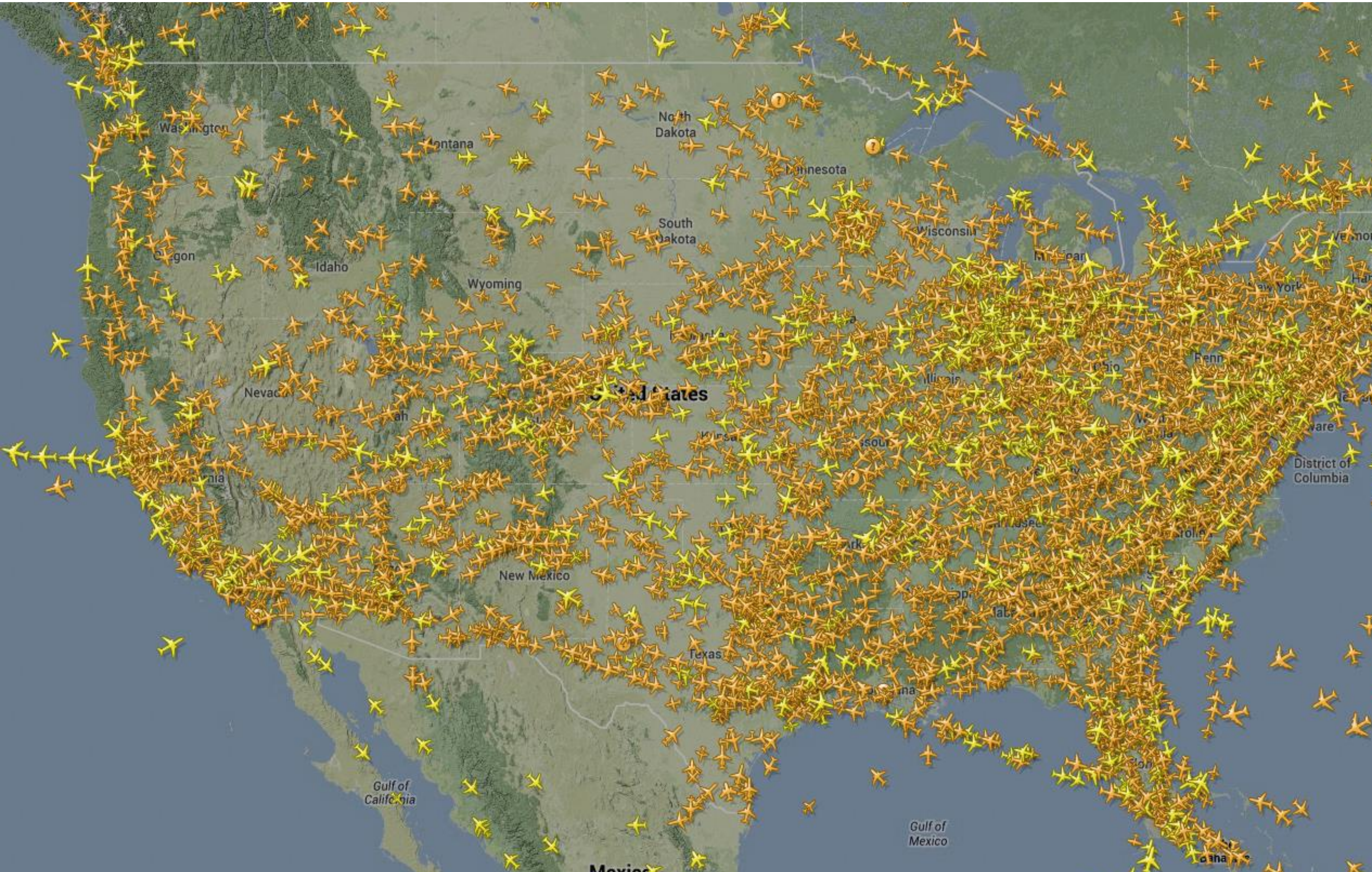
Into the Sky: Aviation



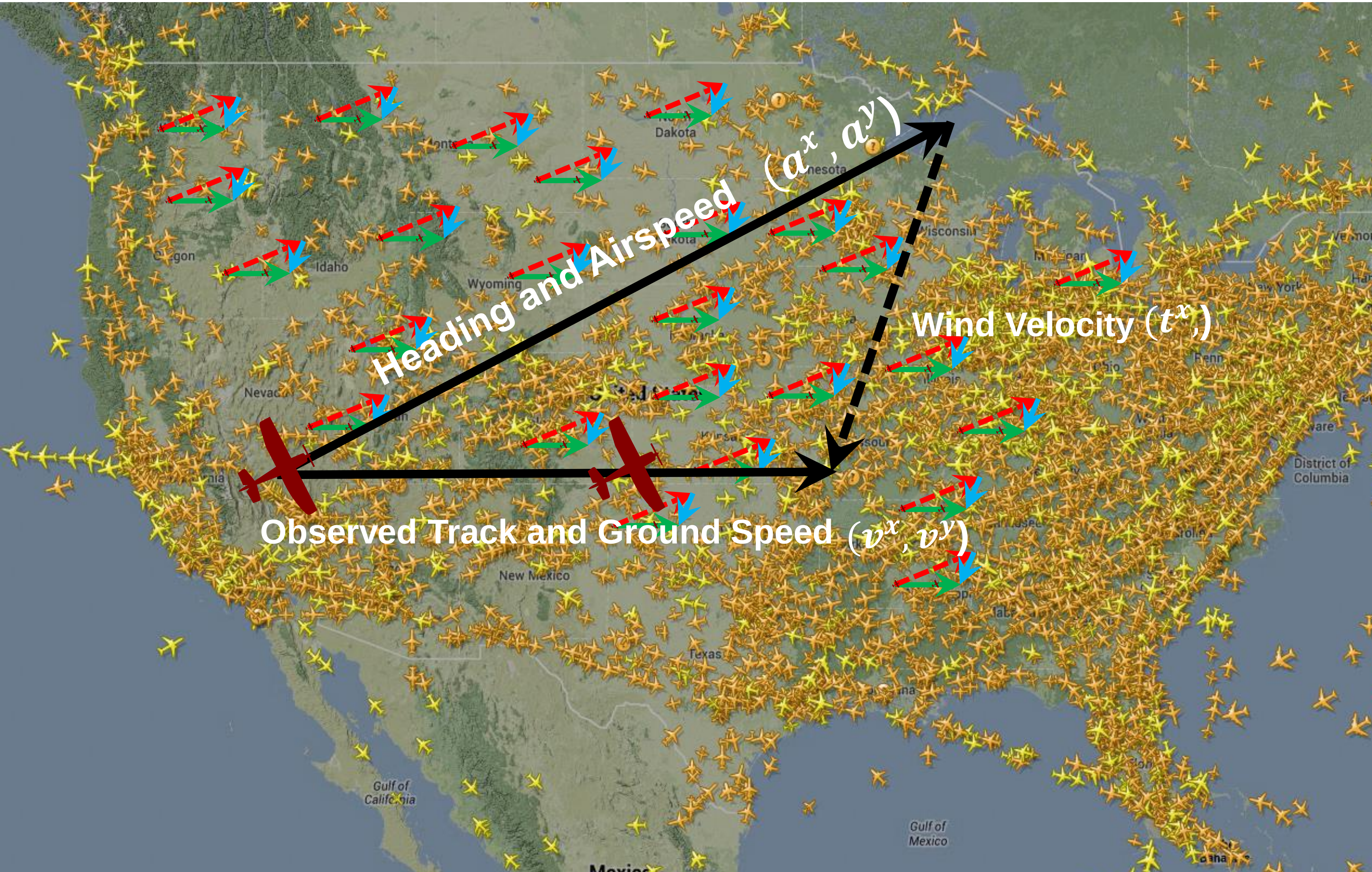
NOAA: Winds Aloft

A. Kapoor, H., et al., IPSN 2014.

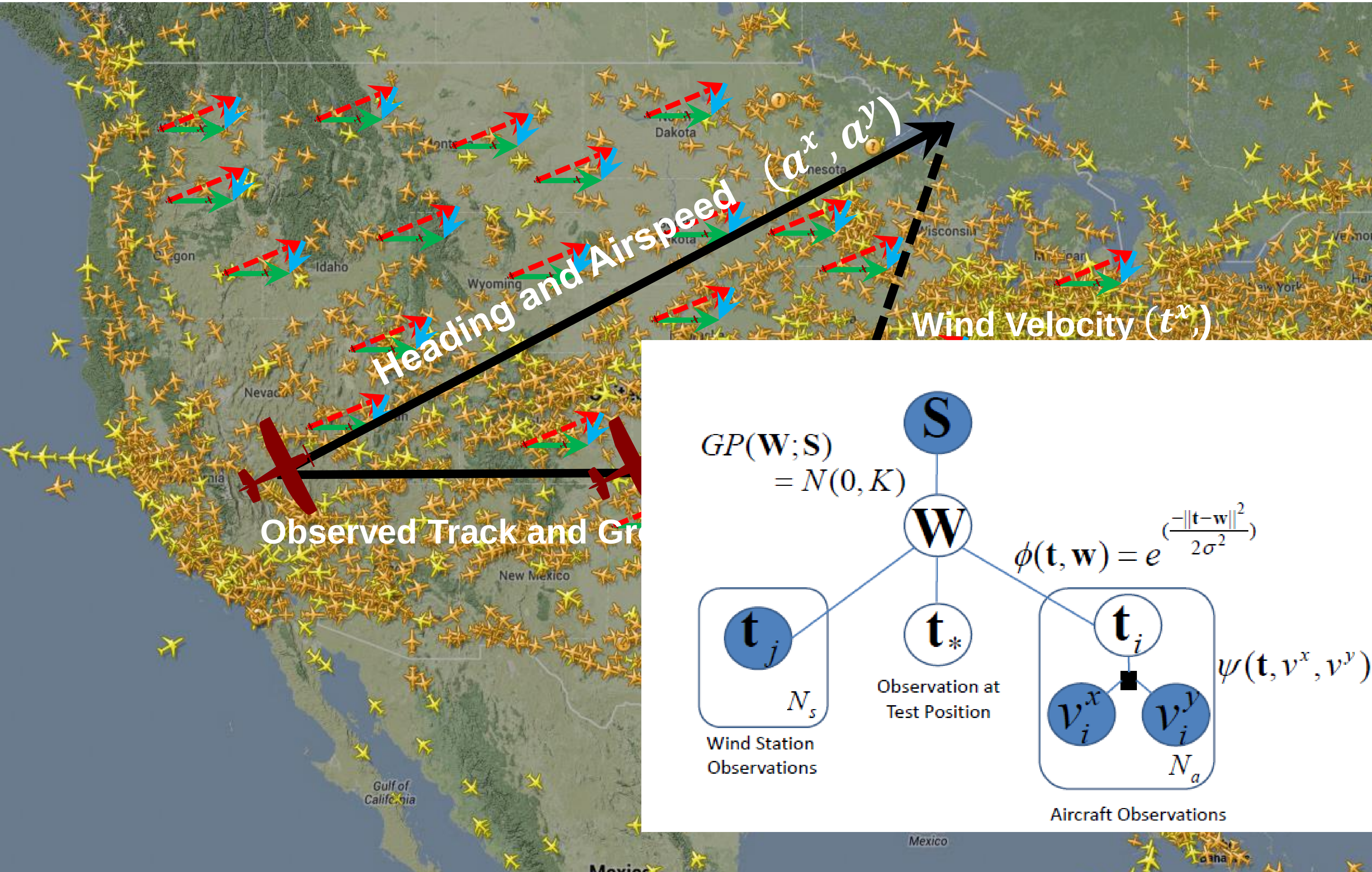
Thousands of Wind Sensors



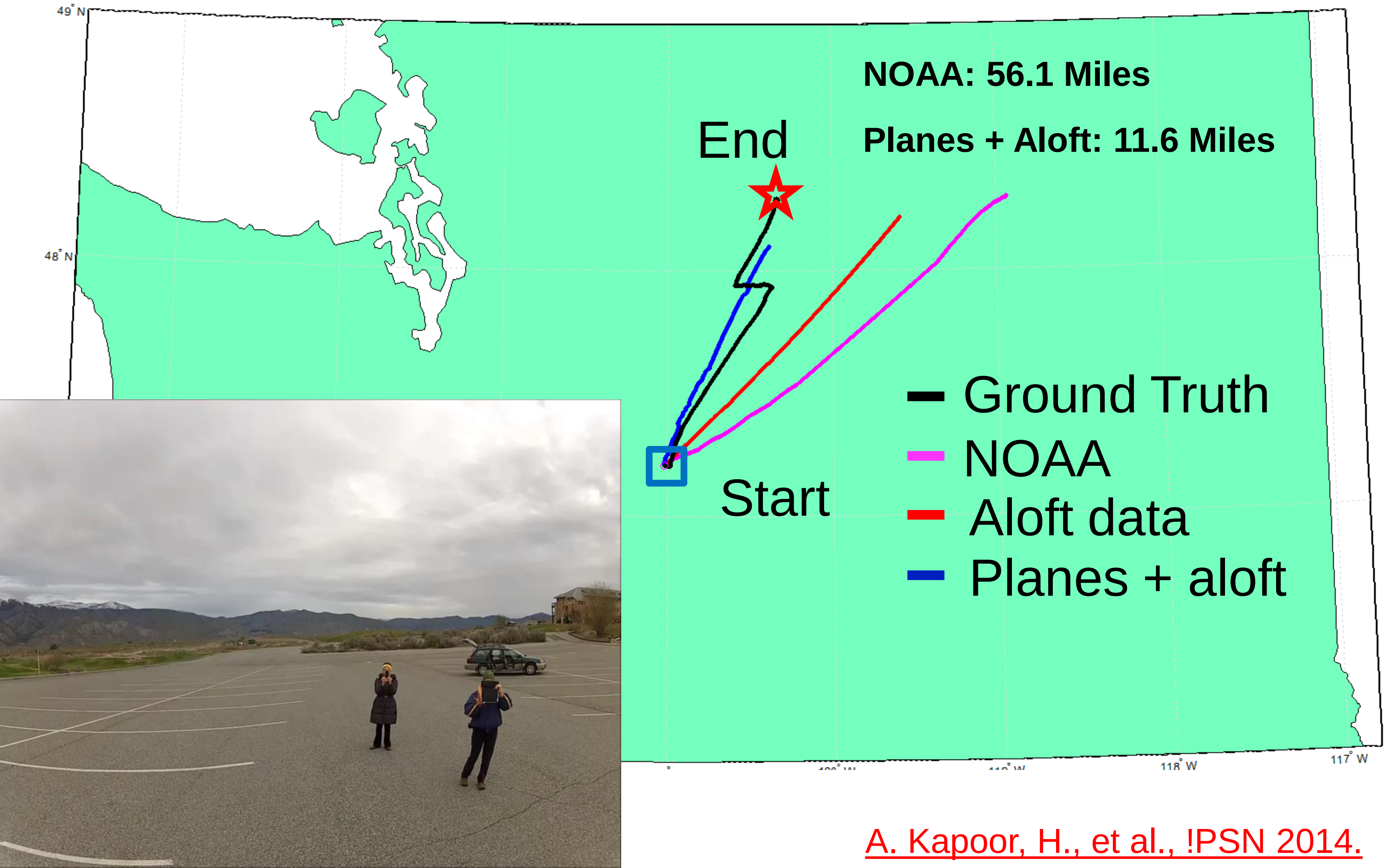
Thousands of Wind Sensors



Thousands of Wind Sensors



Studies

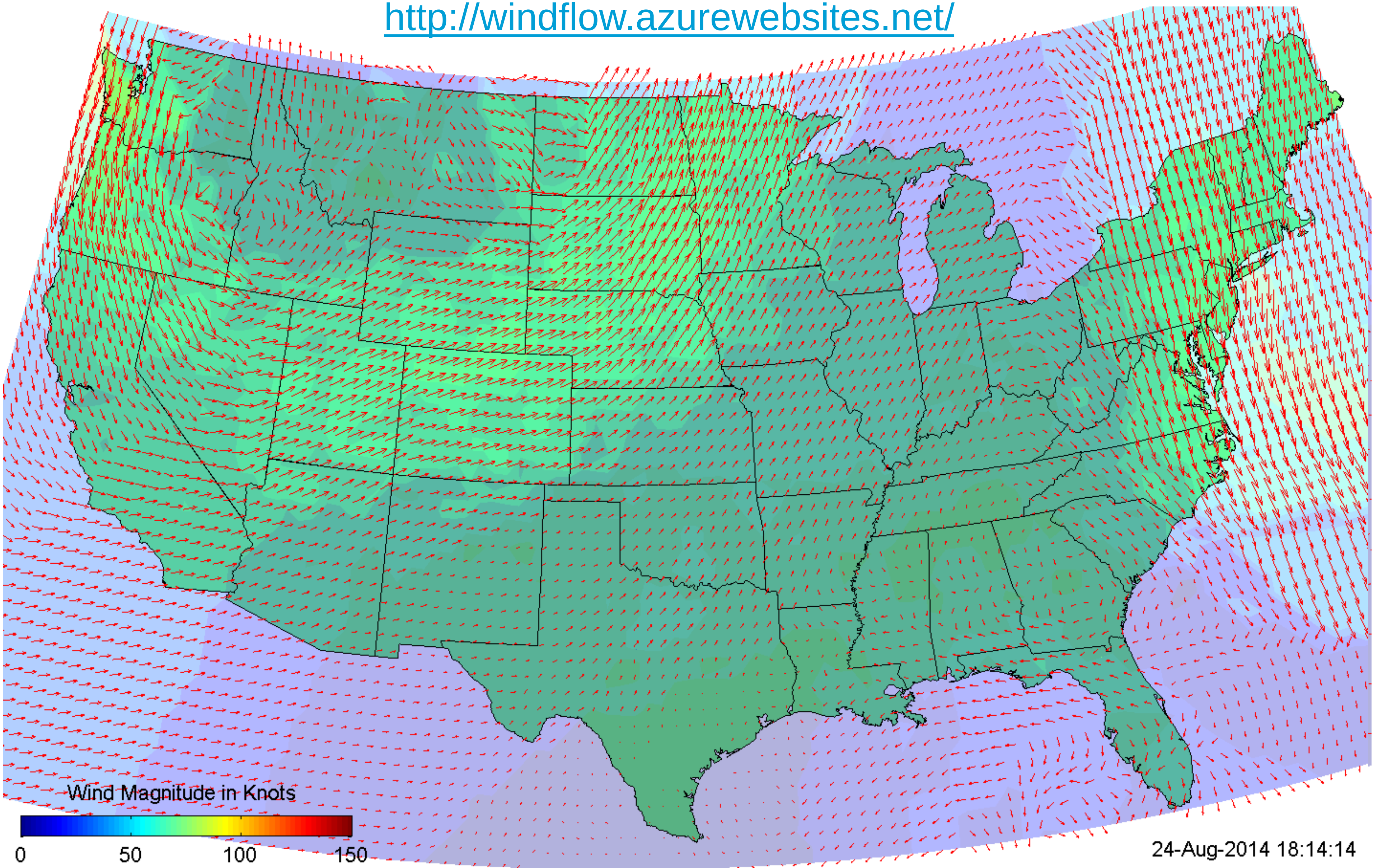


A. Kapoor, H., et al., !PSN 2014.

Windflow

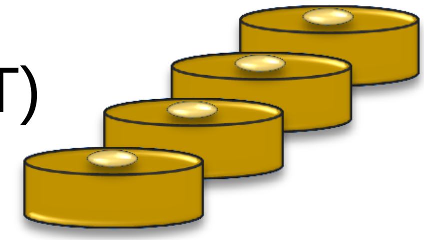
Azure Cloud Service:

http://windflow.azurewebsites.net/



Clinical Medicine

Rich dataset: All visits,15 years of data



- Admissions, discharge, transfer (ADT)
- Chief complaint in free text
- Age, gender, demographics
- Diagnosis codes (ICD-9)
- Lab results and studies
- Medications
- Vital signs
- Procedures
- Locations in hospital
- Admitting and attending MD codes
- Fees and billing

~30,000 variables available in dataset

Readmissions Challenge

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SPECIAL ARTICLE

◄ Previous Volume 360:1418-1428 April 2, 2009 Number 14 Next ►

Rehospitalizations among Patients in the Medicare Fee-for-Service Program

Stephen F. Jencks, M.D., M.P.H., Mark V. Williams, M.D., and Eric A. Coleman, M.D., M.P.H.

ABSTRACT

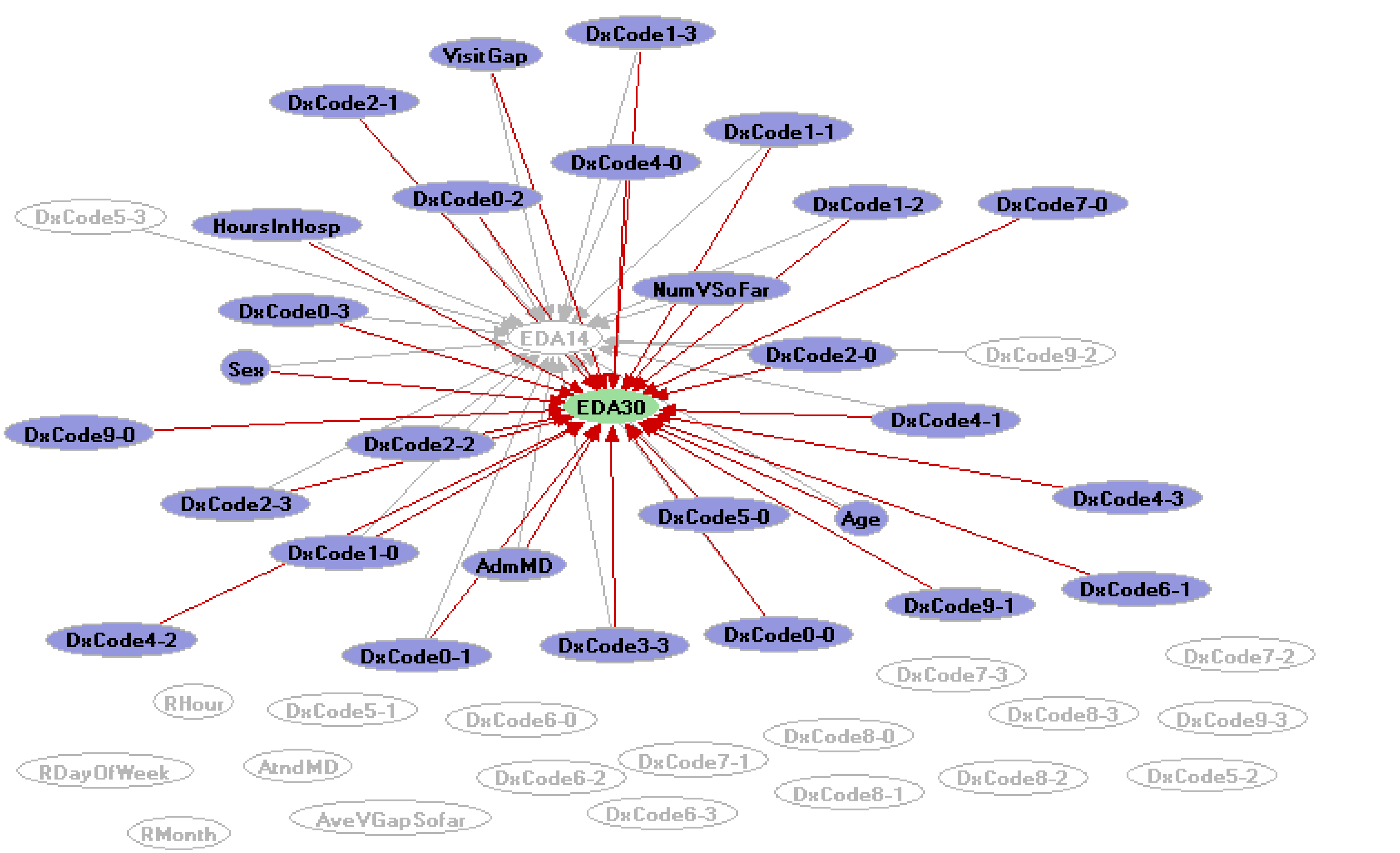
Background Reducing rates of rehospitalization has attracted attention from policymakers as a way to improve quality of care and reduce costs. However, we have limited information on the frequency and patterns of rehospitalization in the United States to aid in planning the necessary changes.

Methods We analyzed Medicare claims data from 2003–2004 to describe the patterns of

- **~20% within 30 days**
- **~35% in 90 days**

➢ ***Estimated cost to Medicare (2004): $17.4 billion***

Predicting Readmission



With M. Bayati, M. Braverman, P. Koch

Going Live

Readmissions Manager

Reducing Hospital Readmissions is an Impending Priority

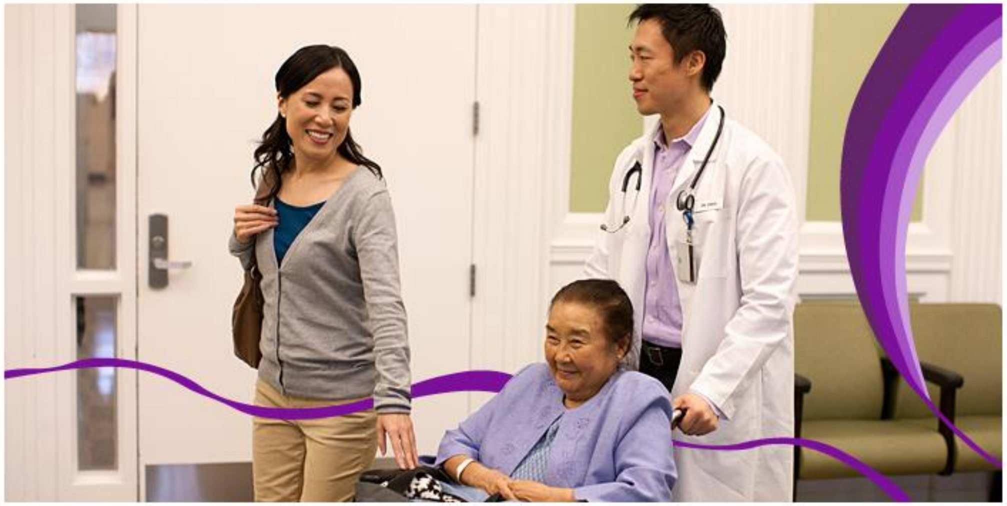
Overview

One in five Medicare inpatients is readmitted within 30 days. The Centers for Medicare and Medicaid Services (CMS) considers 40%-75% of these readmissions to be preventable.

In October 2012, CMS will begin to track readmission and impose financial penalties on hospitals with higher–than–expected readmission rates for certain conditions. Other payers will certainly follow.

It is clear that hospital admissions and readmissions are becoming a critical parameter for tracking care delivery from both a financial and quality perspective.

Readmissions Manager for Microsoft Amalga is an innovative solution to help organizations address this very important business need.



[Readmissions Manager]

At Hospitals around World

ACCOUNT	ADMITDTTM	DISCHARGEDTTM	AGE	SEX	PROB_NUM_%	FACTOR
	12/03/2010 14:57	12/08/2010 18:03	62	F	37.9	Num past 6m visits = 6 to 10 / F
	12/08/2010 18:45	12/08/2010 18:45	74	M	32.72	stayed <1 day in the hospital / Pa
	11/16/2010 16:14	12/08/2010 18:50	48	M	30.83	Patient had dx = Chronic renal fa
	12/02/2010 13:49	12/08/2010 18:14	68	M	29.05	Patient had dx = Disorders of flui
	12/01/2010 05:26	12/08/2010 18:55	44	M	28.54	
	12/01/2010 19:08	12/08/2010 18:13	61	M	27.36	Patient had dx = Acute renal failu
	11/30/2010 21:50	12/08/2010 18:52	70	M	18.05	Patient had dx = Other personal
	12/08/2010 08:51	12/08/2010 18:45	68	M	16.57	stayed <1 day in the hospital
	12/03/2010 20:32	12/08/2010 17:50	80	M	16.18	Patient had dx = Disorders of flui
	12/01/2010 01:13	12/08/2010 18:06	79	M	15.52	
	12/08/2010 18:39	12/08/2010 18:39	22	F	14.53	stayed <1 day in the hospital / Av
	12/08/2010 19:01	12/08/2010 19:01	25	F	14.42	stayed <1 day in the hospital / Pa
	12/08/2010 18:05	12/08/2010 18:05	24	M	14.39	stayed <1 day in the hospital
	12/08/2010 18:26	12/08/2010 18:26	53	F	13.59	stayed <1 day in the hospital / 44

Interpretability

Considering human interpretability

Procedures that allow end users to understand contribution of individual features

What influence does changing observations x have if other values are not changed?

Interpretability--Power Tradeoff

$$y = \beta_0 + \beta_1 x_1 + ... + \beta_n x_n$$

$$y = f_1(x_1) + ... + f_n(x_n)$$

$$y = f(x_1, ..., x_n)$$

Y. Lou, R. Caruana, J. Gehrke, G. Hooker, KDD, 2013.

Interpretability--Power Tradeoff

$$y = \beta_0 + \beta_1 x_1 + \ldots + \beta_n x_n$$

$$y = f_1(x_1) + \ldots + f_n(x_n)$$

$$y = \sum_i f_i(x_i) + \underline{\sum_{ij} f_{ij}(x_i, x_j)}$$

$$y = \sum_i f_i(x_i) + \underline{\sum_{ij} f_{ij}(x_i, x_j)} + \underline{\sum_{ijk} f_{ijk}(x_i, x_j, x_k)}$$

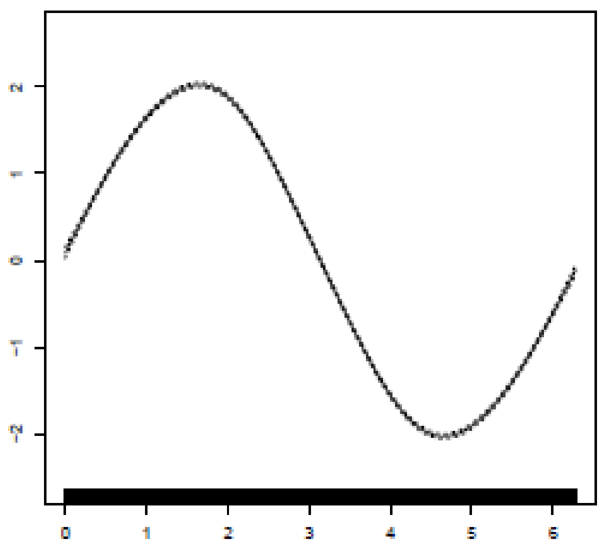
$$y = f(x_1, \ldots, x_n)$$

Y. Lou, R. Caruana, J. Gehrke, G. Hooker, KDD, 2013.

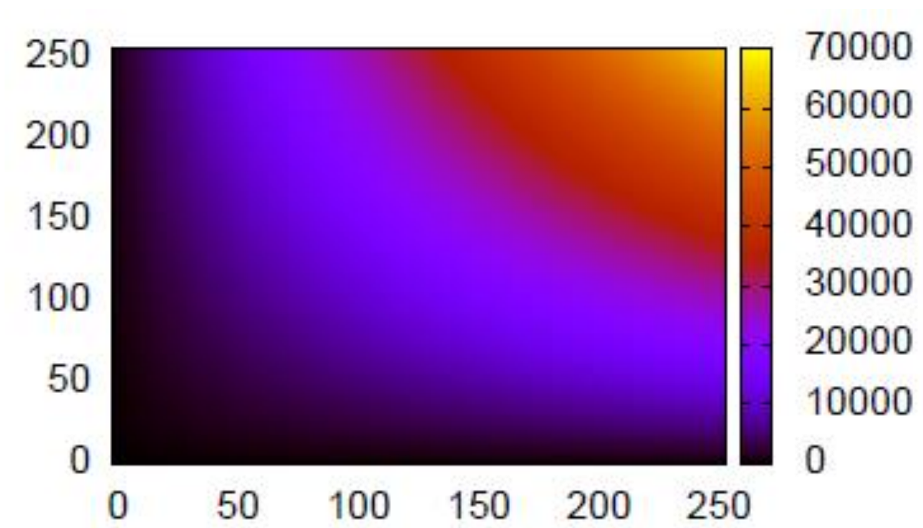
Capturing Key Interactions

Efficient means to identify pairwise interactions

$$y = \sum_i f_i(x_i) + \sum_{ij} f_{ij}(x_i, x_j)$$



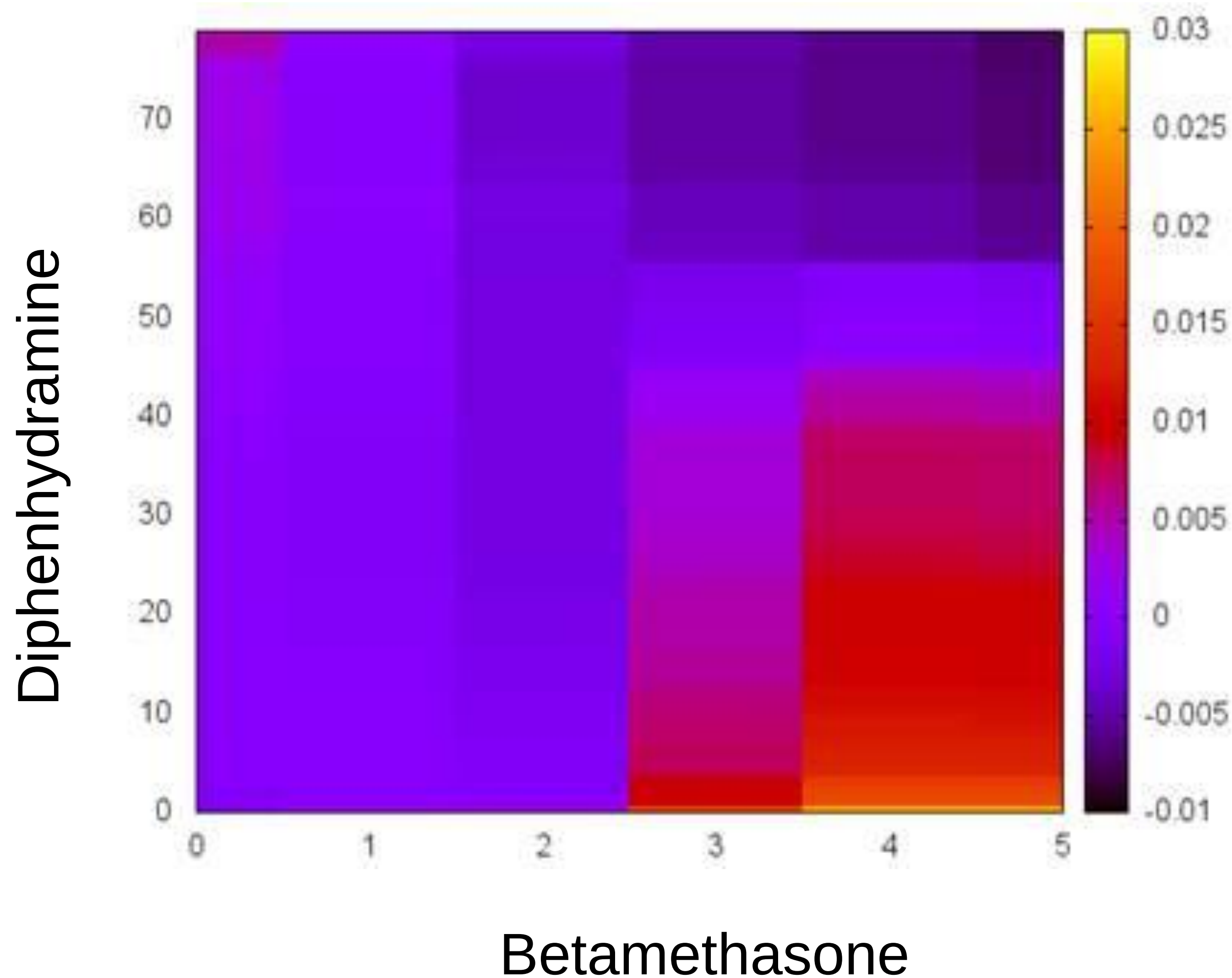
$f_i(x_i)$



$f_{ij}(x_i, x_j)$

Y. Lou, R. Caruana, J. Gehrke, G. Hooker, KDD, 2013.

Insights about Interactions



Decisions

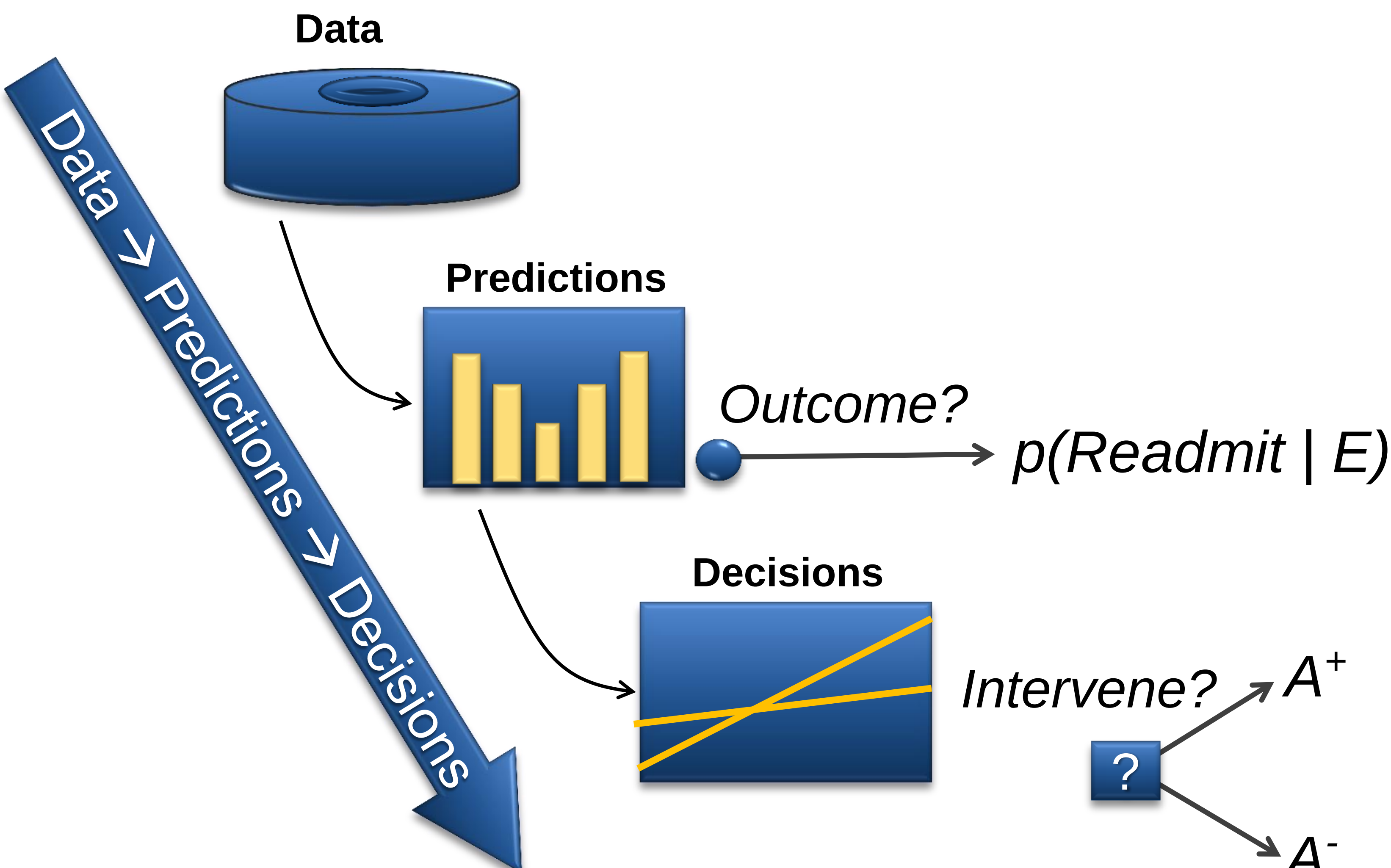
Units 5E/501/8E/9W/8ITCU

Baseline:
Discharges to home/ home health between 10/15/2011 – 4/29/2012
Readmissions Rate (all cases): **13%**
Score ≥ 25: **27%**
Average direct cost/readmission: **$10,888**

	Initial Pilot 4/30/2012 – 7/30/2012	1 Month Post engagement 9/01/2012 – 9/30/2012
Readmissions Rate	12%	10%
Score ≥ 25	23%	20%
# of Admissions Avoided	9	11
Follow up call completion	52%	61%
Follow up call <u>not</u> Completed	32%	21%
Total Annualized savings	$391,968	$1,448,104

↓ Total Readmission Rate by 3% and +$1.4M Savings

Decisions



Data
Data → Predictions → Decisions
Predictions
Outcome?
p(Readmit | E)
Decisions
Intervene?
?
A+
A-

Example: Heart Failure

Most frequent dx for hosp. Medicare patients

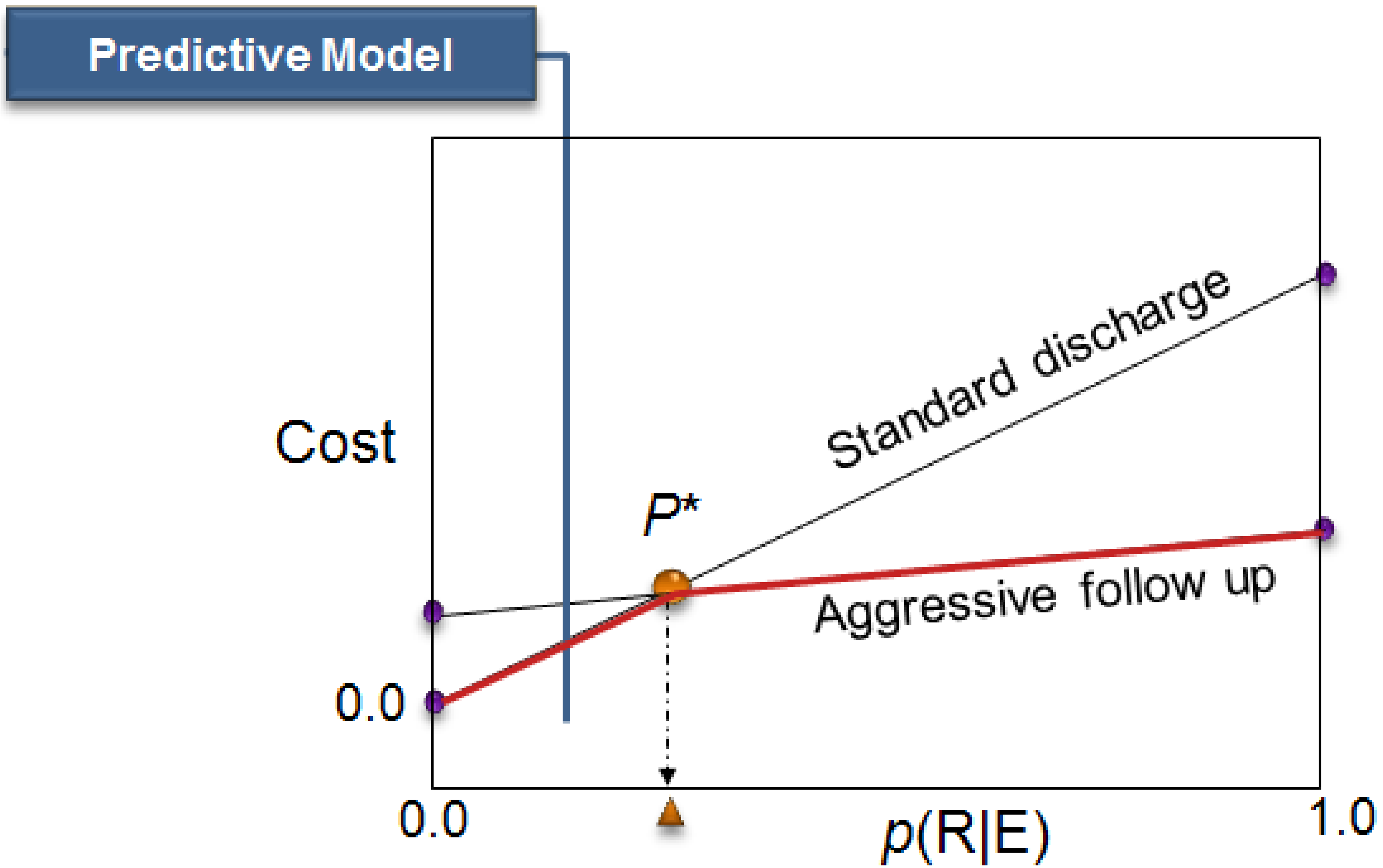
- 6–10% of folks over 65
- $35 billion/yr US

Decision:

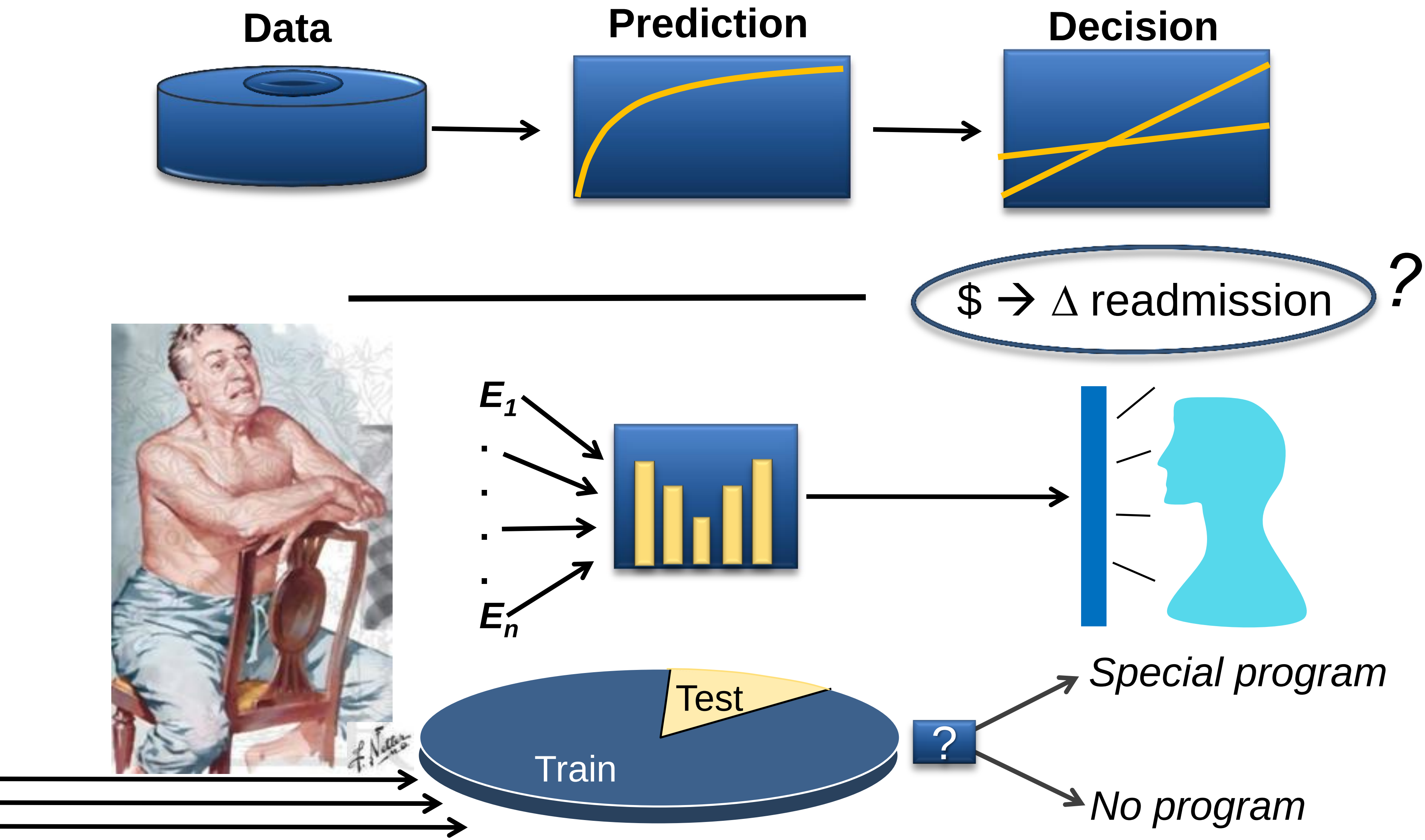
Invest in post-discharge program for patient?

With M. Bayati, M. Braverman, P. Koch, K. Mack, G. Ruiz, M. Smith

Utility Model



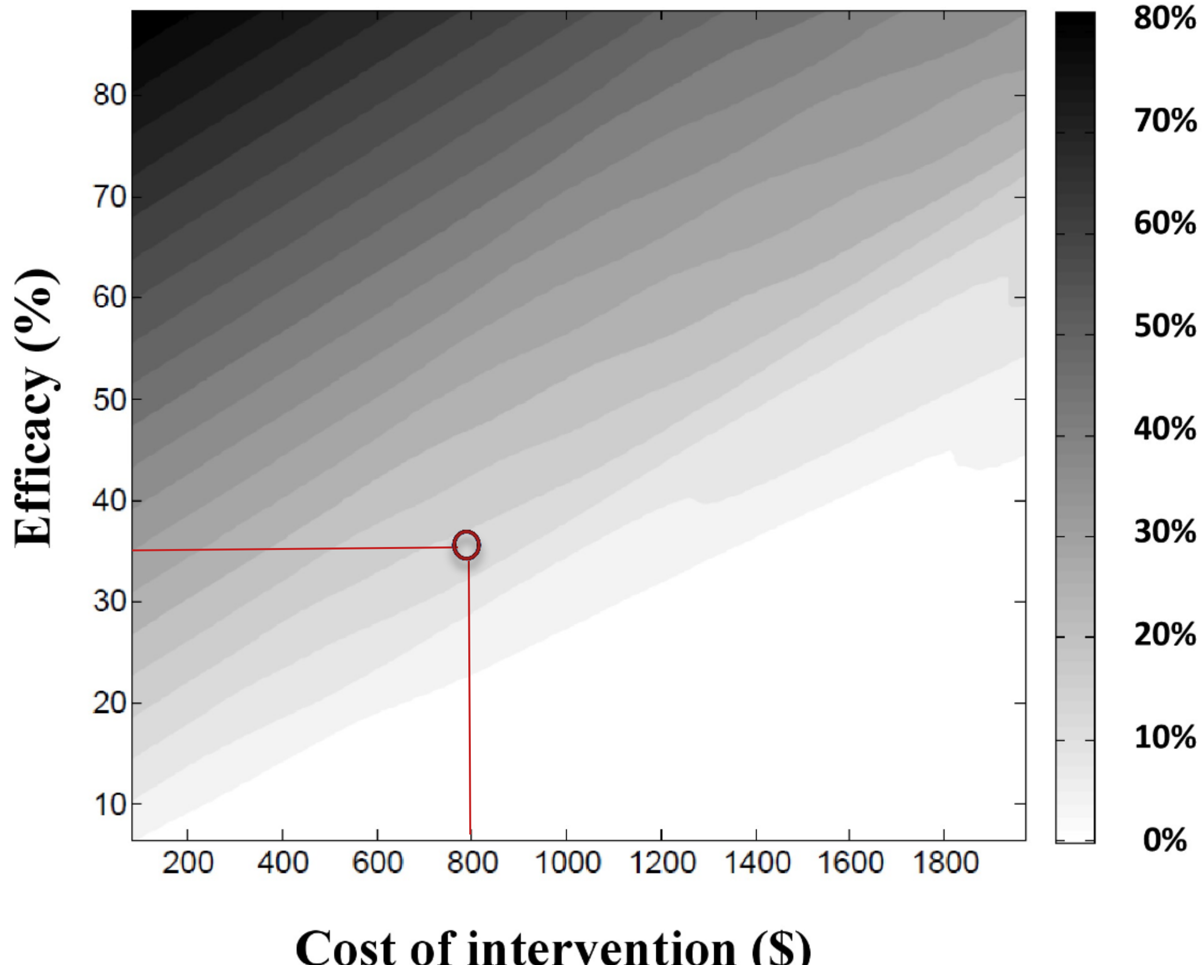
Exploration with Decision Pipeline



Decision Pipeline → Visualization

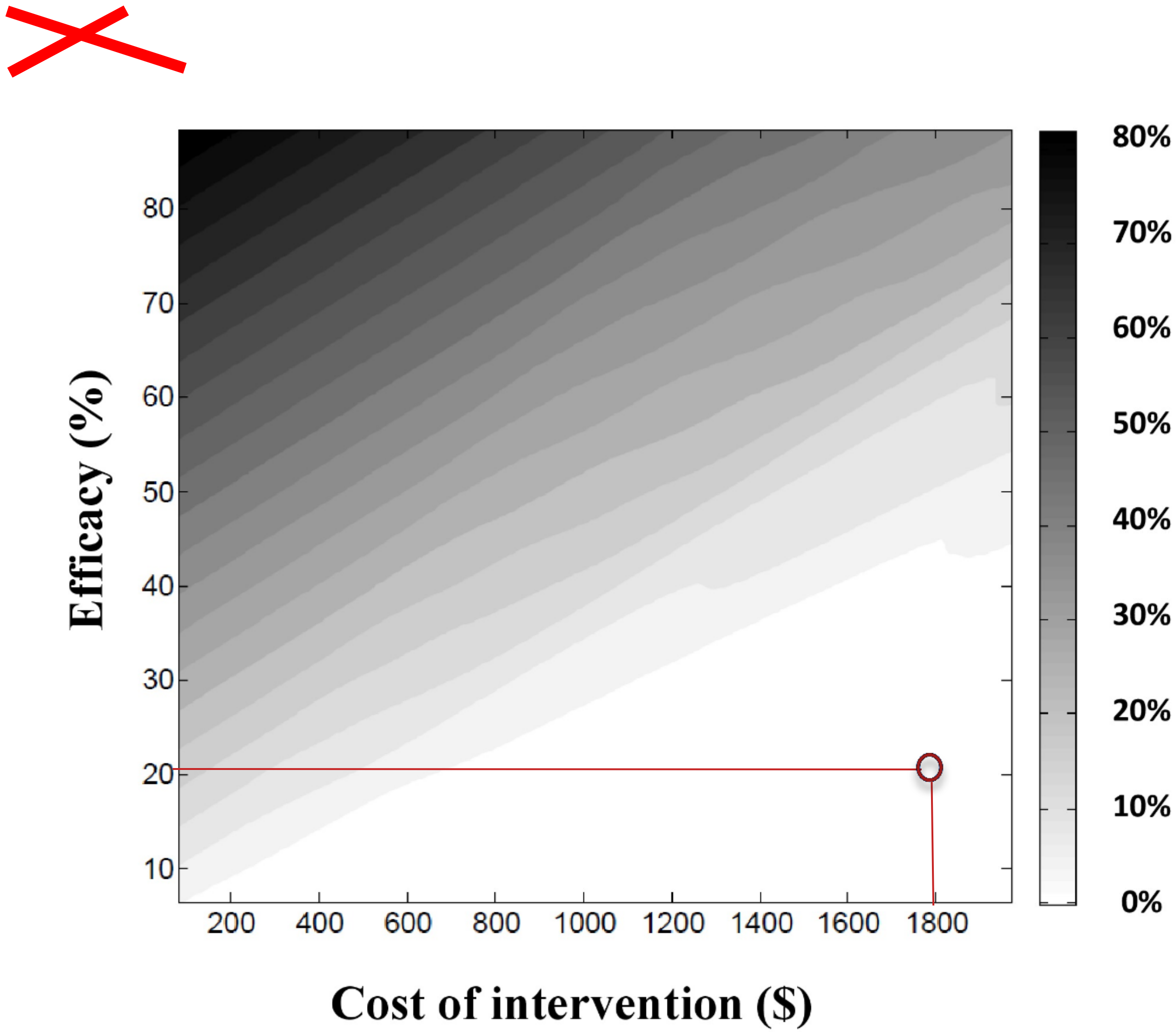
$800 intervention @ 35% efficacy?

↓31.4% readmissions ↓$13.2%.



Decision Pipeline → Visualization

$1800 intervention @ 20% efficacy?



Errors, Adversity, and Deaths

Deaths:

44,000 - 98,000 preventable deaths per year

"*To Err is Human*," *Inst. of Medicine, 2000*

Adverse events:

44% preventable.

Levinson, 2010

Costs:

$17 to $29 billion per year in U.S.

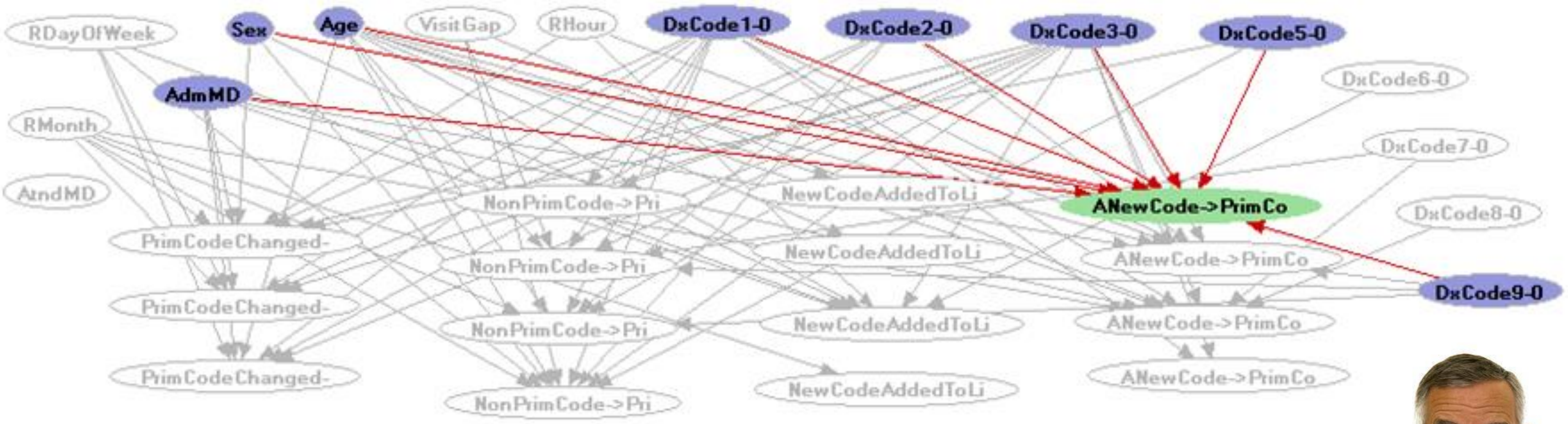
Thomas, et al., 1999

Opportunity to Detect Errors

e.g., Predict surprise at emergency dept.

At discharge time:

→ p(readmit < *72 hrs.*|*E*) with *new primary diagnosis*.



With M. Bayati, M. Braverman, and J. Gatewood

Hospital-Associated Infection

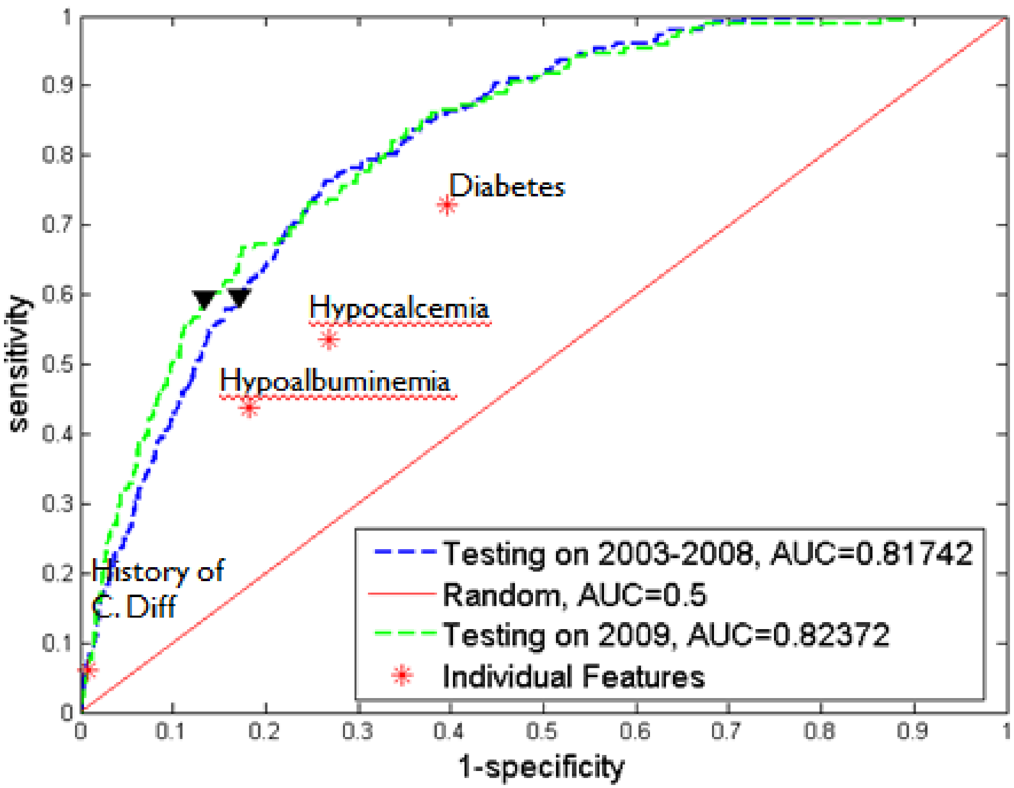
1 in 20 hospitalizations, ~$20 billion/yr.

5% death: top 10 contributor of death in US

Predicting C.Difficile < 48 hrs

SCIENTIFIC AMERICAN™

“Hospitals Fail tc
to Thwart Deadl

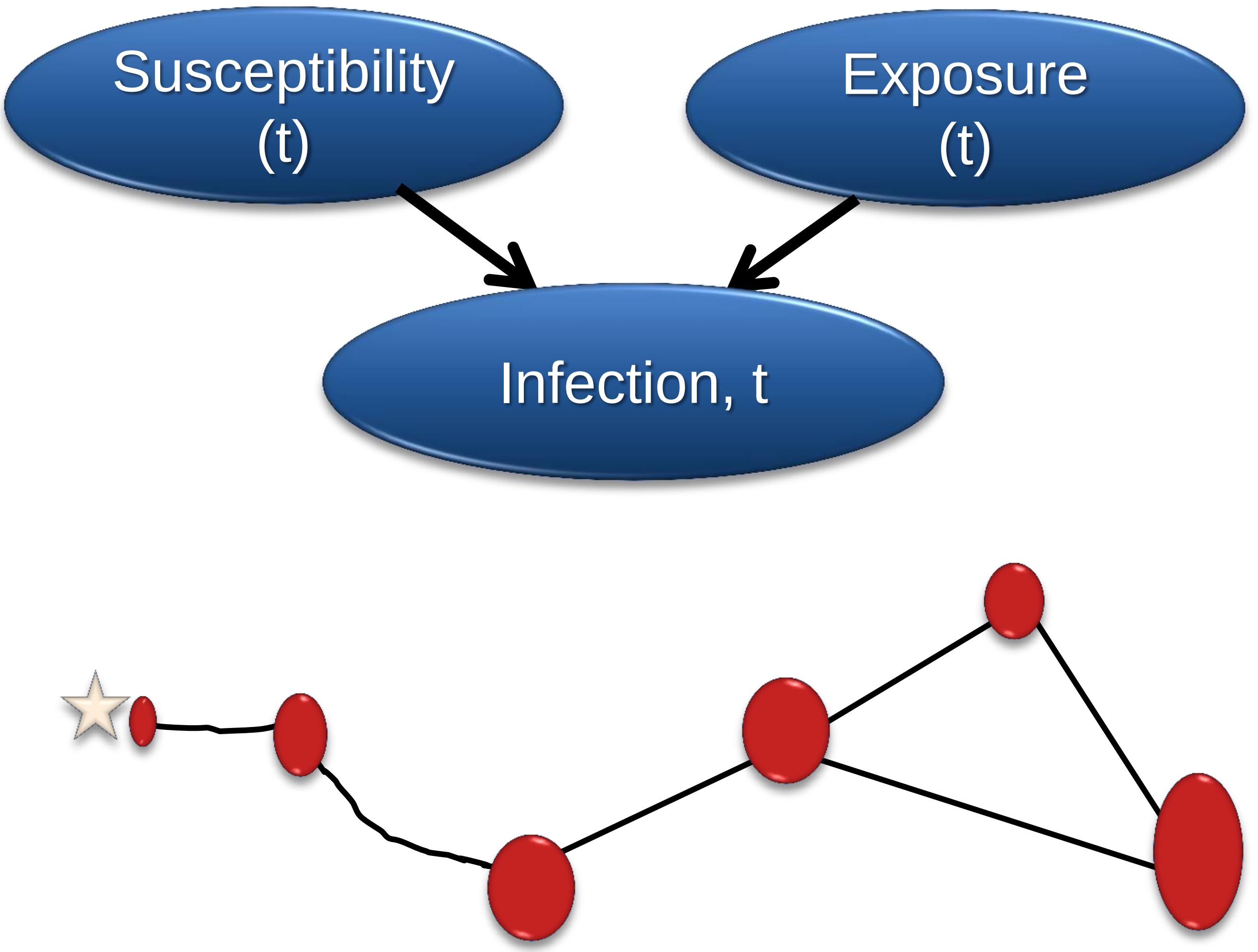


ırk Times

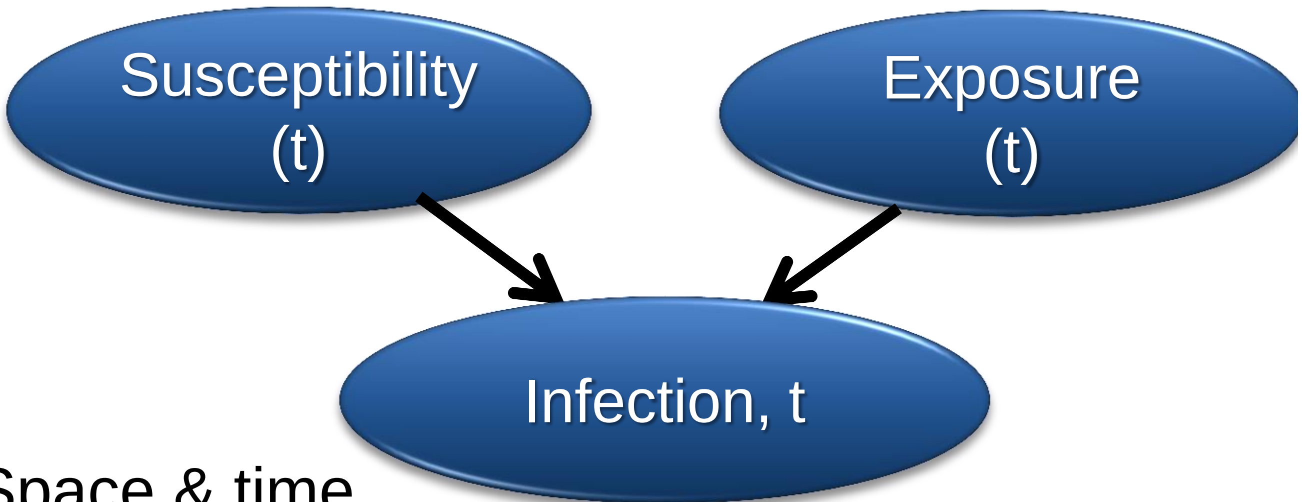
ive Action Urged
ıl Infections”
-May 29th, 2013

[With W. Campbell, E. Franklin, J. Guttag, J. Wiens]()

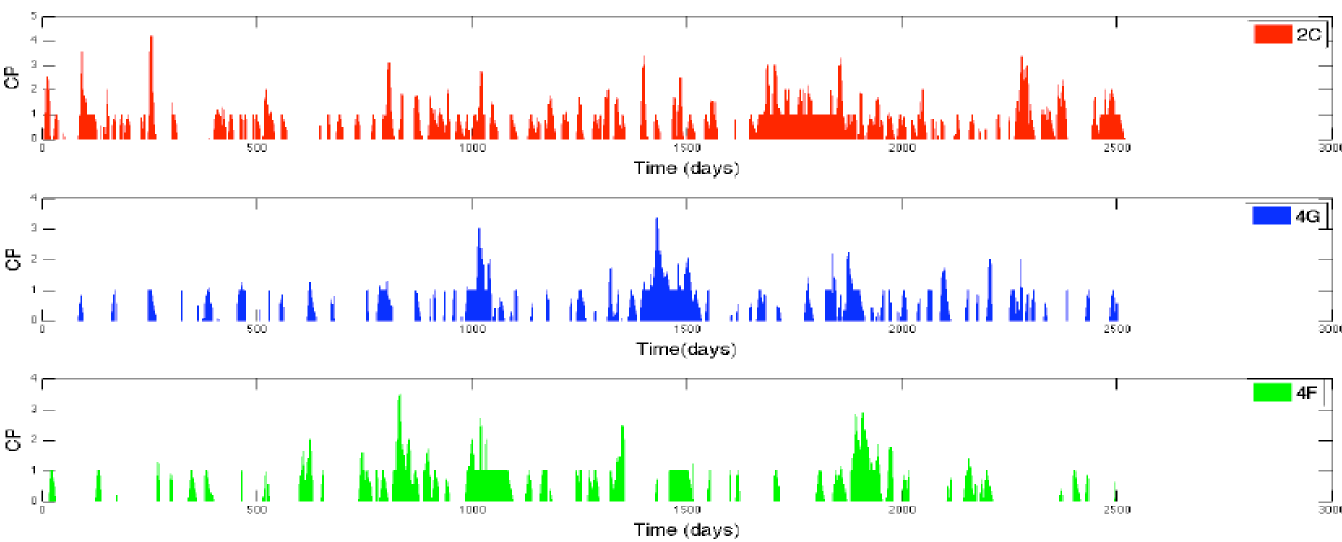
Data on Time and Space



Data on Time and Space



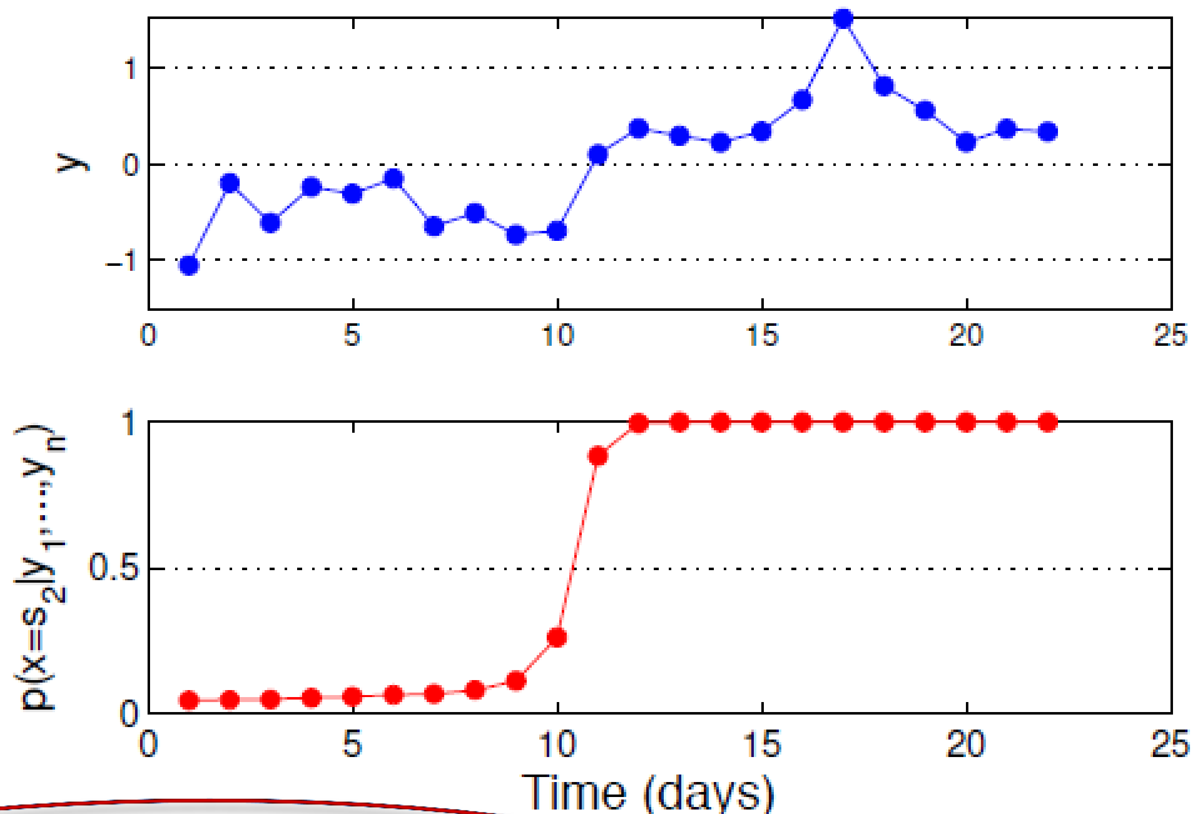
Space & time



Location	Description
1C	Patient Care Unit
1E	Patient Care Unit
1G	MedSTAR ICU
1H	Patient Care Unit
2C	Patient Care Unit
2E	Patient Care Unit
2G	Intensive Care Unit (ICU)
2H	Patient Care Unit
2NE	Patient Care Unit
2NW	Patient Care Unit
3C	Patient Care Unit
3D	Patient Care Unit
3E	Patient Care Unit
3F	Patient Care Unit
3G	Intensive Care Unit (ICU)
3NE	Patient Care Unit
4C	Patient Care Unit
4D	Patient Care Unit
4E	Patient Care Unit
4F	Patient Care Unit
4G	Intensive Care Unit (ICU)
4H	Intensive Care Unit (ICU)
4NW	Patient Care Unit
5C	Patient Care Unit
5D	Patient Care Unit
5E	Patient Care Unit
5F	Patient Care Unit
5NE	Patient Care Unit
5NW	Patient Care Unit

J. Wiens, J. Guttag, H., NIPS 2012

Temporal Models and Prediction



NIPS 2012: AUC: 0.69 → 0.79

J. Wiens, J. Guttag, H., NIPS 2012

Causal Discovery

Cases

Models & Insights

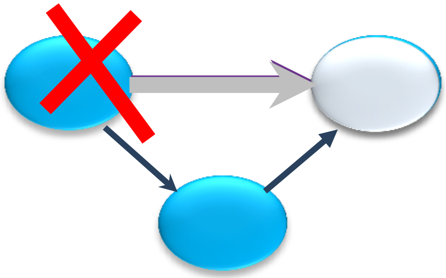
Pt. acquires C. Difficile?

- **diabetes = TRUE**
- **history of C. Diffi = TRUE**
- **hospital service = gsg (general surgery)**
- **meds= acetylcysteine (n-acetylcys)**
- **meds = lidocaine hcl**
- **meds = clindamycin phosphate**
- **platelet count = C (thrombocytosis)**
- **unit = 2g**
- **albumin = L (hypoalbuminemia)**
- **admission source = transfer**
- **attending MD= XXXXXX**
- **unit = 2d**
- **CO2 = L (hypocapnea)**
- **city = XXXXXX**
- **employer name = Not Employed**
- **monocyte percent = H**
- **70<=age<80**
- **wbc = H (white blood cell count)**
- **admission procedure = catheterization**
- **admission complaint =gastrointestinal**
- **last visit meds = fentanyl citrate**
- **meds = hydromorphone hcl**

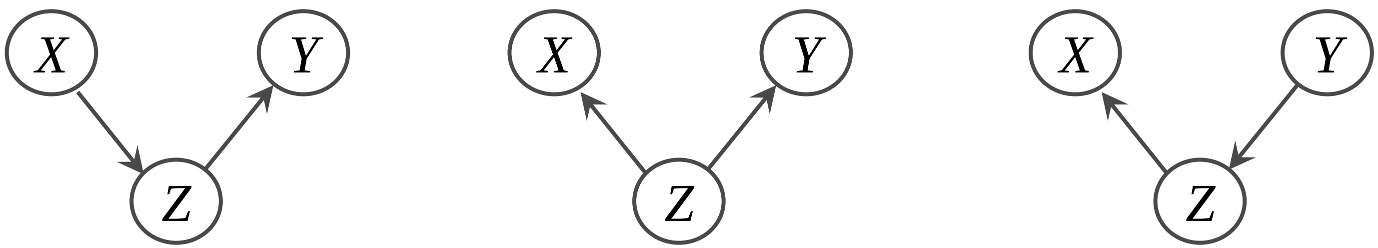
Studies in causality

J. Wiens, H.

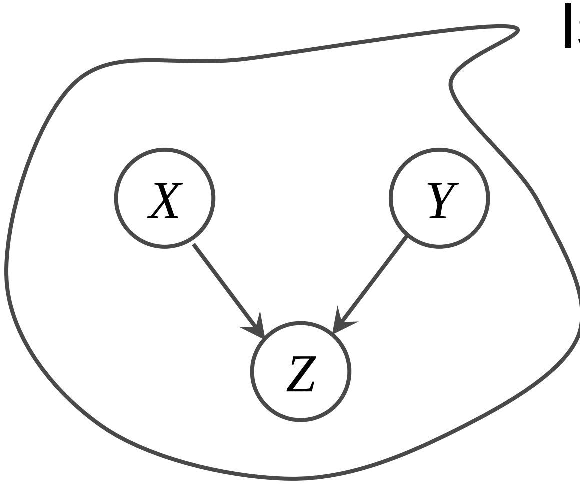
Causal Discovery

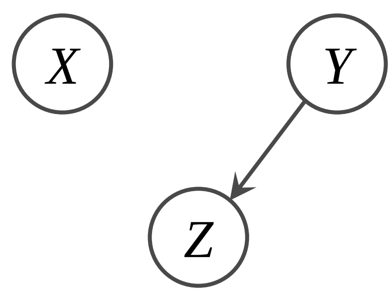


Given $X \perp Y$ *and* $\neg(X \perp Y \mid Z)$,

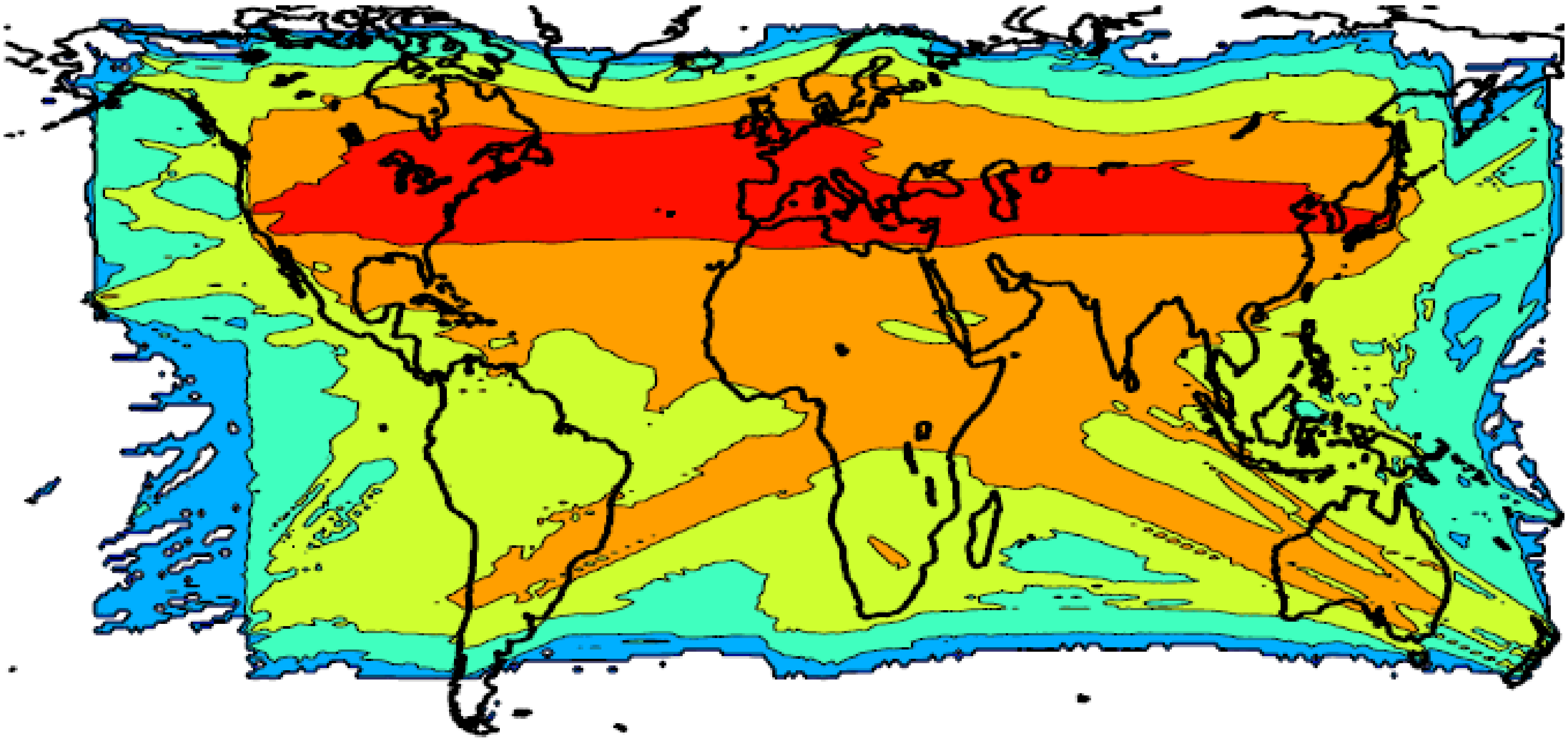


Is the only possible causal model





Web for Planetary-Scale Sensing

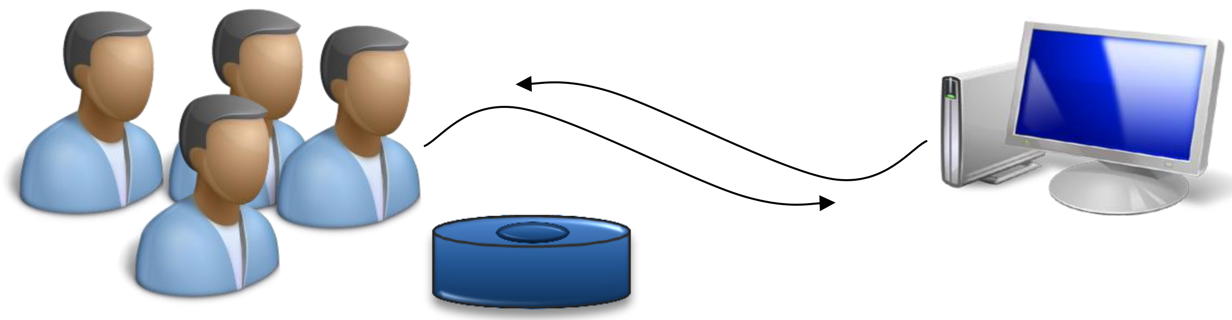


[Leskovec & Horvitz, WWW 2008]

Signals on Medication Adverse Effects

→ Web search as sensor for side effects?

1 in 250 of people query on top-100 drugs.



Signals on Medication Adverse Effects

Pharmacovigilence: spontaneous reports

FDA *Adverse Event Reporting System* (AERS)

2011 finding (Tatonnetti, et al.):

Paxil + Pravachol → ↑ *Hyperglycemia*

Pravachol → ✕ *Hyperglycemia*

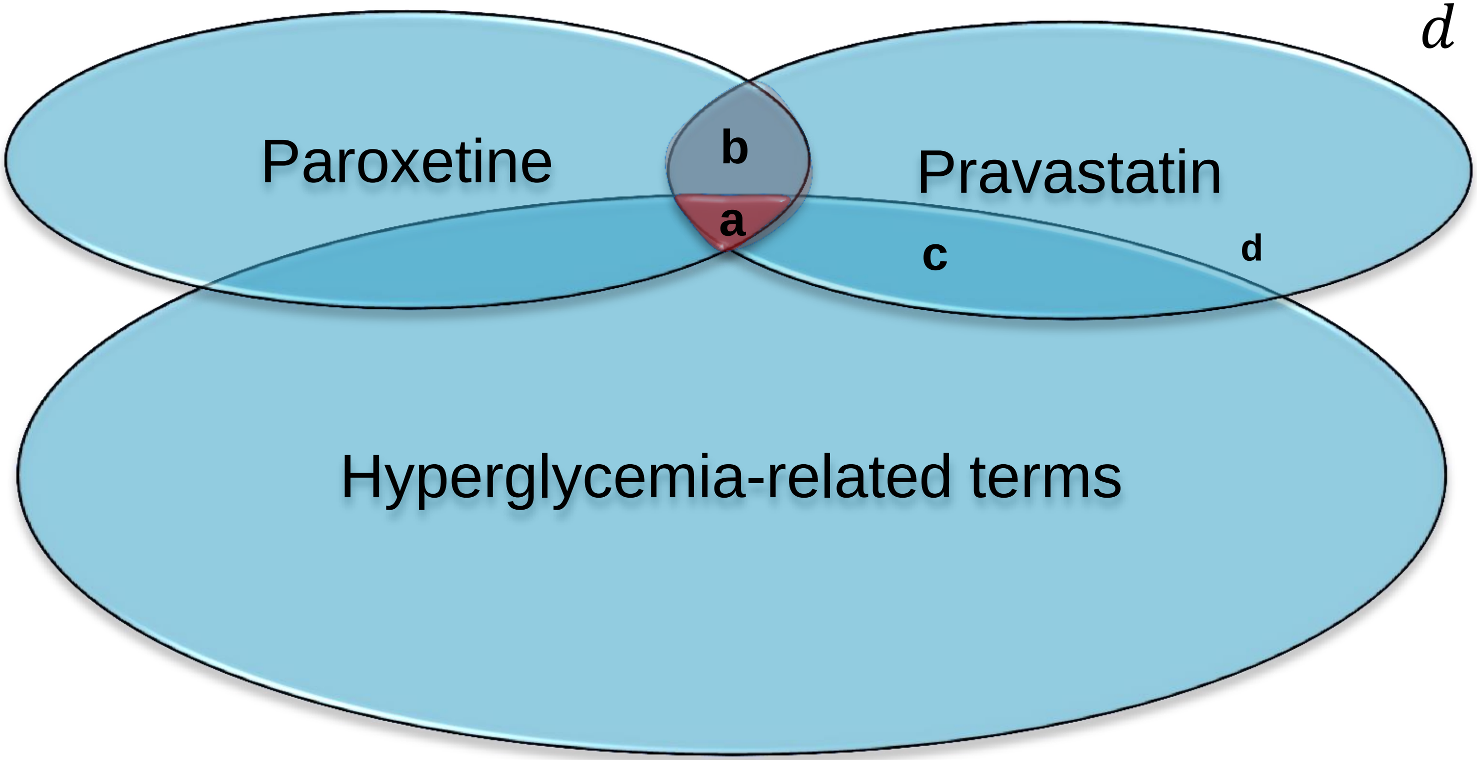
Paxil → ✕ *Hyperglycemia*

R. White, N. Tatonetti, N. Shah, R. Altman, H.

Web-Scale Pharmacovigilance

Disproportionality analysis

- Reporting ratios (RR)--obs. vs. expected: $RR = \frac{\frac{a}{b}}{\frac{c}{d}}$

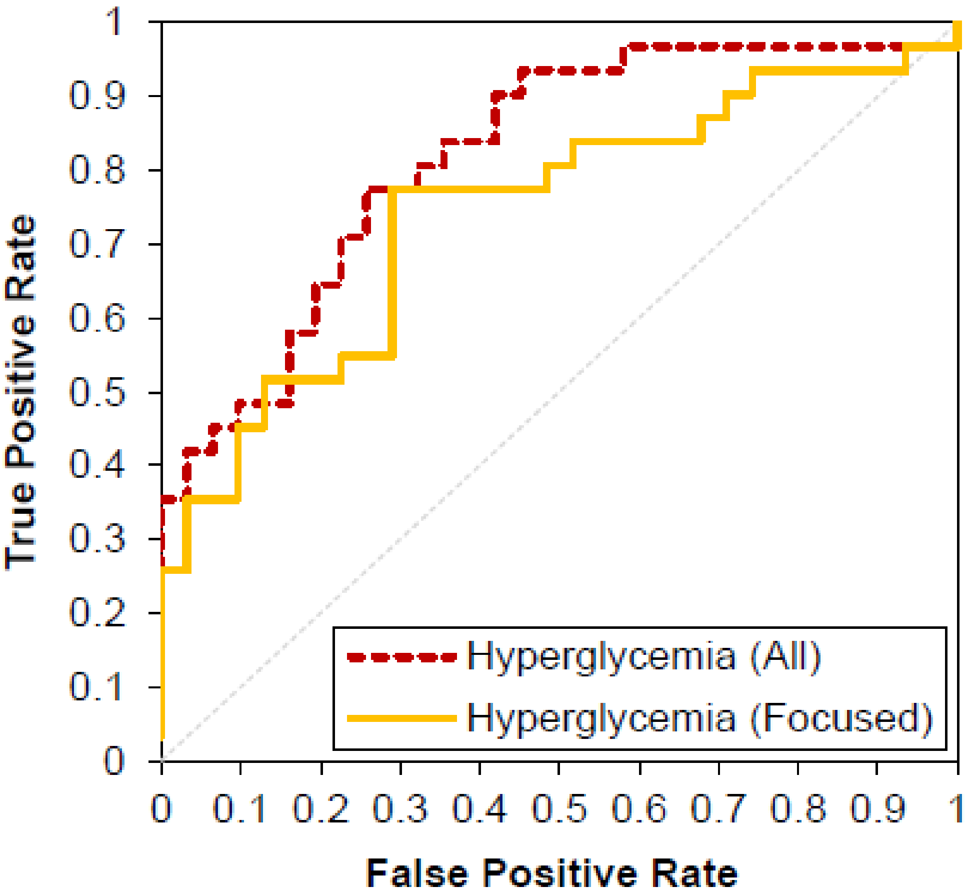


	a	*b*	*c*	*d*	*RR*	*95% CI (Lower, Upper)*	*p-value (one-tailed)*
Expected (pravastatin)	342	2716	2581	56302	2.747	2.438, 3.094	< 0.0001
Expected (paroxetine)	342	2716	3645	71243	2.461	2.189, 2.767	< 0.0001

Characterizing Sensor Error

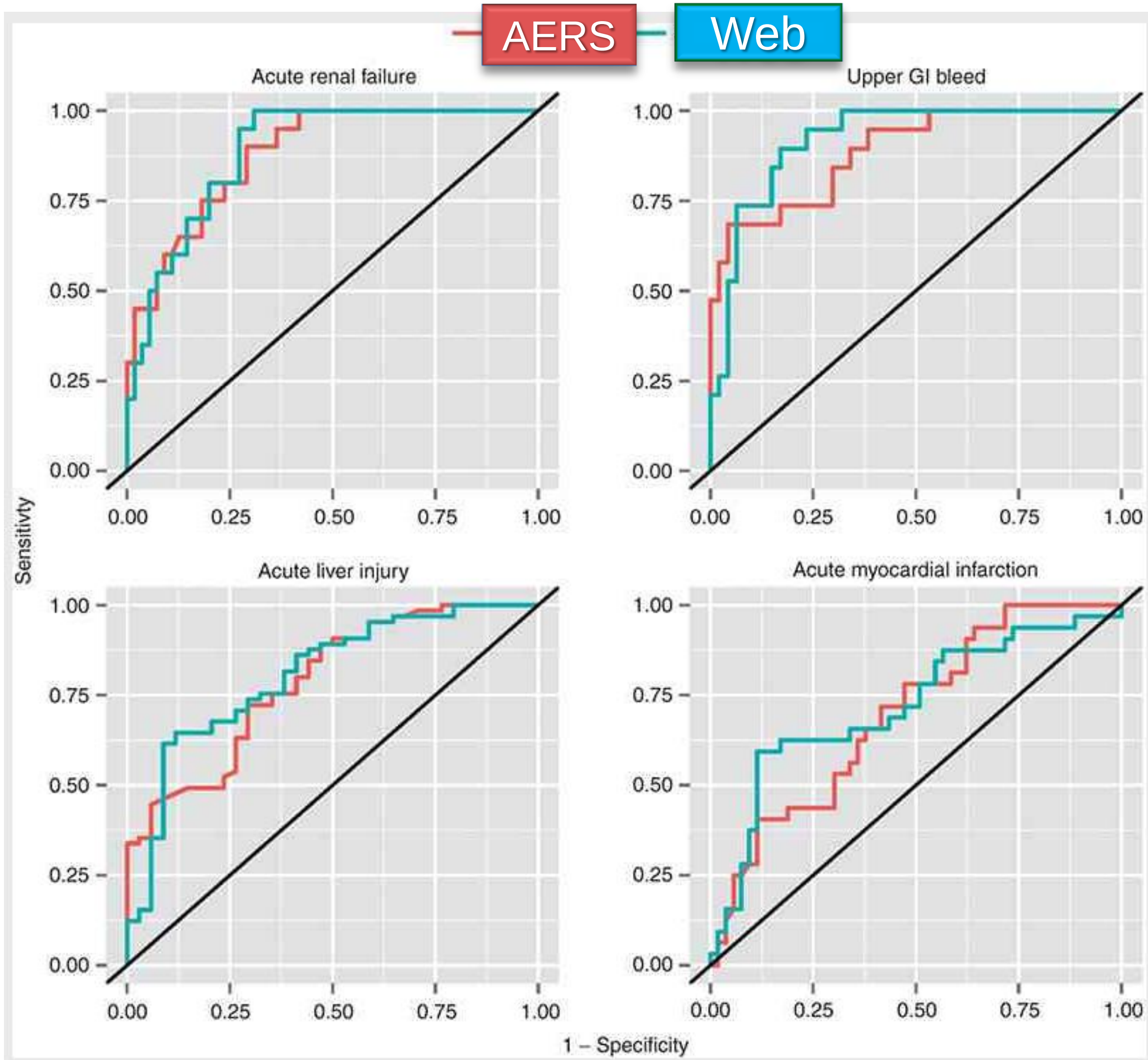
Test on known interactions

- 31 true positives for hyperglycemia
- 31 true negatives for hyperglycemia



Label	*Drug 1*	*Drug 2*
TP	dobutamine	hydrocortisone
TP	dobutamine	triamcinolone
TP	dobutamine	prednisolone
TP	betamethasone	dobutamine
TP	glipizide	phenytoin
TP	dobutamine	methylprednisolone
TP	prednisolone	salmeterol
TP	salmeterol	triamcinolone
TP	betamethasone	terbutaline
TP	dexamethasone	dobutamine
TP	budesonide	salmeterol
TN	hydrochlorothiazide	tazobactam
TN	clindamycin	montelukast
TN	lamotrigine	nystatin
TN	methylprednisolone	rosuvastatin
TP	budesonide	formoterol
TN	loratadine	nystatin
TN	hydroxychloroquine	prochlorperazine
TN	labetalol	sertraline
TN	ciprofloxacin	vecuronium

Rare, Serious Adverse Effects



OMOP

Multi-item Gamma Poisson shrinker algorithm (DuMouchel and Pregibon, KDD)

R. White, R. Harpaz, et al., Nature CPT 2014

Complementarity of Signals

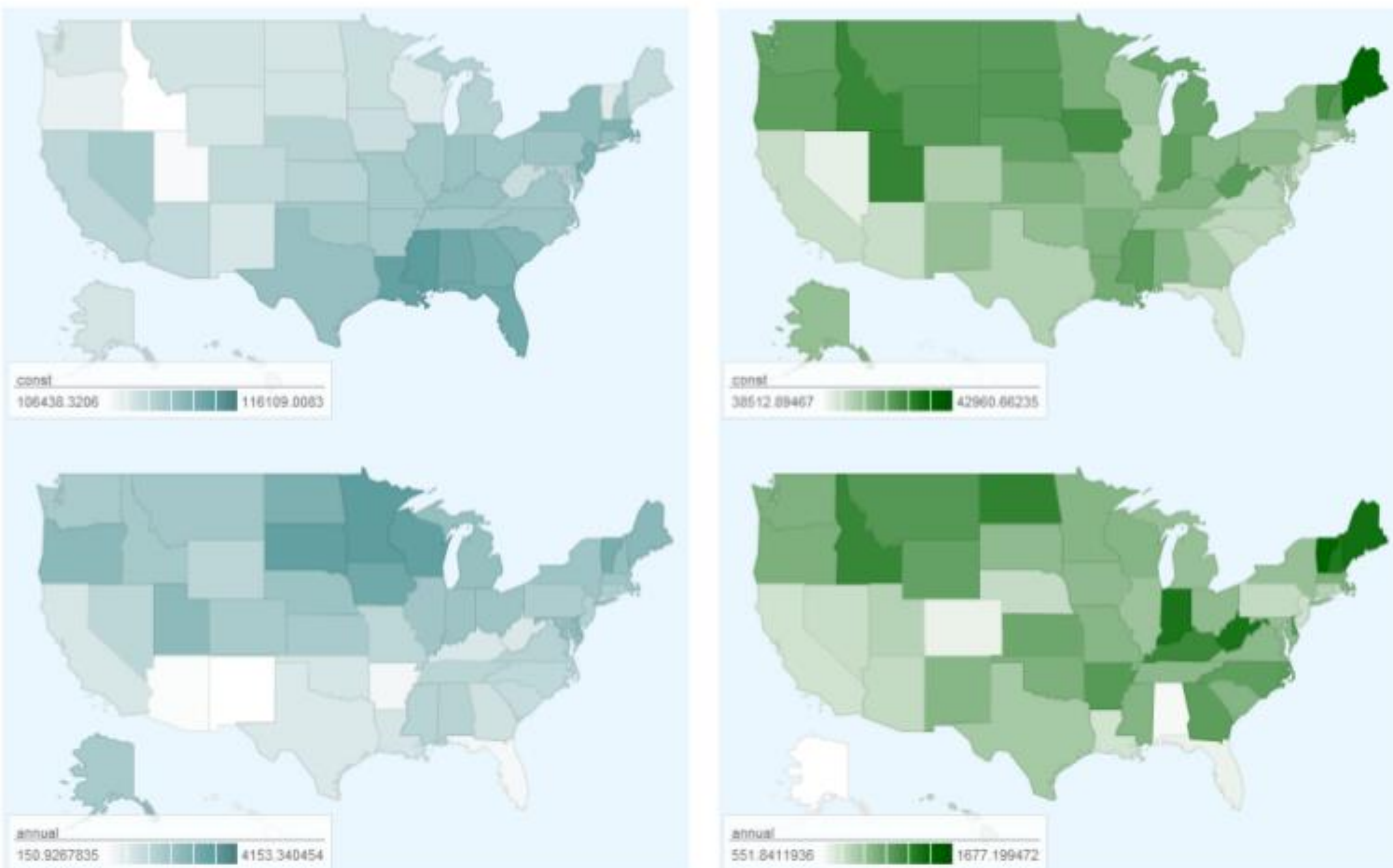
	AERS	Search	Together
Acute Renal Failure	0.88	0.88	0.93
Upper GI Bleed	0.89	0.92	0.92
Acute Liver Injury	0.79	0.81	0.86
Acute Myocardial Infarction	0.70	0.73	0.75
Average	0.81	0.83	0.86

AUC improvements statistically significant ($p<0.05$)

R. White, R. Harpaz, et al., Nature CPT 2014

Wide Range of Studies

e.g., Nutritional content of downloaded recipes



Mean

Annual fluctuation

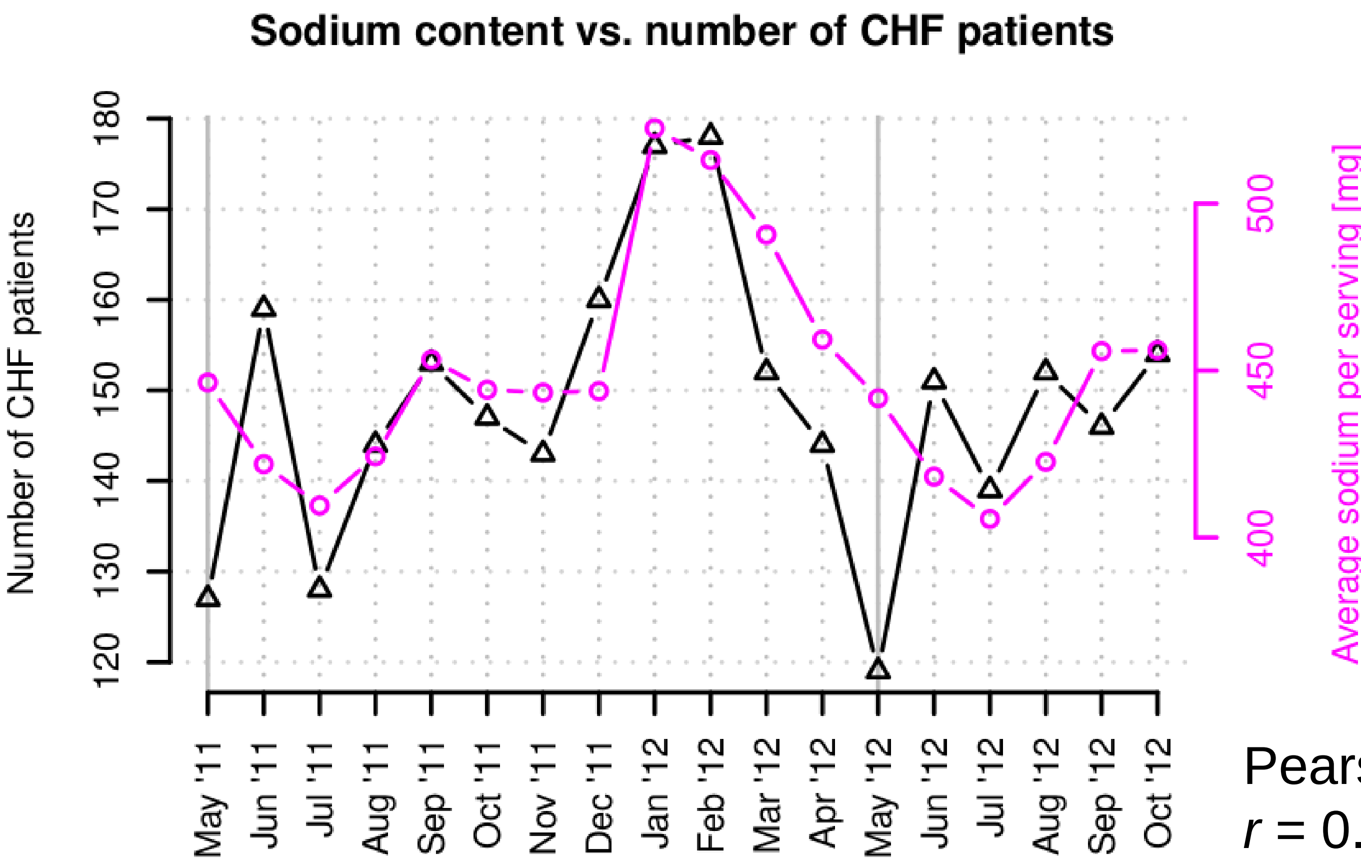
Total calories / serving

Calories from carbohydrates

[R. West, R. White, H., WWW 2013]

Diet & Illness: Heart Failure

Na+ content in downloaded recipes & admissions (DC metro area)



Pearson correlation:
r = 0.62, p = 0.0028

R. West, R. White, H., WWW 2013

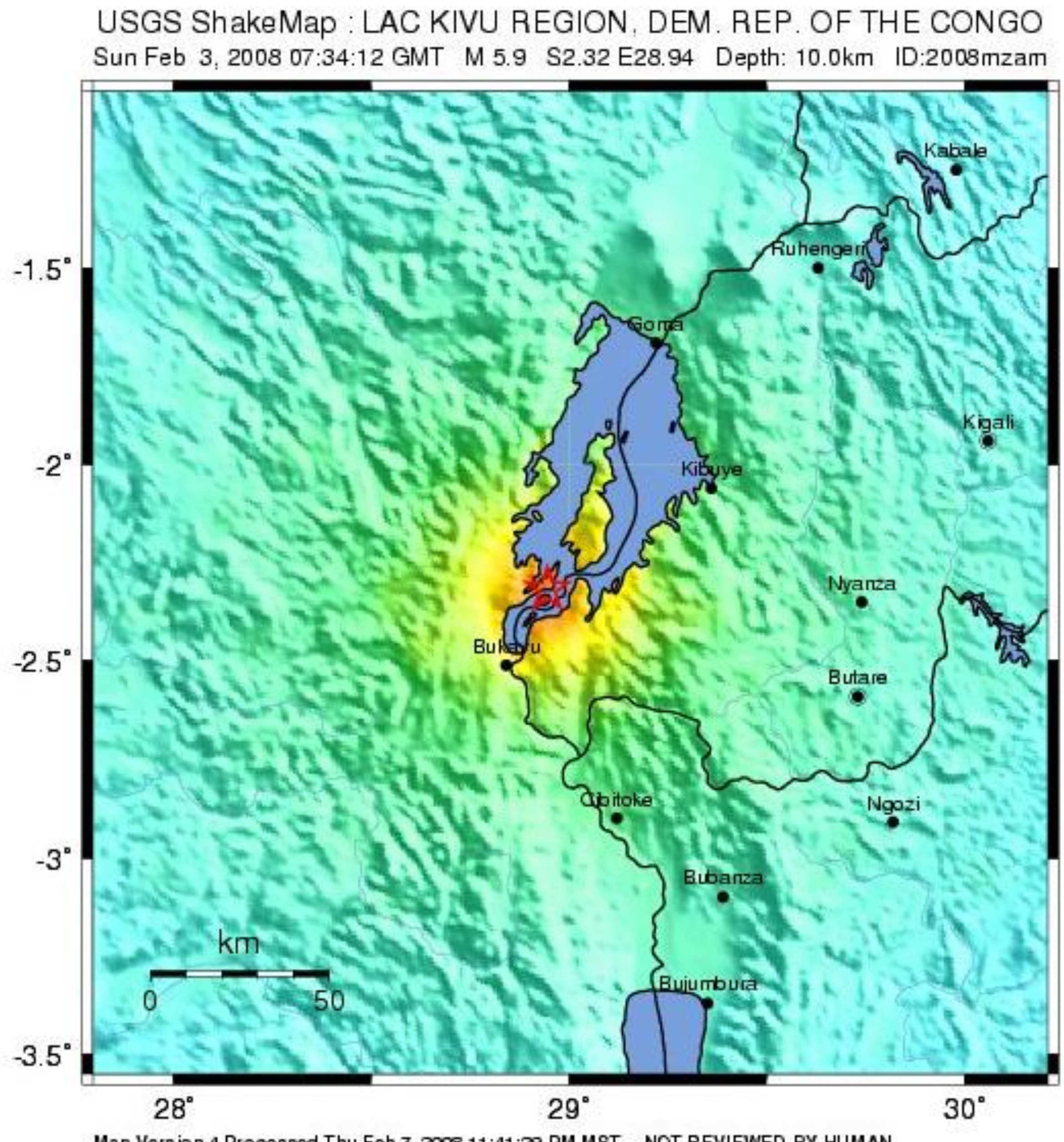
Disruption and Recovery

Disruption and Recovery

Lac Kivu quake

Feb 3, 2008

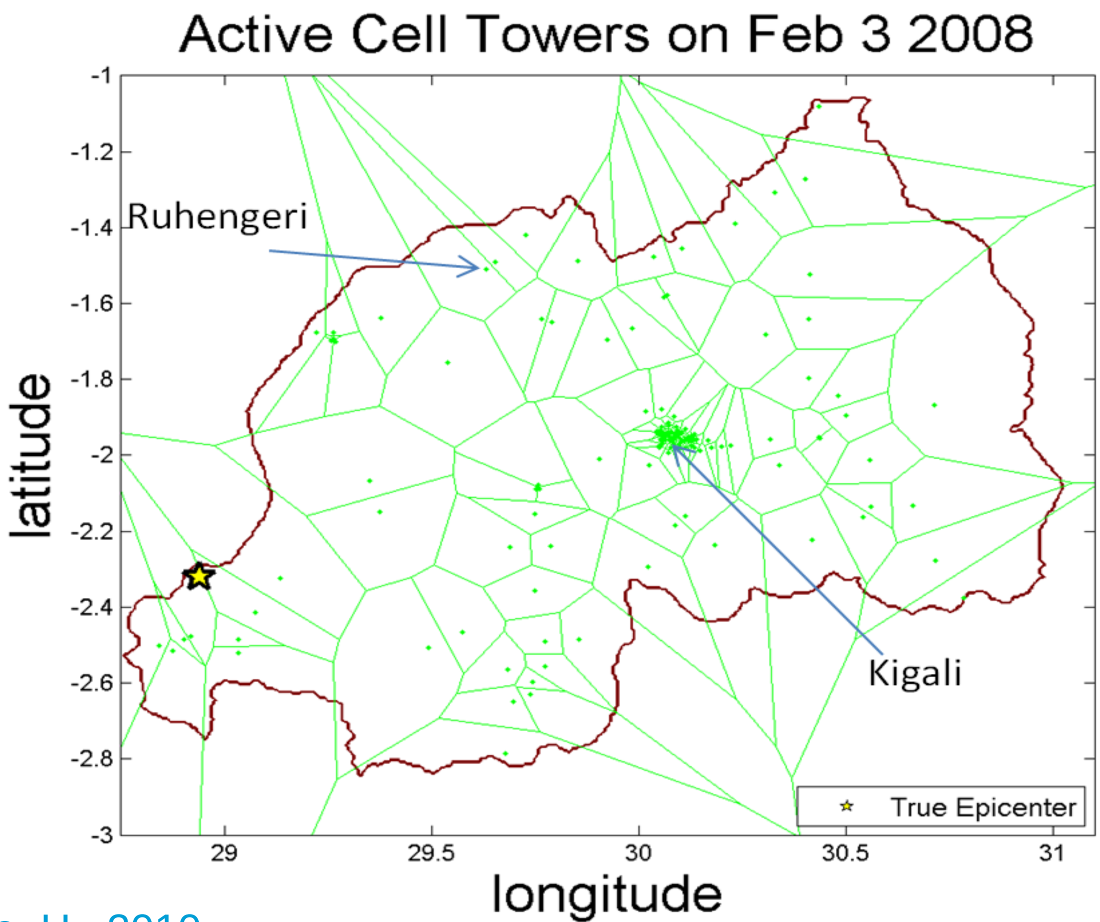
5.9



Cell Tower Call Densities in Rwanda

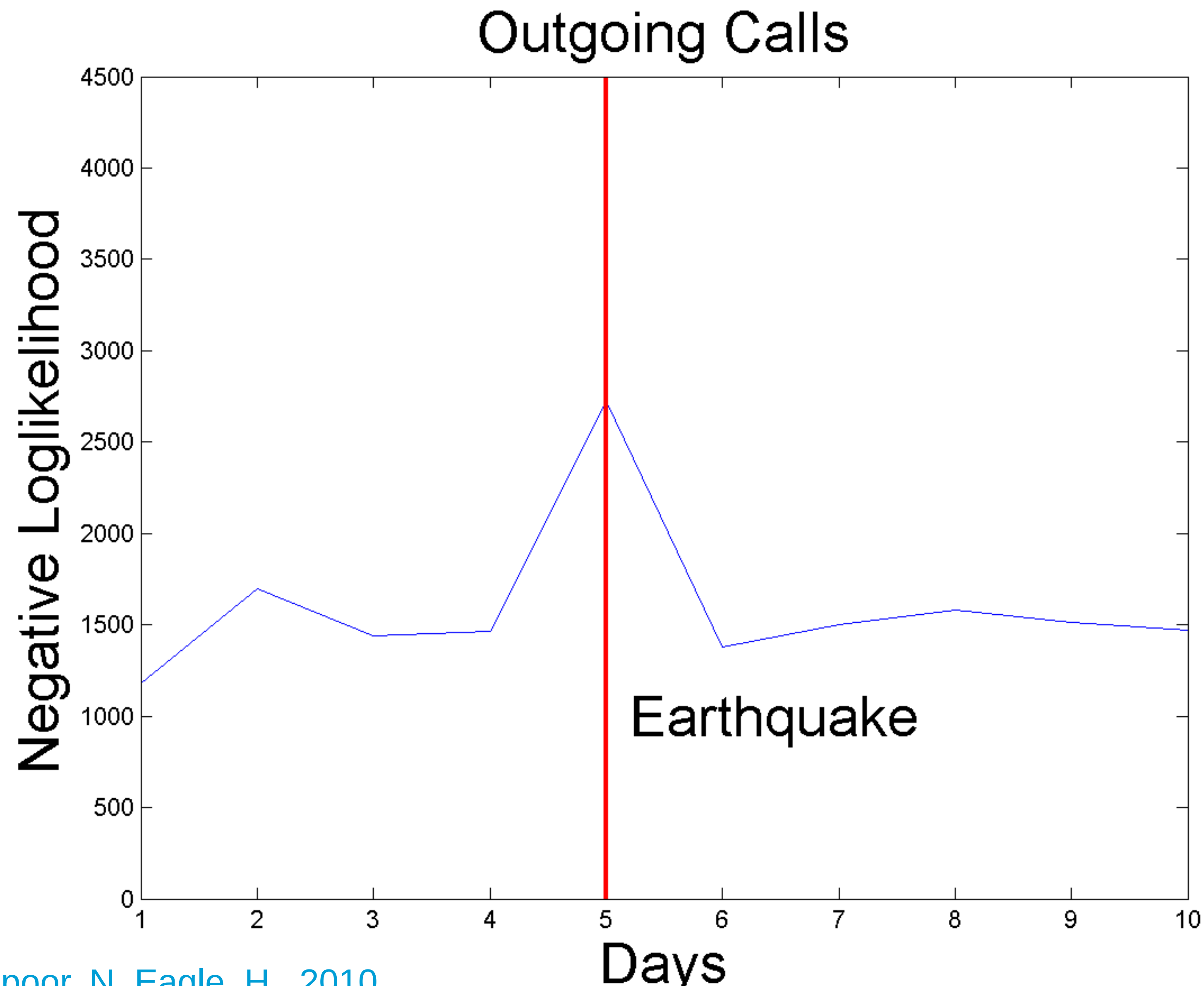
3 years of logs of ins and outs of comms.

140 cell towers, 6 days: 10,527,799 calls



A. Kapoor, N. Eagle, H., 2010

Detecting the Earthquake

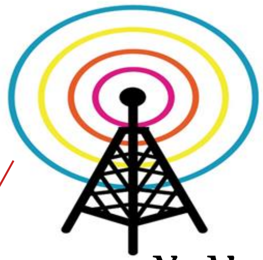


A. Kapoor, N. Eagle, H., 2010

Inferring the Epicenter

Modeling deviations from the trend

$$p(a_i \mid Event) \sim N(m_i(1+\Delta_i), \Sigma_i)$$



$$\Delta_i = \frac{\alpha}{\beta + \left[(e_x - x_i)^2 + (e_y - y_i)^2\right]^{\gamma}}$$

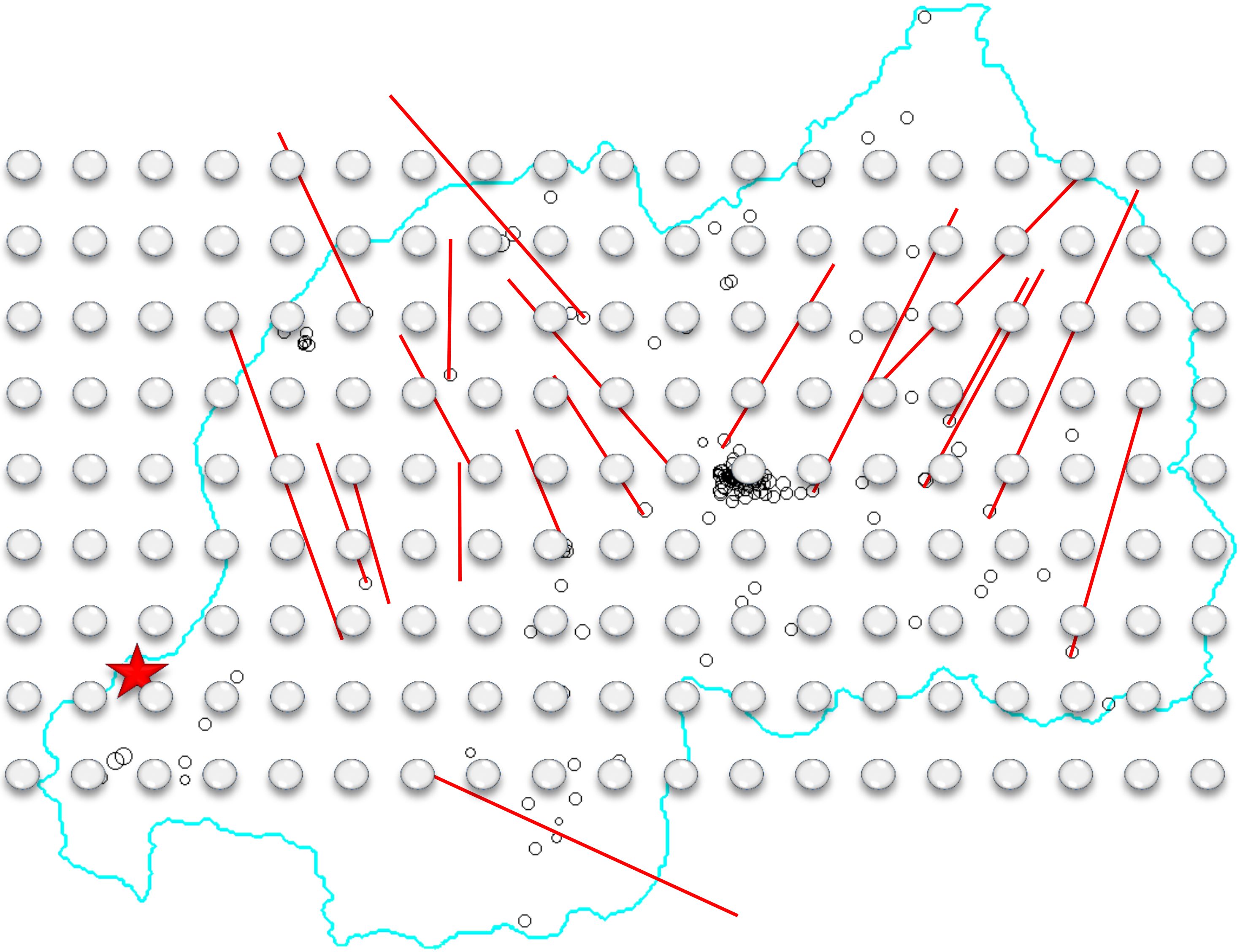
Unknown parameters: $\theta = (\alpha, \beta, \gamma, e_x, e_y)$

epicenter

$$\theta = \arg\max_{\theta} \sum_{i=1}^{T} \log p_{\theta}(a_i \mid Event)$$

Determining the Epicenter

- Radius of towers = % increase in calls



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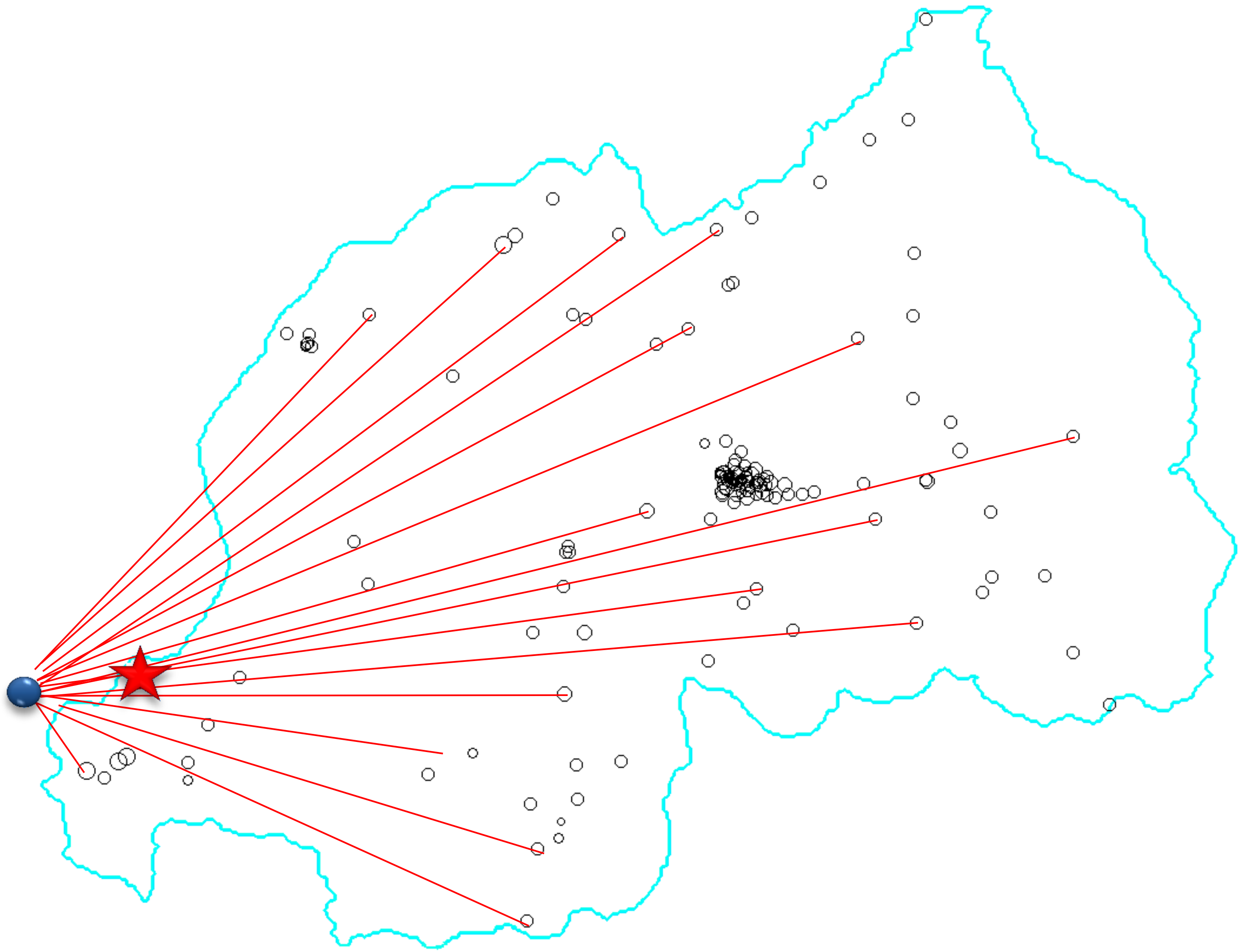
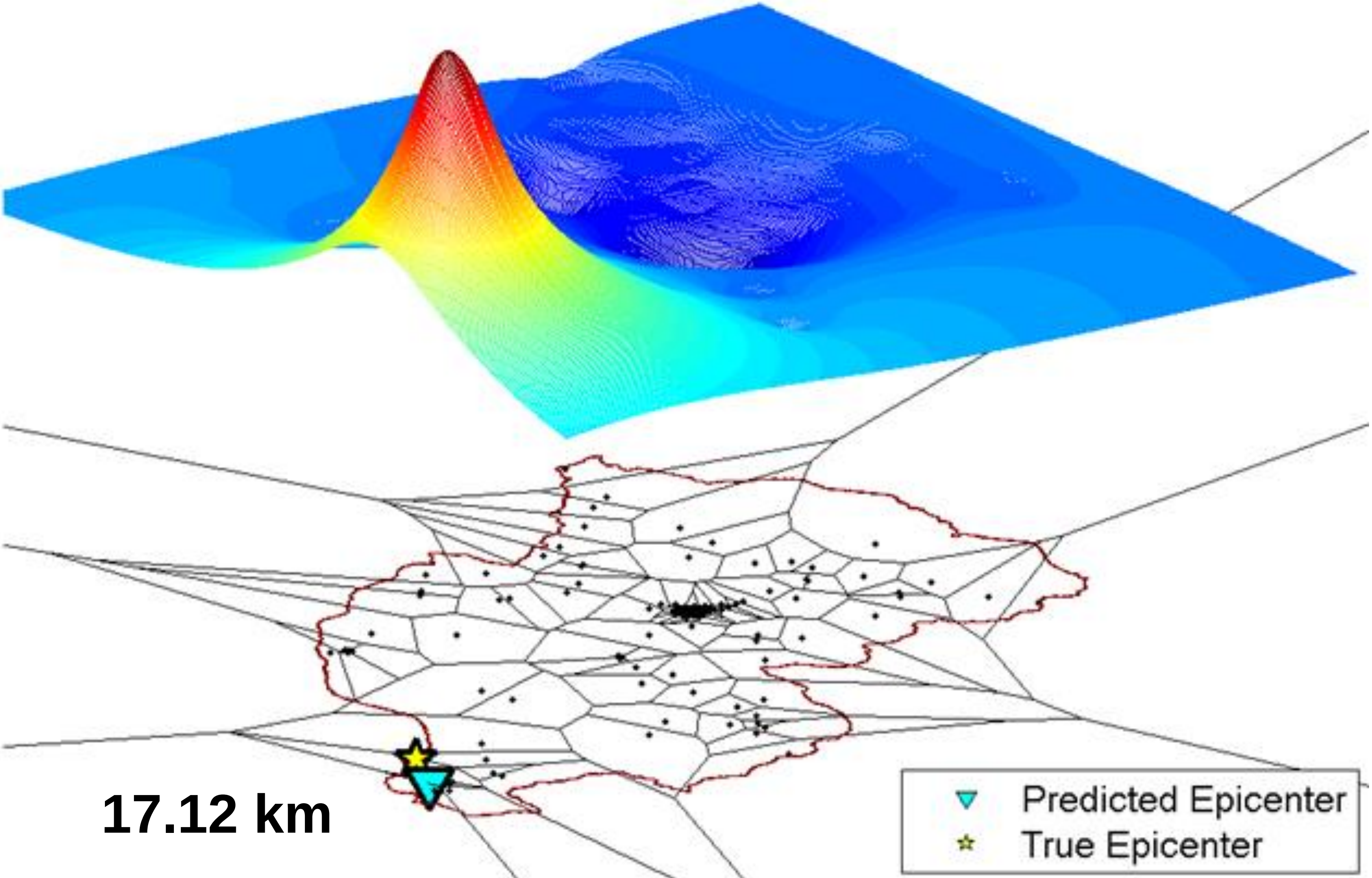


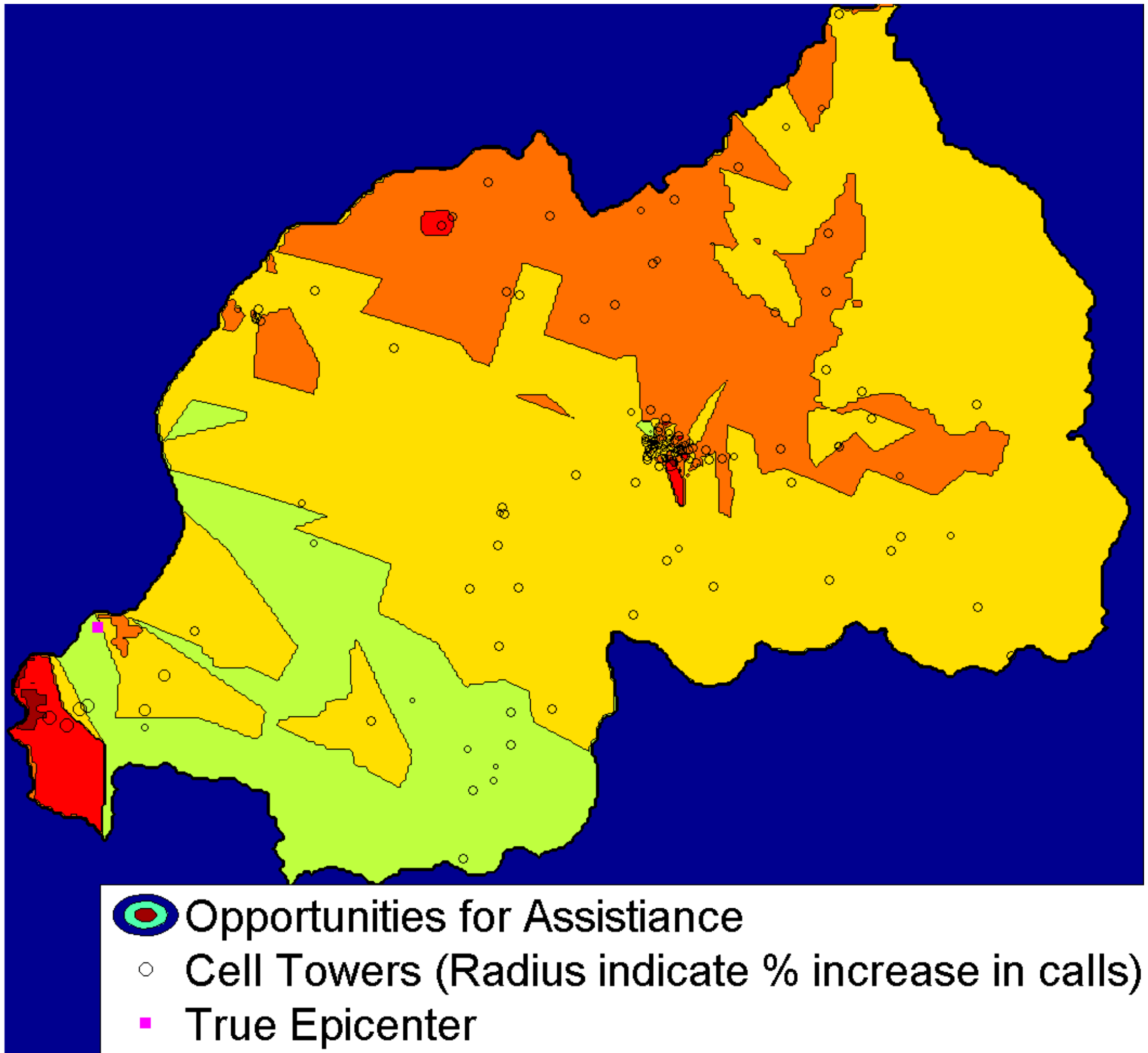
Inferring the Epicenter



17.12 km

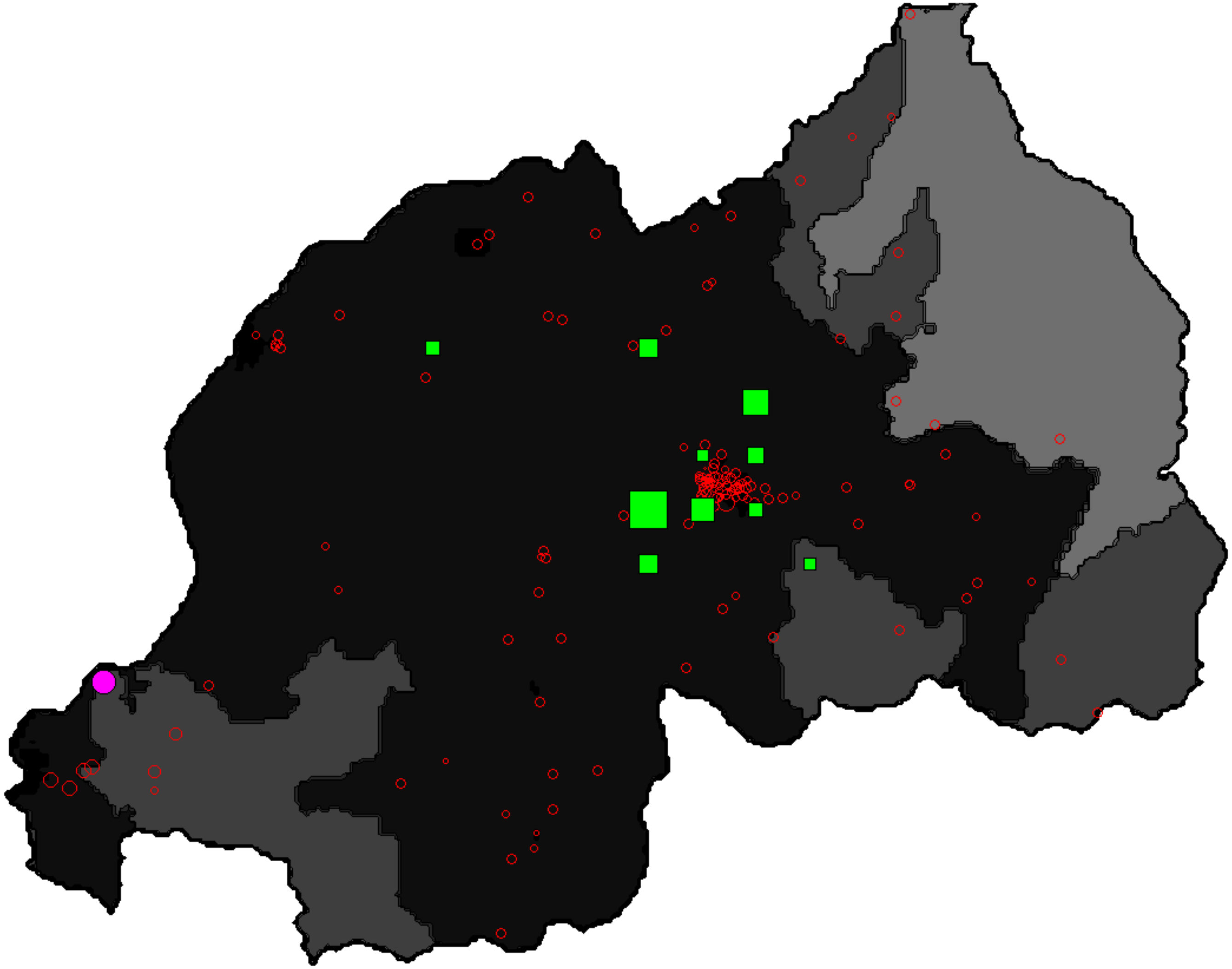
Inferring Opportunities to Assist

- Opportunities for Assistance Day 2



Value of Survey

Ideal Reconnaissance (Day 2)

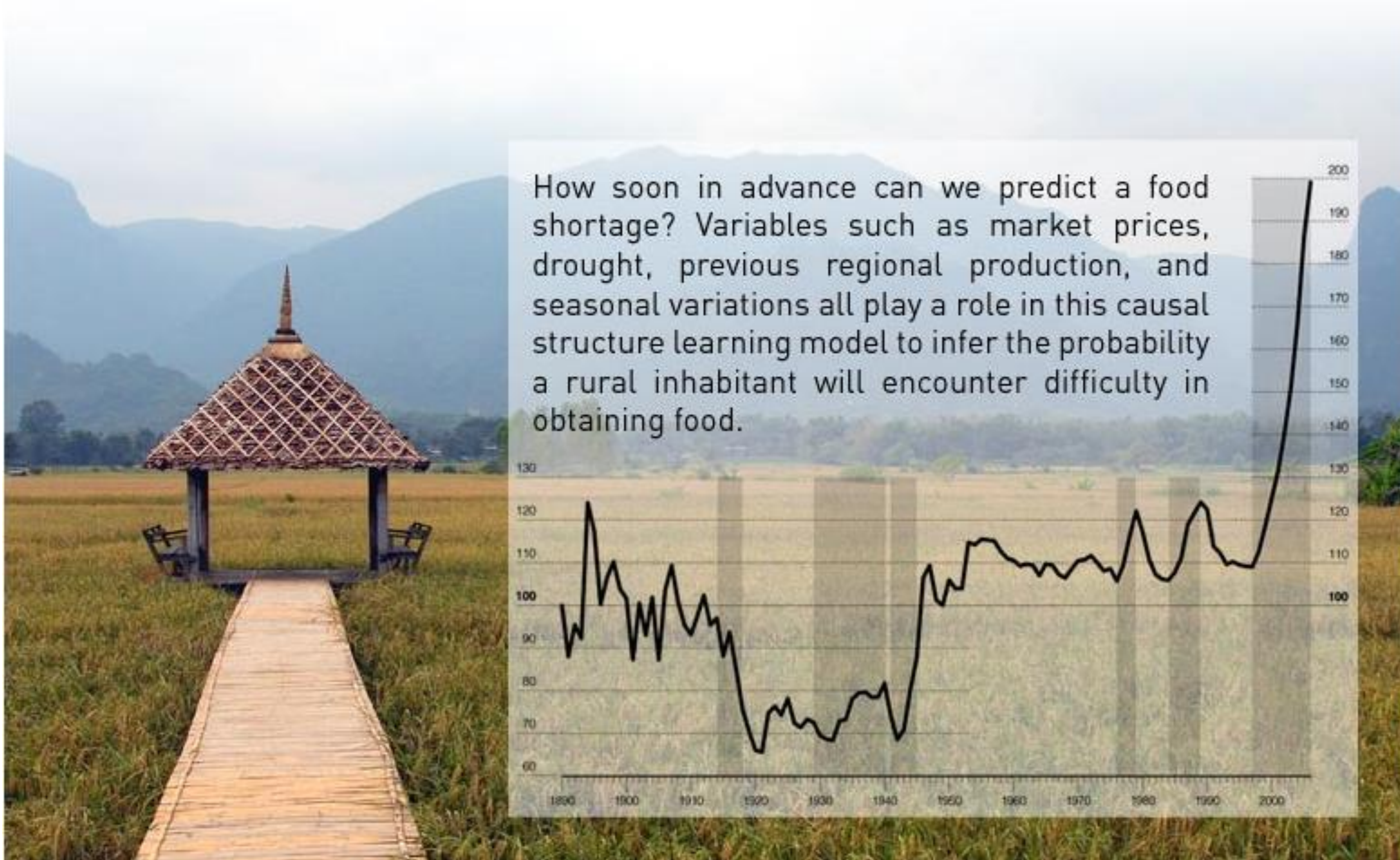


A. Kapoor, N. Eagle, H., 2010

AI-D ARTIFICIAL INTELLIGENCE FOR DEVELOPMENT

AI-D.ORG

HOME RESEARCH DATA PUBLICATIONS PEOPLE GET INVOLVED



Data-Driven Development

The unprecedented volume of data currently being generated in the

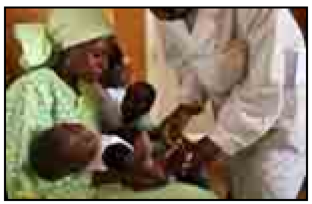
AAAI AI-D Symposium

The AAAI AI-D Spring Symposium at Stanford is being

The Causal Structure of Food Shortage in Uganda

How soon in advance can we predict a food shortage? Variables such as market prices, drought, migrations, previous regional production, and seasonal variations all play a role in this classification and causal structure learning model to predict whether a rural inhabitant is likely to encounter difficulty in obtaining food. - *G. OKORI*

Catastrophe Modeling for Rwandan Disease Surveillance



Can mobile phones be used as an early warning system for disease outbreaks? Bayesian anomaly detection algorithms may be able to quantify behavioral signatures associated with cholera outbreaks in Rwanda. If successful, these alogithms could lead to the deployment of next generation of disease surveillance systems in some of the world's regions that need it the most. - *N. EAGLE, E. HORVITZ*

Spatiotemporal Diffusion of Contraceptive Norms in the D.R.

How do contraceptive norms spread through rural areas of the developing world? Spatiotemporal diffusion models have the potential to better evaluate the efficacy of HIV prevention techniques and inform policy decisions related to public health. - *H. YOSHIOKA, N. EAGLE*

Mobility Models of Malaria in East Africa

How do human mobility patterns affect the spread of malaria? Aggregating longitudinal movement data from 15M mobile phones in East Africa, it may be possible to gain a better understanding of the implications of human movement on the spread of disease. - *N. FERGUSON, D. HOLLINGSWORTH, N. EAGLE*

AI-D Sample Research Projects

Below are a list of active AI-D research projects. If you'd like to add your own project to this list, please feel free to get involved.

Food Shortage
Disease Surveillance
Diffusion of Norms
Mobility and Malaria
Slum Dynamics
Computational City Planning
Urban Growth Models
Expertise Inference
Crime as Contagion
Stability of Society
Shock Modeling
Entropy and Poverty
Realtime Risk

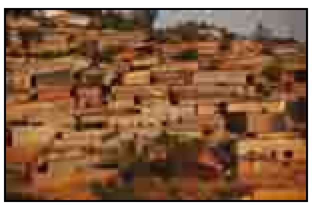
Generative Models of the Nairobi Slums

Over one billion people - or nearly one in every three urban residents - live in informal settlements and slums. Coupling mobile phone data with mathematical models and statistical inference, we hope to better understand the dynamics of these establishments and ultimately develop predictive models to better serve this underrepresented population. - *A. WESOLOWSKI, N. EAGLE*

Computational Transport Planning and Modeling in Kigali

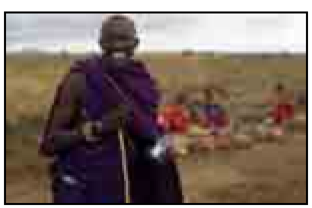
Kigali's cities planners are inundated with data about how urban infrastructure in Rwanda's capital is being utilized. Generative models are needed to better inform decisions ranging from broad transport planning questions to the minutia such as the optimal placement of the next public latrines. - *A. VACCARI, N. EAGLE*

Modeling the Dynamics of Urbanization on Social Support Networks



What is attracting migrants to urban areas within the developing world? Using 4 years of movement and communication data, it is possible to model the reinforcing social mechanisms that could explain their recent rapid growth. - *L. BETTENCOURT, Y. DE MONTJOYE, N. EAGLE*

Expectation-Maximization for Mobile Crowdsourcing



There are over one billion mobile phone subscribers who live on less than 5 dollars a day. Using techniques such as Expectation-Maximization, we are developing a system that enables people to earn small amounts of money by completing simple tasks on their phones. - *N. EAGLE, B. OLDING*

Is Crime a Contagion?

Can we quantify a crime wave? Is crime contagious? Given the time, place, and nature of a crime, we are attempting to infer casual relationships between crimes and locations across a city. - *J. TOOLE, J. PLOTKIN, N. EAGLE*

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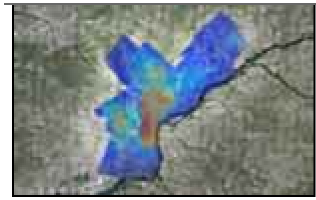
- Crime as Contagion
- Stability of Society
- Shock Modeling
- Entropy and Poverty
- Realtime Risk



Can we quantify a crime wave? Is crime contagious? Given the time, place, and nature of a crime, we are attempting to infer casual relationships between crimes and locations across a city. - *J. TOOLE, J. PLOTKIN, N. EAGLE*

Quantifying the Stability of Society

Is there such a thing as a 'poverty trap'? Logistic classifiers applied on communication and census data point to a new mechanism for poverty that relates to the persistence of relationships. This analysis shows that economic exchanges flow primarily through these persistent edges and the inability to maintain these ties can prevent upward economic mobility. - *Y. DE MONTJOYE, A. CLAUSET, N. EAGLE*

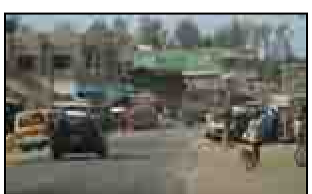
Economic Shocks in Rwanda

Do people react to economic shocks in a similar manner? Time-series analysis of anonymized mobile phone records coupled with random surveys, will hopefully lead to better insight about the dynamics of rural economies. - *J. BLUMENSTOCK, N. EAGLE*

Communication as a Lens into Poverty

How do communication patterns reflect poverty? We find the principal components of a wide range of diversity metrics, including Shannon entropy, explain over two-thirds the variance of regional socioeconomic status. - *N. EAGLE, M. MACY, R. CLAXTON*

Identifying Need and Risk



Can mobile phones identify high-risk behavior? A group of 10 male sex-workers in coastal Kenya where provided with mobile phones that logged communication, proximity and movement behavior. When coupled with self-report surveys, we are attempting to develop a system that can infer the onset of high-risk behavior and deliver salient information in real-time. - *E. SANDERS, N. EAGLE*

AI-D Sample Research Projects

Below are a list of active AI-D research projects. If you'd like to add your own project to this list, please feel free to get involved.

Food Shortage
Disease Surveillance
Diffusion of Norms
Mobility and Malaria
Slum Dynamics
Computational City Planning
Urban Growth Models
Expertise Inference
Crime as Contagion
Stability of Society
Shock Modeling
Entropy and Poverty
Realtime Risk