



# MATHEMATICAL FRONTIERS

*The National  
Academies of* | SCIENCES  
ENGINEERING  
MEDICINE

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**Board on  
Mathematical Sciences & Analytics**

# MATHEMATICAL FRONTIERS

## 2018 Monthly Webinar Series, 2-3pm ET

**February 13\*:**

*Mathematics of the Electric Grid*

**March 13\*:**

*Probability for People and Places*

**April 10\*:**

*Social and Biological Networks*

**May 8\*:**

*Mathematics of Redistricting*

**June 12\*:** *Number Theory: The Riemann Hypothesis*

**July 10\*:** *Topology*

**August 14:** *Algorithms for Threat Detection*

**September 11:** *Mathematical Analysis*

**October 9:** *Combinatorics*

**November 13:**

*Why Machine Learning Works*

**December 11:**

*Mathematics of Epidemics*

**\* Recording posted**

*Made possible by support for BMSA from the  
National Science Foundation Division of Mathematical Sciences and the  
Department of Energy Advanced Scientific Computing Research*

# MATHEMATICAL FRONTIERS

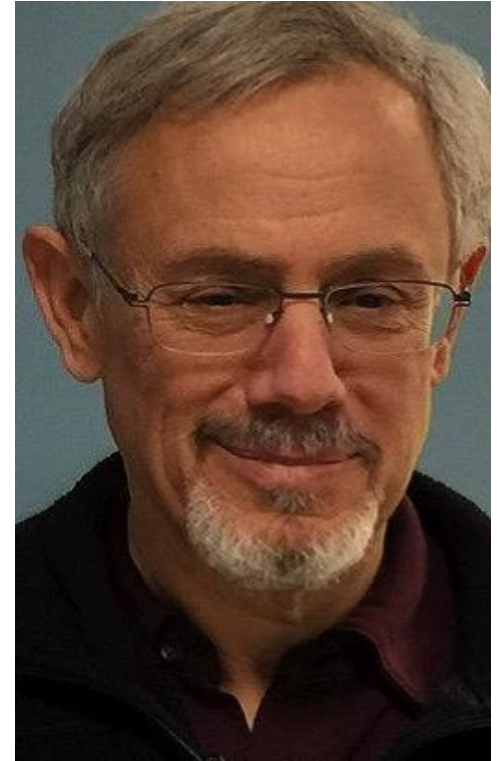
## Algorithms for Threat Detection



**Abel Rodriguez,**  
University of California, Santa Cruz



**Andrea Bertozzi,**  
UCLA



**Mark Green,**  
UCLA (moderator)

# MATHEMATICAL FRONTIERS

## Algorithms for Threat Detection



Abel Rodriguez,  
University of California, Santa Cruz

*Associate Director of the Center for Data,  
Discovery, and Decisions and  
Professor of Statistics at the  
University of California, Santa Cruz*

## **Harnessing the Data Revolution in Defense and National Security Applications**



# Harnessing the data revolution

- Pervasive data collection facilitated by cheap electronics
  - Location data
  - Relational data
- Properly used, these data are a boon for defense and national security applications



Images courtesy of the AAUW and Penn State University

# Outline

- NSF's ATD program
- Some motivating challenges
- How mathematics and statistics can help
- Mind the Dark Side!

# ATD@NSF: Mathematics and Statistics in Defense and National Security

- The Algorithms for Threat Detection (ATD) program was launched in 2008.
- It is run out of the Division of Mathematical Science (DMS) in the Directorate for Mathematical & Physical Sciences (MPS)
- It is the result of a partnership with various other government agencies.
- Has had tremendous impact.



# Social Media

- Identify fake social media accounts
- Identify repeat rule breakers with new accounts



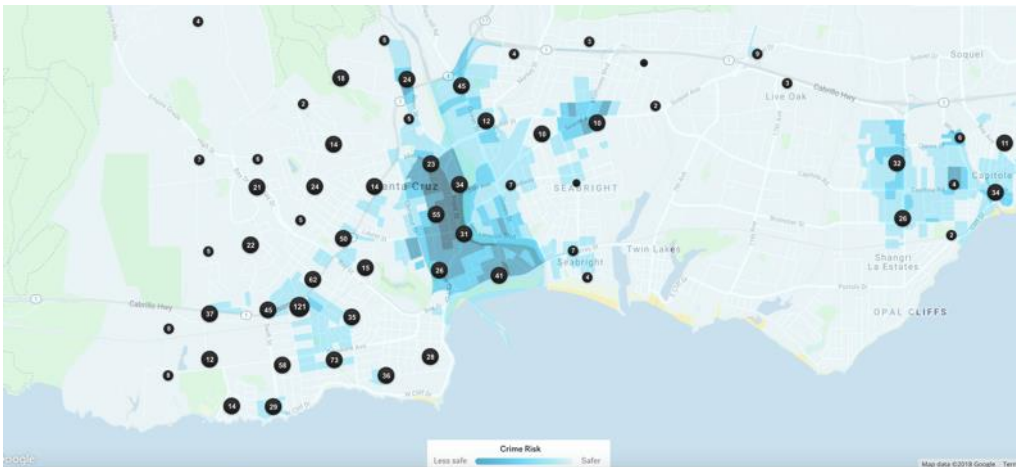
MEMES & FUNNY PICS FRABZ.COM





# Crime and terrorism

- Intervention design
- Policy assessment



Images courtesy of the trulia.com and the the US Army.

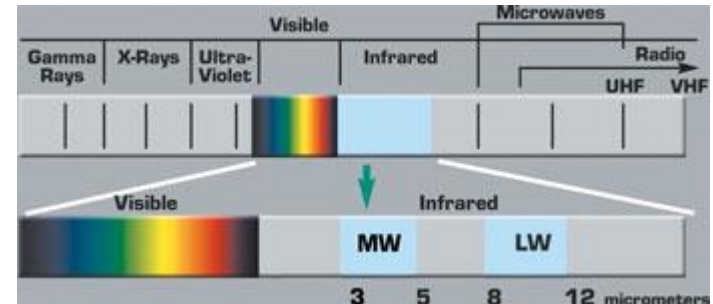
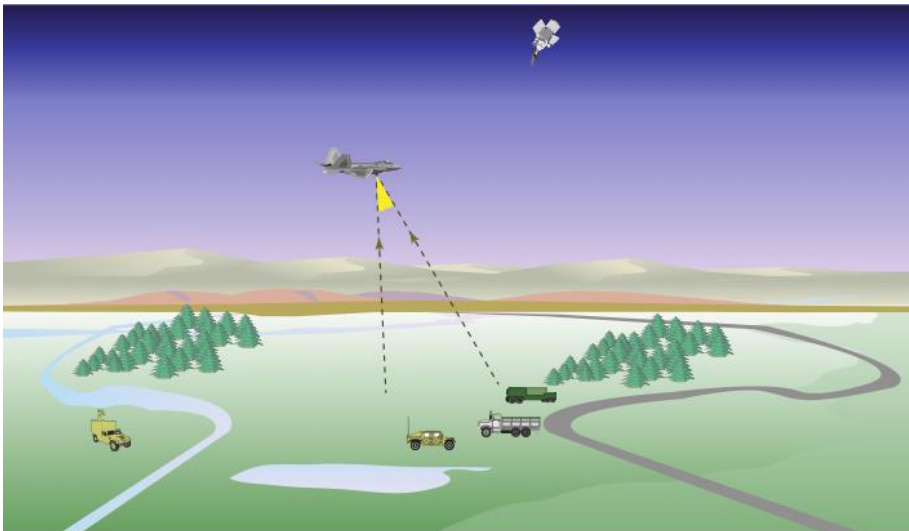
# Environmental Hazards

- Detection
- Analysis
- Tracking, both active and passive

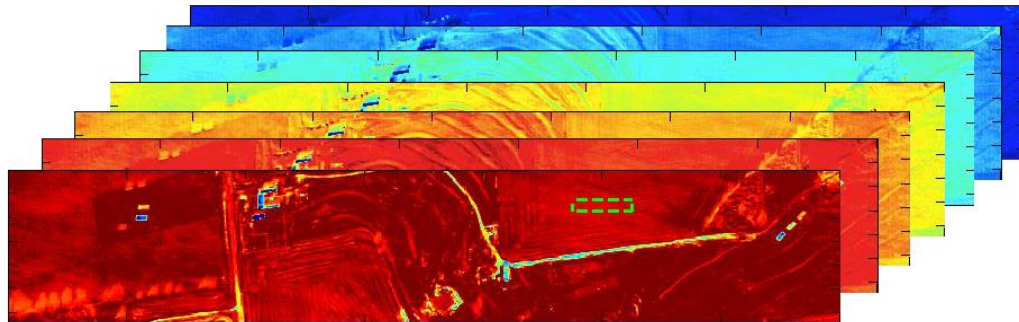


Images courtesy of the NASA, the US Navy and the ICDO

# Analysis of hyperspectral data for plume detection and identification



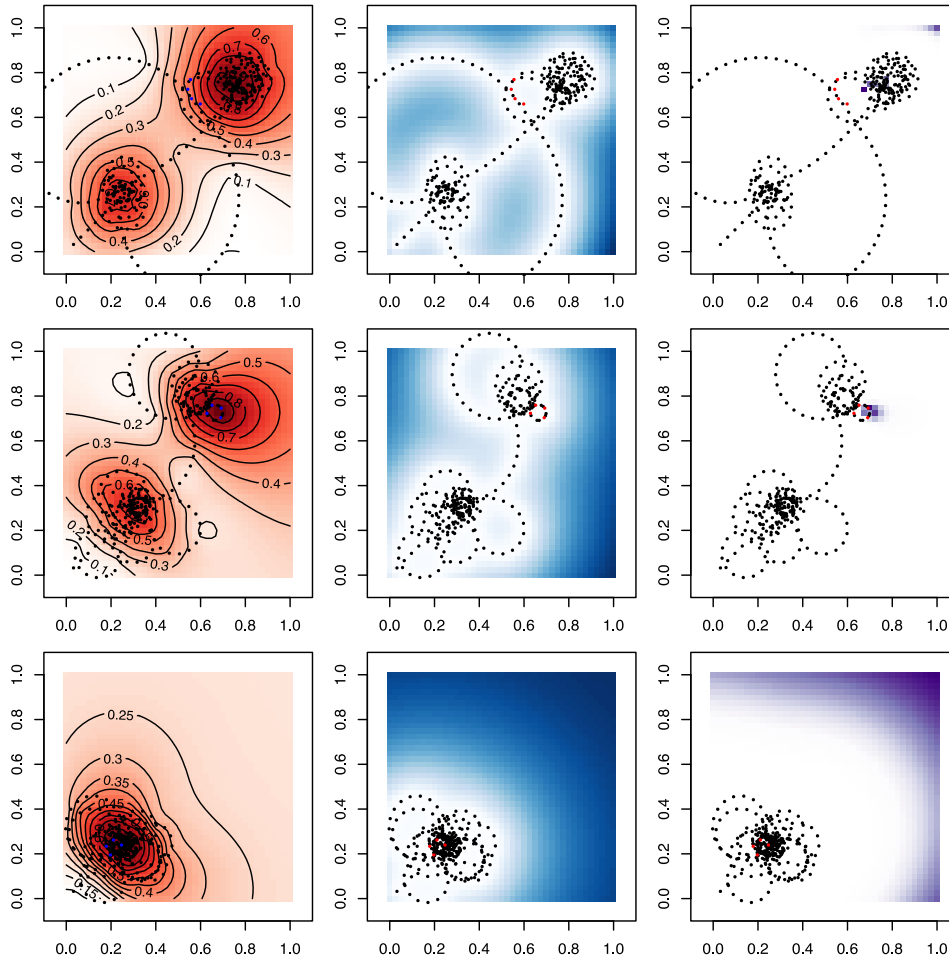
Mendoza, N. and Rodriguez A. (2017) Bayesian spatial model selection for detection and identification in chemical plumes based on hyperspectral imagery data. Technical report, University of California, Santa Cruz



- Plumes are "continuous"
- You need to carefully control for false positive rates
- Include prior information about the likelihood of different chemicals

Images courtesy of the Dimitris Manolakis

# Control of mobile sensor networks in unknown environments



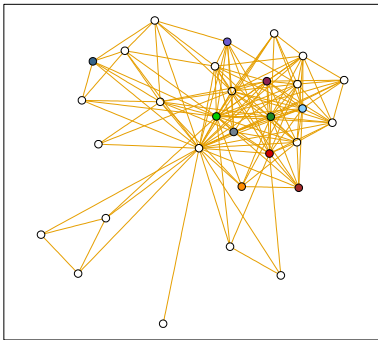
Song, S.; Rodriguez, A. and Teodorescu, M. (2015). "Trajectory planning for autonomous nonholonomic vehicles for optimal monitoring of spatial phenomena." International Conference on Unmanned Aircraft Systems (ICUAS): Denver, Colorado.

- Optimal path planning for source location or field reconstruction
- Carefully incorporates uncertainty about field estimates
- Trade off exploration and exploitation

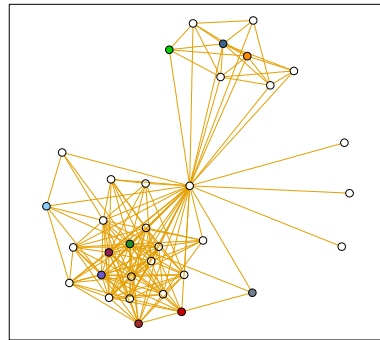


# Using network data for record linkage and entity resolution

Facebook

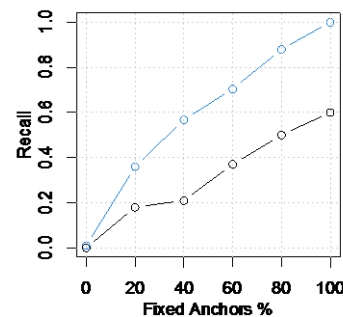
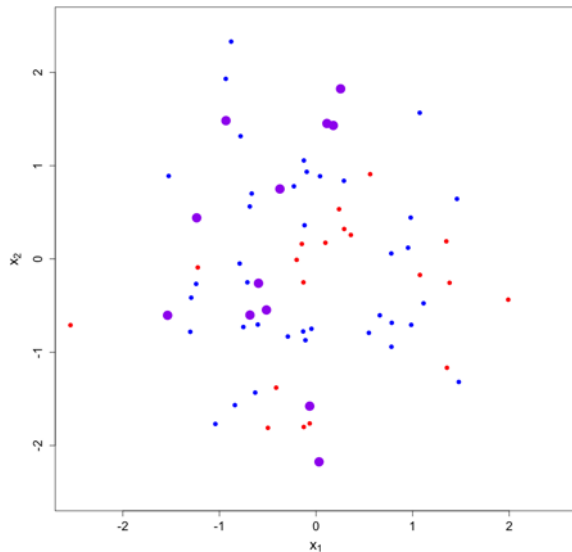


Twitter

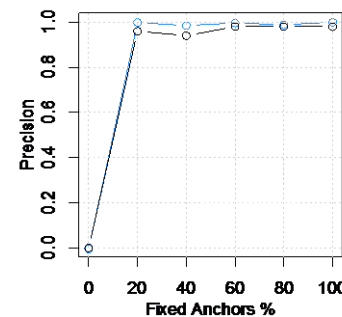


Sosa, J. and Rodriguez A. (2018) Bayesian models for record linkage in the presence of relational information. Technical report, University of California, Santa Cruz

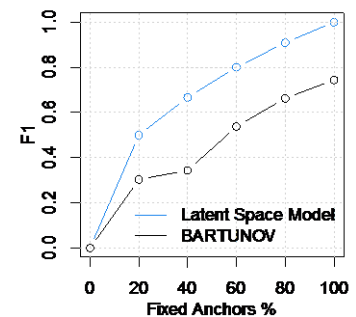
- Project nodes from all networks onto a common “social space”
- Use information from known “bridges” to anchor meaning of the social space
- Carefully control of false positive rates



(a) Recall.



(b) Precision.



(c) F<sub>1</sub> score.

# The Dark Side ...

- Balancing security and civil liberties.
- We still do not have good answers!



Images courtesy of the John Darkow and IMDB.com

# MATHEMATICAL FRONTIERS

## Algorithms for Threat Detection



Andrea Bertozzi,  
UCLA

*Director of Applied Mathematics and  
Professor of Mathematics at the  
University of California, Los Angeles*

**Crime modeling and  
data analysis**



# UC MASC PROJECT

MATHEMATICAL AND SIMULATION MODELING OF CRIME

## Multidisciplinary Collaboration

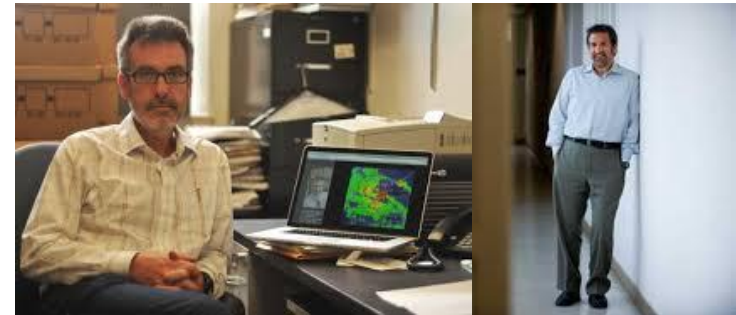
- Local law enforcement: - LAPD, SCPD, LBPD



Sean Malinowski



- Social Sciences:  
Jeff Brantingham (Anthropology) and  
George Tita (Criminology - UCI)



- Mathematics and Statistics: Bertozzi, Chayes, Osher, Schoenberg (many PhD students and postdocs)



# Predictive Policing with LAPD and SCPD

Mohler et al. JASA 2011 – show earthquake models can predict crime.

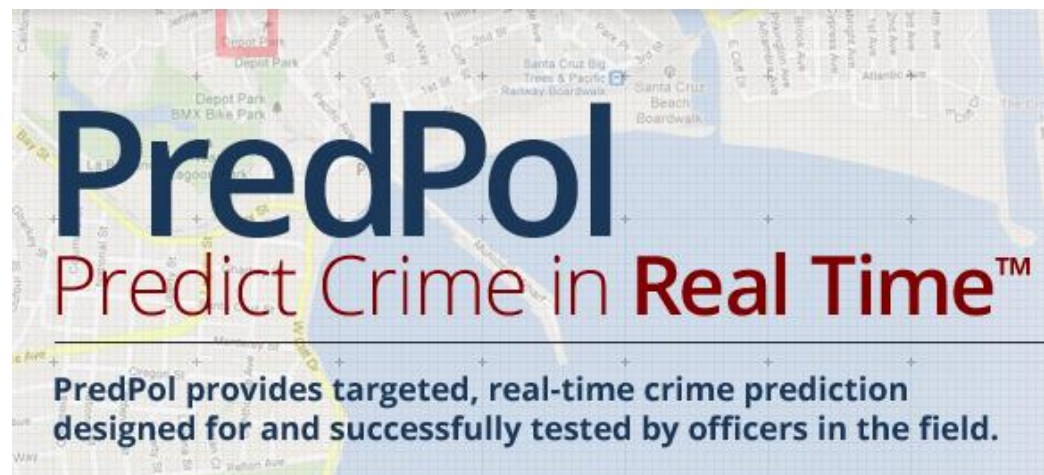
In June 2011 SCPD reduced crime by 27% using this method

Nov 2011 pilot study by LAPD in Foothill Division

Now used in multiple jurisdictions in LAPD and many other cities (including Seattle, Atlanta, Kent UK)

Software Company started :  
PredPol.com

Mohler et al. JASA 2015 – field trials published (software vs. crime analyst)



View webinar videos and learn more about BMSA at [www.nas.edu/MathFrontiers](http://www.nas.edu/MathFrontiers)

# Territorial Animals versus Street Gangs



- PhD thesis work of Laura Smith at UCLA
- P. Moorcroft, M. Lewis, and R. Crabtree. Mechanistic Home Range Models Capture Spatial Patterns and Dynamics of Coyote Territories in Yellowstone. 2006.
- L. M. Smith, A. L. Bertozzi, P. J. Brantingham, G. E. Tita, and M. Valasik, Adaptation of an Ecological Territorial Model to Street Gang Spatial Patterns in Los Angeles, Discrete and Continuous Dynamical Systems A, 32(9), pp. 3223 - 3244, 2012.



home ranges = territories  
coyotes, wolves = gang members  
pack = gang  
scent marks = graffiti  
den site = set space



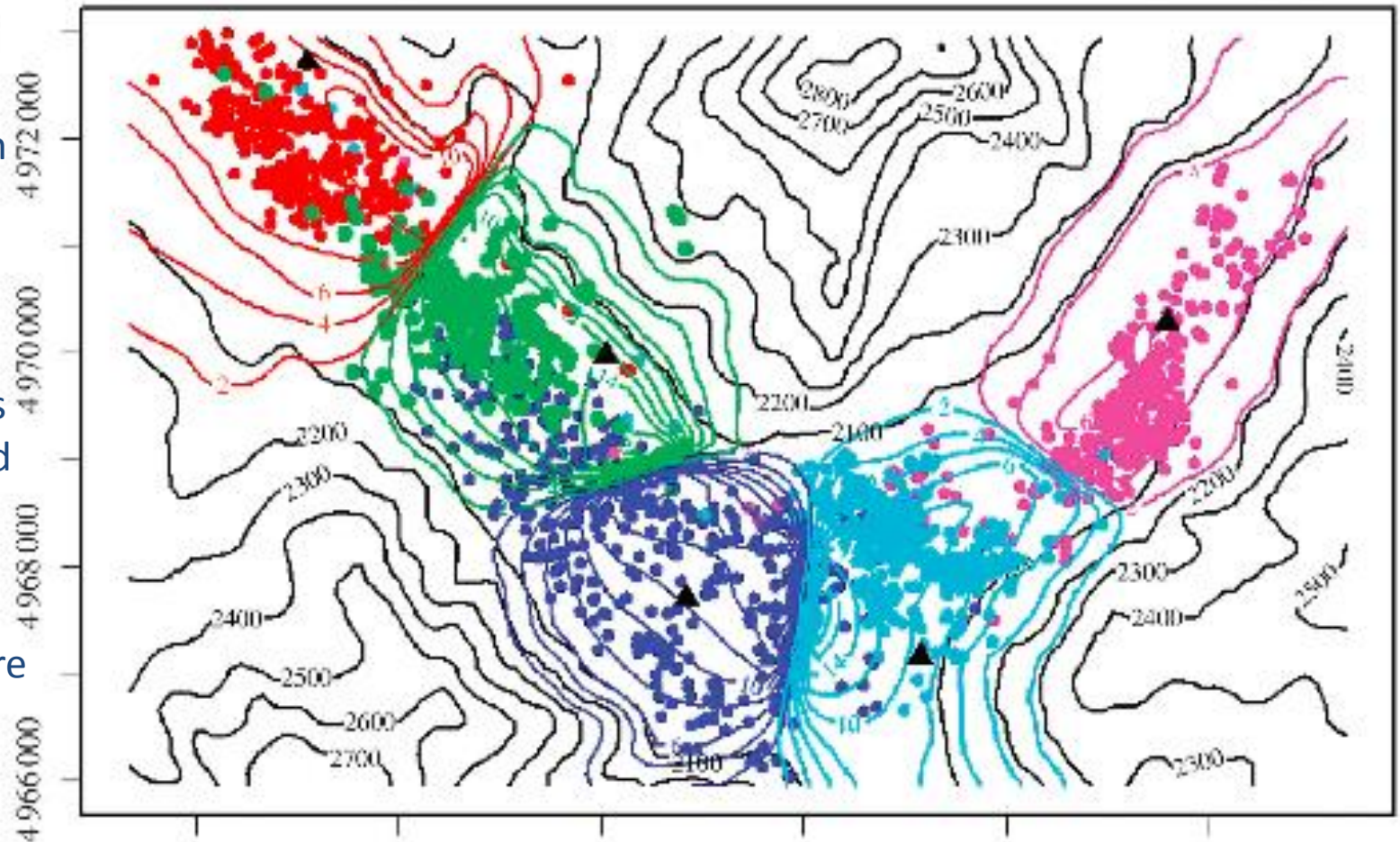
# Paul R. Moorcroft, Mark A. Lewis and Robert L. Crabtree, Proc. Roy. Soc. B, 2006

Mechanistic home range models capture spatial patterns and dynamics of coyote territories in Yellowstone

Dots show location of coyotes from radio collar data.

Colored contour lines are predicted density of packs

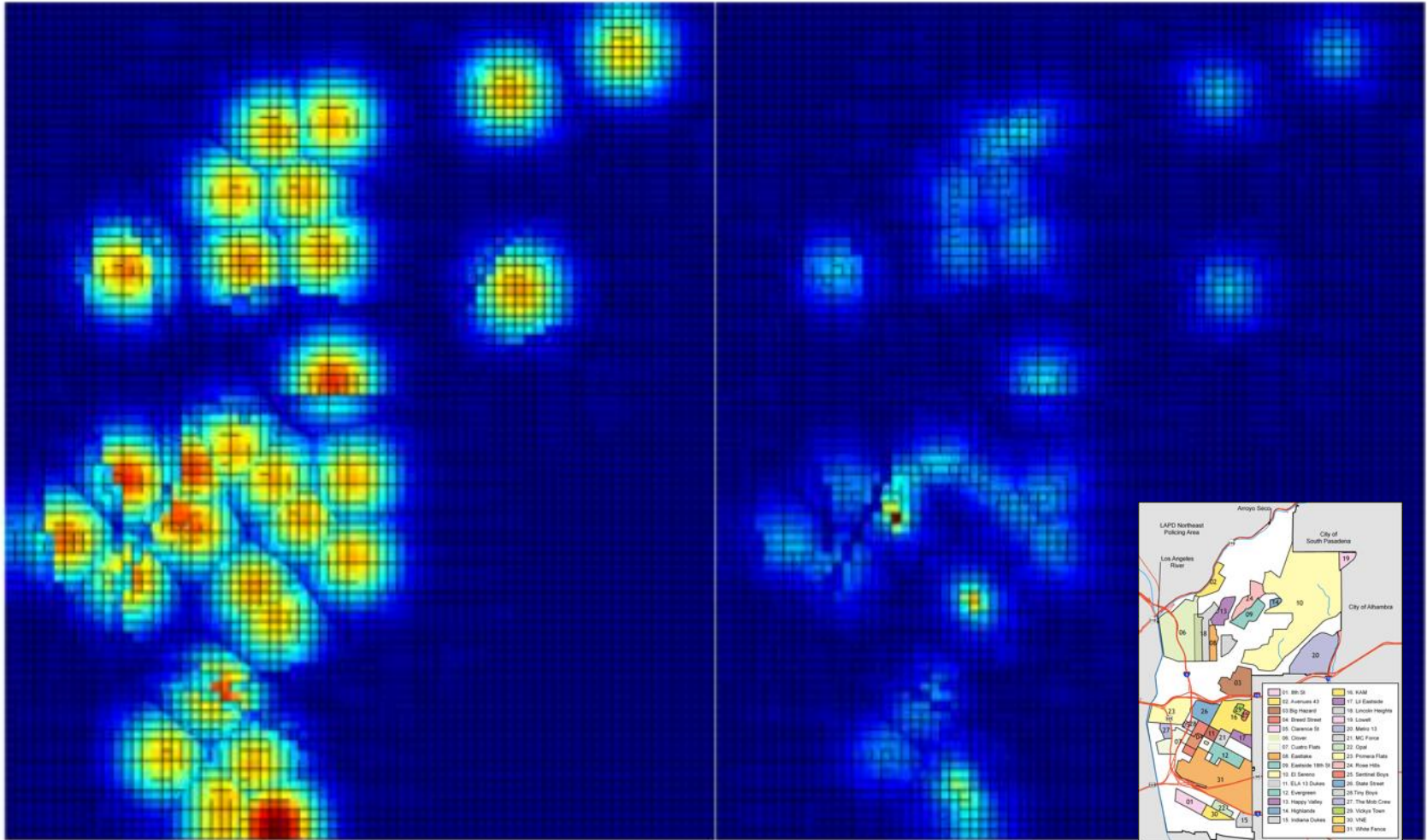
Black lines are terrain elevation.





# Resulting Gang and Marking Densities

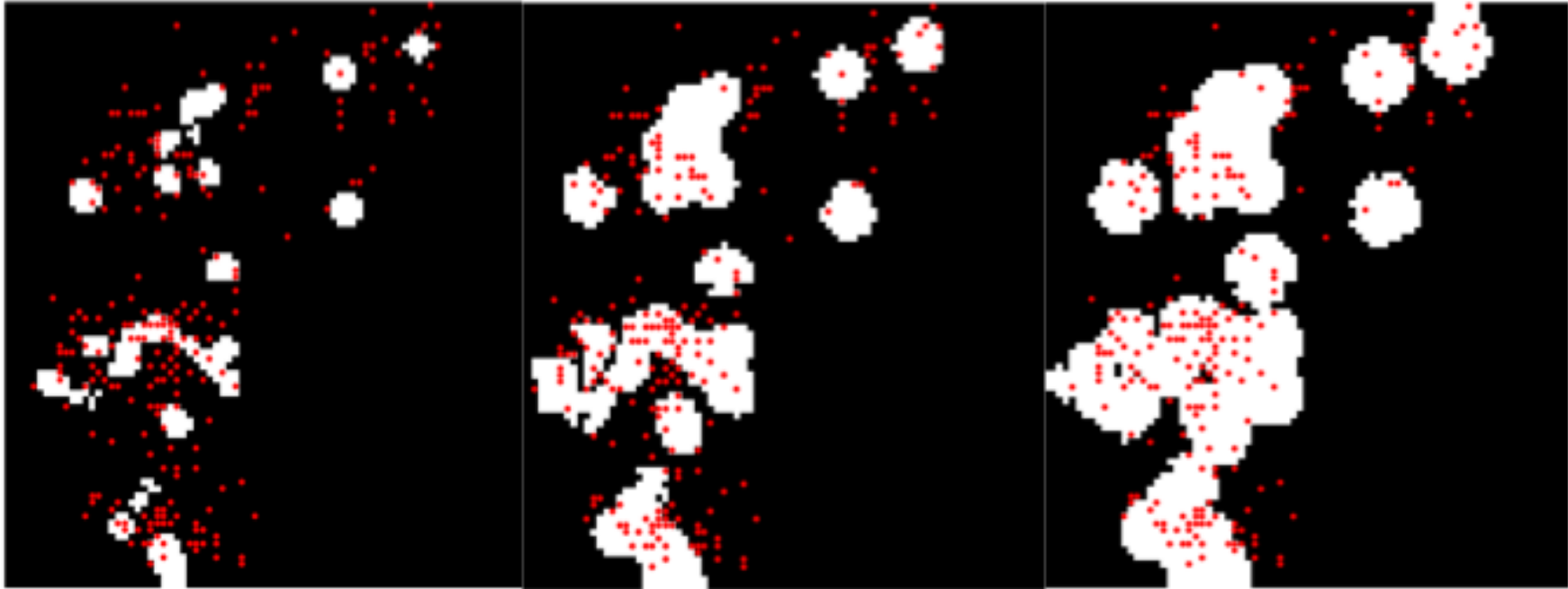
(left) Prediction of street gang activity in Hollenbeck; (right) predicted gang tag densities  
Note: we can not have “radio collar” data for street gangs. Graffiti data could be generated.





# Flagging the Top Marking Densities ( $\gamma = 0.2, 0.1, 0.05$ )

Without graffiti data we compare to gang violence data. Thresholding predicted graffiti Density recovers areas with a proportionately large percentage of violence.

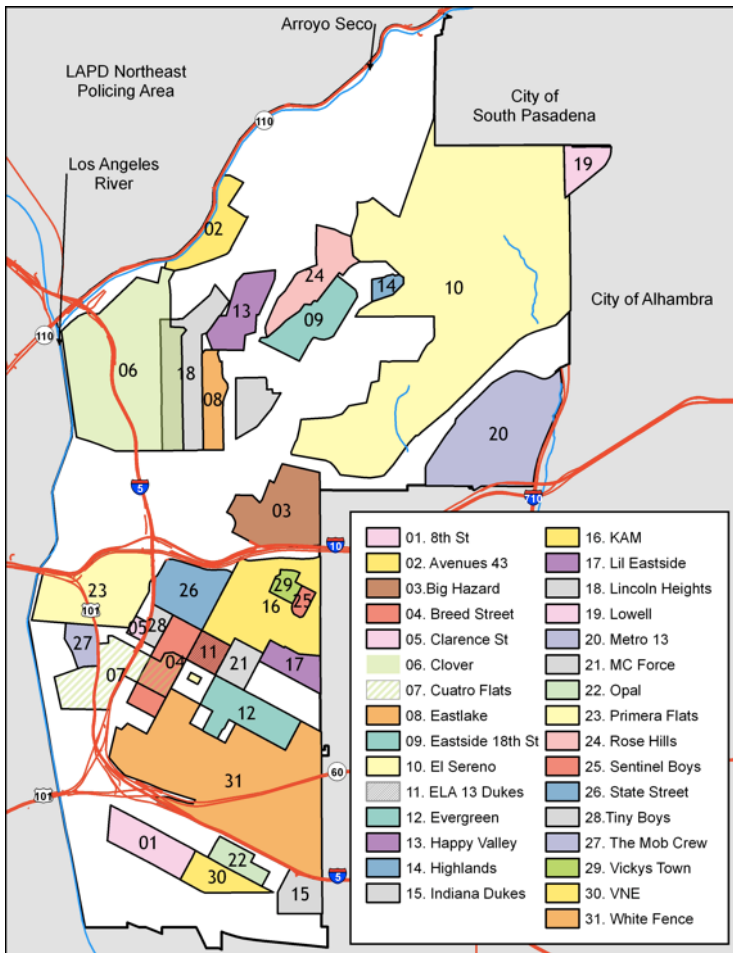


$\gamma$	Percent of City Flagged	Percent of Violence Data Predicted
0.2	5.02%	20.61%
0.1	13.94%	50.91%
0.05	22.46%	71.21%

# Field Interview Cards Hollenbeck LAPD

*home to about 30 adversarial street gangs*

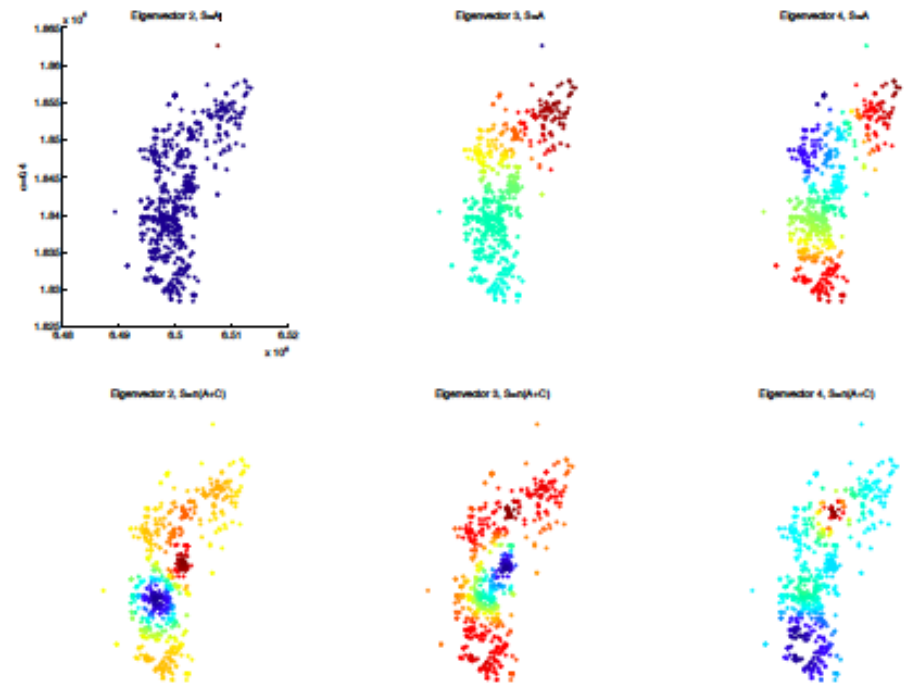
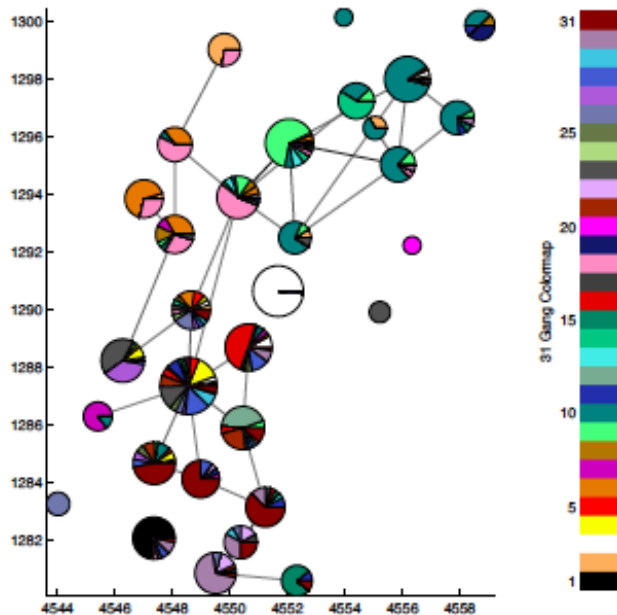
34000 events over several years  
 Geographic area is 15 sq. miles  
 Groups of people observed  
 together in time and space



OP. LIC. NO		STATE	NAME (LAST, FIRST, MIDDLE)			SUFFIX (JR, ETC.)			
O		F		N		J			
RESIDENCE ADDRESS			CITY	STATE	SEX	DESCENT	HAIR	EYES	
A		C		S		D		H	
HEIGHT	WEIGHT	BIRTHDATE		CLOTHING					
T		W		B					
PERSONAL ODDITIES							PHONE NO.		
BUSINESS ADDRESS/SCHOOL/UNION AFFIL.							SOC. SEC. NO.		
							Z		
MONIKER/ALIAS					GANG/CLUB				
<b>SUBJ</b>		1 LOITERER		3 SOLICITOR		5 GANGACTIVITY		7 ON PAROLE	
<b>INFO</b>		2 PROWLER		4 WITNESS		6 HAS RECORD		8 ON PROBATION	
								<input type="checkbox"/> <b>DRIVER</b> <input type="checkbox"/> <b>PASSENGER</b>	
YEAR		MAKE		MODEL		TYPE		COLOR	
V		L		K		G			
INT COLOR		I		N		E		X	
H		1 DAMAGE		3 STICKER		4 LEFT		6 FRONT	
		1 BUCKET SEAT		2 DAMAGED INSIDE		1 CUST. WHEELS		3 LEVEL ALTER	
						2 PAINTED MURAL		4 RUST/PRIMER	
								5 CUST. PAINT	
								6 VINYL TOP	

# Identifying communities in street gangs from field interview card data

- Project started as summer REU. Uses graph theory and social/spatial network structure
- van Gennip et al. SIAM J. Appl. Math 2013



# Ego-motion classification for body-worn videos

Zhaoyi Meng, Javier Sánchez, Jean-Michel Morel, Andrea L. Bertozzi, and P. Jeffrey Brantingham. Ego-Motion Classification for Body-Worn Videos. *manuscript*.

## Movement Signals

- **x:** horizontal translation
- **y:** vertical translation
- **r:** rotation
- **z:** z-axis translation

## Frequency Signals

- $f_x, f_y, f_r, f_z$

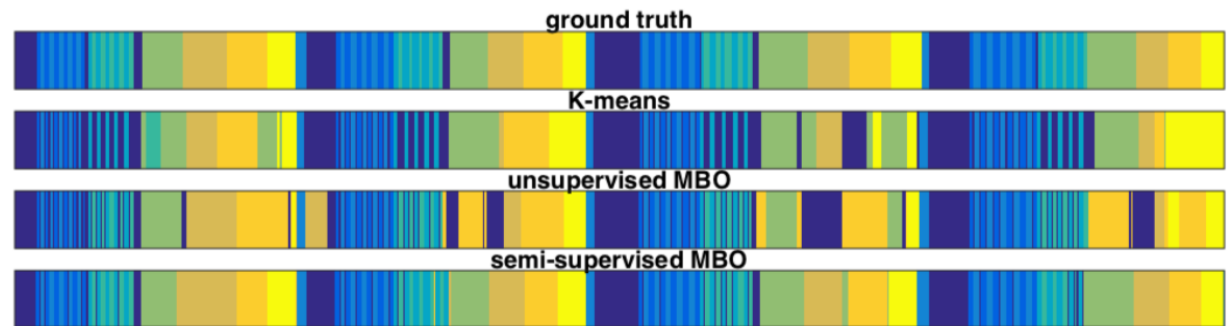
## Feature Vector:

$[x, y, r, z,$   
 $f_x, f_y, f_r, f_z]$

**Table 2** Accuracy Summary of the QUAD data set

Accuracy	Overall	Average	1.Stand still	2.Turn left	3.Turn right	4.Look up
K-means	<b>64.84%</b>	<b>61.79%</b>	95.82%	72.26%	77.28%	73.24%
Unsupervised MBO	<b>66.62%</b>	<b>67.59%</b>	79.99%	76.82%	83.37%	69.41%
Semi-supervised MBO	<b>89.14%</b>	<b>88.74%</b>	87.90%	89.43%	92.80%	80.36%

Accuracy	5.Look down	6.Jump	7.Step	8.Walk	9.Run
K-means	0	83.29%	49.29%	36.66%	68.25%
Unsupervised MBO	77.82%	39.38%	43.54%	83.27%	54.68%
Semi-supervised MBO	84.59%	92.71%	93.98%	84.52%	92.38%



**Fig. 7** Ego-motion classification results of the QUAD video. The 9 colors represent 9 different ego-motion classes: standing still (dark blue), turning left (moderate blue), turning right (light blue), looking up (dark green) and looking down (light green), jumping (bud green), stepping (aztec gold), walking (orange), running (yellow).

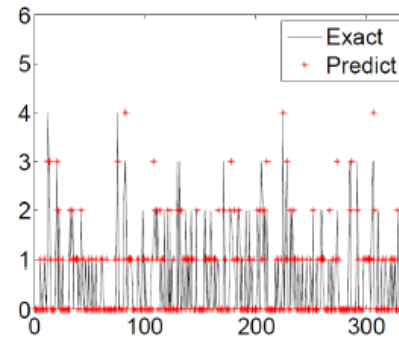


# Temporal Distribution Forecasting

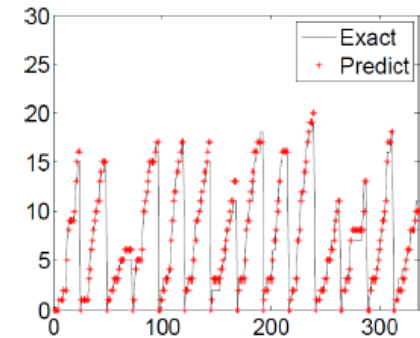
B. Wang, D. Zhang, D. Zhang, P. J. Brantingham, and A. L. Bertozzi, Deep Learning for Real Time Crime Forecasting, NOLTA 2017  
B. Wang, X. Luo, F. Zhang, B. Yuan, A. L. Bertozzi, and P. J. Brantingham, Graph-based deep modeling and real time forecasting of sparse spatio-temporal data, to appear MileTS at KDD London, 2018

Predict # of crimes by the hour in an area the size of a zipcode (typical patrol area). Could be used for resource allocation in real time.

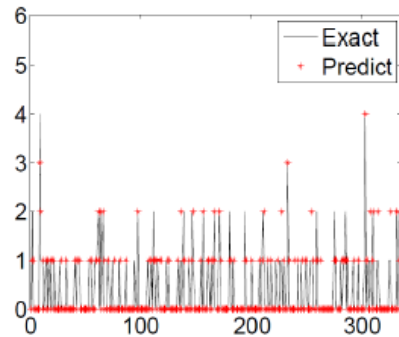
Uses deep learning, point process models, and shows excellent results for both LA and Chicago crime prediction.



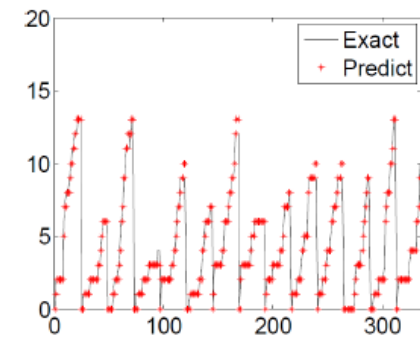
(a)



(b)



(a)



(b)

Predicted vs. exact crime for two sample grid cells in LA (Dec 2015). (a) shows crime intensity (number of events) and (b) shows cumulated intensity per day. Time unit is hours.

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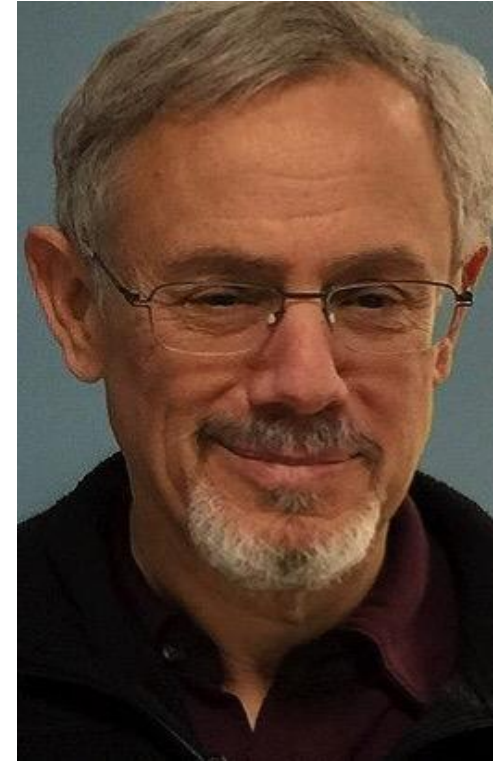
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