Predictive Policing

Data, Discretion, and the Future of Policing

Courts, Corrections, and Justice Committee

September 27th, 2023

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Level Setting: Definitions

Big data: 3 Vs (Volume, Variety, and Velocity)

Algorithm: formally specified set of instructions used to analyze data and automate decisions

Artificial Intelligence: capability of a machine to imitate intelligent human behavior

Machine learning: subfield of artificial intelligence that gives computers the ability to learn without explicitly being programmed (can be ”supervised” or “unsupervised”)

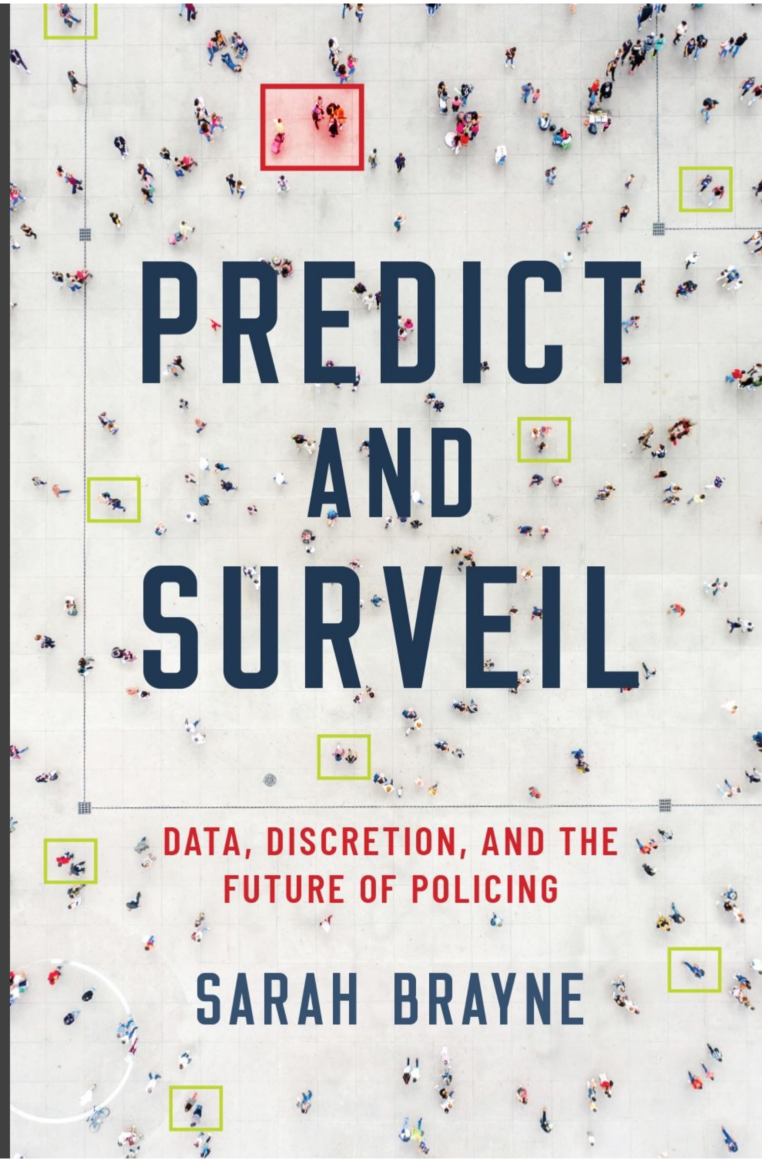
E.g., natural language processing, neural networks, deep learning

Predictive policing: the use of data to predict when and where crime is more likely to occur in the future, and who is likely to be involved

the computational analysis of massive and diverse datasets to automate decisions and make predictions.

Focus: Policing

- Feeder into criminal justice system
- Reforms targeted at policing phase can be very impactful because they cascade into other phases of criminal justice system


PREDICT
AND
SURVEIL
DATA, DISCRETION, AND THE
FUTURE OF POLICING
SARAH BRAYNE

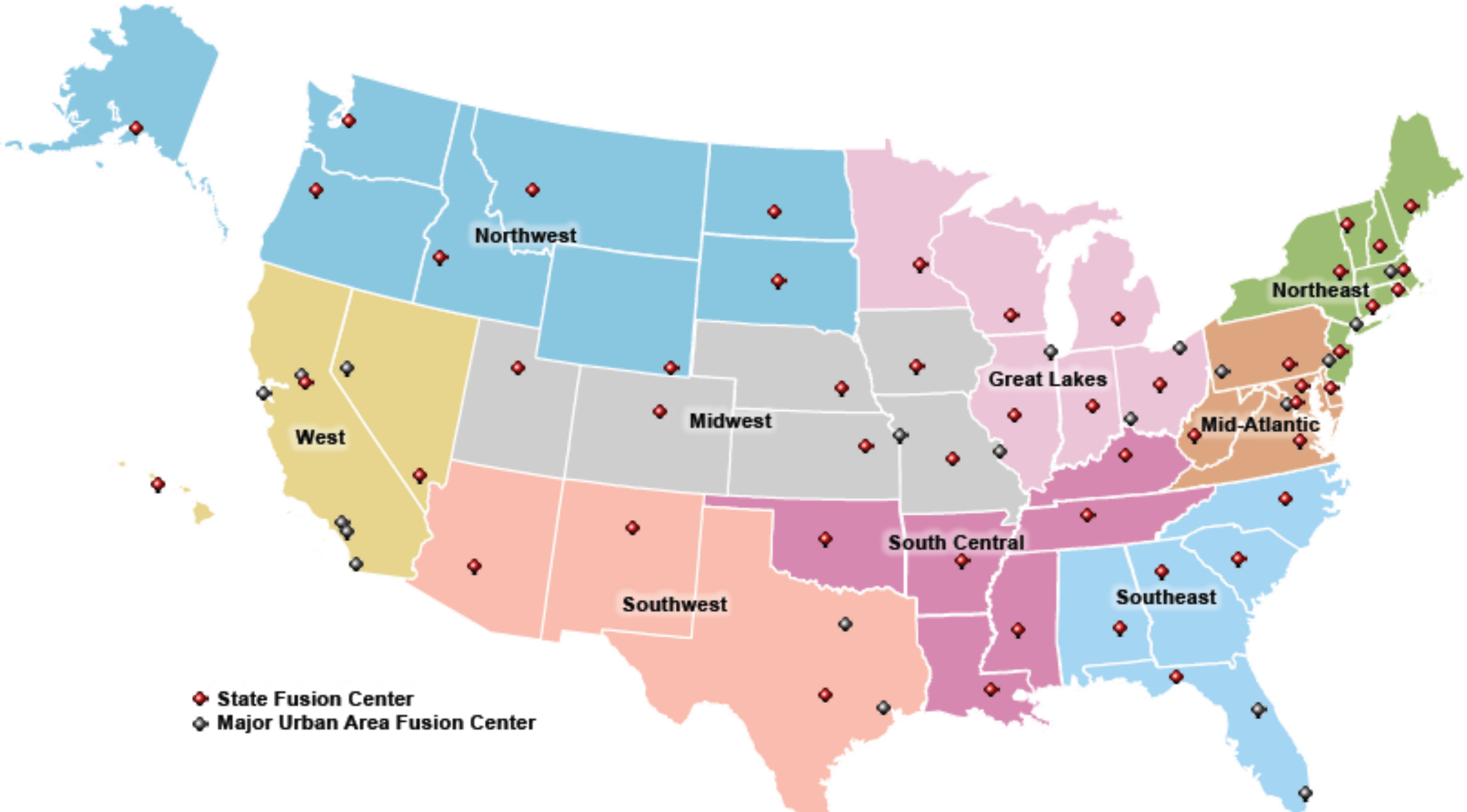
Fieldwork

- **Los Angeles Police Department**
  - Area divisions
  - Specialized divisions: Robbery-Homicide, Information Technology, Fugitive Warrants, Records and Identification, Juvenile, Risk Management, Air Support
  - RACR
  - Ride-alongs
- **LA County Sheriff's Department**
- **JRIC**
- **PredPol**
- **Palantir**
- **Surveillance industry conferences**
- **Training manuals**


12440


Palantir

The National Network



Homeland Security

The state has long used data for governance. What’s new?

- The state has long used data to govern its citizens
- Recently, state actors relying more heavily on private vendors
- Privatization brought the logic of risk, actuarial calculations
- Police use data for: 1) Efficiency; 2) Accountability and Legitimacy

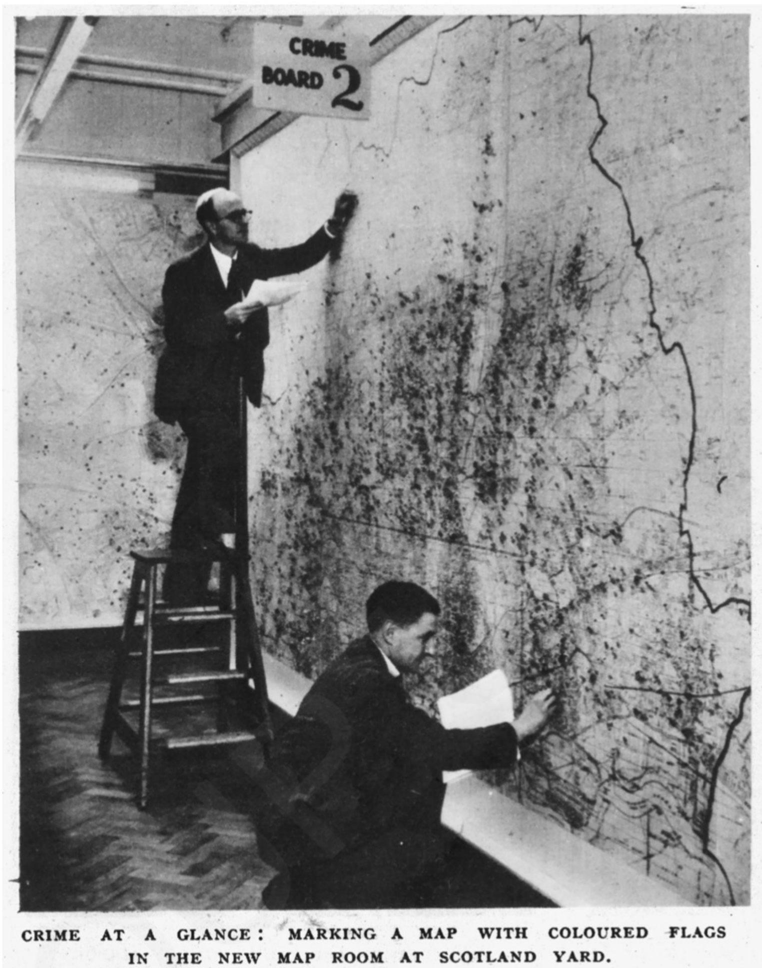


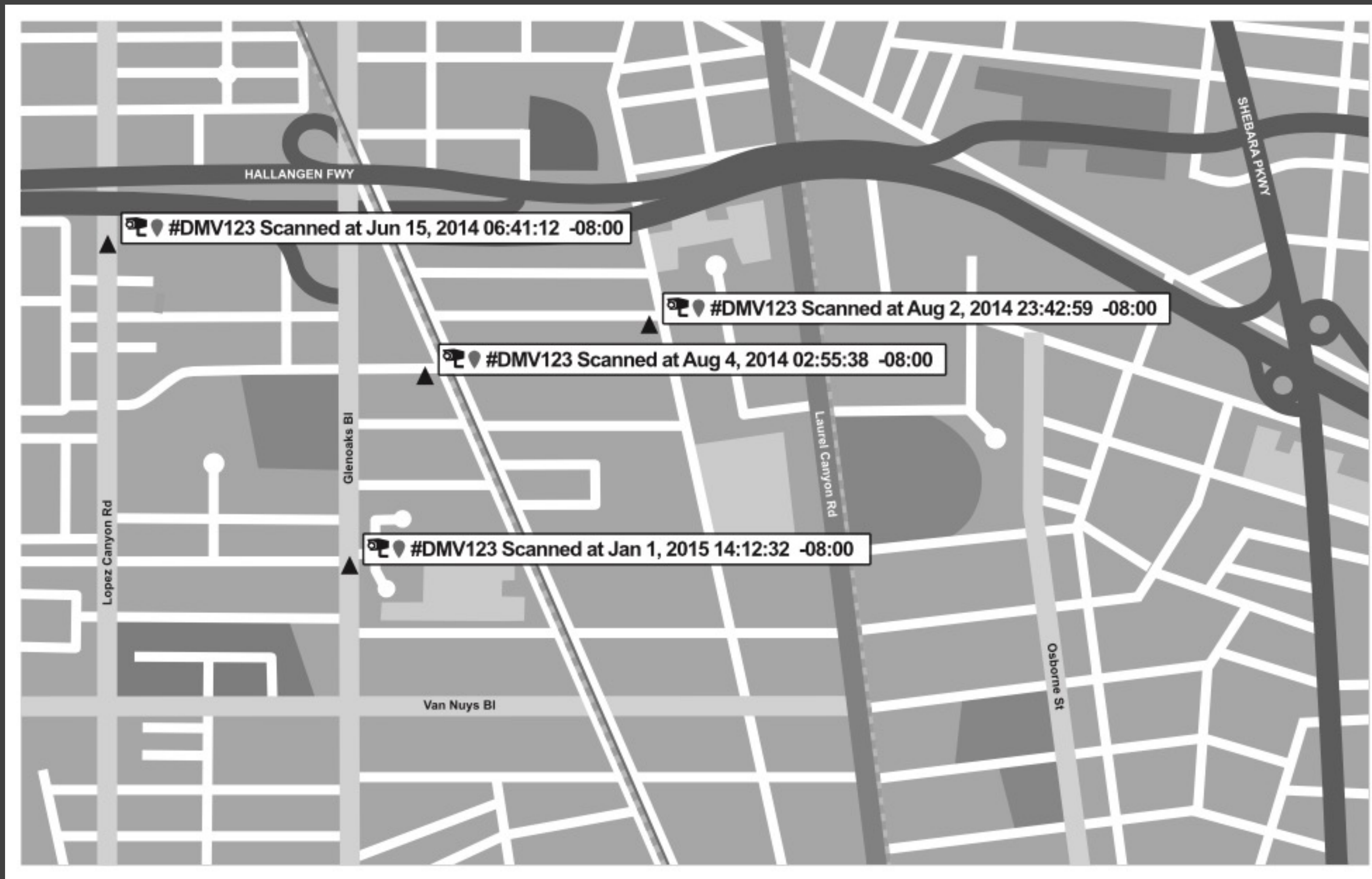
FIGURE 2.1 Crime pin maps at Scotland Yard, 1947
Copyright: Illustrated London News Ltd/Mary Evans

Inside a CompStat meeting. Photo: Bryan R. Smith/The New York Times/Redux


length while
getAttribute
return"undefined"
length
querySelectorAll
length
push
contains
attribute
push

Police use big data to conduct two different kinds of surveillance

1. **Dragnet**: surveillance of everyone, rather than just those under suspicion
2. **Directed**: surveillance of people and places deemed suspicious


HALLANGEN FWY
SHEBARA PKWY
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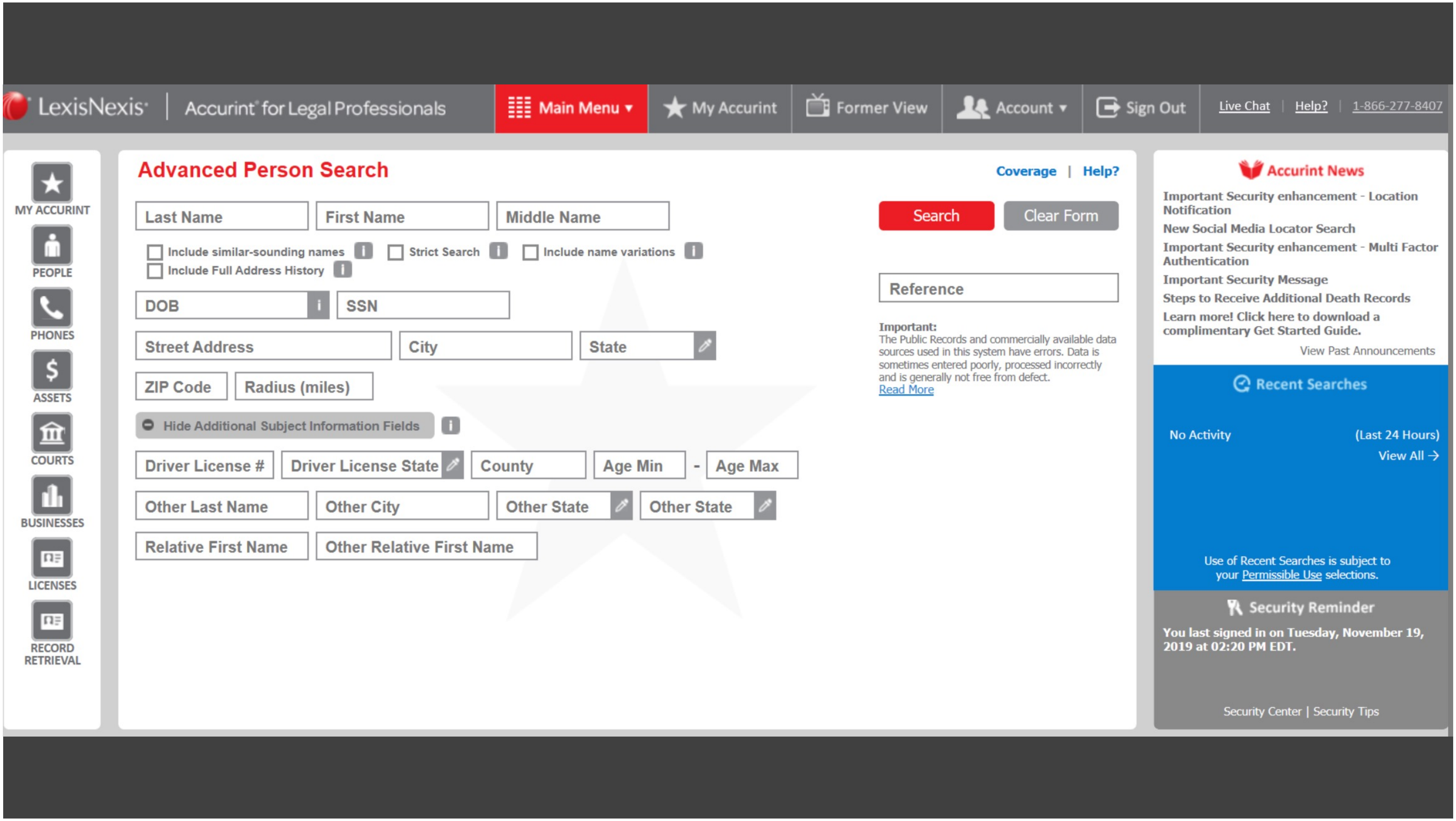
LexisNexis
Accurint for Legal Professionals
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Live Chat | Help? | 1-866-277-8407
MY ACCURINT
PEOPLE
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BUSINESSES
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Advanced Person Search
Coverage | Help?
Last Name
First Name
Middle Name
Search
Clear Form
Include similar-sounding names
Strict Search
Include name variations
Include Full Address History
DOB
SSN
Reference
Street Address
City
State
ZIP Code
Radius (miles)
Important:
The Public Records and commercially available data sources used in this system have errors. Data is sometimes entered poorly, processed incorrectly and is generally not free from defect.
Read More
Hide Additional Subject Information Fields
Driver License #
Driver License State
County
Age Min
Age Max
Other Last Name
Other City
Other State
Other State
Relative First Name
Other Relative First Name
Accurint News
Important Security enhancement - Location Notification
New Social Media Locator Search
Important Security enhancement - Multi Factor Authentication
Important Security Message
Steps to Receive Additional Death Records
Learn more! Click here to download a complimentary Get Started Guide.
View Past Announcements
Recent Searches
No Activity
(Last 24 Hours)
View All
Use of Recent Searches is subject to your Permissible Use selections.
Security Reminder
You last signed in on Tuesday, November 19, 2019 at 02:20 PM EDT.
Security Center | Security Tips

Predictive policing

- Location based: to predict property crime
- Person based: to predict violent crime

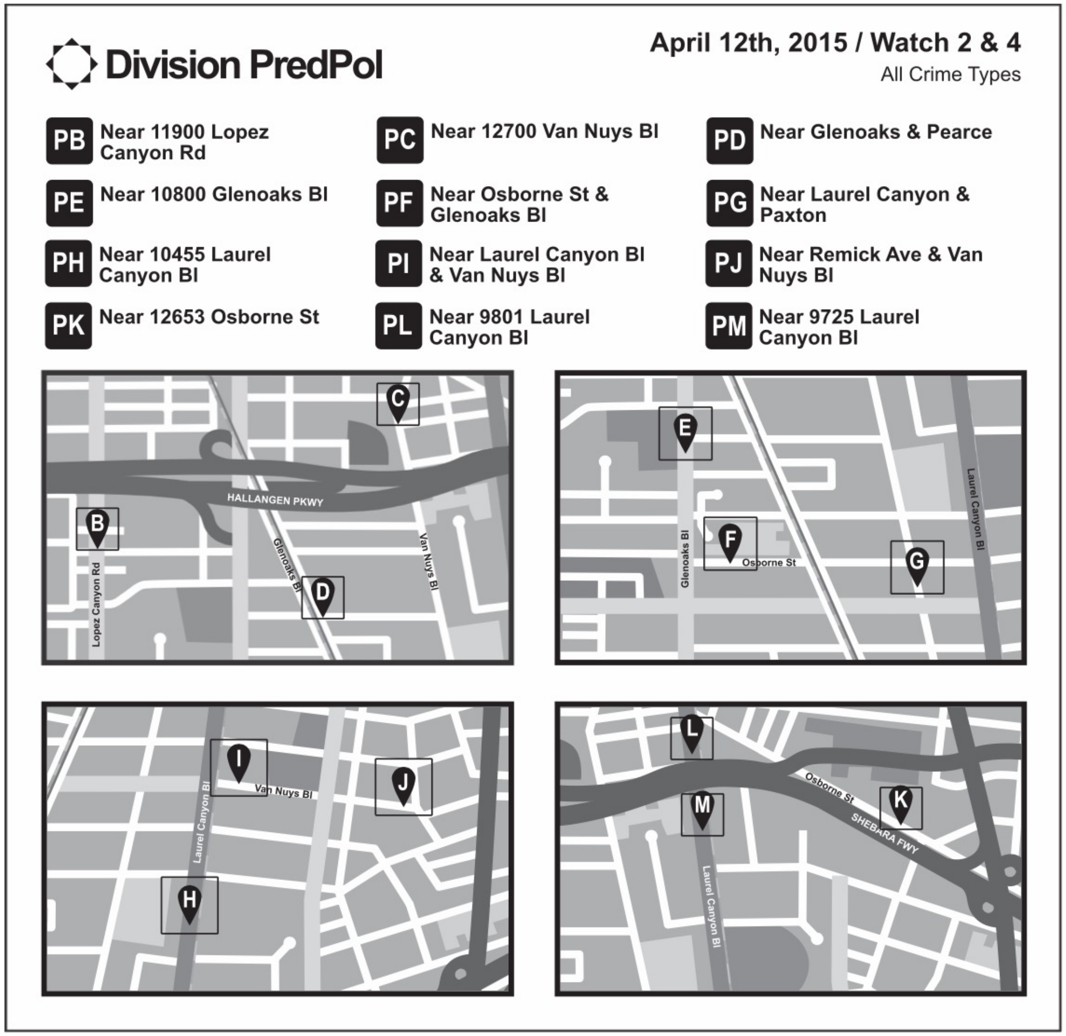


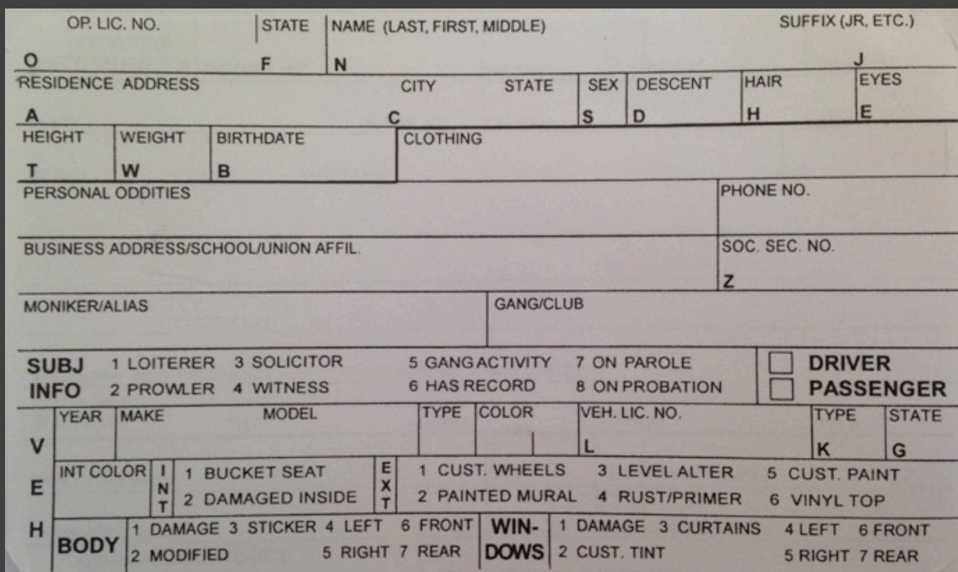
FIGURE 4.4 PredPol printout
SOURCE: LAPD; rendering by David Hallangen

Algorithmic bias

- Systematic errors that lead to unfair outcomes
- If training data is biased, so too will the outcomes be biased
- Feedback loop/self-fulfilling prophecy
- Why might crime data be biased?

Person-based predictive policing

- 5 points for violent crime
- 5 points for gang affiliation
- 5 points for prior arrest w/ handgun
- 5 points for parole/probation
- *1 point for every police contact*



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 E

HEIGHT | WEIGHT | BIRTHDATE | CLOTHING

T W B

PERSONAL ODDITIES | PHONE NO.

BUSINESS ADDRESS/SCHOOL/UNION AFFIL. | SOC. SEC. NO.

Z

MONIKER/ALIAS | GANG/CLUB

SUBJ INFO 1 LOITERER 3 SOLICITOR 5 GANG ACTIVITY 7 ON PAROLE
2 PROWLER 4 WITNESS 6 HAS RECORD 8 ON PROBATION

☐ **DRIVER**
☐ **PASSENGER**

VEH

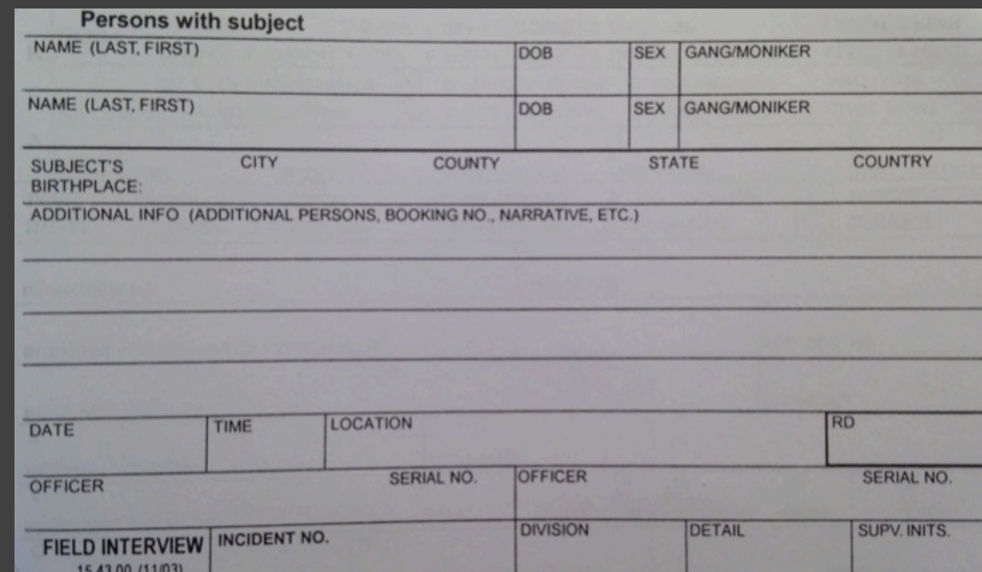
YEAR | MAKE | MODEL | TYPE | COLOR | VEH. LIC. NO. | TYPE | STATE

L K G

INT COLOR | INT 1 BUCKET SEAT 2 DAMAGED INSIDE | EXT 1 CUST. WHEELS 2 PAINTED MURAL 3 LEVEL ALTER 4 RUST/PRIMER 5 CUST. PAINT 6 VINYL TOP

BODY 1 DAMAGE 2 MODIFIED 3 STICKER 4 LEFT 5 RIGHT 6 FRONT 7 REAR

WIN-DOWS 1 DAMAGE 2 CUST. TINT 3 CURTAINS 4 LEFT 5 RIGHT 6 FRONT 7 REAR



Persons with subject

NAME (LAST, FIRST) | DOB | SEX | GANG/MONIKER

NAME (LAST, FIRST) | DOB | SEX | GANG/MONIKER

SUBJECT'S BIRTHPLACE: CITY | COUNTY | STATE | COUNTRY

ADDITIONAL INFO (ADDITIONAL PERSONS, BOOKING NO., NARRATIVE, ETC.)

DATE | TIME | LOCATION | RD

OFFICER | SERIAL NO. | OFFICER | SERIAL NO.

FIELD INTERVIEW | INCIDENT NO. | DIVISION | DETAIL | SUPV. INITS.

15.43.00 (11/03)

> “Yesterday this individual might have got stopped because he jaywalked. Today, he mighta got stopped because he didn’t use his turn signal or whatever the case might be. So that’s two points…you could conduct an investigation or if something seems out of place you have your consensual stops. ‘Hey, can I talk to you for a moment?’ ‘Yeah what’s up?’ You know, and then you just start filling out your card as he answers questions or whatever. And what it was telling us is who is out on the street, you know, who’s out there not necessarily maybe committing a crime, but who’s active on the streets. You put the activity of…being in a street with maybe their violent background and one and one might create the next crime that’s gonna occur.”

LAW ENFORCEMENT SENSITIVE

DIVISION

Chronic Offender List

Monday, April 13, 2015

Thompson, Stephen James **AKA: LIL GHOUL** **26**
A12345678 Unit(s) Assigned: GED
1/17/1984 Laser-1
Primary Gang: 12th Street

Smith, John **25**
A11234567 Unit(s) Assigned: GED
2/20/1991 Laser-1
Wanted For: Warrant - Arrest Felony
Status: Summary Probation

Matthews, Brian **AKA: BOSS HAWG** **22**
A11123456 Unit(s) Assigned: GED
10/16/1985 Laser-1
Primary Gang: Hawg Boyz
Wanted For: Warrant - Arrest Felon, Warrant - Misd
Status: Parole

Davis, Carl **21**
A11112345 Unit(s) Assigned: SPU
2/22/1950 Laser-1
Primary Gang: 12th Street
Status: Formal Probation

Jones, Douglas **21**
A11111234 Unit(s) Assigned: GED
11/19/1994 Laser-1
Status: Summary Probation

Watts, Mark **21**
A11111123 Unit(s) Assigned: GED
10/1/1993 Laser-1
Status: Formal Probation

INFORMATION ONLY

Notification

LOS ANGELES POLICE DEPARTMENT
OFFICIAL PUBLICATION OF THE LAPD DIVISION CRIME INTELLIGENCE DETAIL
NOT TO BE PRINTED OR DISSEMINATED (READ ONLY)

THE BELOW LISTED INDIVIDUAL IS NOT WANTED AT THIS TIME. **THIS PUBLICATION IS DESIGNED TO PROVIDE INFORMATION ON PROMINENT KNOWN OFFENDERS, CAREER CRIMINALS, ETC** AND IS NOT TO BE USED AS THE SOLE BASIS FOR YOUR PROBABLE CAUSE TO DETAIN THE INDIVIDUAL LISTED BELOW FOR ANY FUTURE CONTACTS. **IF YOU BECOME AWARE OF AN INDIVIDUAL THAT MATCHES THE SUSPECT DESCRIPTION ON A CRIME REPORT, PRIOR TO ANY FURTHER INVESTIGATION YOU SHALL CONTACT THE APPROPRIATE DETECTIVE COORDINATOR FOR THAT CRIME.**

NAME: Thompson, Stephen James
DOB: 12/10/1984
CII#: A12345678

CDL#: D1234567

123 W. 12TH STREET, LOS ANGELES, CA, 90009
456 W. 78TH STREET, LOS ANGELES, CA, 90009

SEX: M
HAIR: BLK **HEIGHT:** 602
EYES: BRN **WEIGHT:** 205

PHYSICAL ODDITIES:
TATTOO ON RIGHT HAND "12"
TATTOO ON LEFT HAND "GJ"
TATTOO ON RIGHT ARM "ONE"
TATTOO ON LEFT ARM "DEUCE"
TATTOO ON RIGHT ARM "LIL GHOUL"

ARREST:
211, ADW, 10851 VC AND BURGLARY, GRAND THEFT PERSON, NARCOTICS (POSS. CONT. SUBS. FOR SALE), CRIMINAL THREATS

CALGANGS:
12TH STREET GANGSTER WITH MONIKER OF "LIL GHOUL, LIL GJ"

PAROLE:
NONE

PROBATION:
NONE

WARRANTS:
NONE

VEHICLES:
1995 HONDA ACCORD 4D WHI CA-1ABC123
DRIVER 01/02/2010
2001 TOYOTA CAMRY 4D BLK CA-2CD456
DRIVER 04/05/2011

RECENT STOP:
OFFICERS: SMITH #12345 / CARSON #67890
DATE: 06/07/2013
LOCATION: 12TH ST/MAIN ST
RD: 1234
NARRATIVE/MO: PED STOP POSSIBLE ROBBERY SUSPECTS. WANT AND WARRANT CHECK. SELF ADMITTED 12TH STREET GANGSTER WITH MONIKER OF "LIL GHOUL." QUESTIONED AND RELEASED.
ASSOCIATES: STUART, DAVID (10/20/1987) "LIL MASK"
HOUSEMAN, MICHAEL (11/30/1984)

POLICE CONTACTS IN/NEAR DIVISION:

DATE	RD	LOCATION/DISPOSITION
04/05/2010	1234	12TH PL/MAIN PS/CONSENT Q&R
06/07/2010	5678	T/S FOR EXPIRED REG
08/09/2011	1234	STOPPED FOR PED IN ROADWAY

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Prepared by: <A. BROWN, SERIAL # 12345 > **Crime Intelligence Detail (123) 456-7890** **Date:** 1/02/2012

> “The Code of Federal Regulations. They say you shouldn’t create a—you can’t target individuals especially for any race or I forget how you say that. But we didn’t want to make it look like we’re creating a gang depository of just gang affiliates or gang associates…we were just trying to cover and make sure everything is right on the front end.”

Big data policing harder to challenge

- Looks objective
- Algorithmic opacity
- Trade secrecy


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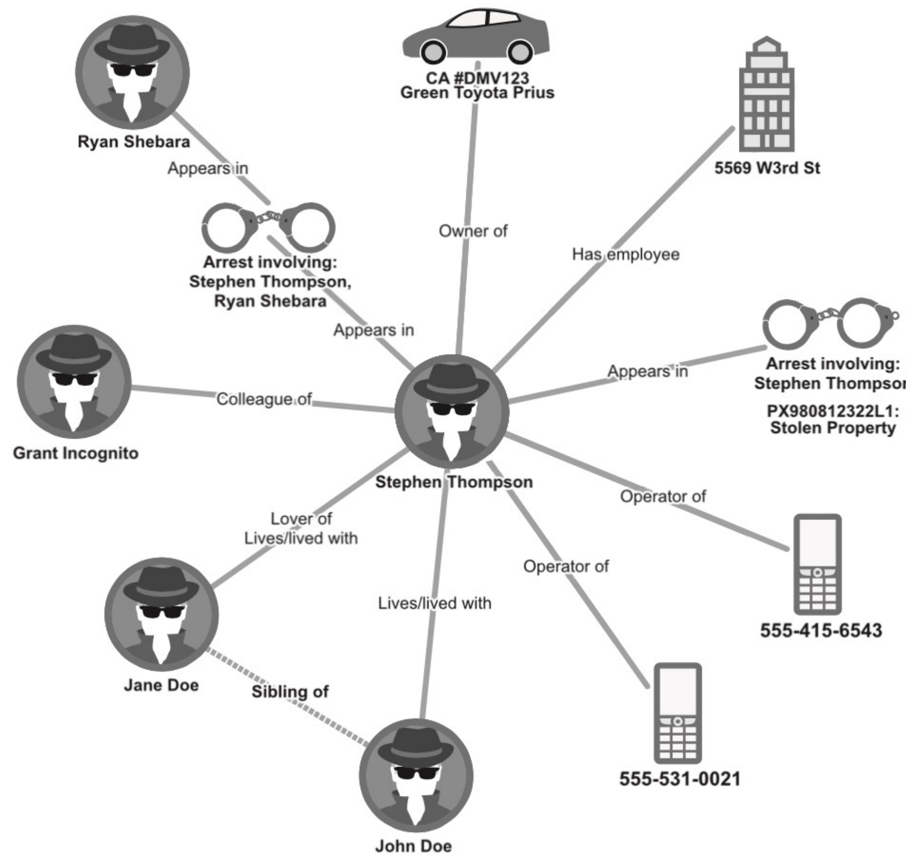
Locations
Crime
Arrests
FIs
Citations
Bulletins
Tips
Everything
0 unread feed messages
View my feeds
Recent investigations


CA #DMV123
Green Toyota Prius
Ryan Shebara
5569 W3rd St
Appears in
Owner of
Has employee
Arrest involving:
Stephen Thompson,
Ryan Shebara
Appears in
Arrest involving:
Stephen Thompson
PX980812322L1:
Stolen Property
Appears in
Colleague of
Grant Incognito
Stephen Thompson
Operator of
Lover of
Lives/lived with
Operator of
Lives/lived with
555-415-6543
Jane Doe
Sibling of
555-531-0021
John Doe

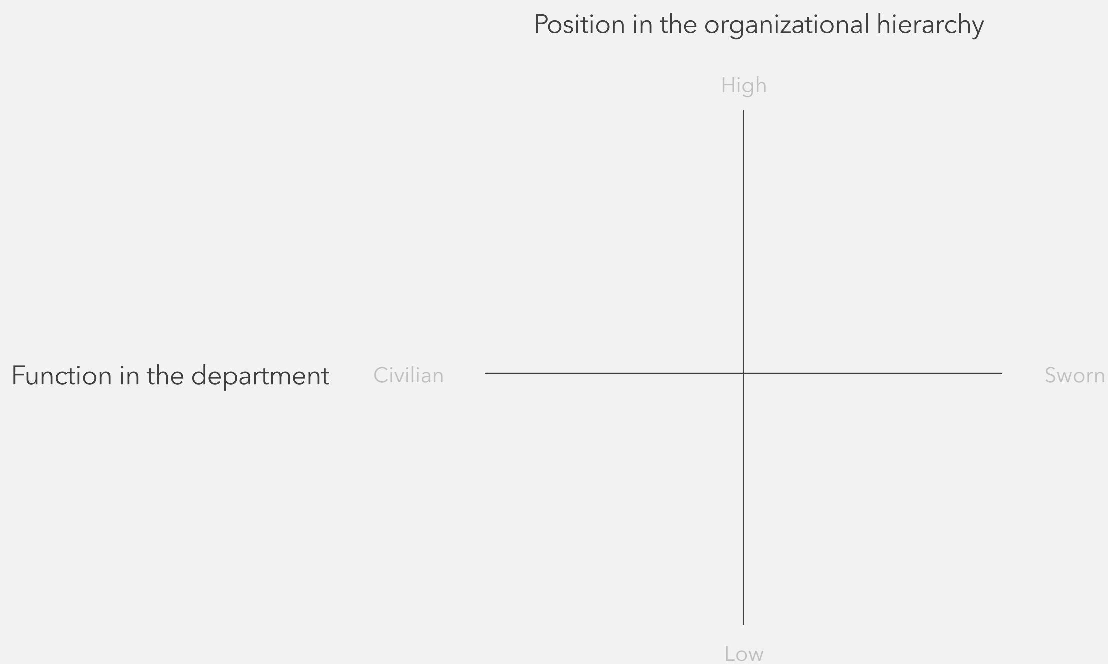
Big data policing is wider and deeper

- Includes a broader swath of people
- Can follow any single individual across a greater range of institutional settings, including those with no police contact

Using big data to police the police?

- Digital policing leaves digital trails
- Potential to police the police?

Resistance varied along two axes



Implications for social inequality

- Reduce existing inequalities?
    1. Less biased predictions of risk (humans as cognitive misers)
    2. Police the police
- Reinforce existing inequalities?

Implications for social inequality

- Reduce existing inequalities?

- Reinforce existing inequalities?
  1. Deepen surveillance of individuals already under suspicion *while appearing to be objective*

Implications for social inequality

- Reduce existing inequalities?

- Reinforce existing inequalities?
  1. Deepen surveillance of individuals already under suspicion *while appearing to be objective*

  2. Widen CJ dragnet unequally along lines of race, class, neighborhood

Implications for social inequality

- Reduce existing inequalities?
- Reinforce existing inequalities?
  1. Deepen surveillance of individuals already under suspicion *while appearing to be objective*
  2. Widen CJ dragnet unequally along lines of race, class, neighborhood
  3. Lead people to avoid surveilling institutions fundamental to social integration

Table 2. Logistic Regression Predicting Institutional Avoidance

	Avoided Surveilling Institutions						Avoided Non-surveilling Institutions			
	Medical Care		Bank Account		School/Work		Volunteer		Religious Group	
	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12	Model 13	Model 14	Model 15
Any Criminal Justice Contact	1.309***		1.186**		1.314***		.906		1.084	
	(.017)		(.068)		(.101)		(.049)		(.072)	
Stopped		1.332***		.939		1.198		.920		.994
		(.096)		(.076)		(.130)		(.064)		(.086)
Arrested		1.293**		1.294**		1.302*		.932		1.141
		(.119)		(.124)		(.162)		(.089)		(.135)
Convicted		1.331**		1.535***		1.304*		.867		1.238
		(.128)		(.153)		(.169)		(.089)		(.167)
Incarcerated		1.102		1.509*		2.181***		.732		1.410
		(.195)		(.273)		(.426)		(.149)		(.369)
Sociodemographic Controls	Yes†	Yes†	Yes	Yes	Yes	Yes	Yes	Yes	Yes‡	Yes‡
Behavioral Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	14,458	14,411	14,515	14,468	14,167	14,120	14,510	14,463	14,400	14,354
Pseudo R-squared	.071	.071	.207	.209	.089	.090	.095	.095	.283	.284

Note: All coefficients expressed as odds ratios. Standard errors are in parentheses. Sociodemographic controls include sex, race, age, education, parental education, marital status, nativity, household configuration (i.e., number in household and whether individuals live with parents), military service, and whether respondents are in school or have a job. Behavioral controls include whether individuals self-report stealing over or under $50, damaging property, carrying a gun or knife to school or work, stabbing someone, using cocaine or methamphetamine, selling drugs, or being in a gang, and whether respondents are classified as impulsive or candid.
†Includes controls for general health and possession of medical insurance.
‡Includes controls for religiosity and regular church attendance.
*$p < .05$; **$p < .01$; ***$p < .001$ (two-tailed tests).

Brayne, Sarah. 2014. "Surveillance and System Avoidance: Criminal Justice Contact and Institutional Attachment." *American Sociological Review*.

Table 3. Effect of Criminal Justice Treatment on Matched Samples

	Propensity Score Matching						Doubly Robust Estimation			
Avoidance	Treated	Controls	Difference	SE	*T*-stat	Significance	OR	SE	*N*	Pseudo R^2
Surveilling Institutions										
Medical care	.321	.282	.039	.019	2.070	$p < .05$	1.186*	.096	3,148	.057
Bank account	.410	.301	.109	.019	5.620	$p < .001$	1.704***	.146	3,160	.191
School/work	.157	.126	.031	.014	2.170	$p < .05$	1.321*	.144	3,088	.096
Non-surveilling Institutions										
Volunteer	.748	.753	–.005	.018	–.280	n.s.	.951	.083	3,162	.087
Religious groups	.837	.818	.018	.016	1.160	n.s.	1.176	.129	3,134	.249

Note: Models include same suite of sociodemographic and behavioral controls as in Models 6 through 15. Sociodemographic controls include sex, race, age, education, parental education, marital status, nativity, household configuration, military service, and whether respondents are in school or have a job. Behavioral controls include whether individuals self-report stealing over or under 50 dollars, damaging property, carrying a gun or knife to school or work, stabbing someone, using coke or meth, selling drugs, or being in a gang, and whether respondents are classified as impulsive or candid. In light of cross-sectional results, criminal justice treatment is defined as arrested, convicted, or incarcerated, although results remain substantially unchanged when stopped is included, with one exception—bank account is only marginally significant at the $p < .1$ level.
*$p < .05$; **$p < .01$; ***$p < .001$ (two-tailed tests).

Brayne, Sarah. 2014. "Surveillance and System Avoidance: Criminal Justice Contact and Institutional Attachment." *American Sociological Review.*

Table 4. Individual-Level Fixed-Effects Logistic Regressions Predicting Institutional Avoidance

	Avoided Surveilling Institutions						Avoided Non-surveilling Institutions			
	Medical Care[a]		Bank Acct.		Work		Volunteer		Religious Group[b]	
	Model 16	Model 17	Model 18	Model 19	Model 20	Model 21	Model 22	Model 23	Model 24	Model 25
Any Criminal Justice Contact	1.478***		1.904***		1.411***		.915		1.067	
	(.115)		(.417)		(.147)		(.178)		(.093)	
Arrested		1.359**		1.827***		1.287		.807		1.025
		(.14)		(.406)		(.185)		(.216)		(.121)
Convicted		1.345*				1.011		1.052		.841
		(.174)				(.169)		(.343)		(.136)
Incarcerated		1.588***		1.702		1.750***		.892		1.247
		(.160)		(.842)		(.224)		(.226)		(.144)
Wave fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	7,620	7,574	2,753	2,753	4,422	4,396	16,576	16,426	6,910	6,882
Pseudo *R*-squared	.069	.069	.092	.092	.137	.137	.87	.869	.106	.108

Note: All coefficients expressed as odds ratios. Models 16, 17, and 20 through 25 estimated using Add Health; Models 18 and 19 estimated using NLSY97. Standard errors are in parentheses.
[a]Models include controls for general health and possession of health insurance.
[b]Models include controls for religiosity and church attendance.
*$p < .05$; **$p < .01$; ***$p < .001$ (two-tailed tests).

Brayne, Sarah. 2014. "Surveillance and System Avoidance: Criminal Justice Contact and Institutional Attachment." *American Sociological Review*.

Implications for law

1. Pacing problem
2. Unsettles underlying legal categories (e.g., individualized suspicion, reasonable suspicion, probable cause, what constitutes a search)
3. Data are different in kind, not just degree
4. New opportunities for parallel construction

Nothing to hide, nothing to fear?

Takeaways

1) Algorithms do not transcend, but rather are shaped by the social world in which they are created and used.
2) Tradeoffs that are not made explicitly are inevitably made implicitly (e.g., fairness, accuracy, transparency, simplicity, privacy). Being explicit and quantifying our values is uncomfortable but necessary. It will allow us to measure progress.
3) Data does not *replace,* but rather *displaces* discretion to earlier, less visible, and therefore potentially less accountable phases of the policing process.
4) Relevant to other parts of the criminal justice system and beyond

Other data and criminal justice projects

1) Use of social media data in criminal cases
2) Civilian use of ”smart” surveillance tech

Thank you

Questions/comments: sbrayne@utexas.edu

Supplemental slides

Table 1. Framework for Analyzing Big Data Surveillance across Institutional Contexts

	Goals		*Means*	*Ends*	
Types of Surveillance	*Institutional Field*	*Relationship between Individual and Institution*	*Shifts in Surveillance Practices Associated with Big Data*	*Institutional Interventions*	*Consequences for Inequality*
Categorical Suspicion	Criminal justice, intelligence	Classifying individuals according to risk; potential as criminals/terrorists	1) Discretionary to quantified risk assessment 2) Explanatory to predictive analytics 3) Query-based to alert-based systems 4) Moderate to low inclusion thresholds 5) Disparate to integrated data	Marking, apprehension, social control	Stigma, spillover into other institutions
Categorical Seduction	Finance, marketing, credit	Classifying individuals according to their value to companies; potential as customers		Different products, perks, access to credit, opportunities, constraints	Upward or downward economic mobility; reproducing current patterns
Categorical Care	Medical care, public assistance	Classifying individuals according to their need; potential as clients		Personalized medicine, welfarist service delivery	May reduce inequality except when intersects with suspicion or seduction