“Modern technology can make many specific contributions to criminal administration. The most significant will come from the use of computers to collect and analyze the masses of data the system needs to understand the crime control process”

- 1967 President’s Commission on Law Enforcement and Administration of Justice

Computation and Criminology

Greg Ridgeway
Department of Criminology
Department of Statistics

Sep 2017

In 1967 data and computing too inaccessible to achieve the vision

- Programming languages with limited support
  - Michigan Algorithm Decoder
- Lack of technical expertise or rough user interfaces
  - LAPD could not adapt software to its data
- Challenges in accessing computing resources
  - NYPD connected to an MIT computer through a telephone line
- Cost of computing
  - IBM System 370 machines with 1MB of memory and 800MB of storage cost $25 million in 2017 dollars.

Effect of computing on criminology and criminal justice

Computation in criminology
- Officer risk factors for shooting
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Computation in criminal justice
- Predictive policing
- Risk assessment
- Benchmarking performance

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Officer features are associated with shooting

- McElvain & Kposowa (2008) noted that Latino officers were more likely to shoot
- Binder (1982) found less experienced, less educated officers more likely to be shooters
- Fyfe (1978) reported black NYPD officers were twice as likely as white officers to have shot at citizens
  - Black officers more likely in "high experience precincts"
  - less likely in managerial ranks (Fyfe 1981)

> "There is virtually no empirical support for assertions that individual officer characteristics are measurably related to any type of performance in office" – Fyfe (1989)

Learn the factors affecting the probability of shooting

$$\log \frac{P(S=1|\mathbf{x},\mathbf{z})}{1-P(S=1|\mathbf{x},\mathbf{z})} = h(\mathrm{z}) + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_d x_d$$

- S is 1 if the officer shoots
- x are the officer's features
- z are the features of a particular scenario (kinds of suspects involved, location, and lighting)

Compare shooting and nonshooting officers on the same scene

1. Multiple officers on the scene
2. They all share the same environment features
3. Test whether officers with certain features are more likely to be the shooter

Consider the likelihood of a shooting involving two officers

$$P(S_A = 1, S_B = 0 | S_A + S_B = 1, \mathbf{x}_A, \mathbf{x}_B, \mathbf{z}) = \frac{e^{\beta' x_A}}{e^{\beta' x_A} + e^{\beta' x_B}}$$

- For shootings involving more officers the denominator becomes more complex
  - One shooting involved 12 officers, 8 shooters
  - Denominator had $8\binom{12}{8} = 3960$ terms

Utilized data on a review of three years of NYPD records

- Gathered data on all shooting incidents adjudicated in 2004, 2005, and 2006
- For each shooting I recorded
  - department ID numbers for shooters in the incident
  - department ID numbers for non-shooting officers that were witnesses or in the immediate vicinity of the shooting
- 106 incidents involving 150 shooting officers and 141 non-shooting officers
- Collected data on age, race, experience, education, training, and past performance

Do male officers shoot more?

Officer feature	Risk difference
Male	

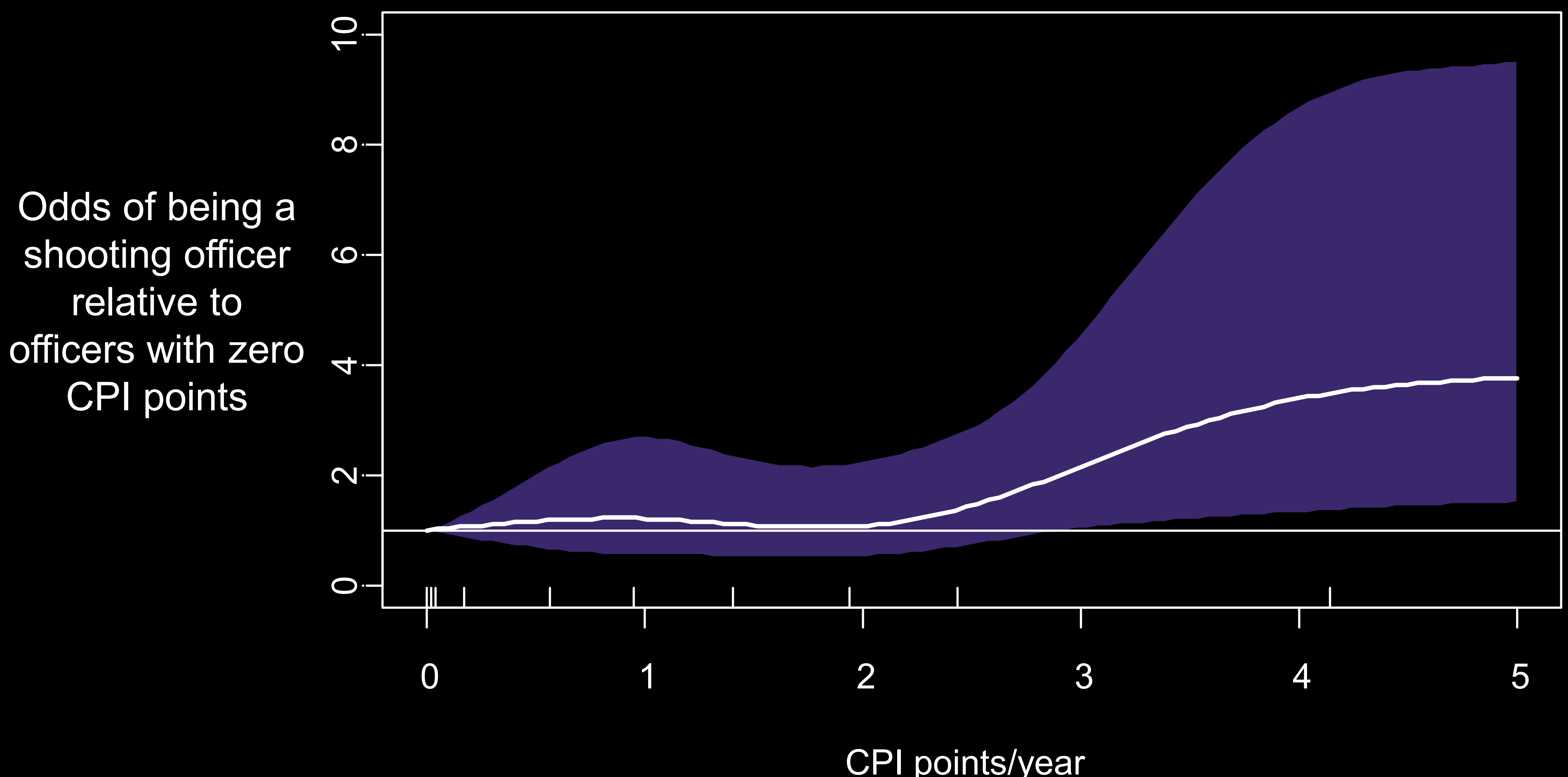
Male and female officers equally likely to shoot

Officer feature	Risk difference
Male	No difference

Race and age at recruitment associated with shooting

Officer feature	Risk difference
Male	No difference
Race	
White (reference)	
Black	+226%
Hispanic	No difference
Years at NYPD	No difference
Age when recruited	-11%
Education	No difference

Exceeding 3 CPI/year triples the shooting risk



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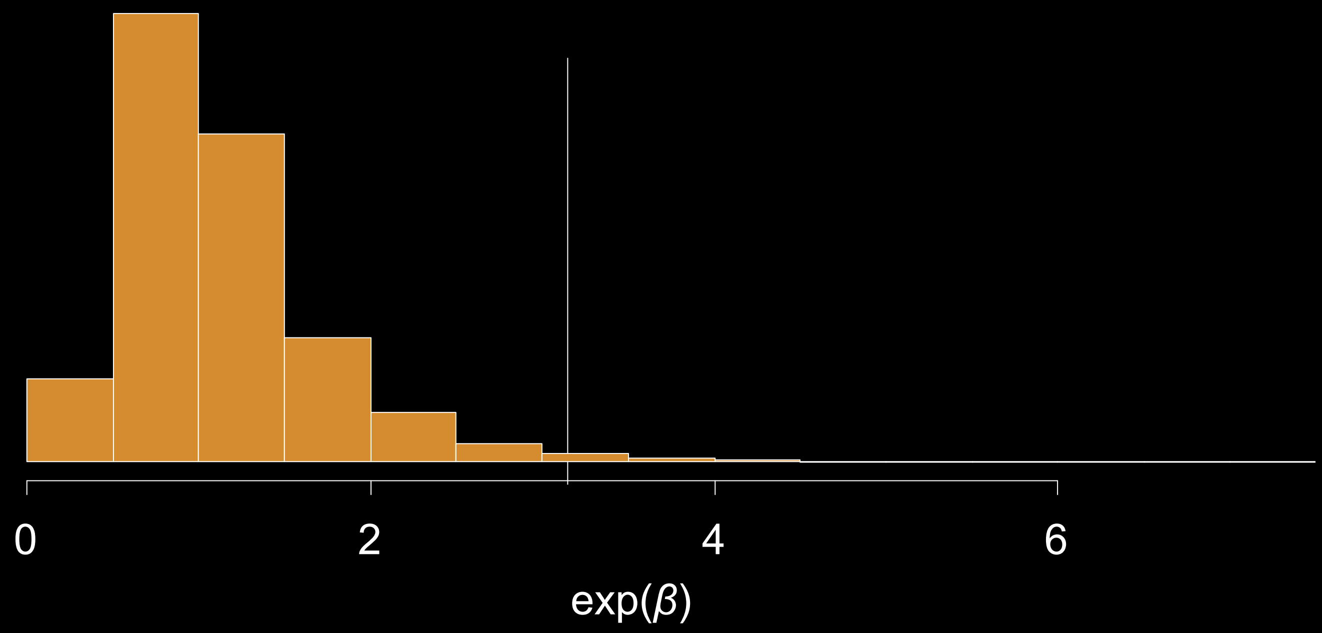
Determining whether effects are noise is computationally intensive

- Determine a range of coefficient values expected if shooting is independent of officer features
- Randomly shuffle the shooting indicator outcome within each shooting 10,000 times
- Refit the conditional logistic regression model
- Collect parameter estimates
- Assess how unusual 3x is compared to the 10,000 values

3x is much larger than we would expect by chance



Method generalizes to the number of rounds fired

- Many departments only document which officers shoot
- Model the shooting rate

$$\log \lambda(\mathbf{x}, \mathbf{z}) = h(\mathbf{z}) + \beta' \mathbf{x}$$

- Consider conditional likelihood

$$P(R_1 = r_1, R_2 = r_2 | R_1 + R_2 = r_1 + r_2, R_1 > 0, R_2 > 0, \mathbf{x}_1, \mathbf{x}_2, \mathbf{z})$$

- The result involves some large, numerically unstable sums

$$\prod_{s=1}^{S} \frac{1}{\sum_{\sum i_p = \sum r_p, i_p > 0} \prod_{p=1}^{P_s - 1} \exp\left(\left(i_p - r_p\right) \beta' \left(\mathbf{x}_p - \mathbf{x}_{P_S}\right)\right) \left(i_1, i_2, \cdots, i_{P_s}\right)!}$$

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Average weight of marijuana is an important, yet unknown, quantity

- Surveys of drug use ask about recent drug use, marijuana often reported as number of joints
- Half of marijuana users consume marijuana as joints
- Official estimates guess the average weight of marijuana in joint in order to
  - Project quantity of drugs imported by drug trafficking organizations
  - Project revenues from taxing marijuana
  - Estimate the effect of dose on health and behavioral outcomes

Commonly used estimate of 0.5g likely too large

- Volume discounting means price per gram of a single joint is higher than the price of a loose gram
- Brown and Silverman (1974) proposed a pricing model linking price to location, time, and volume

$$p_{jk} \approx e^{\beta_j} e^{\alpha_k} v_{ijk}^{\gamma}$$

Arrestee Drug Abuse Monitoring collects drug market transaction data

- Data on 10,628 arrestees reporting marijuana price and quantity 2000-2010 in 43 counties
- Marijuana measured in grams (n = 5,845), ounces (n = 8,027), or joints (n = 2,230)

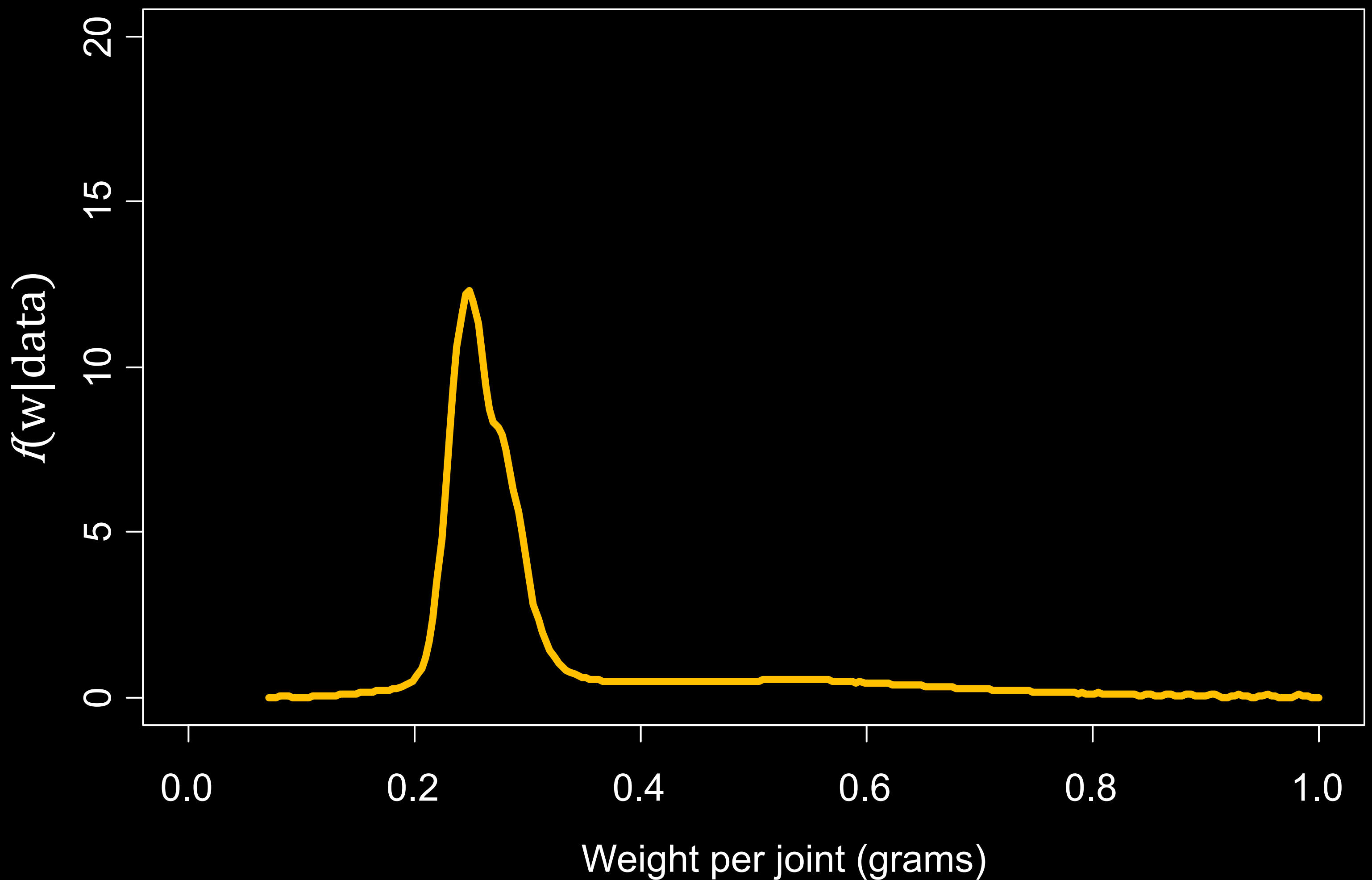
“Jointly” model loose and joint transactions, linking on price

- Brown-Silverman model suggests a log-normal model for loose marijuana purchase price
$$\log(p_{ijk}) \sim N\left(\beta_j + \alpha_k + \gamma \log(v_{ijk}), \sigma^2\right)$$
- Joints should also follow Brown-Silverman
$$\log(p_{ijk}) \sim N\left(\beta_j + \alpha_k + \gamma \log(w_{ijk} n_{ijk}), \sigma^2\right)$$
- Non-parametrically estimate the distribution of w
$$w_{ijk} \sim \text{Dirichlet process}$$
- Simulate from the posterior distribution
$$f(\boldsymbol{w}, \boldsymbol{\alpha}, \boldsymbol{\beta}, \gamma, \sigma | \mathbf{p}, \mathbf{v}, \mathbf{n}) \propto f(\mathbf{p}, \mathbf{v}, \mathbf{n} | \boldsymbol{w}, \boldsymbol{\alpha}, \boldsymbol{\beta}, \gamma, \sigma) f(\boldsymbol{w}, \boldsymbol{\alpha}, \boldsymbol{\beta}, \gamma, \sigma)$$

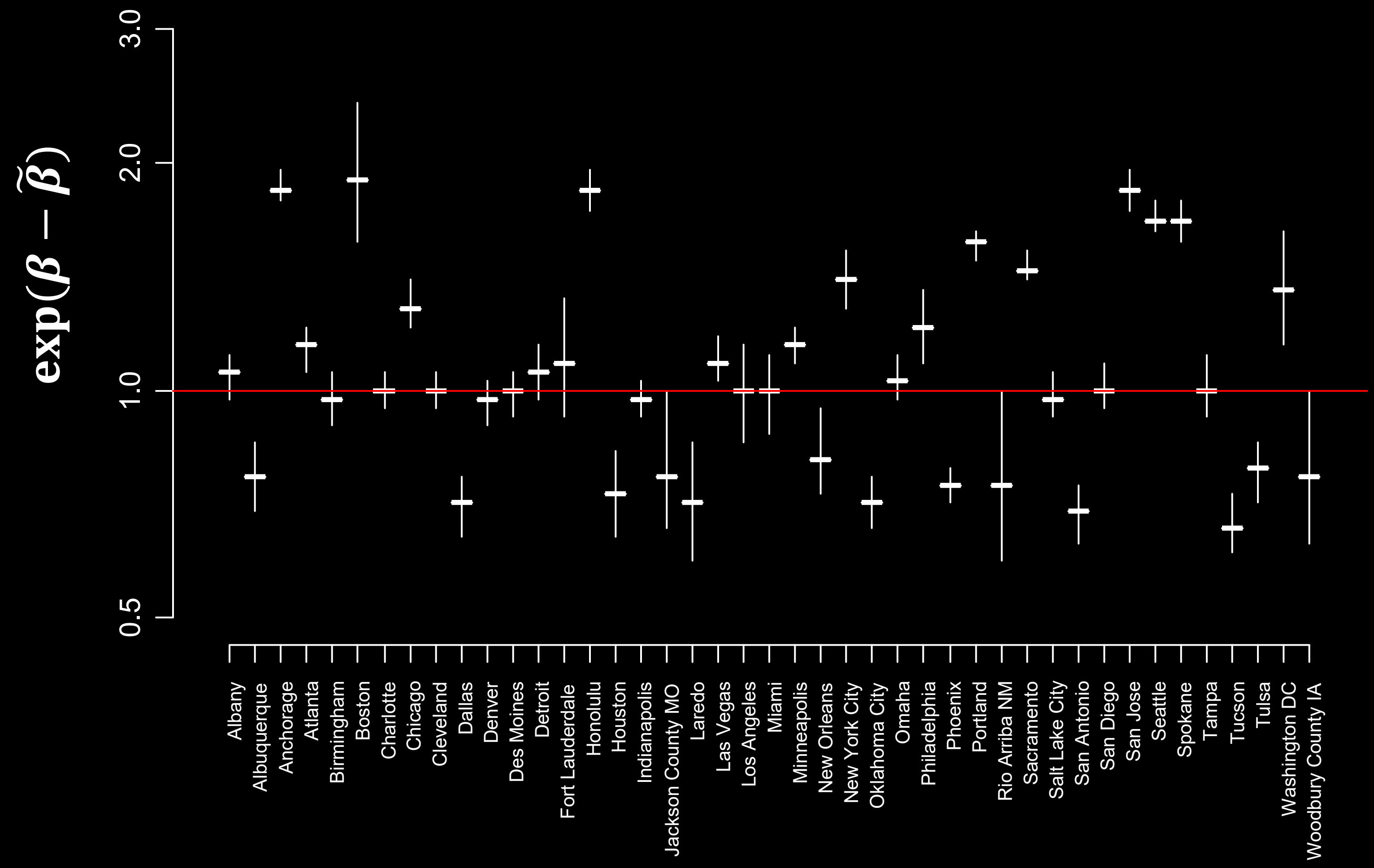
Conclusion

0.32 g/joint

Distribution of joint weights suggests multiple modes



Model allows comparison of drug market prices



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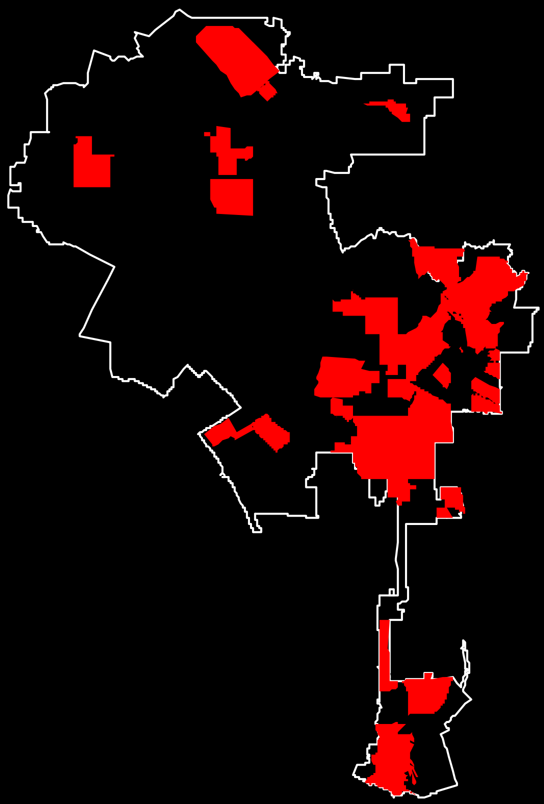
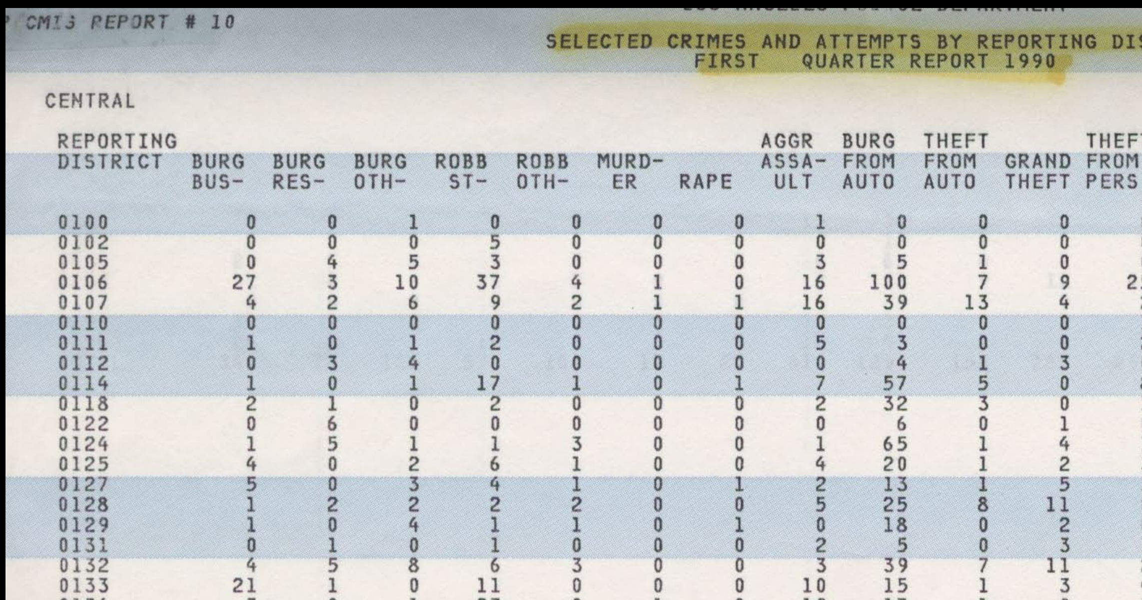
Los Angeles provides useful framework to assess gang injunctions

- LA historically has experienced severe gang-related crime
- Civilly enjoin otherwise-legal activities
- Interfere with routines of gang members within defined geographic areas
- 48 CGIs currently in effect in LA; 3 earlier CGIs terminated
- Analysis of quarterly LAPD crime reports (1988-2014)
  - 939 RDs over 108 quarters



Data from 1988-2004 collected from 2,300 pages at LA library

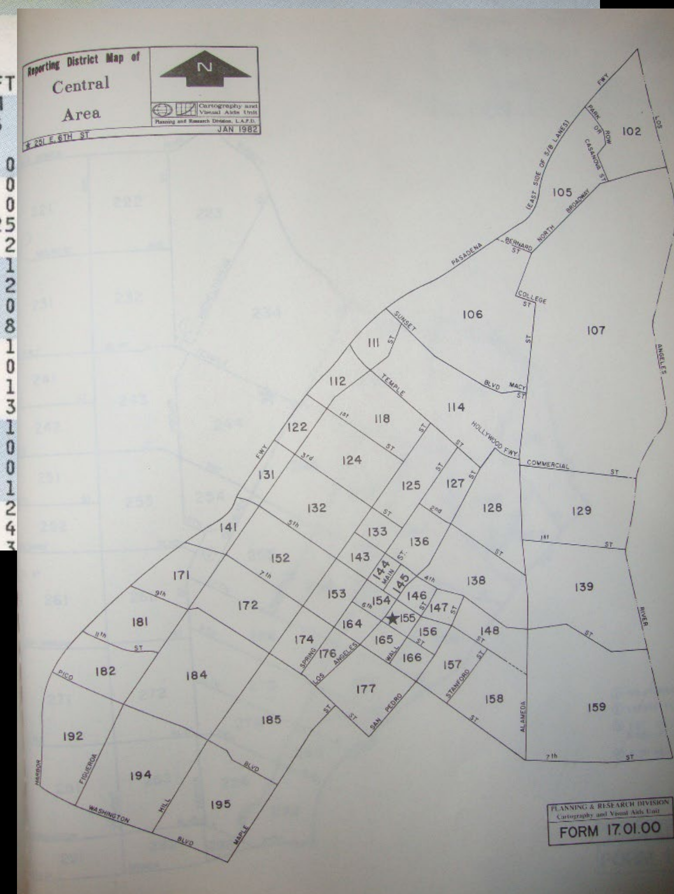


CMIS REPORT # 10

SELECTED CRIMES AND ATTEMPTS BY REPORTING DISTRICT
FIRST QUARTER REPORT 1990

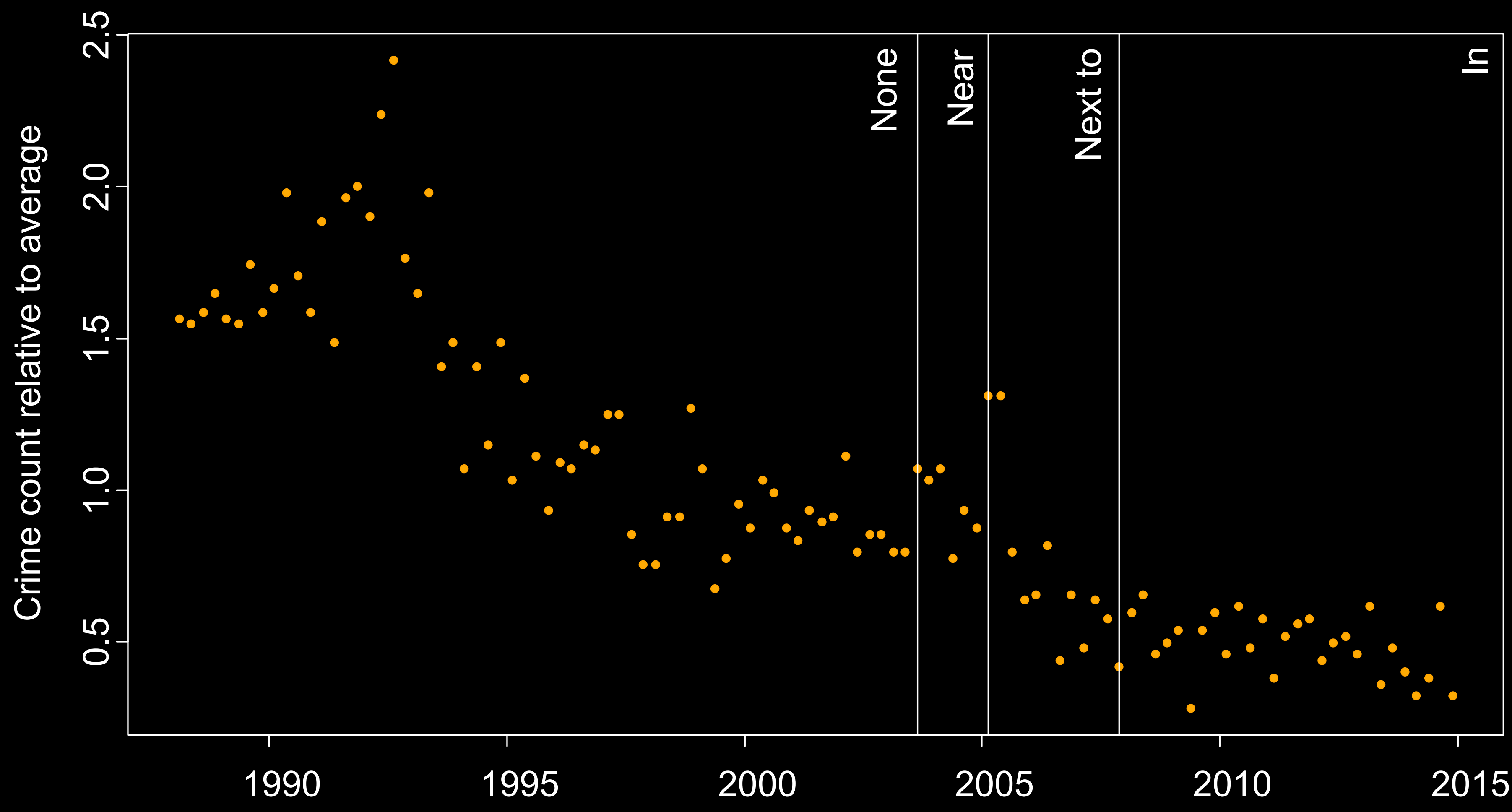
CENTRAL

REPORTING DISTRICT	BURG BUS-	BURG RES-	BURG OTH-	ROBB ST-	ROBB OTH-	MURD-ER	RAPE	AGGR ASSA-ULT	BURG FROM AUTO	THEFT FROM AUTO	GRAND THEFT	THEFT FROM PERS
0100	0	0	1	0	0	0	0	1	0	0	0	0
0102	0	0	0	5	0	0	0	0	0	0	0	0
0105	0	4	5	3	0	0	0	3	5	1	0	0
0106	27	3	10	37	4	1	0	16	100	7	9	25
0107	4	2	6	9	2	1	1	16	39	13	4	2
0110	0	0	0	0	0	0	0	0	0	0	0	1
0111	1	0	1	2	0	0	0	5	3	0	0	2
0112	0	3	4	0	0	0	0	0	4	1	3	0
0114	1	0	1	17	1	0	1	7	57	5	0	8
0118	2	1	0	2	0	0	0	2	32	3	0	1
0122	0	6	0	0	0	0	0	0	6	0	1	0
0124	1	5	1	1	3	0	0	1	65	1	4	1
0125	4	0	2	6	1	0	0	4	20	1	2	3
0127	5	0	3	4	1	0	1	2	13	1	5	1
0128	1	2	2	2	2	0	0	5	25	8	11	0
0129	1	0	4	1	1	0	1	0	18	0	2	0
0131	0	1	0	1	0	0	0	2	5	0	3	1
0132	4	5	8	6	3	0	0	3	39	7	11	2
0133	21	1	0	11	0	0	0	10	15	1	3	4
0136	3	0	1	27	0	1	0	19	17	1	0	3



- Data from 2005-2014 came from LAPD incident level crime data
- All data available at github.com/gregridgeway/LAPDcrimedata

RD1204 transitions from no safety zone, to near, next to, in a safety zone



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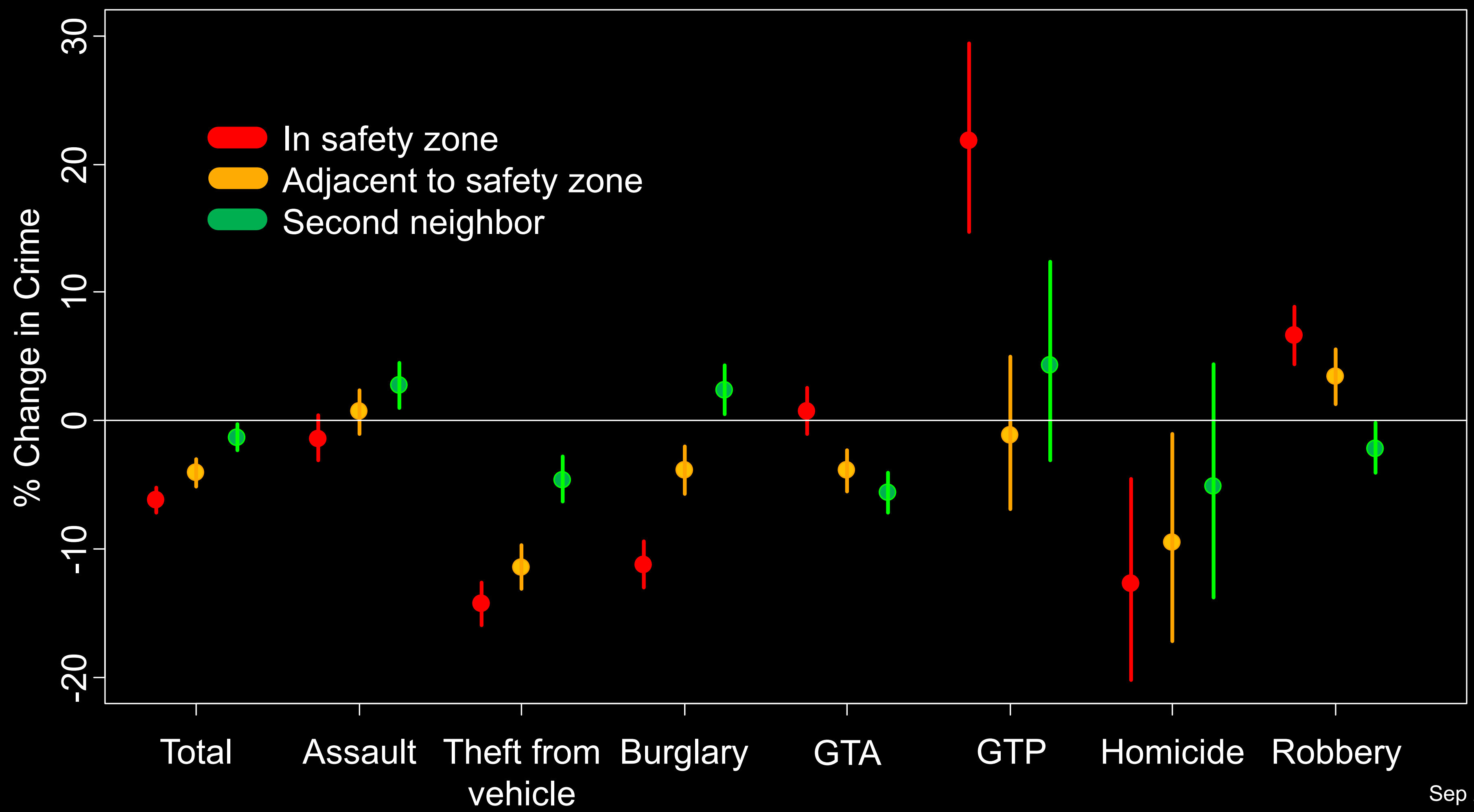
Neighborhoods Closest to Safety Zones See Largest Crime Decreases



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Commission foretold many computing innovations for justice

- "portable recording devices" to facilitate data collection
- computers that could automate the dispatch of patrol cars closest to calls for service
- networked alarms that could notify nearby officers without a dispatcher
- alteration of police deployments in real-time as data reveal emerging problems
- new wireless networks to reduce communication congestion
- …even electronic cocktail olives

Computing is only just starting to have a measurable effect

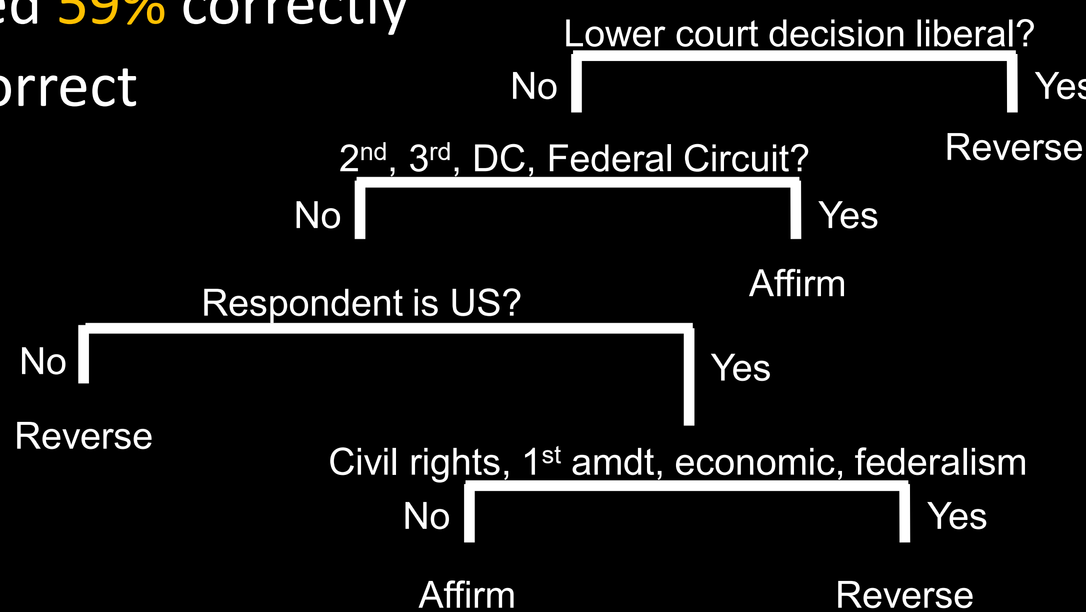
- Crime clearance rates have remained at approximately 45% for violent crimes and just under 20% for property crimes
- Garicano and Heaton (2010) find
  - general IT investments result in improvements in record keeping
  - produce no reduction in crime or improvement in clearance rates
  - when IT is coupled with data-driven management processes crime and clearance rates improve
- Lincoln (NE) PD found officers randomized to have information pushed to them had more arrests
  - However, a similar study in Redlands (CA) found that most officers never opened the app
- Mesa (AZ) police officers randomized to use license plate readers had 2.7 times as many hits on stolen cars

Computers outperform humans on some tasks, but still not used

- MYCIN in 1979 could outperform practitioners in selecting antibiotic treatments
- Engle and Flehinger (1987) noted “physicians have a high regard for their own decision-making ability and are afraid of any competition from computers”

With good data, simple models can outperform experts

- Ruger et al. (2002) pitted 83 supreme court experts against a classification tree
  - aimed to predict the outcome of the 68 cases decided in 2002
  - experts forecasted 59% correctly
  - computer 75% correct



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Predictive policing is the use of data in predictive models to prevent crime

- Detect signals and patterns in crime reports to anticipate
  - if crime will spike
  - when a shooting might occur
  - where the next car will be broken into
  - who the next crime victim will be
- Couple the prediction with a prevention strategy
  - typically… send an officer to the predicted time and place

Predictive policing is in use now

- 2014 survey of 200 police departments
  - predictive policing in use at 38% of respondents
  - 70% stated they will be using predictive policing by 2017
- Police would be negligent if they were not using all the information at their disposal
  - to anticipate the concerns of the community
  - to not allocate resources to times and places where they would be wasted
  - to prevent victimization

Translating prediction to prevention is underdeveloped

- Chicago PD developed a strategic subject list
  - uses data on arrestee social network and homicide victimization within that network
  - predict the likelihood that an individual would be a homicide victim based on those data
  - 7% of those on the SSL became victims/arrestees in shootings compared to 0.2% of other arrestees
- RAND evaluation of the SSL
  - SSL subjects received so little attention the team questioned calling it a prevention strategy

Predictive policing shown to be more effective than human planners

- Epidemic-type aftershock sequence (ETAS)

$$\lambda_n(t) = \mu_n + \theta \sum_{t_n^i < t} \omega \exp\left(-\omega\left(t - t_n^i\right)\right)$$

- Mohler et al. (2015) put ETAS and a crime analyst in a head-to-head prediction competition
  - Each would select areas of fixed size likely to contain a large share of future crime
  - ETAS outperformed the crime analyst by a factor of 1.4 to 2.2
- Mohler et al. also conducted an RCT
  - police spending 1,000 minutes in ETAS-predicted hot spots eliminated one crime on average
  - police need to spend 2,000 minutes in hot spots generated from LAPD's standard practice to have the same one-crime reduction

Predictive policing generates fears

- If police apply predictive techniques to their own outputs, the result is unproductive feedback
  - But actual applications involve anticipating when and where the *public* will call for police
- If police only focus on predictions, then other community problems will be ignored
  - So far the problem is they are not focusing enough on the predictions
  - Predictive policing supports one component of policing, designing a plan for deploying patrol

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Use data and models as decision support in the justice system

- Summons versus arrest
- Pre-trial release versus pre-trial detention
- Parole granted versus parole declined
- Low-intensity probation versus close supervision

RCT showed that low risk offenders can require minimal supervision

- Philadelphia Adult Probation and Parole Department (APPD) randomized 800 predicted low risk probationers to two probation officers
  - No difference in rate of arrest
  - No difference in serious crimes
  - Less likely to abscond
- Large reduction in resources spent on offenders who do not need close attention
- Frees resources to focus on high risk offenders

Predict domestic violence reoffending from data

- 28,646 domestic violence cases between 2007 and 2011
- Collected data on prior arrests, days in detention, age, sex, probation status, ZIP code
- Forecast who would have in the next two years
  - no new arrest
  - a new domestic violence arrest not involving injury
  - a new domestic violence arrest involving injury

Data-driven decisions would cut domestic violence arrests in half

- 80% of those released after arraignment have no arrests within 2 years
- 90% of those forecasted as low risk would have no arrests within 2 years
  - 40% of cases can be released expecting 1 in 10 to fail
  - translates to 1,000 fewer victimizations per year

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Create benchmarks to identify problematic system components

- Fair comparisons
  - Match an officer's activities with activities conducted by other officers in the same time, place, and context
  - Existing systems group officers by just precinct or division and shift
- Outlier thresholds
  - Compute the probability that the data indicate an officer is a problem
  - Existing methods use fixed thresholds (more than 3 complaints) or traditional statistical choices (more than 2 or 3 standard deviations above the average)

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We wish to determine if Officer A’s stop patterns are unusual

Stop Characteristic		**Officer A (%)** **n = 392**	
Outcomes	Black	86	
	Frisk	12	

We know a lot about the time, place, and context of Officer A's stops

Stop Characteristic		Officer A (%) n = 392	
Outcomes	Black	86	
	Frisk	12	
Month	January	3	
	February	4	
	March	8	
Day of the week	Monday	13	
	Tuesday	11	
	Wednesday	14	
Time of day	(4-6 pm]	9	
	(6-8 pm]	8	
	(8-10 pm]	23	
	(10 pm-12 am]	17	
Patrol borough	Brooklyn North	100	
Precinct	B	98	
	C	1	
Outside		96	
In uniform	Yes	99	
Radio run	Yes	1	

Find stops made by other officers occurring at the same time, place, and context

Stop Characteristic		Officer A (%) n = 392	Internal Benchmark (%) ESS = 3,676
Outcomes	Black	86	
	Frisk	12	
Month	January	3	**3**
	February	4	**4**
	March	8	**9**
Day of the week	Monday	13	**13**
	Tuesday	11	**10**
	Wednesday	14	**15**
Time of day	(4-6 pm]	9	**10**
	(6-8 pm]	8	**8**
	(8-10 pm]	23	**23**
	(10 pm-12 am]	17	**17**
Patrol borough	Brooklyn North	100	**100**
Precinct	B	98	**98**
	C	1	**1**
Outside		96	**94**
In uniform	Yes	99	**97**
Radio run	Yes	1	**3**

Benchmark also matches on fine location data

A higher percentage of people who Officer A stops are black

Stop Characteristic		Officer A (%) n = 392	Internal Benchmark (%) ESS = 3,676
Outcomes	Black	86	**55**
	Frisk	12	**11**
Month	January	3	**3**
	February	4	**4**
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Precinct	B	98	**98**
	C	1	**1**
Outside		96	**94**
In uniform	Yes	99	**97**
Radio run	Yes	1	**3**

Officers make stops for different reasons

Crime suspected	Officer A (%) n = 392	Internal Benchmark (%) ESS = 3,676
Criminal trespass	4	**2**
Burglary	13	**13**
Weapon possession	3	**13**
Robbery	15	**14**
Drug possession	6	**27**
Drug sale	47	**20**

Officers may interpret and record activities differently

Crime suspected	Officer A (%) n = 392	Internal Benchmark (%) ESS = 3,676
Criminal trespass	4	**2**
Burglary	13	**13**
Weapon possession	3	**13**
Robbery	15	**14**
Drug possession	6	**27**
Drug sale	47	**20**

53%

47%

Idea: Reweight stops made by other officers to resemble this officer's stops

Example Officer

- Align their distributions
  $f(\mathbf{x}|t=1) = w(\mathbf{x})f(\mathbf{x}|t=0)$
- Solving for $w(\mathbf{x})$ yields the propensity score weight
  $$w(\mathbf{x}) \propto \frac{P(t=1|\mathbf{x})}{1-P(t=1|\mathbf{x})}$$
- Estimate $P(t=1|\mathbf{x})$ using boosted logistic regression as implemented in `gbm`

Good benchmark construction is a computational challenge

- Logistic regression models $\log \frac{P(t=1|\mathbf{x})}{P(t=0|\mathbf{x})} = \beta'\mathbf{x}$
- Select β to maximize

$$\sum_{i=1}^{N} t_i \beta' \mathbf{x}_i - \log(1 + \exp(\beta' \mathbf{x}_i))$$

- Easy to optimize even with large datasets
- Performs poorly with correlated features, interactions, saturation, threshold effects, …

Penalizing coefficients can produce a more stable model

- Logistic regression models $\log \frac{P(t=1|\mathbf{x})}{P(t=0|\mathbf{x})} = \beta'\mathbf{x}$
- Instead select β to maximize

$$\sum_{i=1}^{N} t_i\beta'\mathbf{x}_i - \log(1 + \exp(\beta'\mathbf{x}_i)) - \lambda \sum_{j=1}^{d} |\beta_j|$$

- If λ=0 results in ordinary logistic regression
- If λ=∞ produces constant predictions, $\bar{t}$
- Stabilizes model for correlated features

Use a large, flexible class of basis functions

- Logistic regression models $\log \frac{P(t=1|\mathbf{x})}{P(t=0|\mathbf{x})} = \beta' \mathbf{h}(\mathbf{x})$

$$\sum_{i=1}^{N} t_i \beta' \mathbf{h}(\mathbf{x}_i) - \log(1 + \exp(\beta' \mathbf{h}(\mathbf{x}_i))) - \lambda \sum_{j=1}^{d} |\beta_j|$$

- Let $h_1(\mathbf{x}),\ldots,h_K(\mathbf{x})$ be all piecewise constant functions of **x** and their interactions
- K is huge, h spans a large class of functional forms

Iterative, tree-structured search makes computation possible

$$\sum_{i=1}^{N} t_i \beta' \mathbf{h}(\mathbf{x}_i) - \log(1 + \exp(\beta' \mathbf{h}(\mathbf{x}_i))) - \lambda \sum_{j=1}^{d} |\beta_j|$$

- Relaxing λ from infinity to a little less than infinity is equivalent to modifying one of the βs
- The associated $h(\mathbf{x})$ is the one most correlated with $t_i - \hat{P}(t = 1|\mathbf{x}_i)$
- Tree structured search can find that $h(\mathbf{x})$ fast
- Then relax λ a little more…

That computation produces a well-matched, fair, credible benchmark

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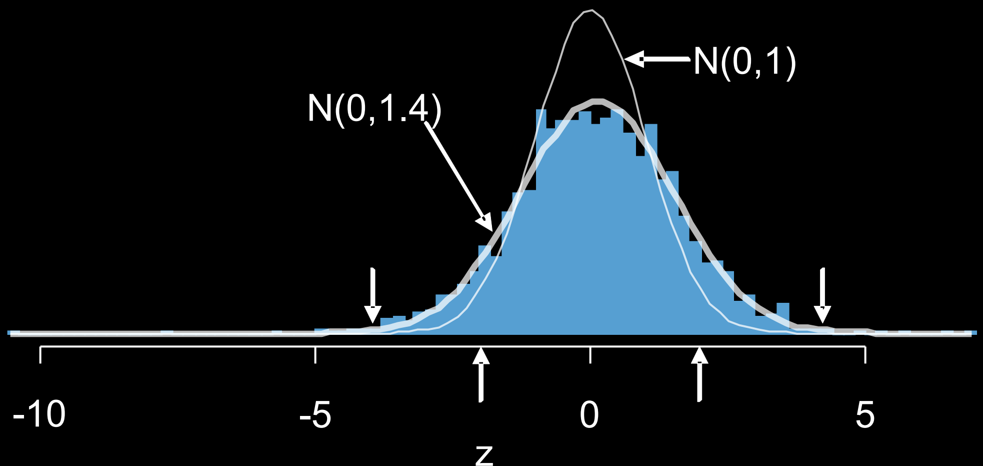
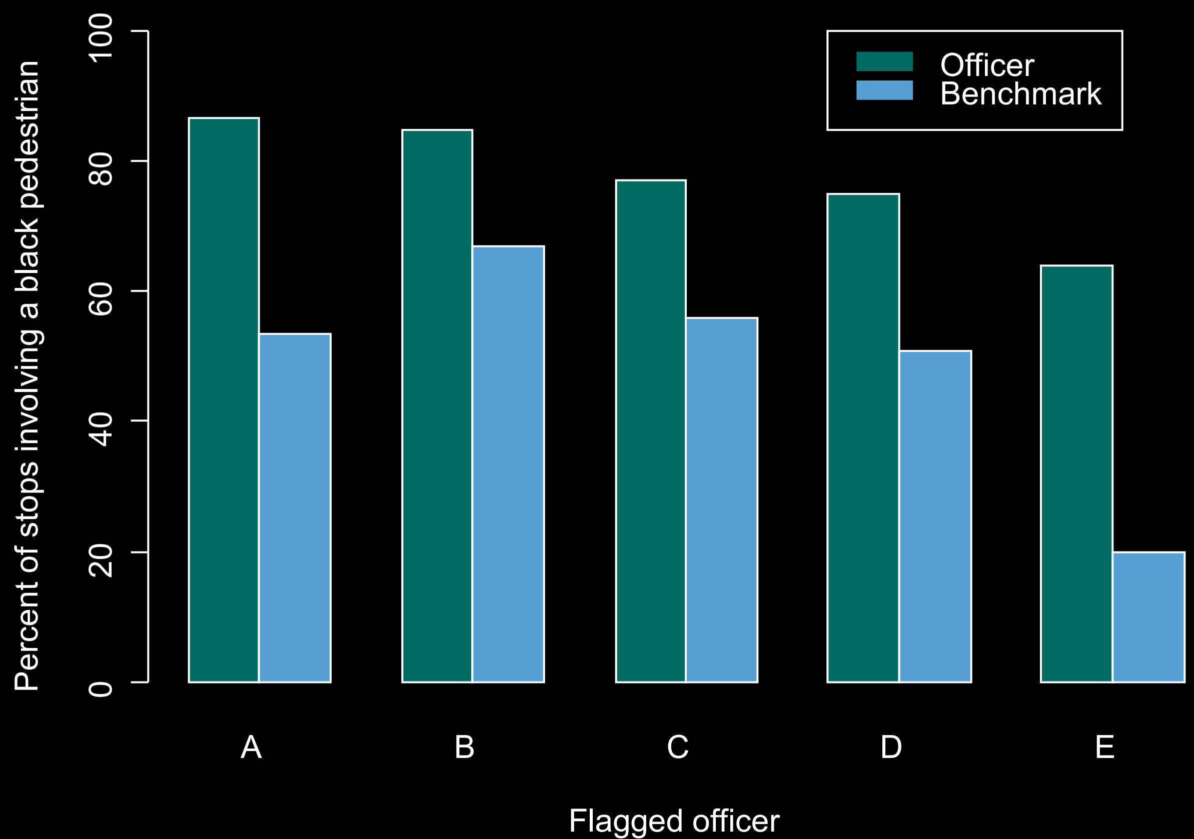
Repeat for Every NYPD Officer Actively Involved in Stops



- $P(\text{problem}|z) = 1 - \dfrac{f(z|\text{no problem})f(\text{no problem})}{f(z)}$
  $\geq 1 - \dfrac{f_0(z)}{f(z)}$
- Right tail consists of 5 officers with "problem officer" probabilities in excess of 50%
- Standard cutoff of z > 2.0 flags 242 officers, 90% of which have false discovery rate estimated to be greater than 0.999

Analysis flagged five officers overstopping black pedestrians



Benchmarking is applicable to numerous contexts… like opioid prescriptions

Patient features	Hospital X	Benchmark patients treated at other hospitals
Opioid Rx rate	63.6	
Days supply	8.5	
Male (%)	48.0	
Age at admission	49.9	
Primary admission reason (%)		
Circulatory	22.2	
Musculoskeletal	7.5	
Injury	11.2	
Diagnosis history (%)		
Arthritis	2.3	
Obesity	31.7	
Tobacco use	42.4	
Alcohol liver damage	13.6	
Prior prescriptions (%)		
Hypolipidemics	41.8	
Antihypertension	15.6	
NSAID	48.8	
Antidiabetes	30.9	
Antidepressants	45.5	

Hospital X prescriptions are more frequent and larger than its benchmark

Patient features	Hospital X	Benchmark patients treated at other hospitals
Opioid Rx rate	63.6	36.1
Days supply	8.5	4.6
Male (%)	48.0	47.1
Age at admission	49.9	49.5
Primary admission reason (%)		
Circulatory	22.2	21.8
Musculoskeletal	7.5	7.1
Injury	11.2	10.8
Diagnosis history (%)		
Arthritis	2.3	2.0
Obesity	31.7	32.4
Tobacco use	42.4	41.6
Alcohol liver damage	13.6	13.2
Prior prescriptions (%)		
Hypolipidemics	41.8	40.7
Antihypertension	15.6	15.1
NSAID	48.8	49.3
Antidiabetes	30.9	30.3
Antidepressants	45.5	45.3

Effect of computing on criminology and criminal justice

- Computation in criminology
  - Officer risk factors for shooting
    - Simulating independence
    - Large sums
  - Grams of marijuana in a joint
    - MCMC integration for learning weight distribution
  - Effect of gang injunctions on crime
    - MCMC integration for spatial correlation
- Computation in criminal justice
  - Predictive policing
    - Connecting forecasting model with prevention model
  - Risk assessment
    - High quality classifiers
  - Benchmarking performance
    - Search over benchmarks

Modern information technology now permits a massive assault on these problems at a level never before conceivable

- 1967 President's Commission on Law Enforcement and Administration of Justice

Computation and Criminology

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