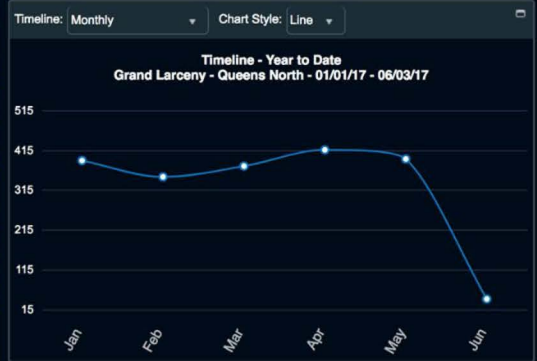
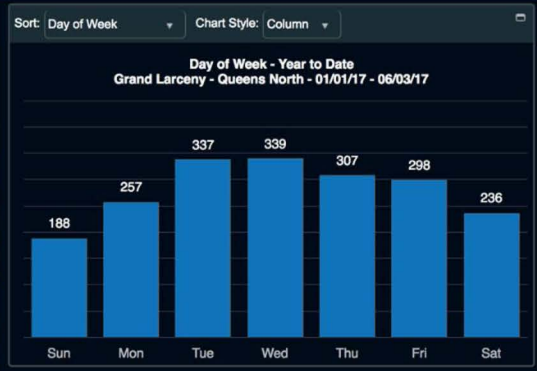
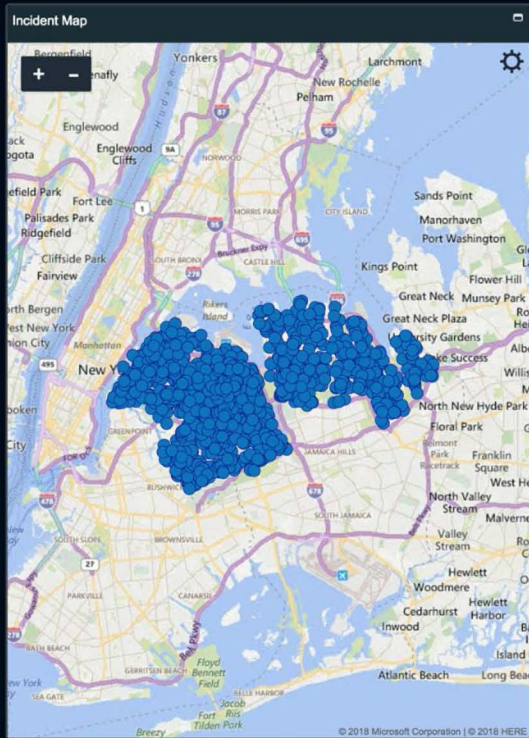




Patrol Borough: Queens North Precinct: All

	Week to Date			28 Day			Year to Date		
	2018	2017	% Chg	2018	2017	% Chg	2018	2017	% Chg
Murder	0	1	-100.0 %	1	3	-66.7 %	7	6	16.7 %
Rape	5	3	66.7 %	23	8	187.5 %	93	52	78.8 %
Robbery	20	20	0.0 %	101	91	11.0 %	504	580	-13.1 %
Felony Assault	35	37	-5.4 %	169	130	30.0 %	675	686	-1.6 %
Burglary	13	26	-50.0 %	92	112	-17.9 %	621	695	-10.6 %
Grand Larceny	109	91	19.8 %	380	349	8.9 %	1,859	1,962	-5.2 %
Grand Larceny Auto	16	19	-15.8 %	55	55	0.0 %	295	324	-9.0 %
<b>Total</b>	<b>198</b>	<b>197</b>	<b>0.5 %</b>	<b>821</b>	<b>748</b>	<b>9.8 %</b>	<b>4,054</b>	<b>4,305</b>	<b>-5.8 %</b>
Patrol	192	188	2.1 %	793	721	10.0 %	3,897	4,137	-5.8 %
Transit	4	2	100.0 %	13	13	0.0 %	72	88	-18.2 %
Housing	2	7	-71.4 %	15	14	7.1 %	85	80	6.3 %
Shooting Victims	0	1	-100.0 %	2	2	0.0 %	11	7	57.1 %
Shooting Incidents	0	1	-100.0 %	2	2	0.0 %	9	7	28.6 %
Rape 1	4	3	33.3 %	14	7	100.0 %	65	41	58.5 %
Petit Larceny	171	192	-10.9 %	701	706	-0.7 %	3,752	3,602	4.2 %
Misd. Assault	102	96	6.3 %	406	370	9.7 %	1,939	1,876	3.4 %
Misd. Sex Crimes	10	7	42.9 %	42	34	23.5 %	156	141	10.6 %

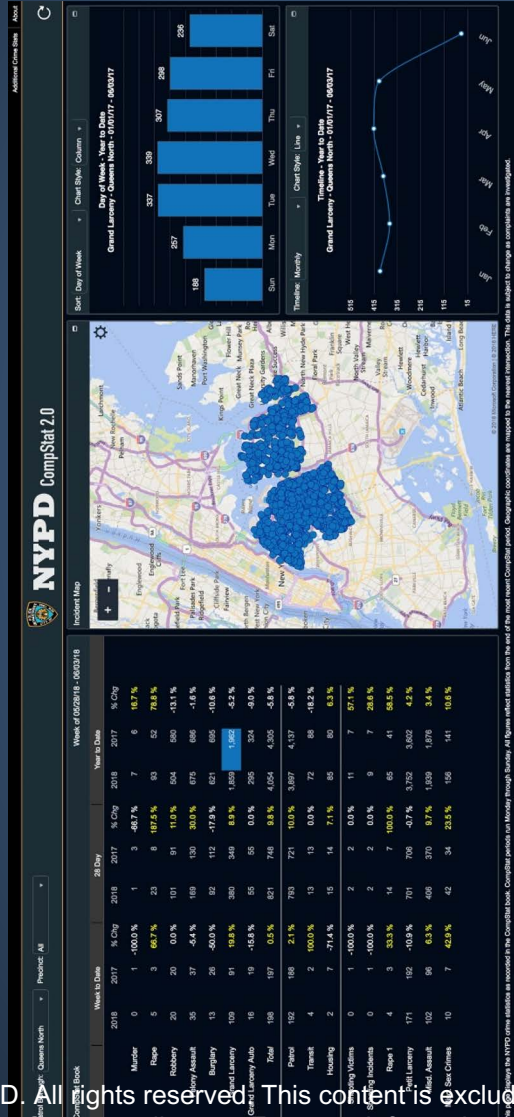


This page displays the NYPD crime statistics as recorded in the CompStat book. CompStat periods run Monday through Sunday. All figures reflect statistics from the end of the most recent CompStat period. Geographic coordinates are mapped to the nearest intersection. This data is subject to change as complaints are investigated.

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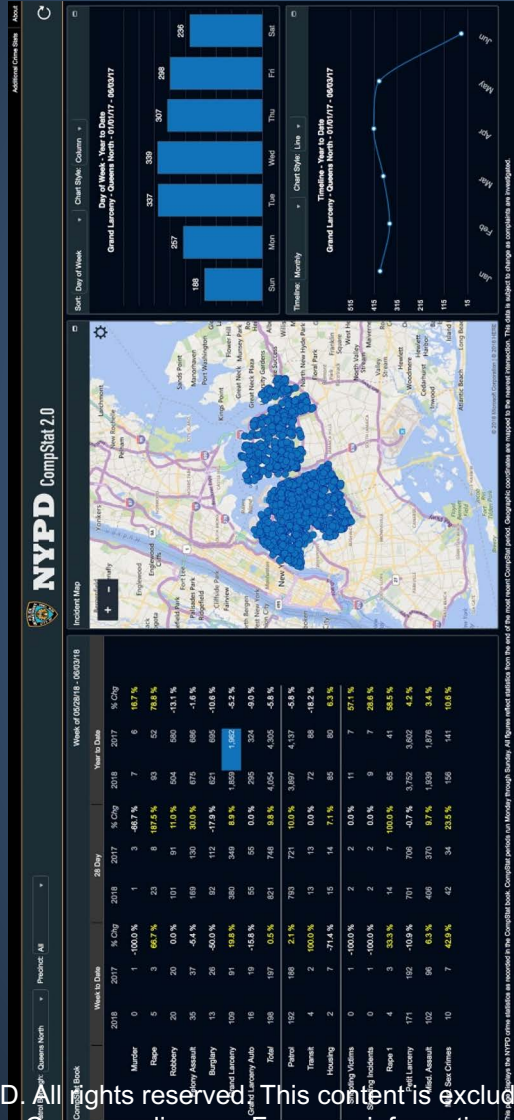
# Quantify and Punish: Data, Race, and Policing From the Burgess Method to Big Data

# Logistics



- For next Thursday: come prepared to give a brief (3/5 minute) presentation on an empowering work of recent social science
- Individually or in pairs (if in pairs, both partners should talk, presentation should be proportionally longer)
- Slides/visuals optional...
- Post links on Canvas board

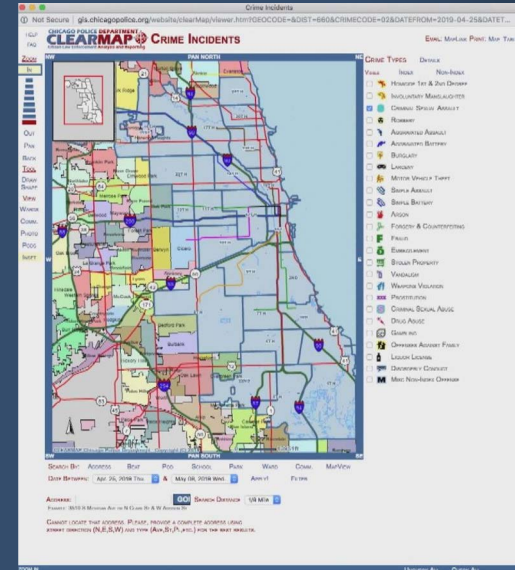
# Today's Plan



- I. Statistics, policing, and racial injustice: an overview
- II. Crime statistics and the “condemnation of blackness,” c. 1890-1940
- III. Risk assessment and the “actuarial” approach to policing and punishment, from the Burgess Method (1928) to AI
- IV. “Data-driven” policing from CompStat (1990s) to Big Data


# Quantify and Punish: Overview

- Module 11 considers: what role have quantitative data, computational methods, and social science played in the construction of modern systems of criminal justice?
- How has quantification contributed to the injustices of modern policing and punishment – to the creation and maintenance of a system that disproportionately and unjustly targets, punishes, incarcerates, and kills people of color, especially Black citizens?
- What can history tell us about the role that data and computation should – or should not – play in efforts to create a more just system of justice in the future?




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# Quantification-Race-Policing: Big Themes



Police Department  
City of New York



Michael R. Bloomberg  
Mayor

Raymond W. Kelly  
Police Commissioner

Volume 17 Number 38

**CompStat** Citywide

Report Covering the Week 9/20/2010 Through 9/26/2010


**Crime Complaints**

	Week to Date			28 Day			Year to Date*			2 Year % Chg	9Year % Chg (2001)	17Year % Chg (1993)
	2010	2009	% Chg	2010	2009	% Chg	2010	2009	% Chg			
<b>Murder</b>	10	11	-9.1	38	41	-7.3	386	341	13.2	-1.8	-16.6	-73.7
<b>Rape</b>	23	29	-20.7	109	104	4.8	989	871	13.5	-2.1	-31.0	-59.4
<b>Robbery</b>	477	428	11.4	1,530	1,503	1.8	13,698	13,261	3.3	-13.8	-30.6	-77.9
<b>Fel. Assault</b>	354	345	2.6	1,363	1,356	0.5	12,701	12,585	0.9	3.5	-28.2	-59.3
<b>Burglary</b>	405	427	-5.2	1,542	1,742	-11.5	13,399	13,558	-1.2	-9.8	-42.5	-81.8
<b>Gr. Larceny</b>	742	828	-10.4	3,038	3,250	-6.5	26,893	28,664	-6.2	-16.5	-19.3	-57.3
<b>G.L.A.</b>	264	215	22.8	916	889	3.0	7,726	7,646	1.0	-15.2	-63.4	-90.5
<b>TOTAL</b>	<b>2,275</b>	<b>2,283</b>	<b>-0.35</b>	<b>8,536</b>	<b>8,885</b>	<b>-3.93</b>	<b>75,792</b>	<b>76,926</b>	<b>-1.47</b>	<b>-11.62</b>	<b>-35.25</b>	<b>-75.98</b>


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- Turn to data and quantification often driven by desire to create fairer, more accountable, less biased systems – often in response to crisis, calls for reform
- While quantitative turn has brought some positive effects and reforms, it has also brought harms
- Efforts to quantify policing and punishment rely on historical data, which reflect biases of previous system – histories of data shape their futures
- Data is *always already* mediated through previous criminal justice apparatus – the crime data” is in fact always “policing data”

# Quantification-Race-Policing: Big Themes



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- In fact, data has played a central role in the historical construction of ideas about criminality that undergird structural racism of modern criminal justice system
- Computational tools can obscure, launder, and exacerbate existing patterns of discrimination – behind veil of “objectivity”
- The establishment of quantitative systems for guiding and evaluating policing can reshape policing behaviors in detrimental ways:
  - “Ratchet effects”
  - “Juking the stats”

# Crime, Numbers, and Social Science

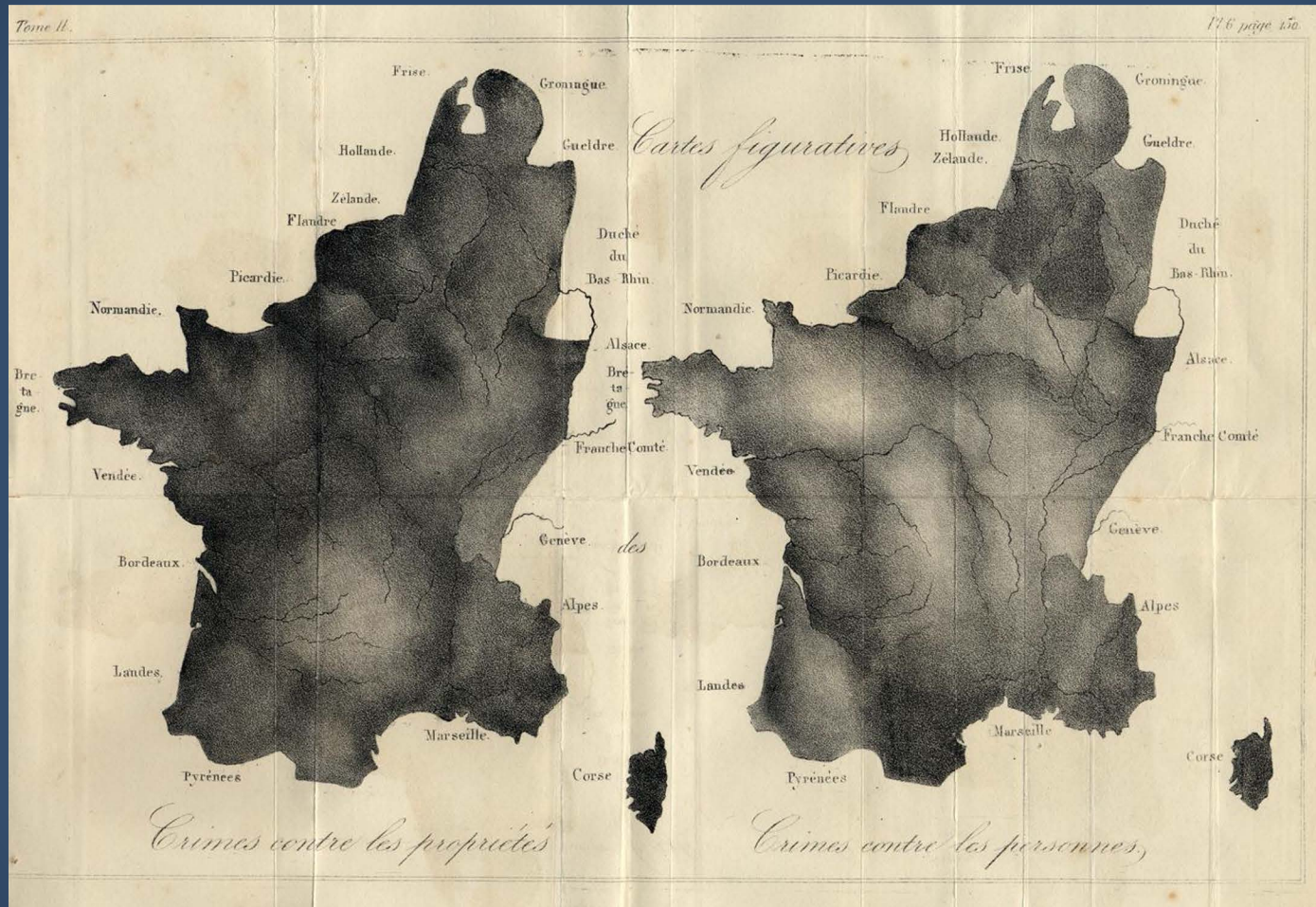
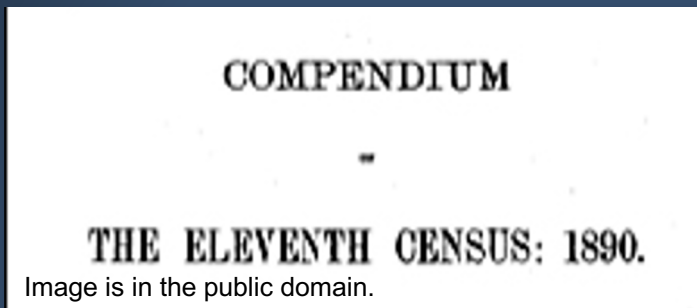


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“Cartes figurative: Crimes contre les propriétés / Crimes contre les personnes.” Two lithograph maps within one border, 21.5 × 33 cm. From Quetelet’s *Sur l’homme et le développement de ses facultés; ou, Essai de physique sociale*, 2 vols. in 1 (Brussels: Louis Hauman, 1836) [Historic Maps Collection]. ([Princeton Historical Maps Collection](#))

# Three Episodes



- Crime statistics and the “condemnation of blackness,” c. 1890-1940
- Risk assessment and the “actuarial” approach to policing and punishment, from the Burgess Method (1928) to AI
- “Data-driven” policing from CompStat (1990s) to Big Data



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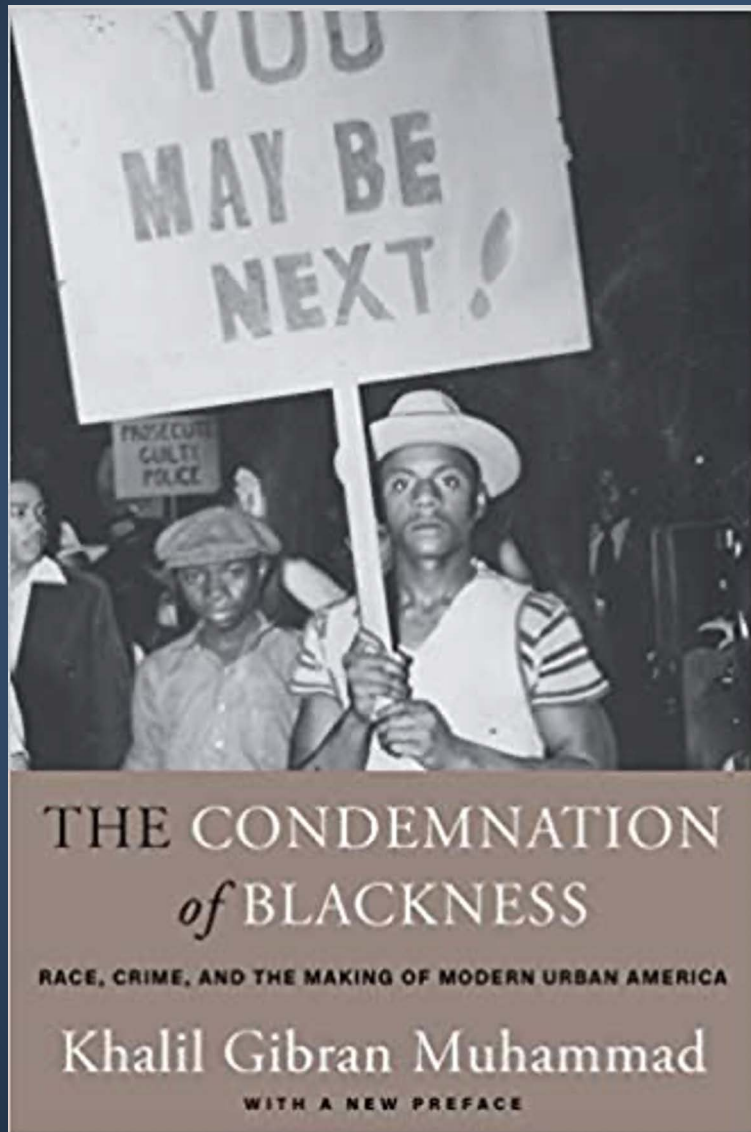
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**Crime statistics and the “condemnation of  
blackness,” c. 1890-1940**

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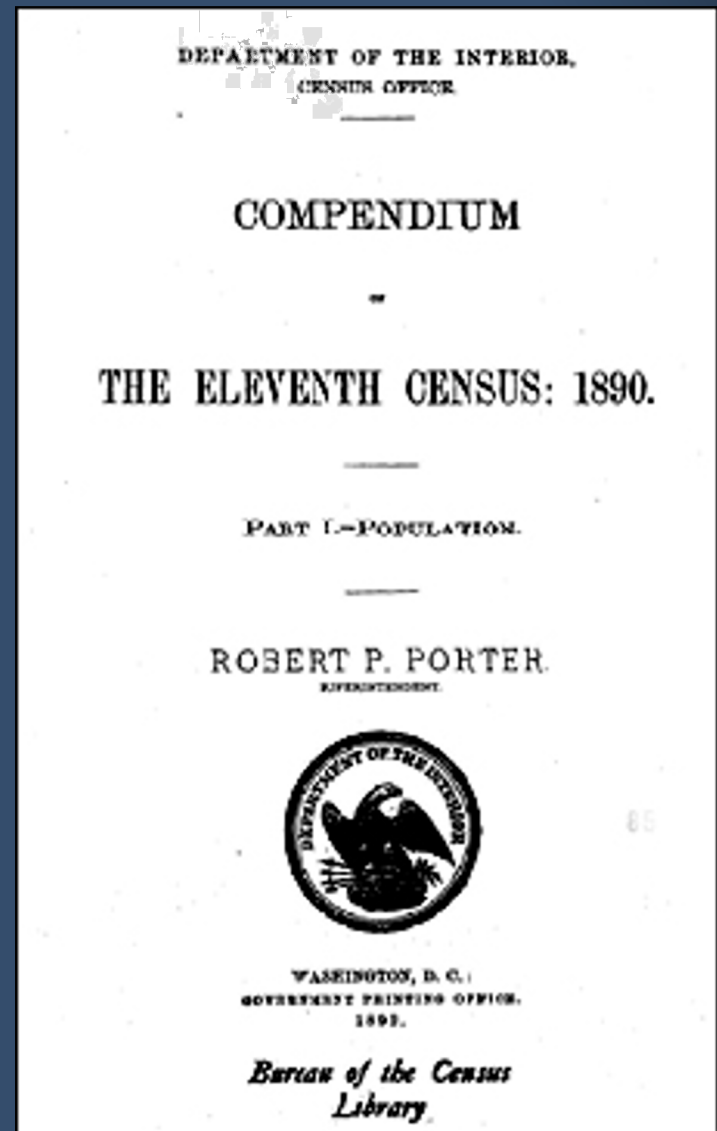
# The Statistical Condemnation of Blackness



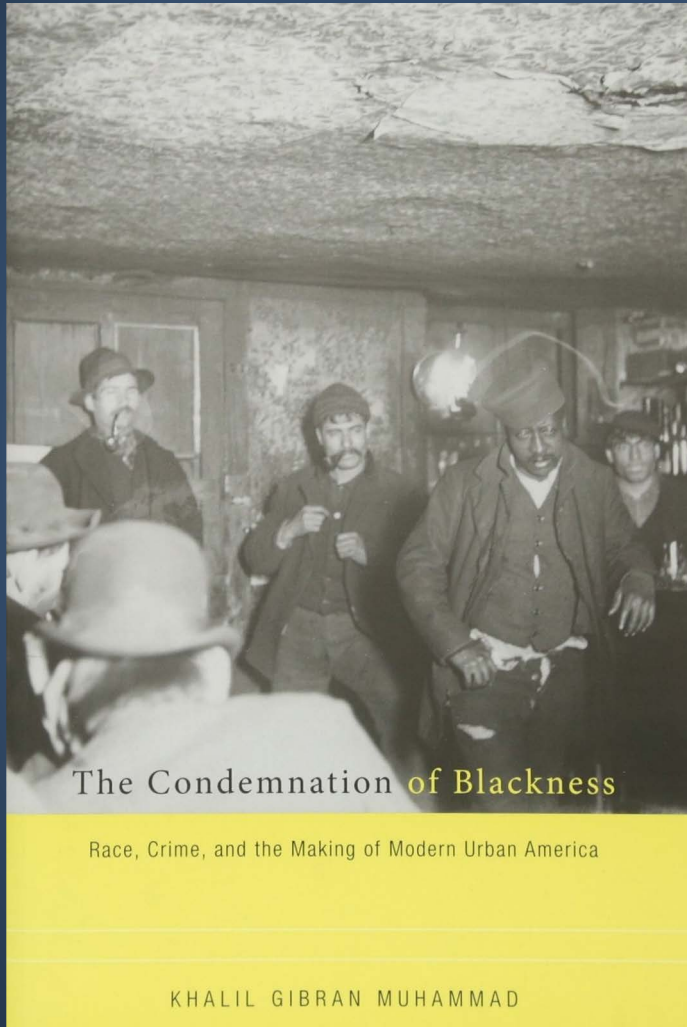
- In 2011 book, Khalil Gibran Muhammad argues that statistics played a crucial role in the establishing a link between Blackness and criminality
- Notion that criminality was a feature of Black Americans as a *group*, while crime by white Americans was masked as individual failure
- “Black criminality [became] the most significant and durable signifier of black inferiority in white people’s minds” (p. 3)
- Gibran argues this link was forged in the Jim Crow era (1890-1940)

# The 1890 Census

- 1890 Census was a watershed moment
- Context: 25 years after emancipation; more than a decade after end of Reconstruction – question of status and future of African Americans in American society
- 1890 census publicized data about prison populations by race: Black Americans were 12% of population and 30% of prisoners
- Statistical racists like Frederick T. Hoffman (*Module 7*) drew heavily on 1890



# Comparing Black and Foreign-Born



- Crucial to the creation of what Muhammad calls the “statistical ghetto” was comparison between Black and foreign-born white Americans
- Progressive era social scientists interpreted (or dismissed) statistics on crime by European immigrants as evidence that Irish, Italians, Poles, etc. could be assimilated into US culture
- Charles R. Henderson, U. Chicago sociologist, 1901: “the [evil of immigrant crime] is not so great as statistics carelessly interpreted might prove...”

# Comparing Black and Foreign-Born



## The Condemnation of Blackness

Race, Crime, and the Making of Modern Urban America

KHALIL GIBRAN MUHAMMAD

- Henderson (1901), cont'd: But where the “Negro factor” is concerned, “racial inheritance, physical and mental inferiority, barbarian and slave ancestry and culture...” were among the “most serious factors in crime statistics.”

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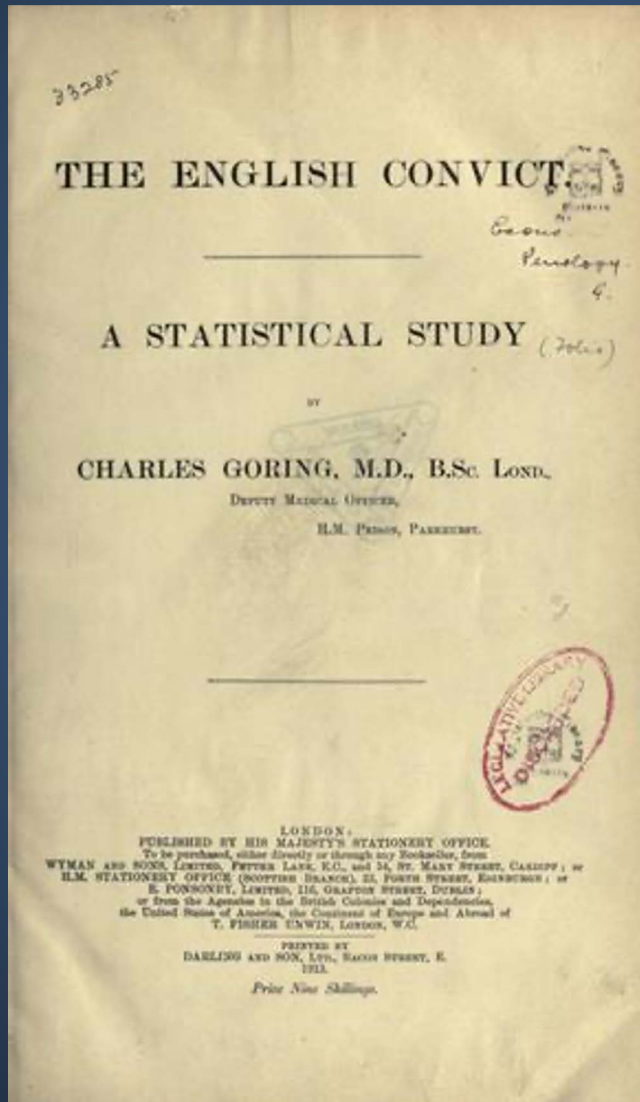
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**Risk assessment and the “actuarial”  
approach to policing and punishment, from  
the Burgess Method (1928) to AI**

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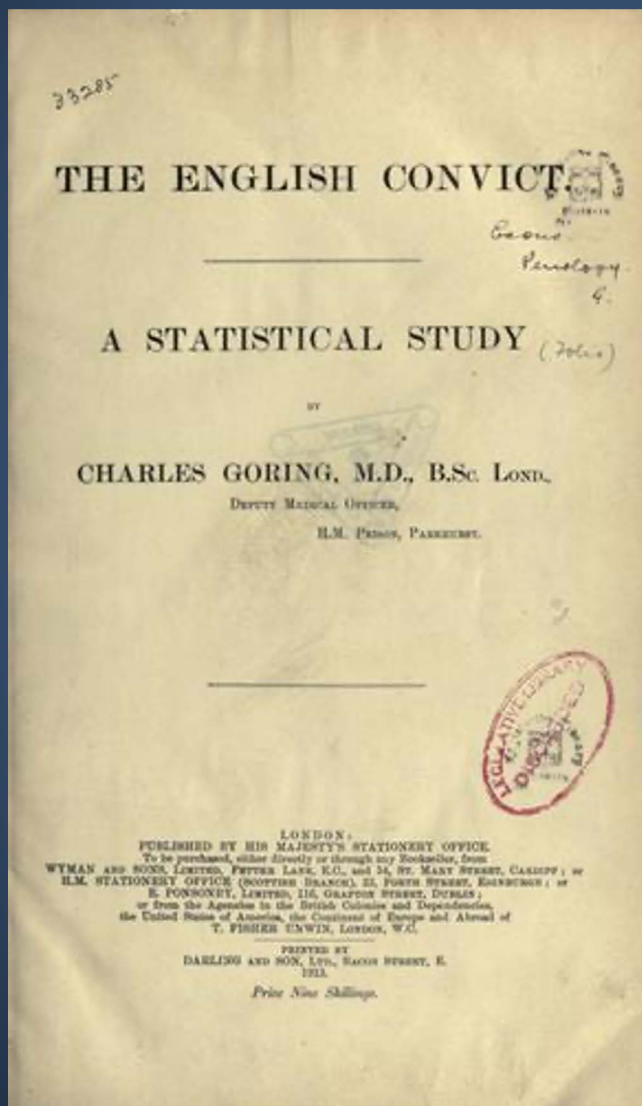
# “Positive Criminology” & “Individualization”



This image is in the public domain.

- Key finding of 19<sup>th</sup> c. quantitative soc. sci. was regularity of “laws” of crime – Quetelet’s “budget of the scaffold”
- Crime was not random, but predictably steady
- Advocates of “positive criminology” like **Cesare Lombroso (1835-1909)** and **Charles Goring (1870-1919)** held criminals were not randomly chosen from population
- Criminality seen to be correlated with home conditions, physical traits, genetic makeup, neighborhood, and race

# “Positive Criminology” & “Individualization”



- Circa 1900: international interest in the “individualization of penal treatment”
- National Conference on Criminal Law and Criminology, 1909: U. Chicago law profs. Ernst Freund and Roscoe Pound set agenda:
- “Modern science recognizes that penal or remedial treatment cannot possibly be indiscriminate and machine-like, but must be adapted to the causes, and to the man as affected by those causes”

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# Ernest Burgess and Parole Prediction

- Goal of “Individualization” encouraged move toward indeterminate sentencing for crimes: local parole boards to determine length of sentence
- 1920s: researchers like Hornell Hart (Iowa Child Research Station) argue that statistics might make it possible to create a “prognostic score for each man coming up for parole”
- **Robert Burgess (1886-1966):** PhD in Sociology from U. Chicago in 1913; faculty 1916
- Co-wrote *Introduction to the Science of Sociology* w. Chicago mentor Robert Park (1921)



Ernest W. Burgess photographed by Stephen Deutch, [University of Chicago Photographic Archive](#), apf1-02325, Special Collections Research Center, University of Chicago Library.

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# Ernest Burgess and Parole Prediction

- Burgess emphasized quant. methods over “ecological” approach dominant at Chicago
- Burgess: “Prediction is the aim of the social sciences as it is of the physical sciences.” (1929)
- 1927-28: Burgess and four colleagues requested by chairman of Illinois parole board to study Ill. procedures
- Understaffed, overworked parole officials in Ill. had been unable to give much attention or deliberation to parole cases
- Burgess conducts study of 3,000 parole cases in Illinois ~1920-1924



Ernest W. Burgess photographed by Stephen Deutch, [University of Chicago Photographic Archive](#), apf1-02325, Special Collections Research Center, University of Chicago Library.

# Ernest Burgess and Parole Prediction

- Burgess attempted to find a statistical relationship between who did/did not violate terms of parole and 22 other independent factors
- Factors included: racial and ethnic categorization, social & personality type, mental age, circumstances of crime, and prior criminal record
- Burgess develops 21-factor test: those with high scores (16-21) had low parole-offense rates (1.5%); those with low scores (2-4) had highest offending rates (76%)
- ***Reading for this module...***



Ernest W. Burgess photographed by Stephen Deutch, [University of Chicago Photographic Archive](#), apf1-02325, Special Collections Research Center, University of Chicago Library.

# The Burgess Method Takes Hold

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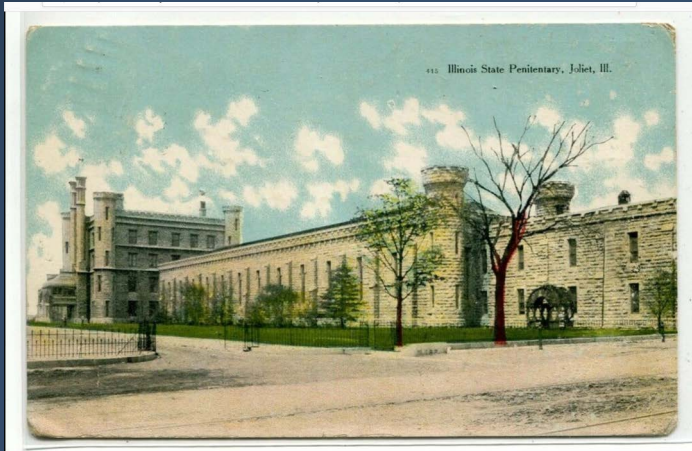
Illinois State Penitentiary, Joliet  
([Source](#))

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- Burgess Method implemented quickly at Joliet Penitentiary, 1932-33
- 1932 election: Democratic wave leads to Dem. Governor elected in IL; appoints John Landesco, Burgess's research assistant, to State Parole Board
- Landesco urges IL legislature to pass bill to hire sociologists and actuaries to “make analyses and predictions in the cases of all men being considered for parole”
- 1930s-40s: Adoption of Burgess Method in IL triggers outpouring of academic research

# The Burgess Method Takes Hold

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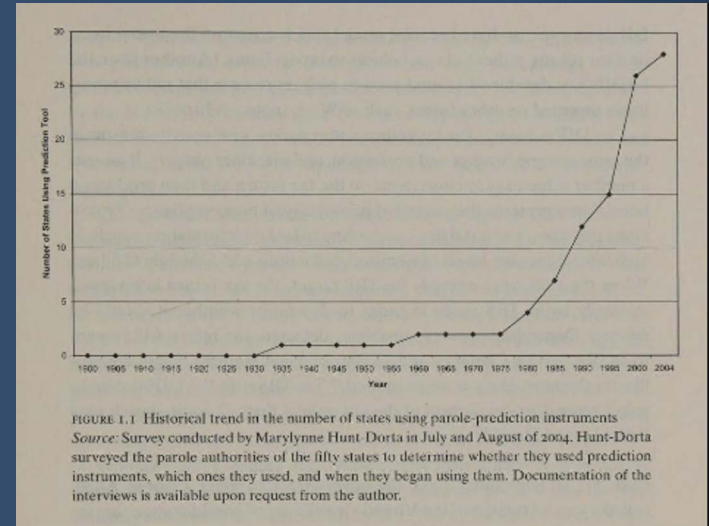
Illinois State Penitentiary, Joliet  
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- Others seek to critique, improve Burgess Method through more data and development of new risk-assessment tools using different variables and weighting different variables more/less
- Some explored more sophisticated statistical techniques (e.g. multiple regression) to develop assessment tools
- Researchers studying Burgess Method found prominent positions at top institutions like U. Chicago, Harvard Law School, University of Southern California, and University of Minnesota

# The Actuarial Approach Takes Off

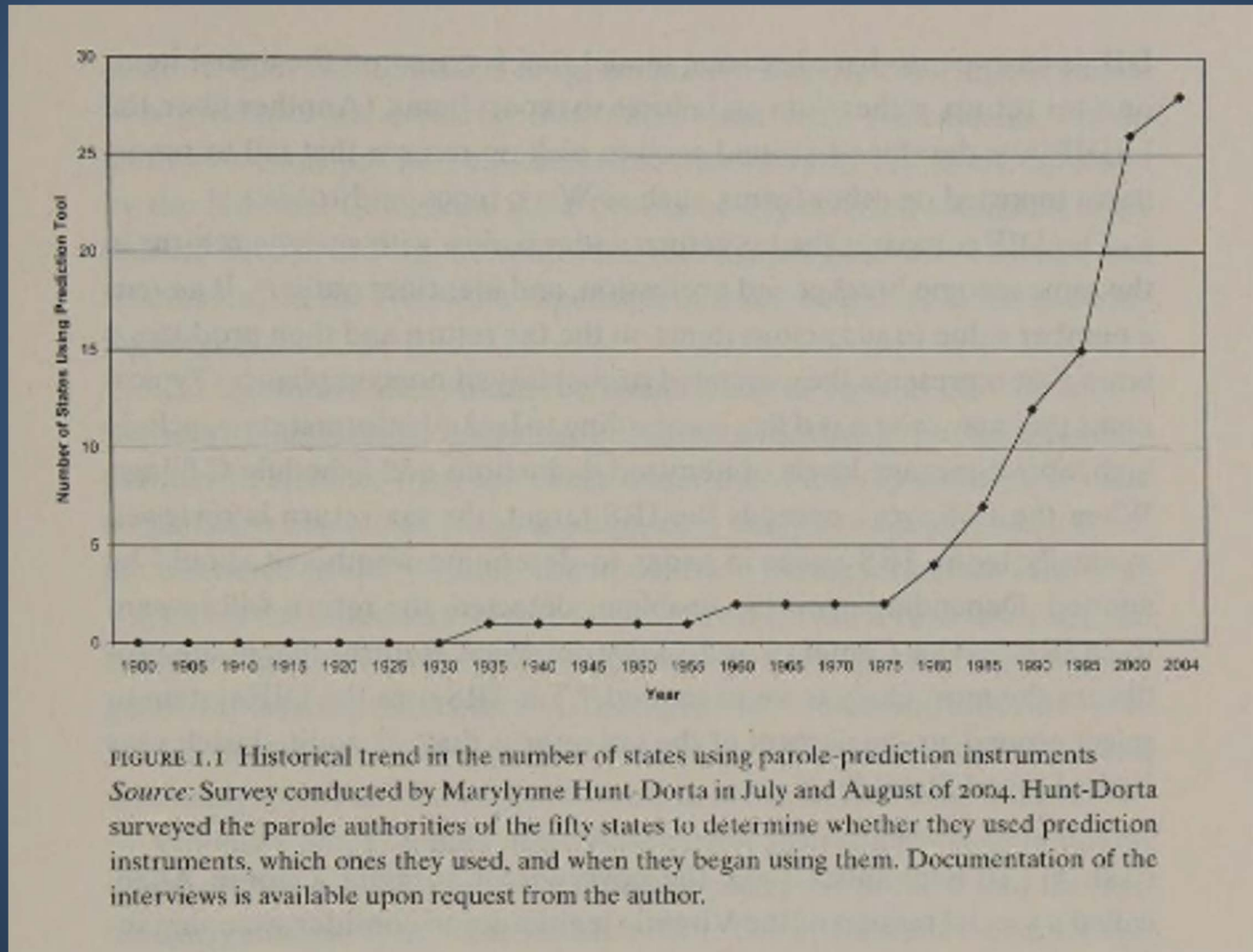
- For the first few decades, application actuarial parole methods confined to Illinois
- Other states begin to adopt similar tools in 1960s
- Prior to 1970s, race and nationality were common factors in these tools
- Early 1970s: federal gov't adopts slim, 7-factor "Salient Factor Score"
- Federal adoption stimulates widespread interest in parole prediction tools – first in California, then wave of other states in the 1980s-90s



From Harcourt, *Against Prediction: Policing, Punishing, and Profiling in an Actuarial Age* (Chicago, 2007), p. 9.

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# The Actuarial Approach Takes Off



# Drug/Other Section A

Offender Name: \_\_\_\_\_

◆ **Primary Offense** \_\_\_\_\_

A. Other than listed below (1 count) .....	1
B. Sell, etc. 1 ounce - 5 pounds of marijuana for profit; Sell, etc. marijuana to inmate for accommodation	
1 count .....	3
2 counts .....	8
C. Sell, etc. more than 5 pounds of marijuana for profit; Sell, etc. third or subsequent felony (1 count) .....	12
D. Sell, etc. marijuana to minor (1 count) .....	11
E. Manufacture marijuana not for personal use (1 count) .....	8
F. Transport 5 pounds or more of marijuana into Commonwealth (1 count) .....	12
G. Sell, etc. Schedule III or IV drug to minor (1 count) .....	11
H. Sell, etc. Schedule III drug-not anabolic steroid	
1 count .....	8
2 counts .....	10
I. Sell, etc. Schedule IV drug	
1 count .....	6
2 counts .....	8

Score  
▼

◆ **Primary Offense Remaining Counts** Total the maximum penalties for counts of the primary not scored above

Years: 5 - 10 .....	0
11 - 21 .....	2
22 - 30 .....	3
31 - 42 .....	4
43 or more .....	5

◆ **Additional Offenses** Total the maximum penalties for additional offenses, including counts

Years: Less than 4 .....	0
4 - 10 .....	1
11 - 21 .....	2
22 - 30 .....	3
31 - 42 .....	4
43 or more .....	5

◆ **Knife or Firearm in Possession at Time of Offense** \_\_\_\_\_ If YES, add 2 →

◆ **Conviction in Current Event Requiring Mandatory Minimum Term (6 mos or more)** \_\_\_\_\_ If YES, add 5 →

◆ **Prior Convictions/Adjudications** Total the maximum penalties for the 5 most recent and serious prior record events

Years: Less than 7 .....	0
7 - 26 .....	1
27 - 48 .....	2
49 or more .....	3

◆ **Prior Incarcerations/Commitments** \_\_\_\_\_ If YES, add 2 →

◆ **Prior Felony Drug Convictions/Adjudications** \_\_\_\_\_

Number of Counts: 1 - 2 .....	1
3 - 4 .....	2
5 .....	3
6 or more .....	4

◆ **Prior Juvenile Record** \_\_\_\_\_ If YES, add 1 →

◆ **Legally Restrained at Time of Offense** \_\_\_\_\_

None .....	0
Other than parole/post-release, supervised probation or CCCA .....	1
Parole/post-release, supervised probation or CCCA .....	4

**Total Score** \_\_\_\_\_  
If total is 10 or less, go to Section B. If total is 11 or more, go to Section C.

Drug/Other Section A

Example of a criminal sentencing worksheet from the Virginia Criminal Sentencing Commission ([Source](#))



# From Parole Prediction to Profiling



Image from hijacking of TWA flight 847, 1985  
([CNN](#))

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- By 1951, Burgess argued actuarial risk assessment could be applied much more widely than parole selection
- Later part of the 20<sup>th</sup> century saw adoption of risk-assessment methods to policing *potential* crimes as well (“profiling”)
- 1968: Federal Aviation Administration implements “airline-highjacker” profile – 25 characteristics
- 1970s+: increasing use of profiles for specific crimes “drug-courier”

# From Parole Prediction to Profiling

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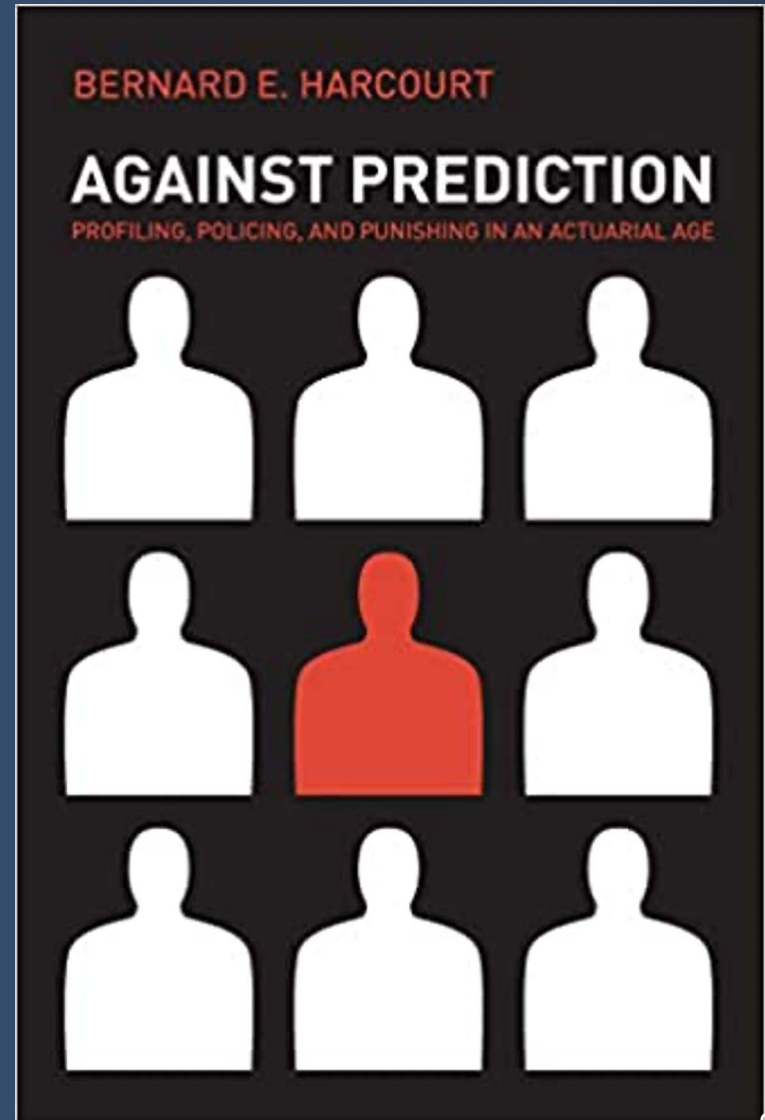
Image from hijacking of TWA flight 847, 1985  
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- Starting in 1969, IRS began to use computerized assessment of past income tax returns to develop predictive tools (secret “Discriminant Index Function”) to flag income tax return for audit

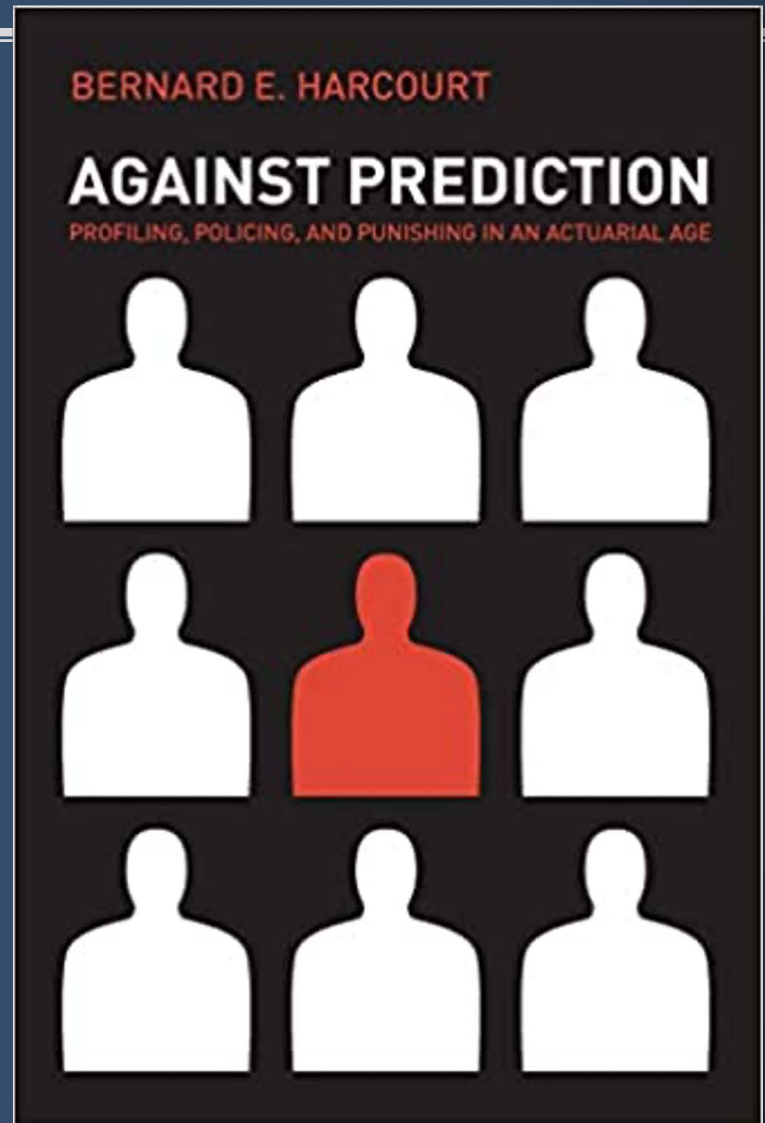
# Social Costs of Prediction: the “Ratchet”

- Legal scholar Bernard Harcourt and others have identified crucial social costs to the actuarial, predictive approach to criminal justice
- Using statistical techniques to target policing/ punishment will increase success rate of searches, audits, parole decisions, etc.
  - More searches (of specific group) will find more contraband...
  - More parole denials (of specific group) will prevent re-offenses...



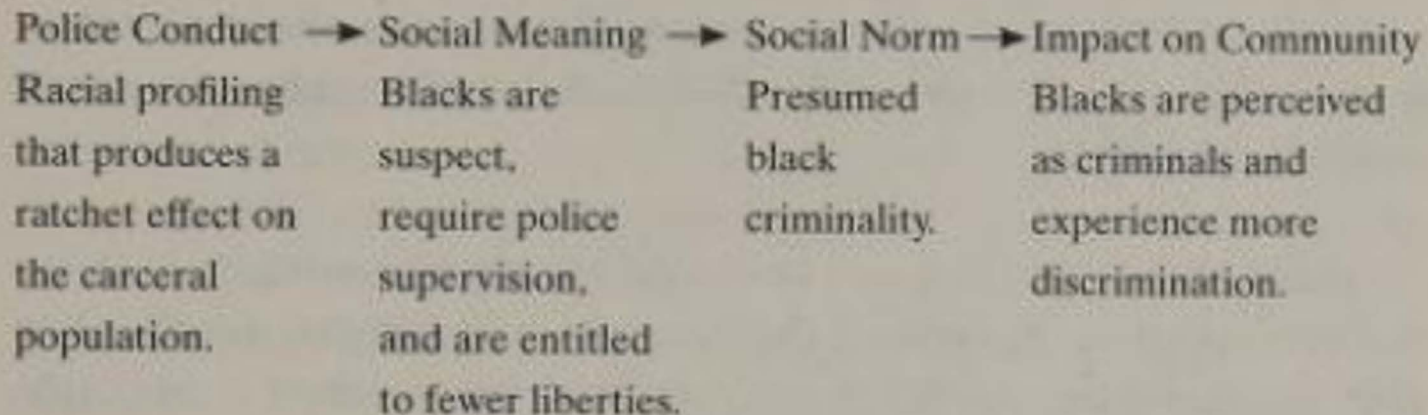
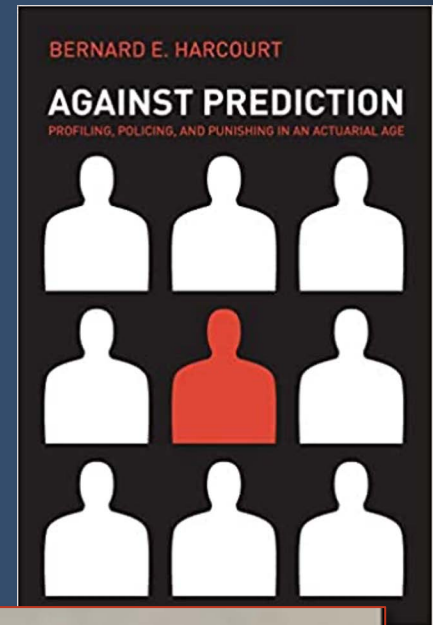
# Social Costs of Prediction: the “Ratchet”

- If the actuarial methods disproportionately target a specific group – e.g. drywall contractors for tax audits, young Black men for street frisks – then over time the extra policing attention will produce more infractions from that group
- This may be taken as confirmatory evidence that the specific group offends at a higher rate (not that the group is under heightened attention)
- This creates a “ratchet”:
  - increased police attention
  - more evidence of infractions
  - increased police attention
  - ...



# Social Costs of Prediction: the “Ratchet”

- subject to police contacts, even with small/no punishment or for minor infractions, can have significant social costs
- Harcourt: “Disproportionate criminal supervision and incarceration reduces work opportunities, breaks down families and communities, and disrupts education.” (161)



# Algorithmic Predictions and Their Biases



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Prediction Fails Differently for Black Defendants

	WHITE	AFRICAN AMERICAN
Labeled Higher Risk, But Didn't Re-Offend	23.5%	44.9%
Labeled Lower Risk, Yet Did Re-Offend	47.7%	28.0%

Overall, Northpointe's assessment tool correctly predicts recidivism 61 percent of the time. But blacks are almost twice as likely as whites to be labeled a higher risk but not actually re-offend. It makes the opposite mistake among whites: They are much more likely than blacks to be labeled lower risk but go on to commit other crimes. [Source: ProPublica analysis of data from Broward County, Fla.]

- Today, “risk assessment” for criminal sentencing and parole are increasingly conducted by algorithms
- E.g. the COMPAS -- Correctional Offender Management Profiling for Alternative Sanctions – algorithm from for-profit company Northpointe
- Algorithmic risk scores widely used in assigning bail, criminal sentencing, and parole decisions
- As of 2016, risk scores given directly to judges during sentencing in at least 11 states
- COMPAS algorithm based on 137 questions/data points; not race

# Algorithmic Predictions and Their Biases



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“The survey asks defendants such things as: “Was one of your parents ever sent to jail or prison?” “How many of your friends/acquaintances are taking drugs illegally?” and “How often did you get in fights while at school?” The questionnaire also asks people to agree or disagree with statements such as “A hungry person has a right to steal” and “If people make me angry or lose my temper, I can be dangerous.””

Julia Angwin, Jeff Larson, Surya Mattu and Lauren Kirchner, “[Machine Bias](#),” *ProPublica* (May 23, 2016).

# Algorithmic Predictions and Their Biases



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## Prediction Fails Differently for Black Defendants

	WHITE	AFRICAN AMERICAN
Labeled Higher Risk, But Didn't Re-Offend	23.5%	44.9%
Labeled Lower Risk, Yet Did Re-Offend	47.7%	28.0%

Overall, Northpointe's assessment tool correctly predicts recidivism 61 percent of the time. But blacks are almost twice as likely as whites to be labeled a higher risk but not actually re-offend. It makes the opposite mistake among whites: They are much more likely than blacks to be labeled lower risk but go on to commit other crimes. [Source: ProPublica analysis of data from Broward County, Fla.]

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- 2016 study by ProPublica found that COMPAS algorithm was...
- ...very bad at predicting violent crime: 20% of those predicted to commit future violent crime did
- ...only moderately good at predicting all crime (including misdemeanor): 61% of those deemed likely recidivists committed future crimes
- ...racially biased: Black defendants much more likely to be flagged incorrectly as likely re-offenders (*false positive*), and white defendants more likely to be mislabeled as low risk (*false negative*)



# Algorithmic Predictions and Their Biases

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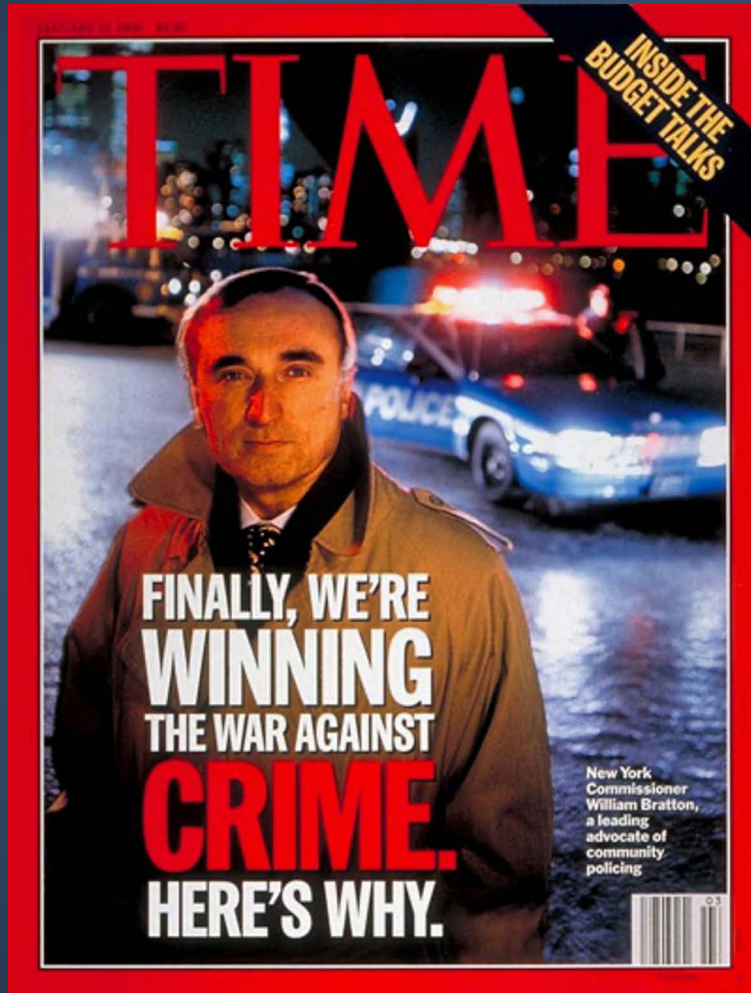
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**“Data-driven” policing from CompStat  
(1990s) to Big Data**

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# Bill Bratton and Data-Driven Policing



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- No single individual more responsible for expansion of “data-driven policing” than Bill Bratton
- Across two stints as police chief in NYC and one in L.A., Bratton led three major expansions of use of data and computation
- Critically: in all three cases, Bratton was brought in to reform police depts. in crisis
- In each case, Bratton turned to data and computation as a remedy for corruption, malpractice, and bias

# Compstat: Quantitative Policing in the '90s

- Early 1990s, NYC experiencing high crime and raft of police corruption
- Mollen Commission (created 1992) revealed widespread, unchecked corruption in NYPD: “characterized by brutality, theft, abuse of authority, and active police criminality.”
- 1994: Mayor Rudolph Giuliani appoints Bratton new Police Commissioner; previously Boston police chief and head of NYC Transit Police
- As head of Transit Police, Bratton had overseen work of **Jack Maple**



<https://www.innovations.harvard.edu/compstat-crime-reduction-management-tool>

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# Jack Maple's "Charts of the Future"



Jack Maple ([Source](#))

- Jack Maple started in NYPD in 1970; became a transit police officer, inc. undercover Times Square / 42<sup>nd</sup> Street Station
- In 1970s-80s, subways major sites of crime, esp. violent robberies
- As detective, Maple took to mapping patterns of subway crime with pushpins on wall maps – “Chart of the Future”
- Charts allowed Maple to observe repeated patterns in subways crimes – large %age of crimes from serial offenders tracing set routes
- Targeting policing to key locations disrupted these patterns; led to **27% reduction in subway crime**

# CompStat in Practice

- When appointed Commissioner in 1994, Bratton promoted Maple from lieutenant to Deputy Chief
- Maple and Bratton institute new COMPuterized STATistics program
- CompStat required personnel from each of city's 77 precincts and other units to submit weekly report on complaints, arrests, summons, open crimes, etc.
- NYPD CompStat system produced regular reports showing weekly, monthly, annual trends



<https://www.innovations.harvard.edu/compstat-crime-reduction-management-tool>

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# CompStat in Practice

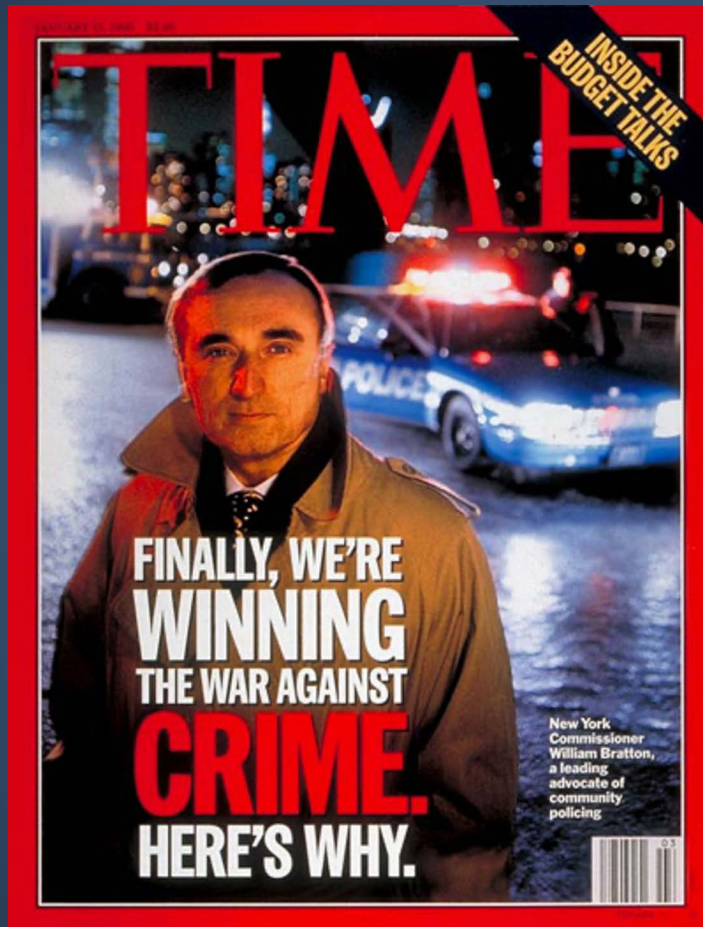
- Systems of regular meetings with leading NYPD officials and precinct/unit commanders enabled sharing of data, discussion of crime control strategies, and oversight of units
- One key objective of CompStat including improving accountability and professionalism of local force while giving more responsibility to local commanders
- Also sought to address problems of inadequate police attention in certain areas: e.g. major crimes in poor, predominantly Black and Latinx areas outside Manhattan core went routinely unsolved



<https://www.innovations.harvard.edu/compstat-crime-reduction-management-tool>

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# The “Marvel” of CompStat

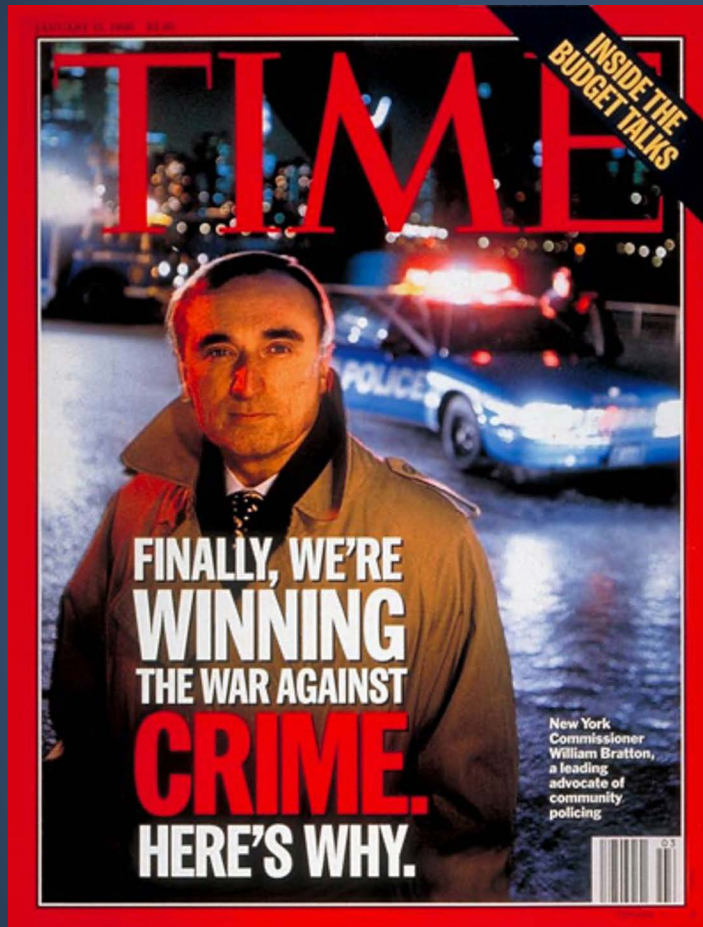


- Institution of CompStat coincided with notable decline in crime in New York City – inc. stark decline in murders, from record 2,245 in 1990 to 673 in 2000 (and 289 in 2018)
- Bratton publicly targeted 10%+ reductions in crime; achieved 12% in first CompStat years
- NYT called results under Bratton “marvel of modern law enforcement”; “simply breathtaking”
- But debate over role of CompStat in decline in crime (decline began in 1990, before CompStat, and occurred across major cities)

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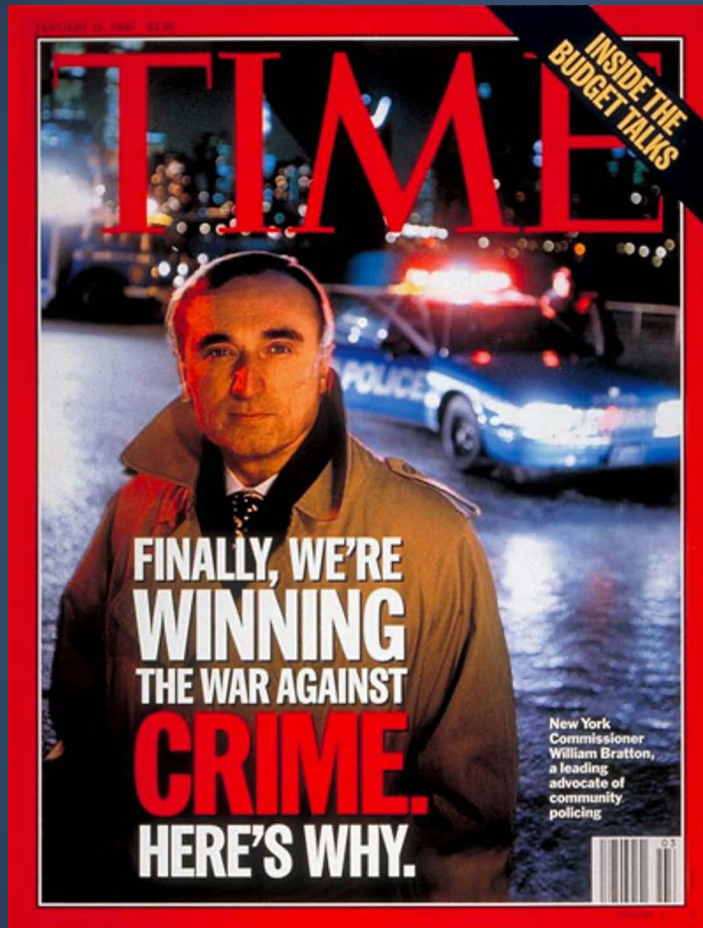
# The “Marvel” of CompStat



- Apparent successes of CompStat in New York led to widespread uptake of data-driven methods across other US police departments over early 2000s, inc. Philadelphia, Miami, Chicago, Baltimore, DC, San Francisco, etc.
- 2002: Bratton recruited to lead Los Angeles PD; wracked by longstanding abuses, poor community relations, poor morale, and major corruption scandal in anti-gang unit (“Rampart Scandal”)
- Bratton instituted CompStat in LA

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# The “Marvel” of CompStat



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- For opposing perspectives on the role of CompStat in crime decline:

Lauren-Brooke Eisen, Oliver Roeder, and Julia Bowling, “What Caused the Crime Decline?” *The Brennan Center for Justice* (Feb. 12, 2015)

Steven D. Levitt, “Understanding Why Crime Fell in the 1990s: Four Factors that Explain the Decline and Six That Do Not,” *Journal of Economic Perspectives* 18, no. 1 (Winter 2004): 163-190.

# “Juking the Stats”: Critiques of CompStat

- Introduction of CompStat had major effects on practice and culture of policing
- Increasing political, managerial emphasis on reducing CompStat numbers created pressure on commanders and officers to make it appear crime was falling
- Emphasis on measurable stats distracted from public safety goals, community relationships
- “Juking the Stats”: statistical manipulation designed to make CompStat figures *appear* better: e.g. through reclassifying crimes into lesser categories (aggravated assaults □ assaults)



Mayor Rudolph W. Giuliani, right, and Police Commissioner William Bratton at a 1995 news conference reporting a decline in crime statistics. James Estrin for The New York Times.

<https://archive.nytimes.com/www.nytimes.com/interactive/2013/12/06/nyregion/bratt-on-on-the-issues.html> - /

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# “Juking the Stats”: Critiques of CompStat

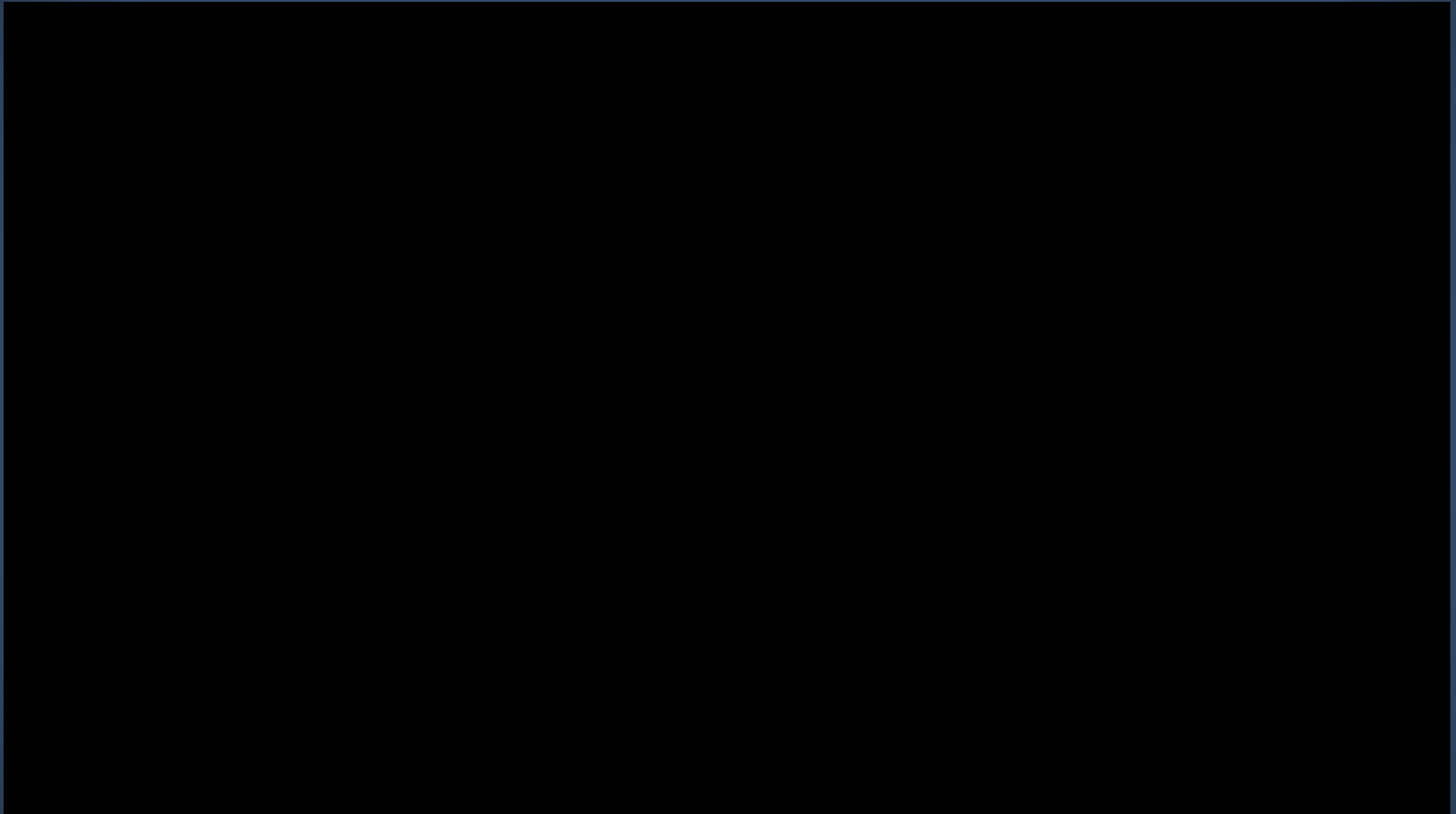
- Rewarding measurable indicators of police activity – e.g. arrests and tickets – incentivized officers to increase punishment for minor offenses (e.g. transit fare evasion, vandalism, loitering)
- Especially combined with “broken windows” theory (as in Bratton in the 90s): theory that rigorously policing minor “anti-social” crimes creates environment of order, lawfulness that prevents more serious crime
- Black and Latino citizens disproportionately targets of minor-crime enforcement: 2001-2013, Blacks and Latinos in NY (57% of population) were 80% of misdemeanor arrests and summonses



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# “Juking the Stats”

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*The Wire*, Season 4, Episode 9  
(2006).

# The Rise of Big Data Policing in the 2000s

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NYPD Joint Operations Center ([City Journal](#))

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- Bratton returned as NYPD chief Jan. 1, 2014 – in wake of widespread anger about “stop-and-frisk” and legal ruling declaring it unconstitutional
- Bratton oversees construction of real-time crime-command center in Manhattan; orders tens of thousands of crime mapping tablet computers
- “Intelligence-led policing” purported to go beyond “hunches,” offer alternative to stop and frisk

# Data & the Who/Where/When/How of Policing

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- **Whom...**
  - In 2012, Kansas City PD used social-network analysis to identify 884 people deemed likely to commit homicides □ “focused deterrence”
  - Chicago developed algorithmic “heat list” to identify likely perpetrators and victims of gun violence
- **Where...**
  - Jeff Brantingham (UCLA) uses earthquake-prediction techniques to develop PredPol algorithm for identifying likely sites of crime □ implemented by LAPD in 2011 (25% reduction in burglaries)



# Data & the Who/Where/When/How of Policing

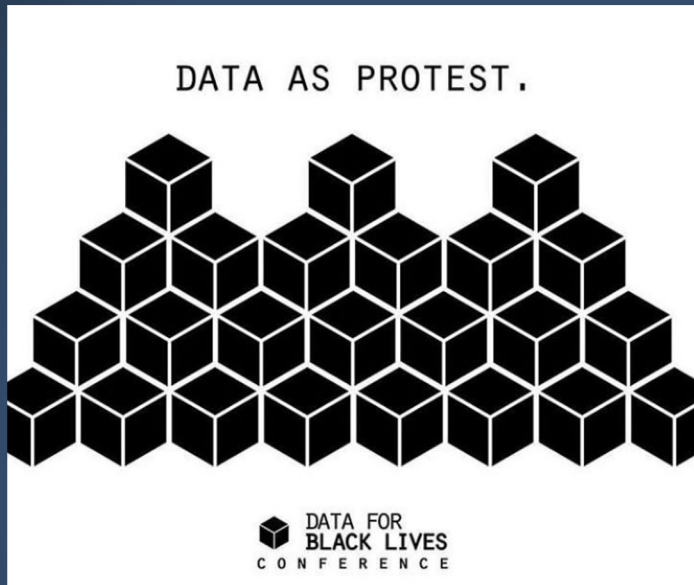
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- **When...**
  - Networks of surveillance devices (cameras, license plate readers, etc.) used for real-time tracking and alerts; e.g. NYPD-Microsoft “Domain Awareness system” monitoring southern Manhattan
- **How...**
  - Data mining to search “cellular, digital, and biological data trails”
  - Facial recognition
- Notably, much of this done in concert with private for-profit companies – as in Palantir and LAPD Real-Time Analysis Critical Response section





# The Future of Big Data and Policing?



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- Andrew Guthrie Ferguson proposes five-point checklist for safe application of big data techniques:
  1. Can you identify the risks your technology is trying to address?
  2. Can you defend the inputs into the system?
  3. Can you defend the outputs (how they will impact policing practice/community)?
  4. Can you test the technology (transparency/accountability)?
  5. Is police use of the technology respectful of the autonomy of the people it will impact?
- Or, abolish big data? (Data for Black Lives)

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Fall 2021

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