port_Output

ObjectID	ADDRESS	INC_	TYPE_CODE	CALL_TYPE	LOC_CODE	CASE_NUMBE	TIME_	DATE_	DAY_FROM	DATE_FROM	TIME_FROM	DAY_TO	DATE_TO
18185207	003811 TIERRA DR	23500	6301	LFA $200 +	84	B6-097264	1849	10-16-2016	SAT	10-15-2016	1900	SUN	10-16-2016
18185344	4300 BLK OF HUNTINGTON	23500	6302	LFA $50-199	1	B6-097713	0635	10-18-2016	MON	10-17-2016	1730	TUE	10-18-2016
18185356	008700 YANKEE WOODS DR	06000	5213	BURG NRU FE	37	B6-097792	1200	10-18-2016	MON	10-17-2016	1800	TUE	10-18-2016

> ***"Opacity in algorithmic processes, when they have real welfare effects, is a problem in all contexts. But in the case of public governance, it poses particular dangers to democratic accountability, to the efficacy and fairness of governmental processes, and to the competence and agency of government employees tasked with doing the public's work."***
>
> – "Algorithmic Transparency for the Smart City" by Ellen P. Goodman and Robert Brauneis in the forthcoming Yale Journal of Law and Technology

The Injustice of Algorithms

Prejudice is often coded into software, including tools used by the government.

BY **ETHAN CHIEL** | January 23, 2018

VIRGINIA EUBANKS BUSINESS 01.15.18 08:00 AM

A CHILD ABUSE PREDICTION MODEL FAILS POOR FAMILIES

How New Jersey Is Leading the Post-Bail Revolution

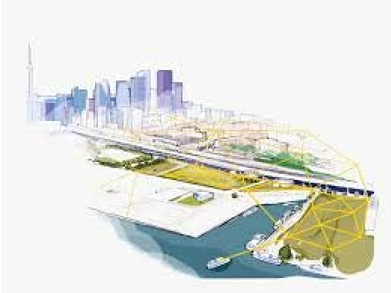
RENTIN MOCK NOV 2, 2017

Algorithmic Accountability

Inscrutability of Big Tech

- Black Box Society (Pasquale)
- Weapons of Math Destruction (O’Neil)
- The Platform is Political (Gillespie)
- AI ethics in place –

  Autonomous vehicles, Uber...



At the same time...

The Smart City rhetoric reprises the techno liberation creed of the 1990’s Internet.
Private power? Public interest?

Local government use of predictive algorithms – what can we know?

1. About performance and fairness
2. About politics
3. About private power and control

Transparency → Accountability

Research

We filed

- 43 open records requests
- to public agencies in 23 states
- about six predictive algorithm programs:
    - PSA-Court
    - PredPol
    - Hunchlab
    - Eckerd Rapid Safety Feedback
    - Allegheny County Family Risk
    - Value Added Method – Teacher Evaluation

Predictive Algorithms: Pretrial Disposition

Arnold Foundation PSA - Court: Predicts likelihood that criminal defendant awaiting trial will fail to appear, or commit a crime (or violent crime) based on nine factors about him/her.

RELATIONSHIP BETWEEN RISK FACTORS AND PRETRIAL OUTCOMES

Risk Factor	FTA	NCA	NVCA
1. Age at current arrest		X	
2. Current violent offense			X
Current violent offense & 20 years old or younger			X
3. Pending charge at the time of the offense	X	X	X
4. Prior misdemeanor conviction		X	
5. Prior felony conviction		X	
Prior conviction (misdemeanor or felony)	X		X
6. Prior violent conviction		X	X
7. Prior failure to appear in the past two years	X	X	
8. Prior failure to appear older than two years	X		
9. Prior sentence to incarceration		X	

The PSA does NOT look at any of the following factors:

from http://www.arnoldfoundation.org/wp-content/uploads/PSA-Infographic.pdf

Predictive Algorithms: Child Welfare

Eckerd Rapid Safety Feedback: Helps family services agencies triage child welfare cases by scoring referrals for risk of injury or death

The Eckerd Rapid Safety Feedback℠ model represents a pivotal shift in the approach to child safety.

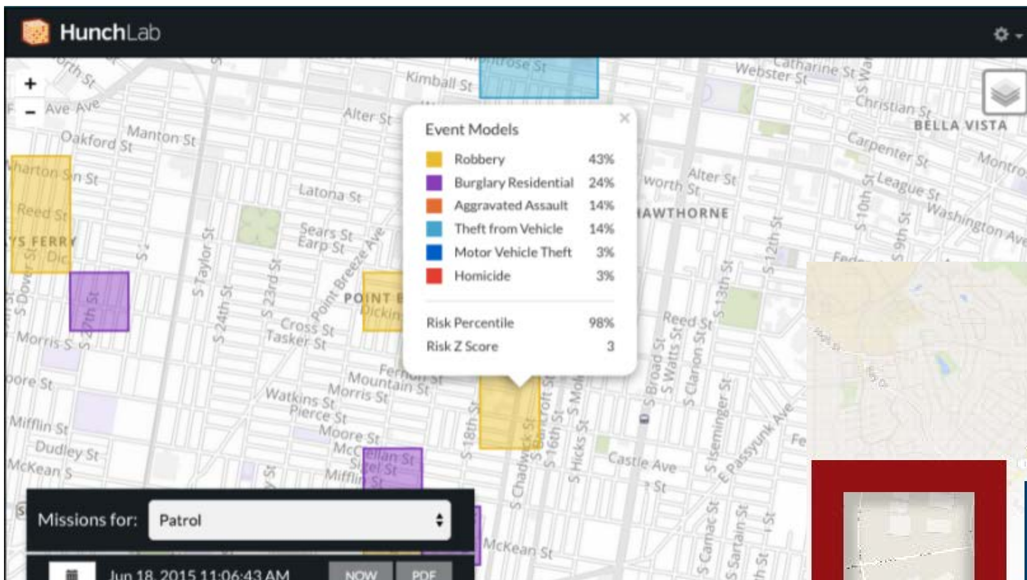
MARCH 30, 2016

Using data now to keep children safe in the future

Unlike many traditional child welfare systems, which intervene only after a problem happens, some jurisdictions are using models designed to keep children safe before trouble escalates. In recognition of National Child Abuse Prevention Month in April, we'd like to look at one promising approach.

Predictive Algorithms: Policing

HunchLAB and Predpol: use historical data about where and when crimes occurred to direct where police should be deployed to deter future crimes



The Public Interest in Knowing

Democratic accountability

- What are the policies the program seeks to implement and what tradeoffs does it make?

Performance

- How does the program perform as implemented? As compared to what baseline?

Justice

- Does the program ameliorate or perpetuate bias? Systemic inequality?

Governance

- Do government agents understand the program? Do they exercise discretion w/r/t algorithmic recommendations?

What disclosures would lead to knowing?

1. Basic purpose and structure of algorithm
2. Policy tradeoffs – what and why
3. Validation studies and process before and after roll-out
4. Implementation and training

Basic Purpose and Structure

1. What is the **problem to be solved?** What outcomes does the program seek to optimize? e.g., Prison overcrowding? Crime? Unfairness?
2. What **input data** (e.g., arrests, geographic areas, etc.) were considered relevant to the predicted outcome, including time period and geography covered.
3. **Refinements.** Was the data culled or the model adjusted based on observed or hypothesized problems?

Policy Tradeoffs Reflected in Tuning

Predictive models are usually refined by minimizing some cost function or error factor. What policy choices were made in formulating that function?

For example, a model will have to trade off false positives and false negatives

> Philadelphia's APPD decided on a cost ratio where false negatives were 2.6 times more costly than false positives.

(Adult Probation and Parole Department) from https://www.nij.gov/journals/271/pages/predicting-recidivism.aspx

Validation Process

1. It is standard practice in machine learning to withhold some of the training data when building a model, and then use it to test the model.

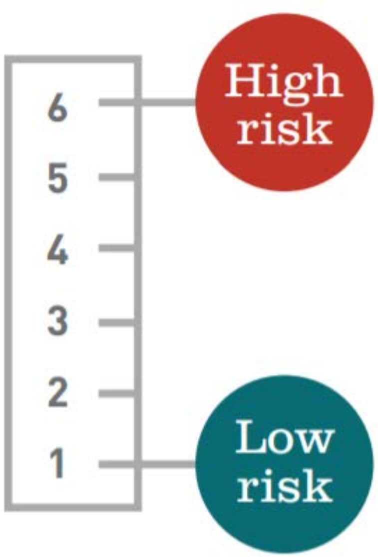
   Was that "validation" step taken, and if so, what were the results?

2. What steps were taken or are planned after implementation to audit performance?

Implementation and Training

Interpretation of results: Do those who are tasked with making decisions based on predictive algorithm results know enough to interpret them properly?

PSA-Court



Philadelphia APPD

$$\left.\begin{array}{r}\textbf{High}\\ \textbf{Medium}\\ \textbf{Low}\end{array}\right\}\ \textbf{Risk}$$

http://www.arnoldfoundation.org/wp-content/uploads/PSA-Infographic.pdf

Open Records Responses

- 25 either did not provide or reported they did not have responsive documents
- 5 provided confidentiality agreements with the vendor
- 6 provided some documents, typically training slides and materials
- 6 did not respond
- 1 responded in a very complete way with everything but code – has led to an ongoing collaboration on best practices

Impediments

1. Open Records Acts and Private Contractors
2. Trade Secrets / NDAs
3. Competence of Records Custodians and Other Government Employees
4. Inadequate Documentation
5. [Non-Interpretability, Dynamism of Machine Learning Algorithms]

Impediment 1: Private Contractors

- Algos developed by private vendors
- Vendors give very little documentation to governments
- Open records laws typically do not cover outside contractors unless they are acting as records managers for government

Impediment 2: Trade Secrets/NDAs

- Mesa (AZ) Municipal Court (PSA-Court): “Please be advised that the information requested is solely owned and controlled by the Arnold Foundation, and requests for information related to the PSA assessment tool must be referred to the Arnold Foundation directly.”
- 12 California jurisdictions refused to supply Shotspotter data – detection of shots fired in the city – even though it’s not secret, and not IP
- Overbroad TS claims being made by vendors, and accepted by jurisdictions

Impediment 3: Govt. Employees

Records custodians are not the ones who use the algorithm

Those who use the algorithm don’t understand it

Impediment 4: Inadequate Records

Jurisdictions have to supply only those records they have (with some exceptions for querying databases). Governments are not insisting on obtaining, and are not creating, the records that would satisfy the public's right to know.

FIXES

Government procurement: don’t do deals without requiring ongoing documentation, circumscribing TS carve-outs, data and records ownership

Data Reasoning with Open Data

Lessons from the COMPAS-ProPublica debate

Anne L. Washington, PhD

NYU - Steinhardt School

Sunday February 11, 2018

Regulating Computing and Code - Governance and Algorithms Panel

Silicon Flatirons 2018 Technology Policy Conference

University of Colorado Law School

>>

DATA SCIENCE REASONING

Can you argue with an algorithm?

Reasoning

- Arguments
  - Convince, Interpret, or Explain
  - Arguments logically connect evidence and reasoning to support a claim
    - Quantitative Statistical Reasoning
    - Inductive Reasoning
    - Data Science Reasoning

2016 WI 68

SUPREME COURT OF WISCONSIN

2015AP157-CR

E: State of Wisconsin,
Plaintiff-Respondent,
v.
Eric L. Loomis,
Defendant-Appellant.

ON CERTIFICATION FROM THE COURT OF APPEALS

: July 13, 2016

BRIEFS:

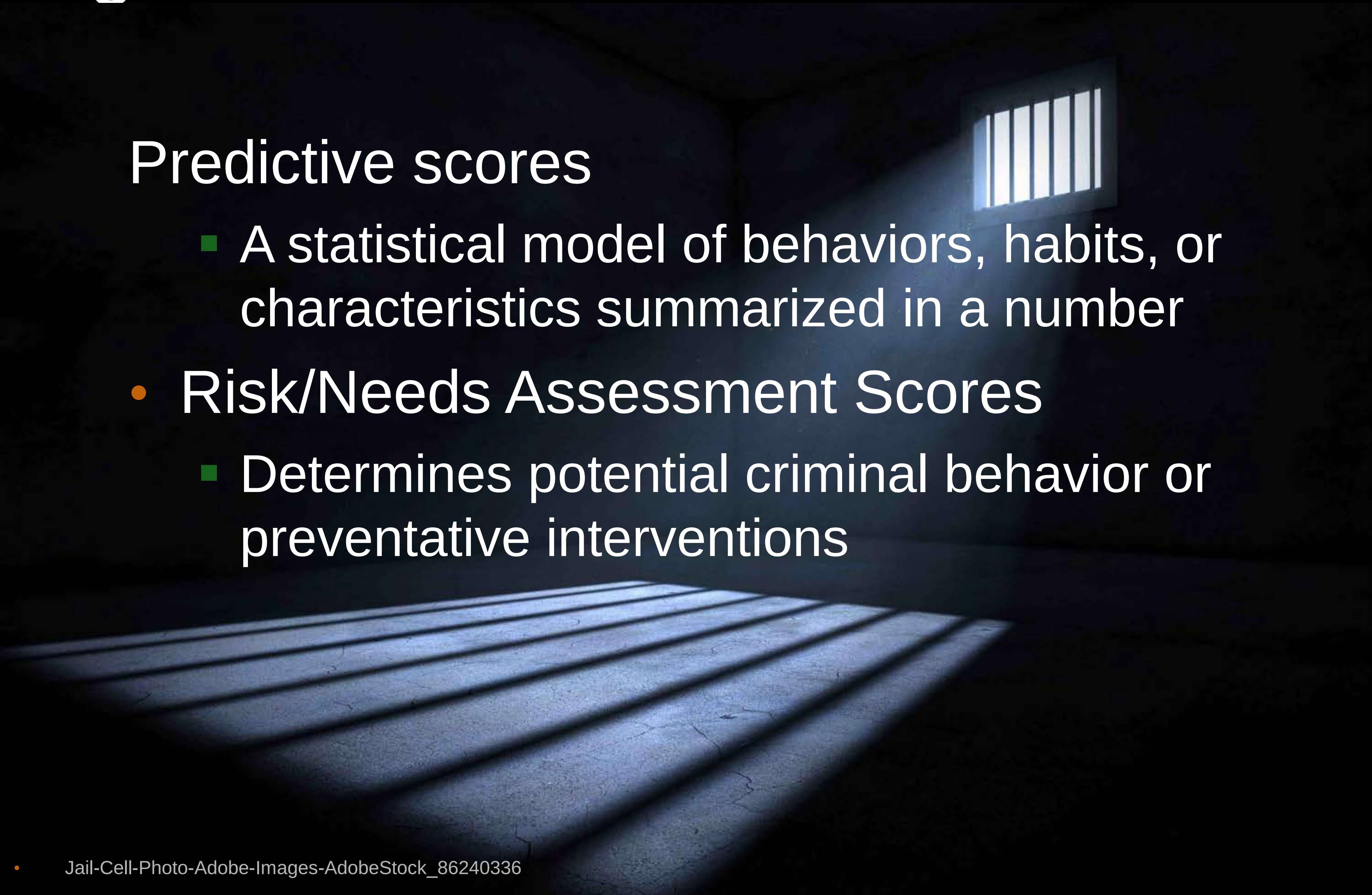
: April 5, 2016

¶ 49 The Skaff court explained that if the PSI Report was incorrect or incomplete, no person was in a better position than the defendant to refute, supplement or explain the PSI.*
(State v. Loomis, 2016)

* State v. Skaff, 152 Wis. 2d 48, 53, 447 N.W.2d 84 (Ct. App. 1989).

.. but what if a Presentence Investigation Report ("PSI") is produced by an algorithm?

Algorithms in Criminal Justice



Predictive scores

- A statistical model of behaviors, habits, or characteristics summarized in a number

- Risk/Needs Assessment Scores
  - Determines potential criminal behavior or preventative interventions

- Jail-Cell-Photo-Adobe-Images-AdobeStock_86240336

THE DEBATE

Are risk assessment scores biased?

Summer 2016

- US Congress
  H.R 759 Corrections and Recidivism Reduction Act
- Wisconsin v Loomis
  881 N.W.2d 749 (Wis. 2016)
- Machine Bias
  ProPublica Journalists

- COMPAS risk scores
  Correctional Offender Management Profiling for Alternative Sanctions

The Public Debate: ProPublica vs COMPAS

- Machine Bias www.propublica.org
  - By Angwin, Larson, Mattu, Kirchner
- COMPAS Risk Scales: volarisgroup.com
  - By Northpointe (Volaris)

Correctional Offender Management Profiling for Alternative Sanctions

The Scholarly Debate: Is COMPAS fair ?

Open data

ProPublica Data repository

github.com/propublica/compas-analysis

- From May 2016 – Dec 2017
- nearly 230 publications
- cited Angwin (2016), Dieterich (2016), Larson (2016) or ProPublica's github data repository

- Abiteboul, S. (2017). Issues in Ethical Data Manag
In PPDP 2017-19th International Symposium on
Principles and Practice of Declarative Programmin
- Angelino, E., Larus-Stone, N., Alabi, D., Seltzer, M
Rudin, C. (2017). Learning Certifiably Optimal Rule
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- Barabas, C., Dinakar, K., Virza, J. I. M., & Zittrain,
(2017). Interventions over Predictions: Reframing t
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- Berk, R., Heidari, H., Jabbari, S., Kearns, M., & Ro
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- Chouldechova, A. (2017). Fair prediction with dispa
impact: A study of bias in recidivism prediction
instruments. ArXiv:1703.00056 [Cs, Stat].
- Corbett-Davies, S., Pierson, E., Feller, A., Goel, S.
Huq, A. (2017). Algorithmic decision making and th

Fairness requires interpretation

Kleinberg (2016)

- No mathematical ideal choice
  - Not possible to satisfy the three constraints simultaneously
  - Algorithmic estimates are generally not pure yes-no decisions

Kleinberg, J., Mullainathan, S., & Raghavan, M. (2016). Inherent Trade-Offs in the Fair Determination of Risk Scores. *ArXiv [Cs, Stat]*.

Inherent Trade-Offs

- (A) Calibration within groups
- (B) Balance for the negative class
- (C) Balance for the positive class

Berk (2017)

- Impossible to maximize accuracy and fairness at the same time

Berk, R., Heidari, H., Jabbari, S., Kearns, M., & Roth, A. (2017). Fairness in Criminal Justice Risk Assessments: The State of the Art. *ArXiv:1703.09207 [Stat]*.

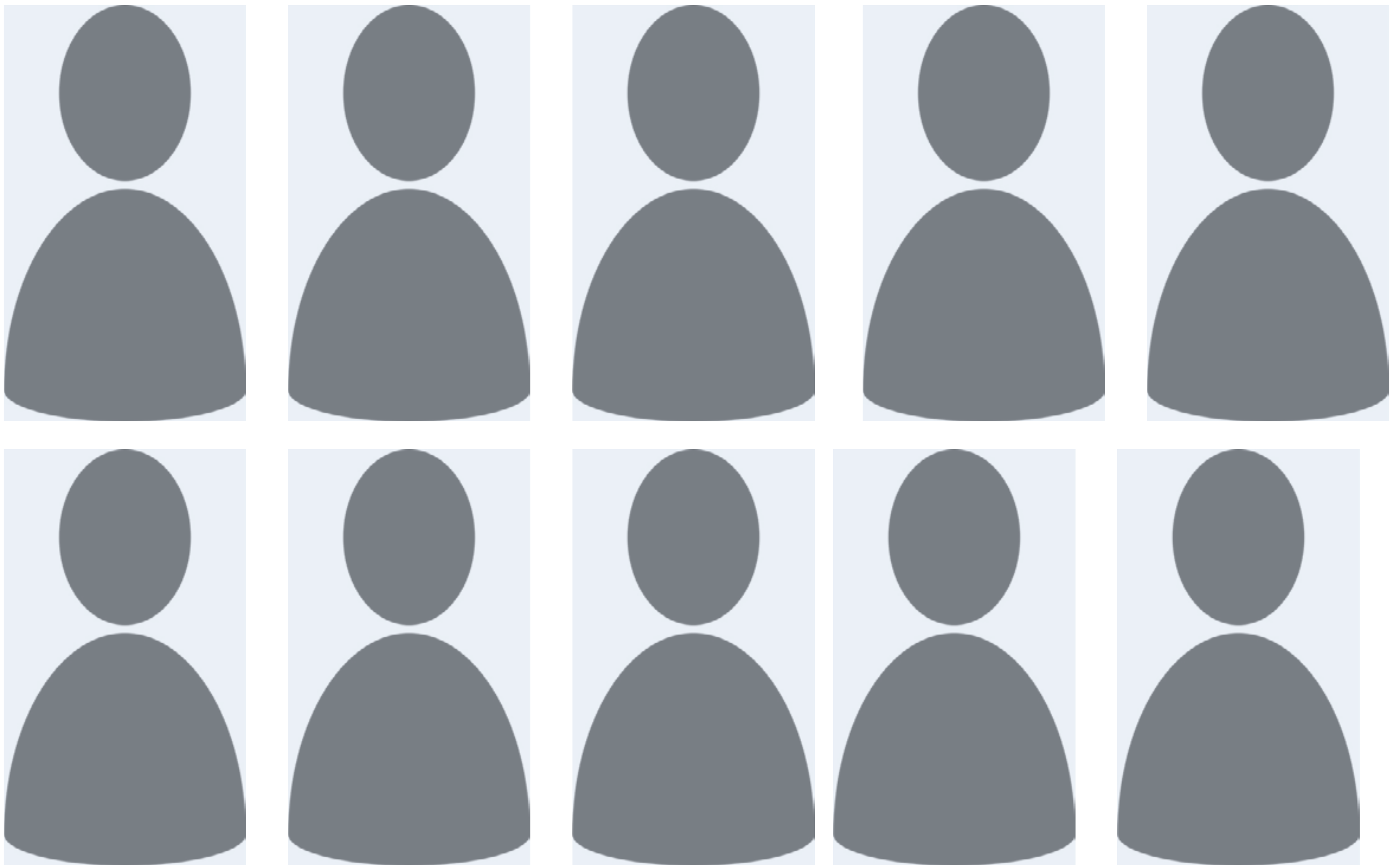
Seven types of Fairness

- 1. Overall accuracy equality
- 2. Statistical parity
- 3. Conditional procedure accuracy
- 4. Conditional use accuracy equality
- 5. Treatment equality
- 6. Total fairness

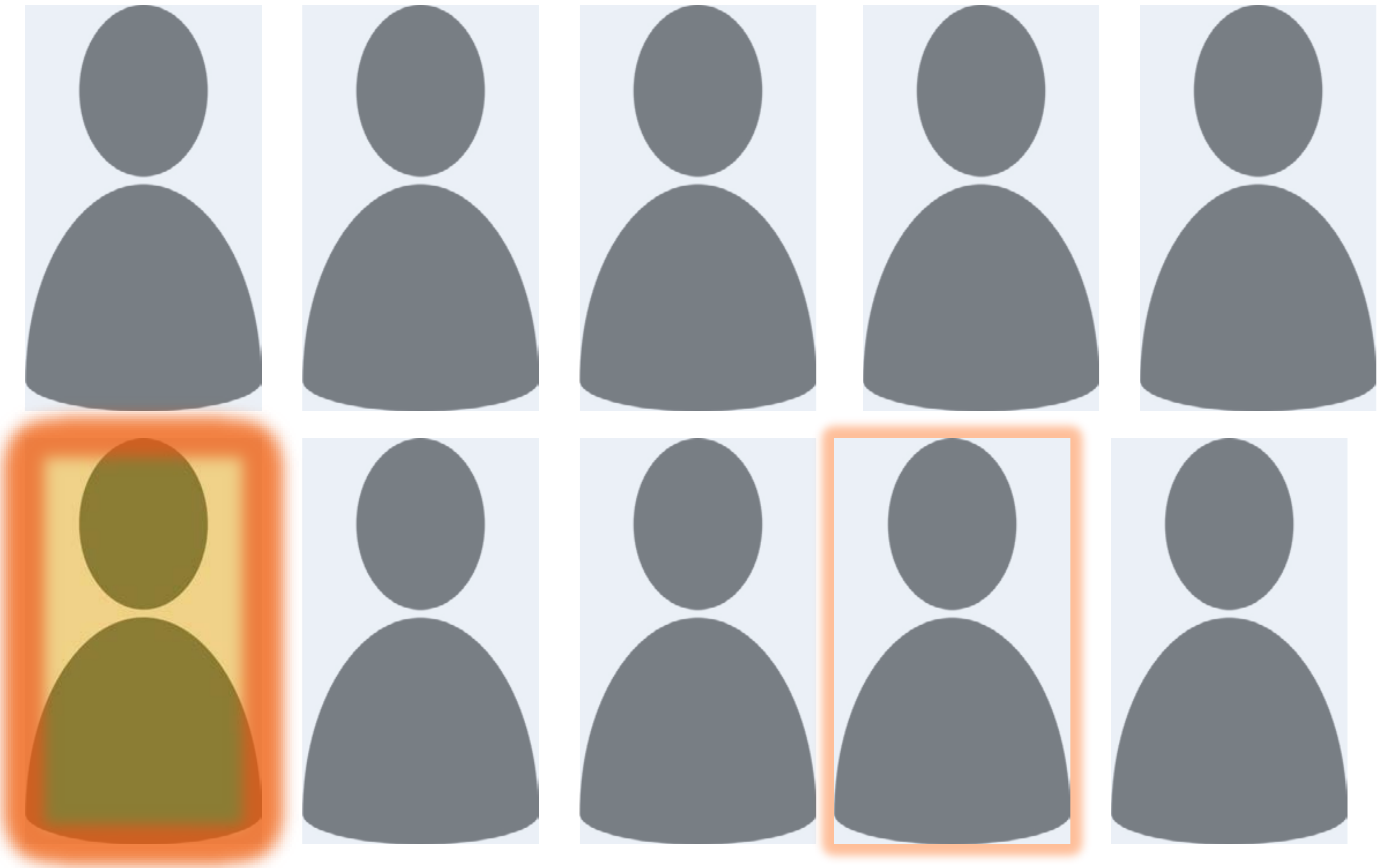
AN INTERPRETIVE ADVANTAGE

Why the defense had no ability to refute, supplement, or explain without comparative data

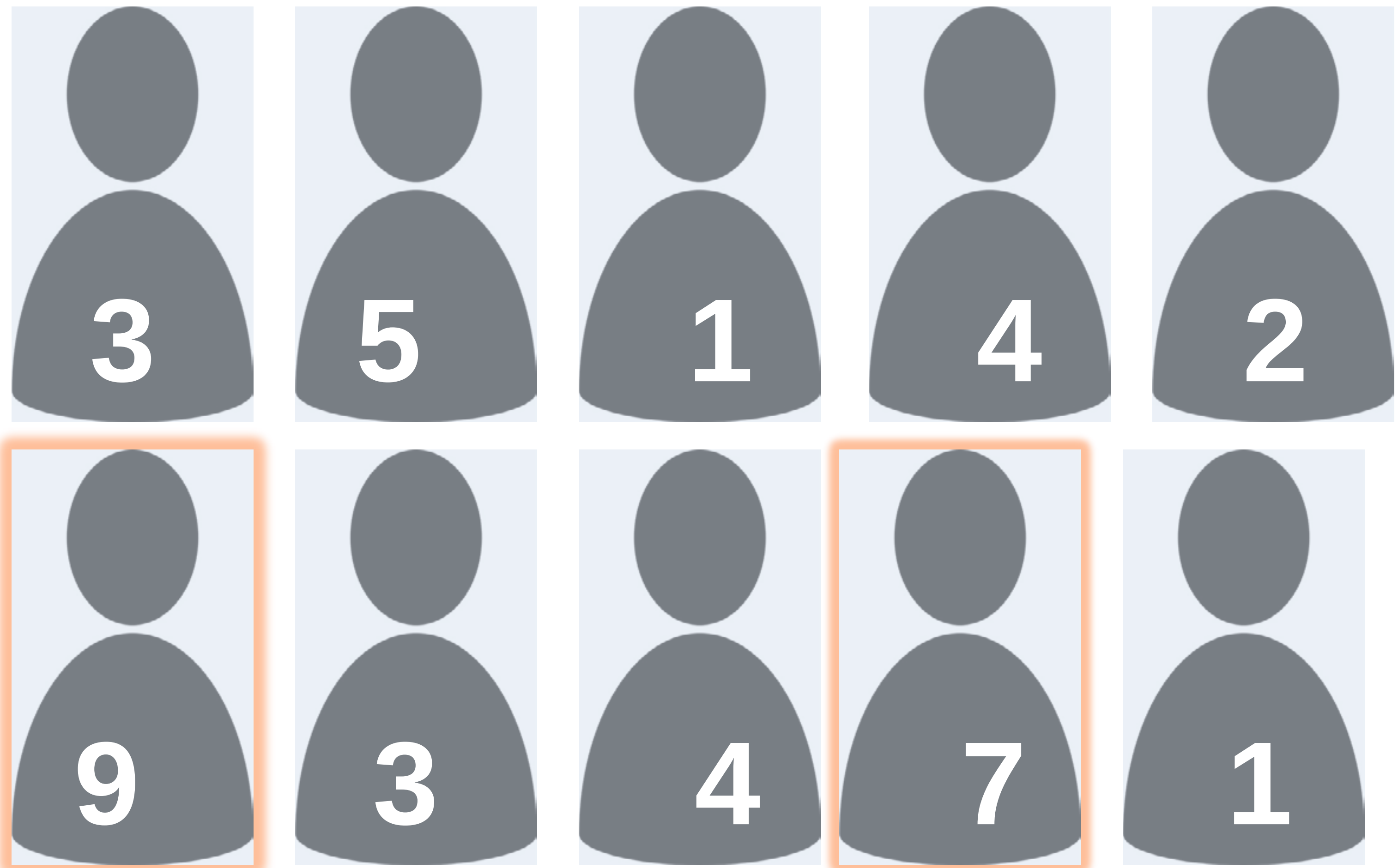
Who will commit crime?



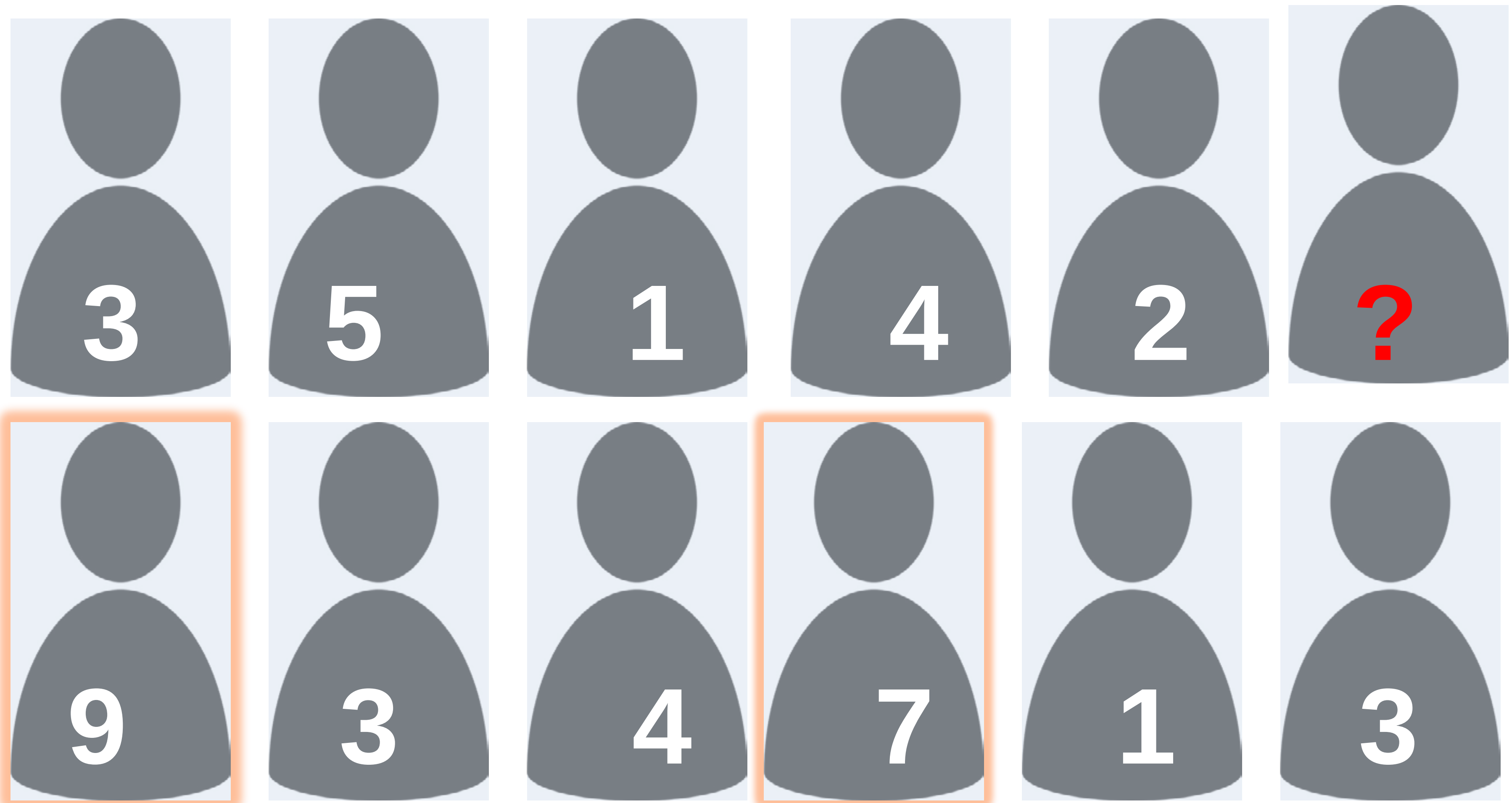
Risk Assessment:
Who is likely to commit crime?



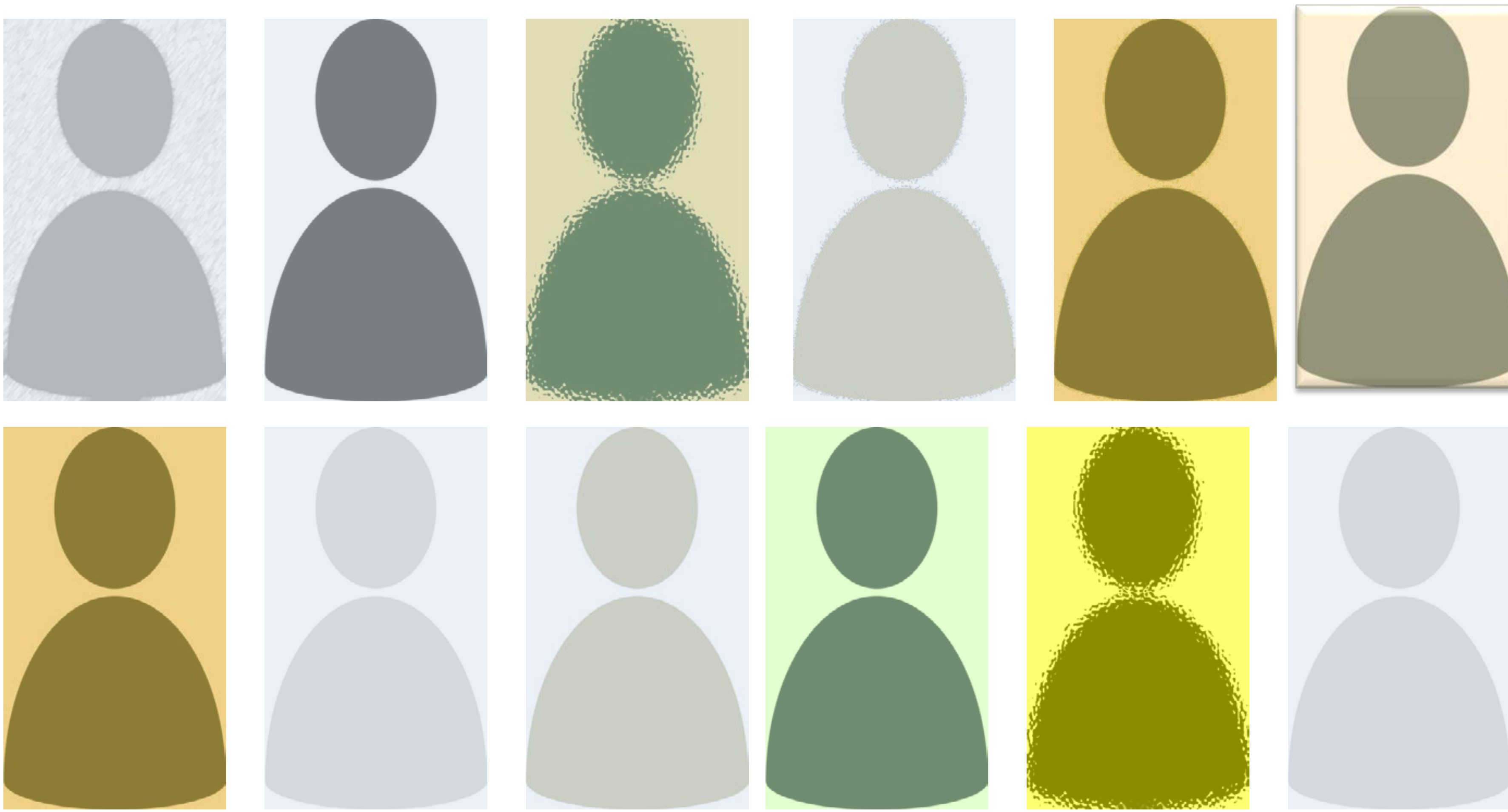
Risk Scores: Who was a threat to public safety?



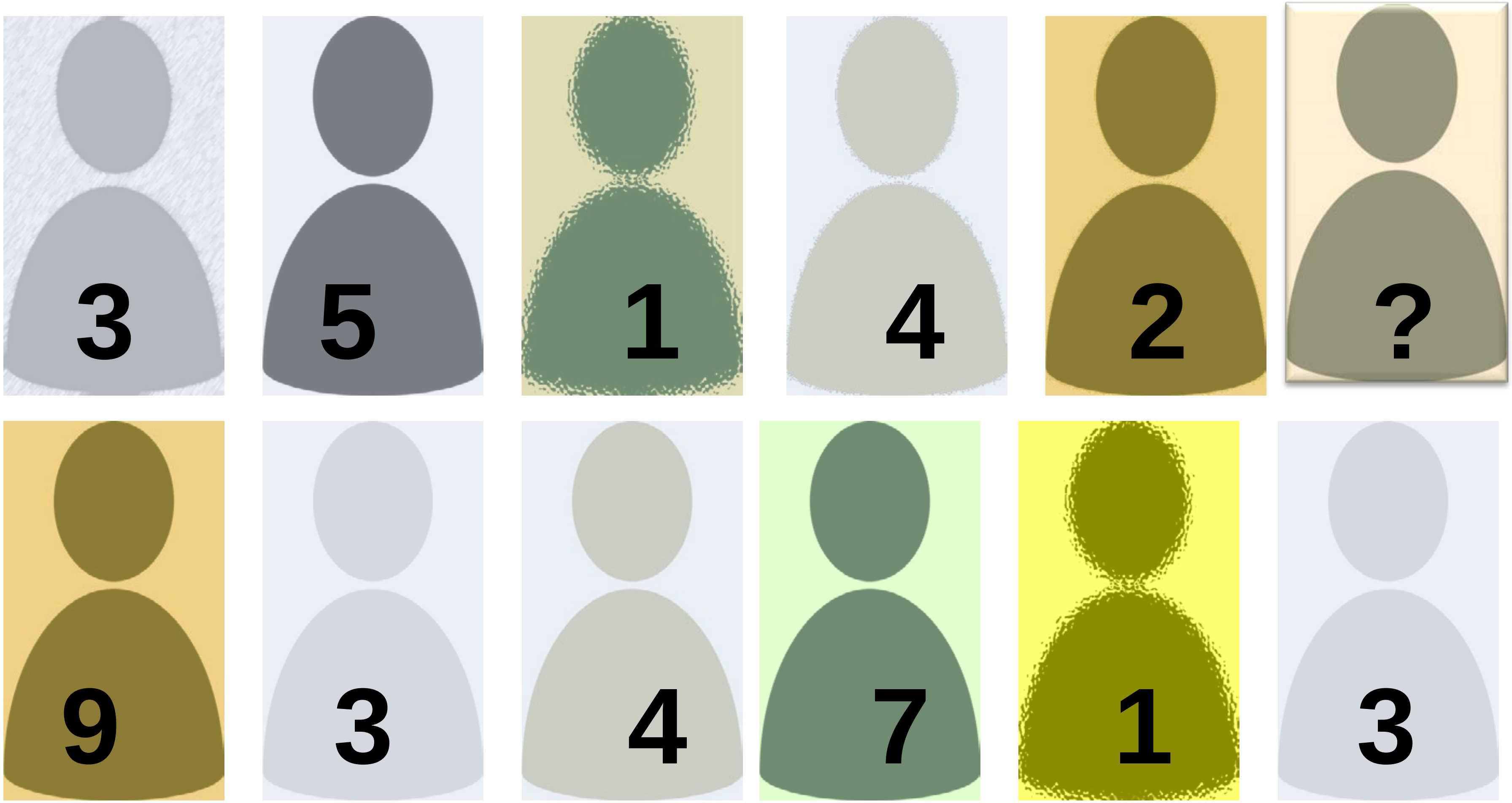
Can we predict new scores?



Needs Assessment:
Who needs help to succeed?



Why the court has additional information



Judging the judge's scales ... with open data

1 Verification with test data
2 Proof of verification with open data

LESSONS

What can we learn from the debate?

Innovating bureaucracy

USB Typewriters created by Jack Zylkin https://www.usbtypewriter.com/collections/typewriters/products

Data transparency

- Analytics does not provide “an answer”
- Data science requires interpretation

trust in allah, but tie your camel’s leg at night

Доверяй, но проверяй

Data Science Reasoning

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Steinhardt School, New York, NY
New York University
http://annewashington.com

FUNDING

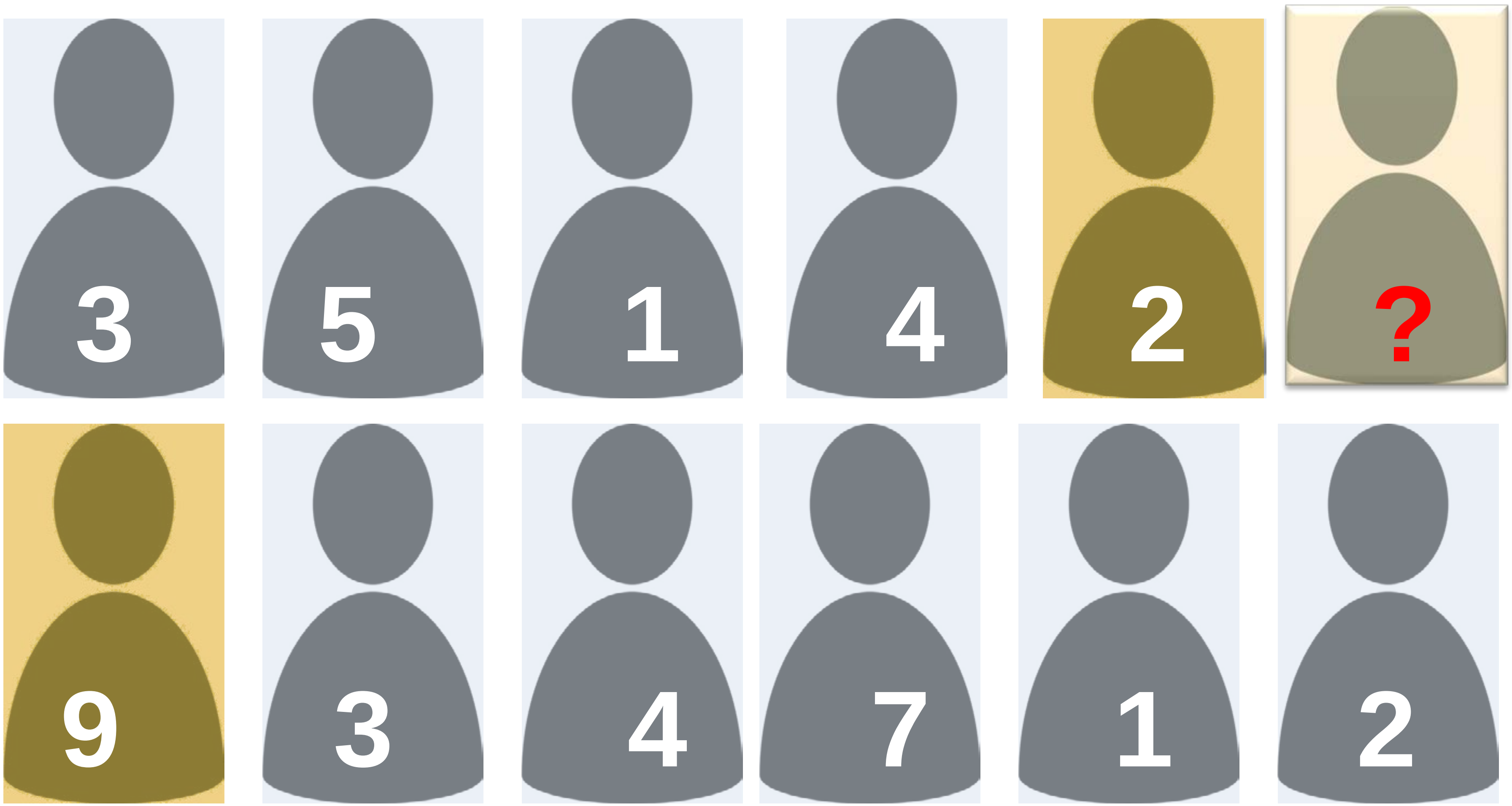
Data&Society

2016-2017 Fellowship
New York, NY

Currently funded under
National Science Foundation

APPENDIX

What if the score conflicts with other indicators?



¶30 "This court reviews sentencing decisions under the erroneous exercise of discretion standard." An erroneous exercise of discretion occurs when a circuit court imposes a sentence "without the underpinnings of an explained judicial reasoning process."

McCleary v. State, 49 Wis. 2d 263, 278, 182 N.W.2d 512 (1971); see also State v. Gallion, 2004 WI 42, ¶3, 270 Wis. 2d 535, 678 N.W.2d 197.

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Data Science Reasoning

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LOOK THROUGH MY WINDOW · DANCING IN THE STREET · GO WHERE YOU WANNA GO · 'GOT A FEELIN'
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