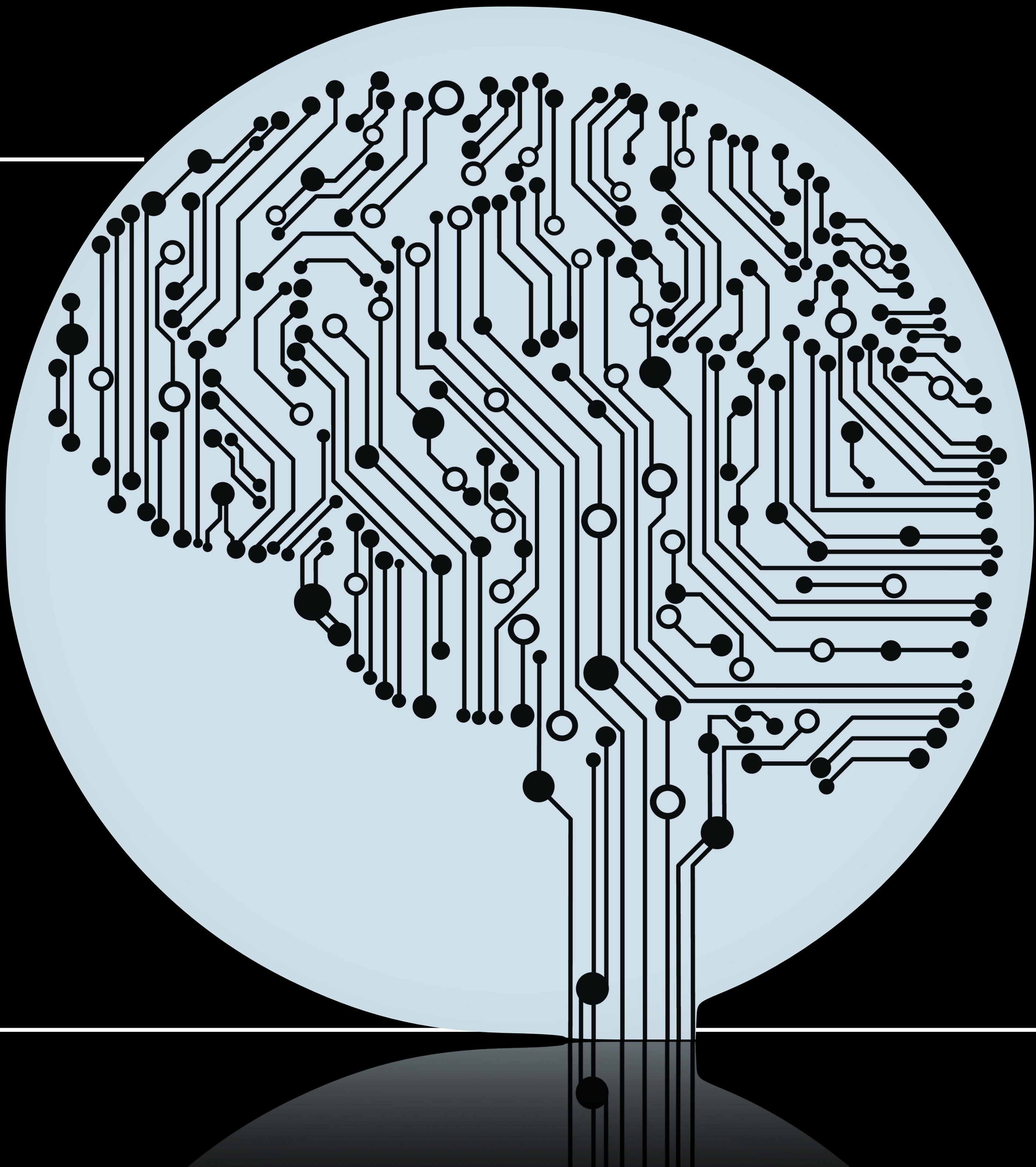
Mass Surveillance and Artificial Intelligence

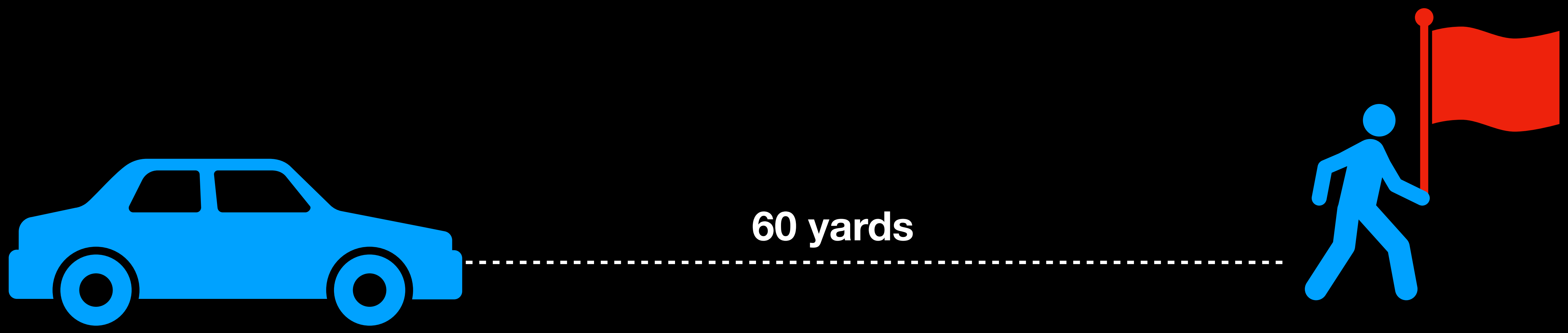
New Legal Challenges

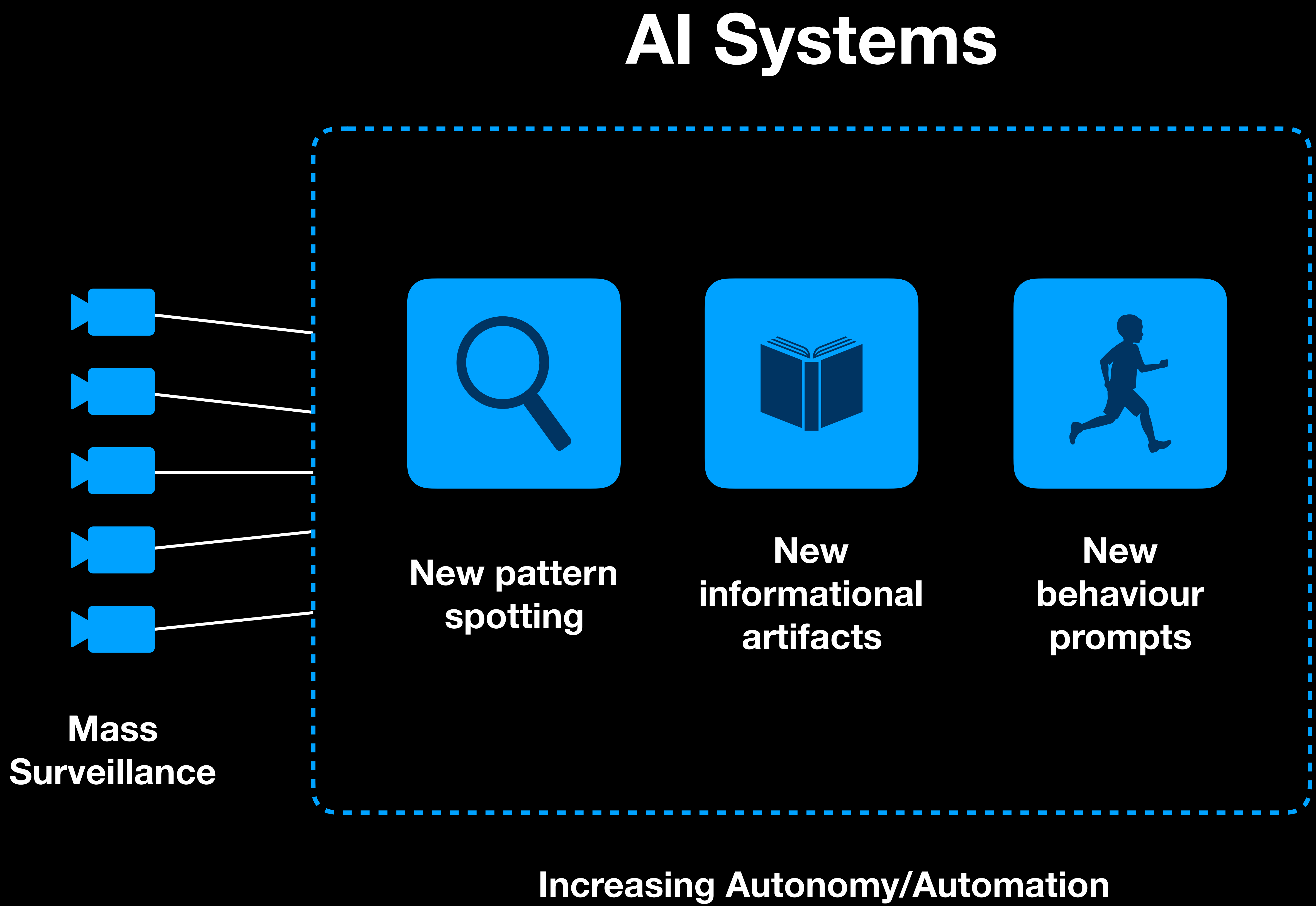


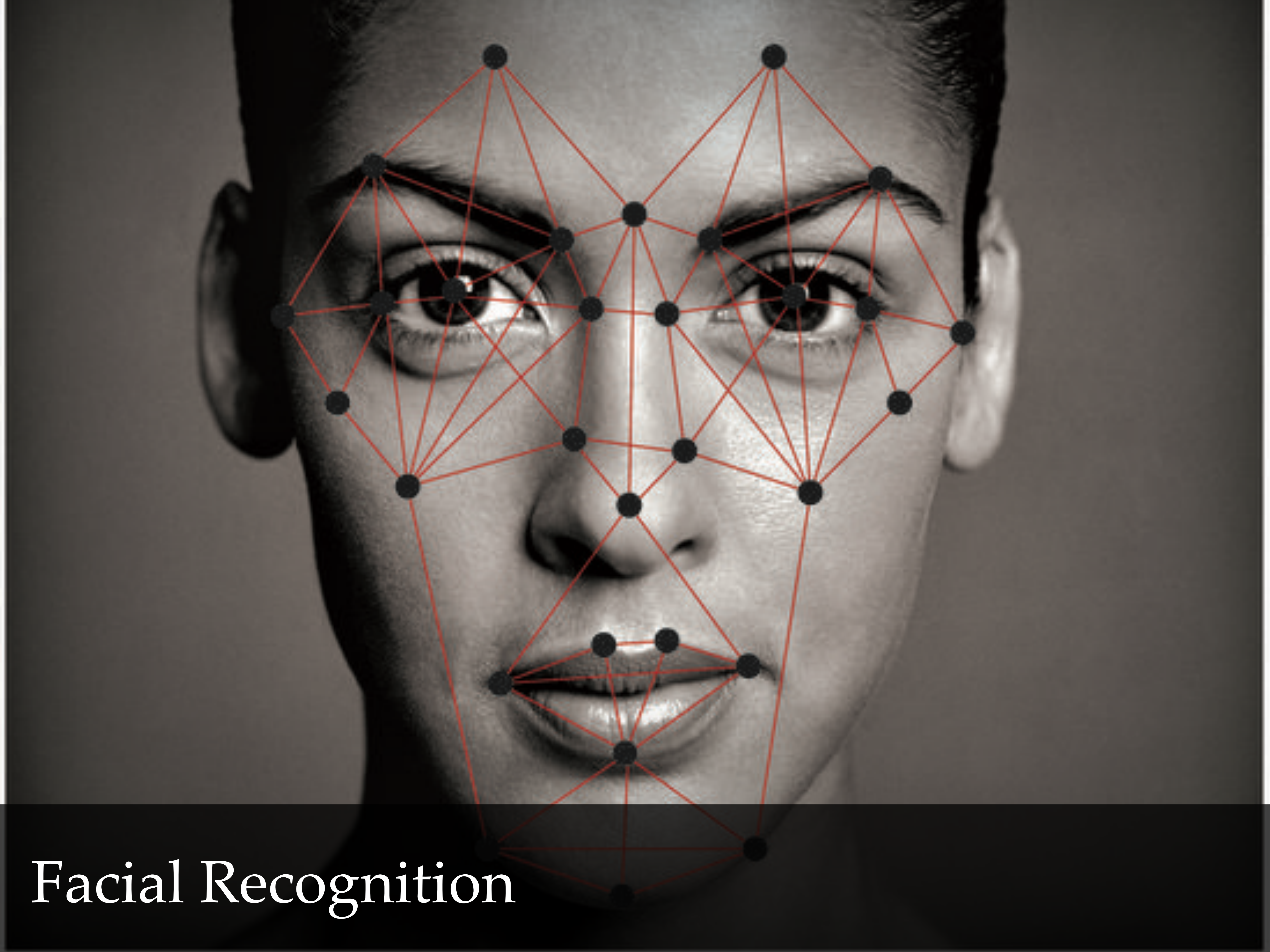
John Danaher

NUI Galway

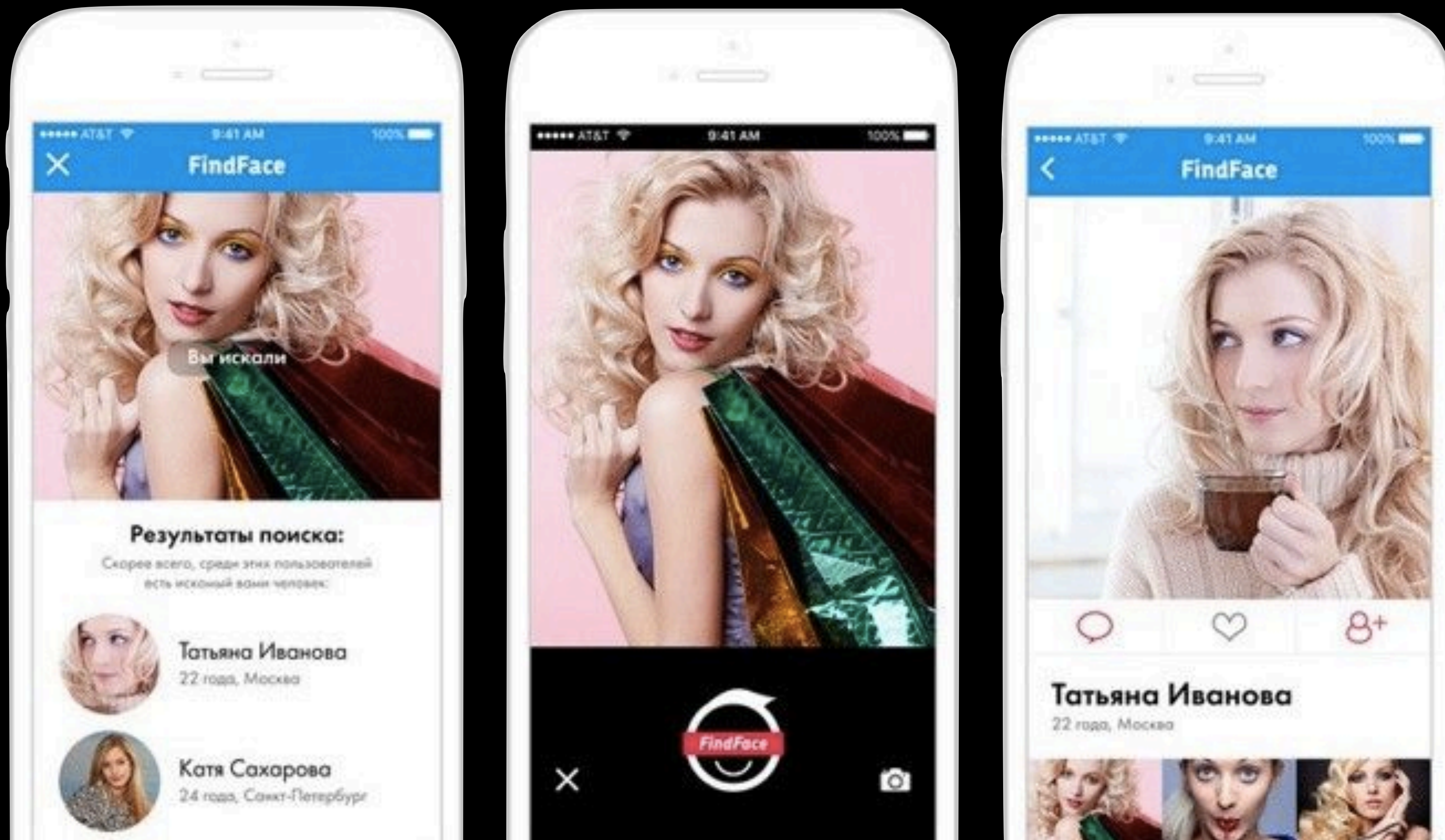
“…while any locomotive is in motion, shall precede such locomotive on foot by not less than sixty yards, and shall carry a red flag constantly displayed, and shall warn the riders and drivers of horses of the approach of such locomotives…”




AI Systems
Mass Surveillance
New pattern spotting
New informational artifacts
New behaviour prompts
Increasing Autonomy/Automation



Facial Recognition



FindFace App


Amazon Rekognition
FALSE MATCHES
28 current members of Congress

"The future of human flourishing depends upon facial recognition technology being banned before the systems become too entrenched in our lives. Otherwise, people won't know what it's like to be in public without being automatically identified, profiled, and potentially exploited."

Evan Selinger and Woodrow Hartzog

Deepfake Technology

Synthesizing Obama: Learning Lip Sync from Audio

SUPASORN SUWAJANAKORN, STEVEN M. SEITZ, and IRA KEMELMACHER-SHLIZERMAN, University of Washington

Output Obama Video


Townhall
THE VIEW
abc

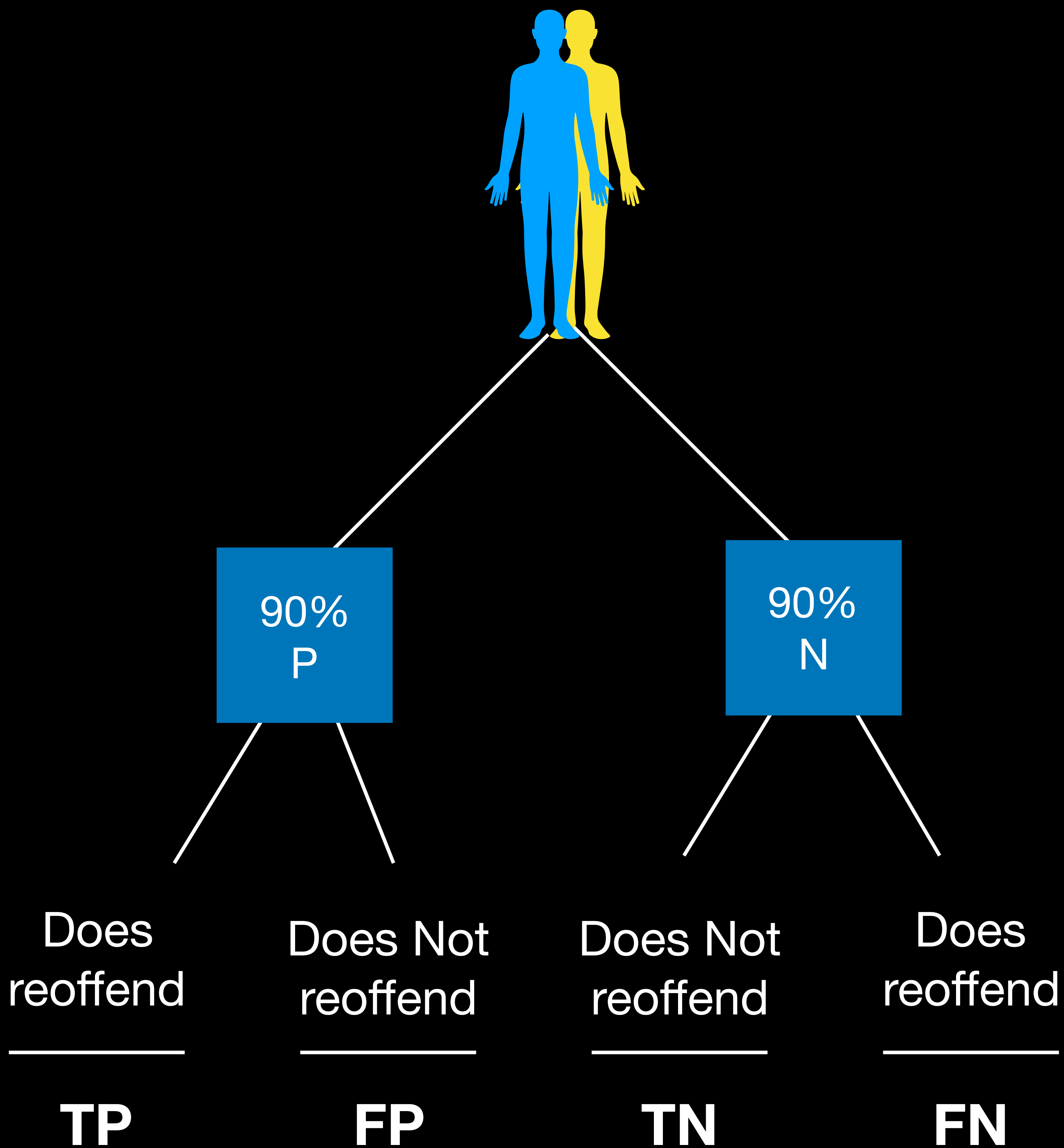
"Our awareness of the possibility of being recorded provides a quasi-independent check on reckless testifying, thereby strengthening the reasonability of relying on the words of others. Recordings do this in two distinctive ways: actively correcting errors in past testimony and passively regulating ongoing testimonial practices."

Regina Rini

S 4.2 - “intimate image” means a visual recording of a person made by any means including a photographic, film or video recording (whether or not the image of the person has been ***altered*** in any way)—

Harassment, Harmful Communications and Related Offences Bill 2017

Algorithmic Risk Prediction



Individual
Could be a member of group 1 (black) or group 2 (white)

Risk Score
A prediction of what the individual will do

Actual Outcomes
What the individual actually did

Black Defendants	Higher Risk	Lower Risk	Total	White Defendants	Higher Risk	Lower Risk	Total
Did Reoffend	1369	532	1901	**Did Reoffend**	505	461	966
Didn't Reoffend	805	990	1714	**Didn't Reoffend**	349	1139	1488
Total	2174	1522	3615	**Total**	854	1600	2454

Source: Angwin et al 2016, available at https://www.propublica.org/article/machine-bias-risk-assessments-in-criminal-sentencing (this version taken from Sumpter 2018)

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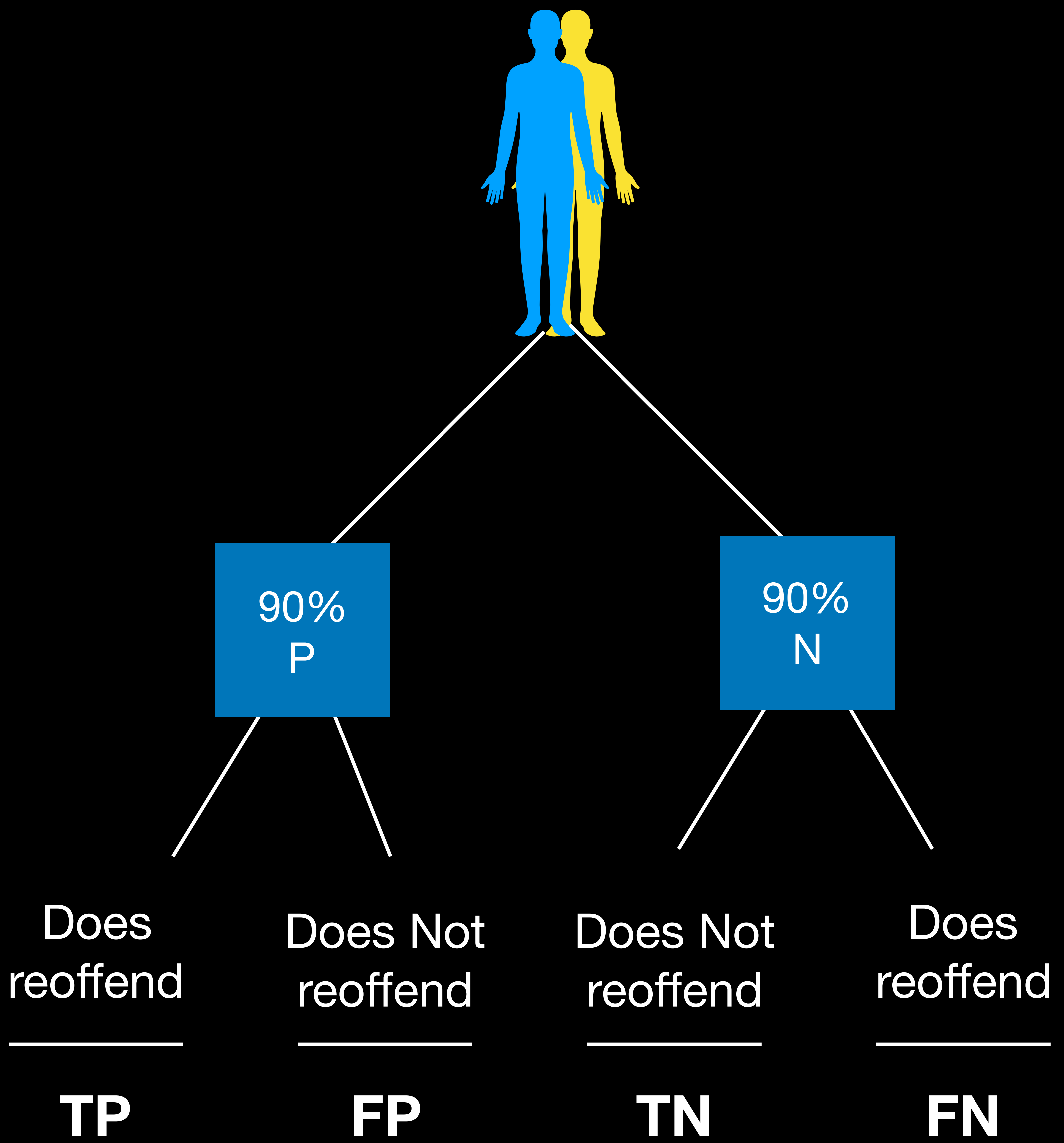
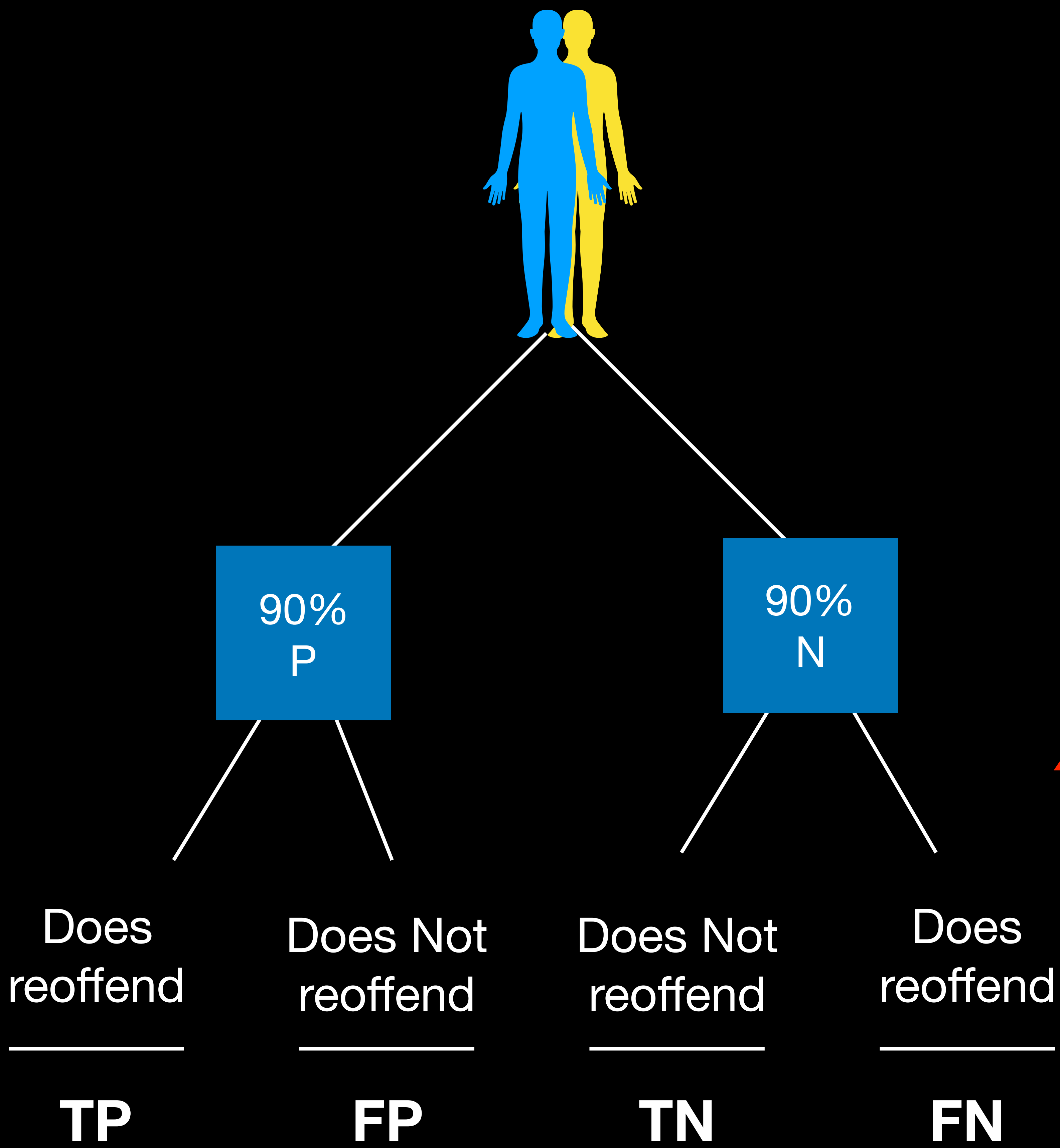


CRITERION 1
Well-calibrated

+

CRITERION 2
Fair representation
in outcome classes


90%
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reoffend
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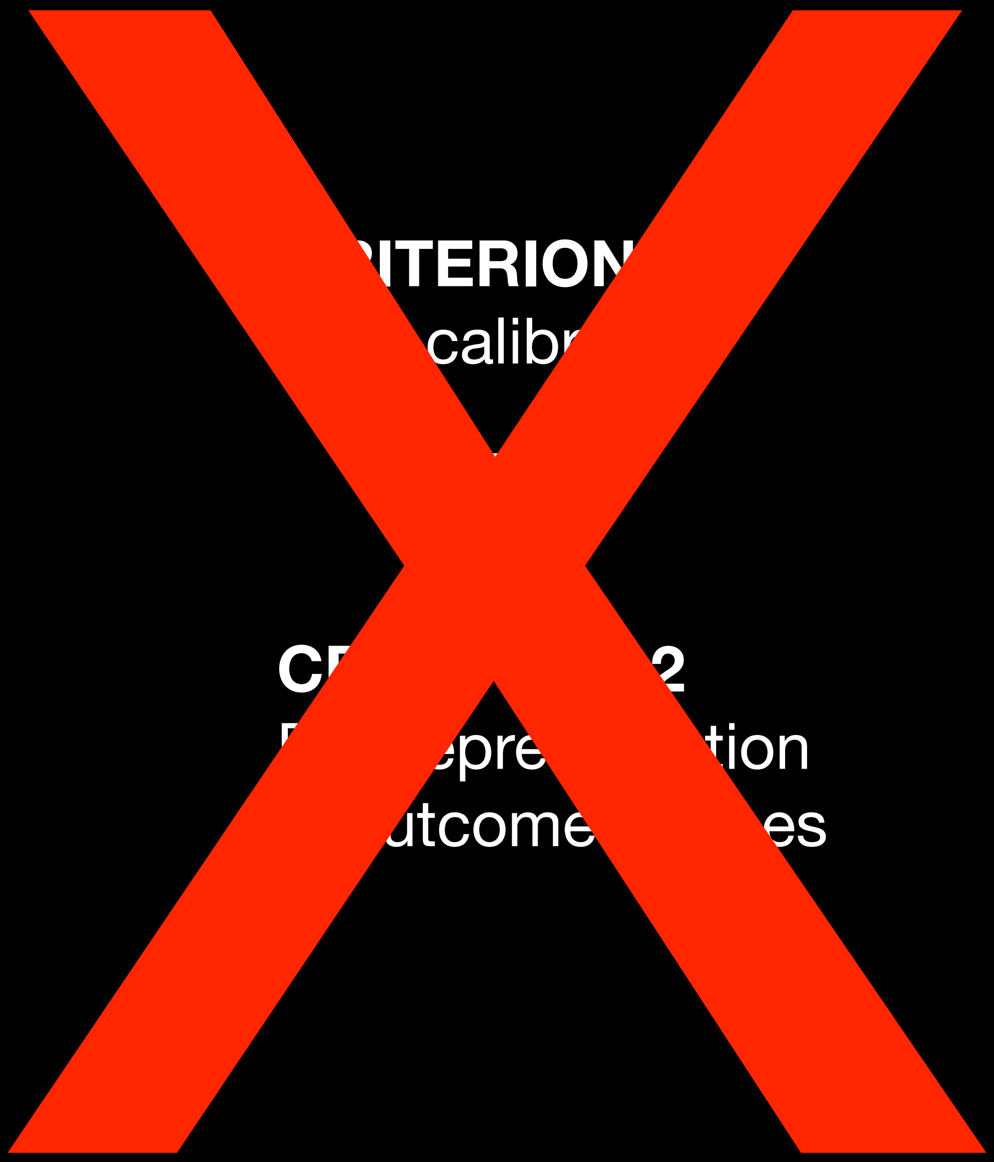
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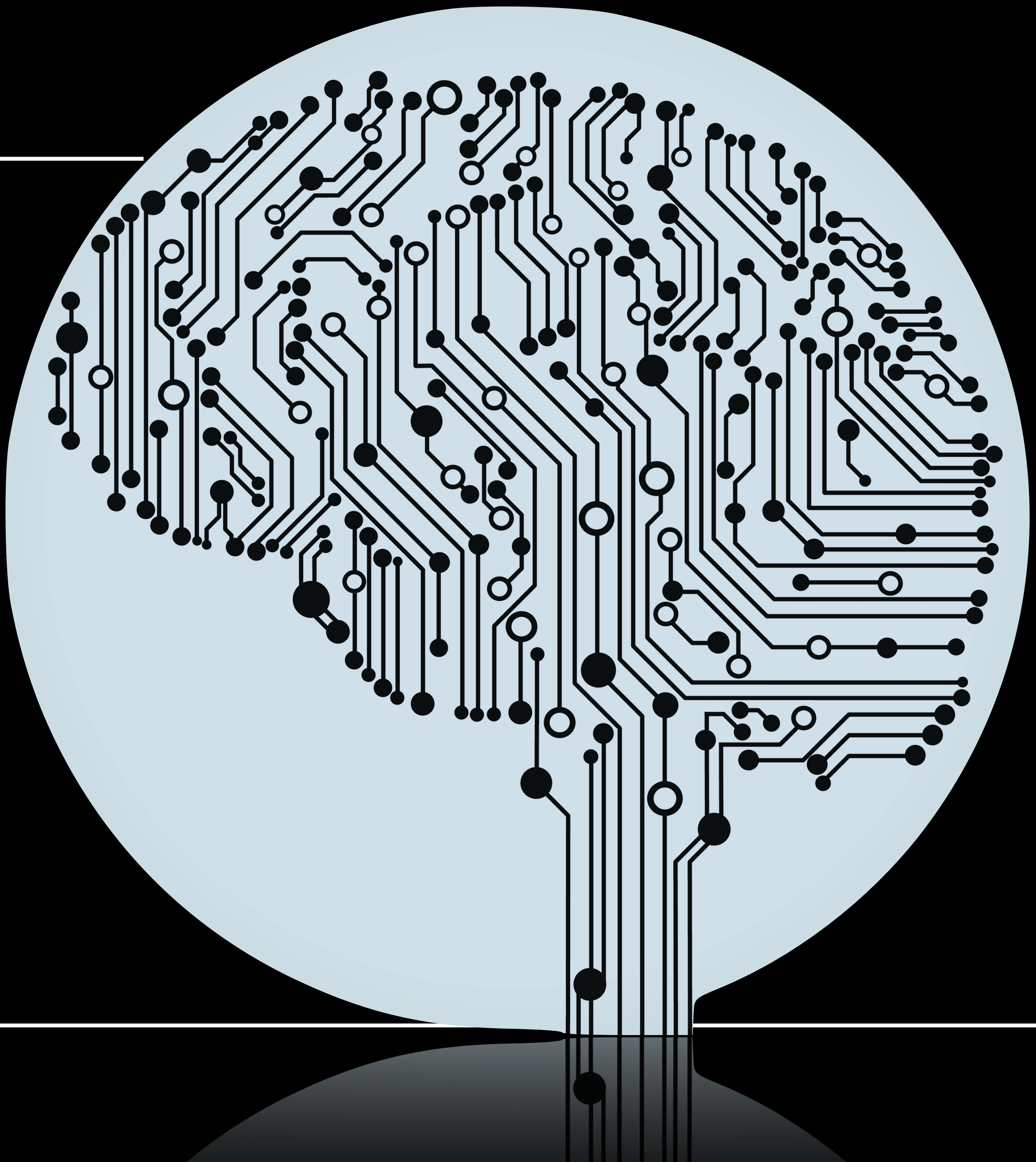
Thank You

For Your Attention



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