Errors of human cognition

COGNITIVE BIAS CODEX

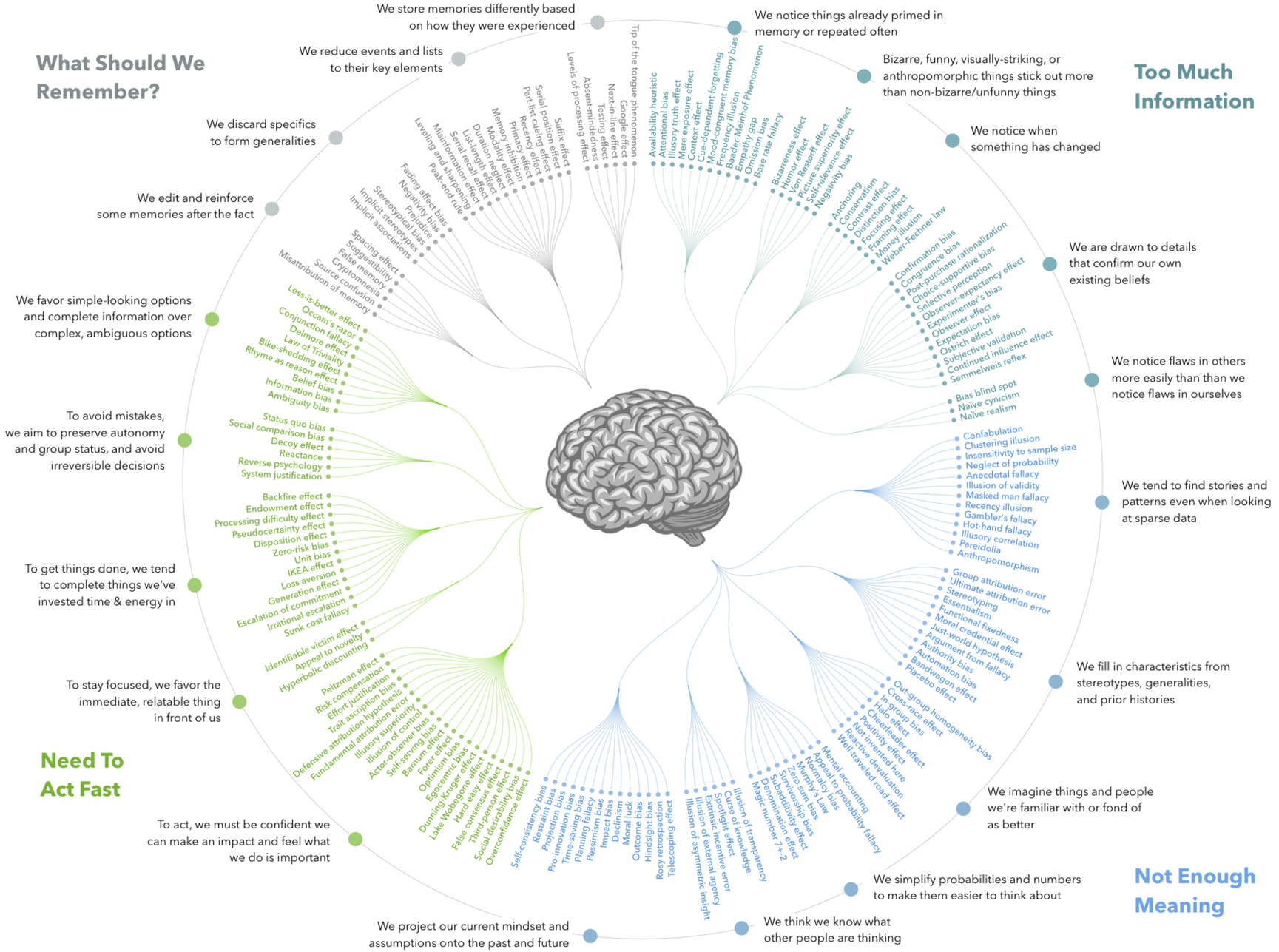
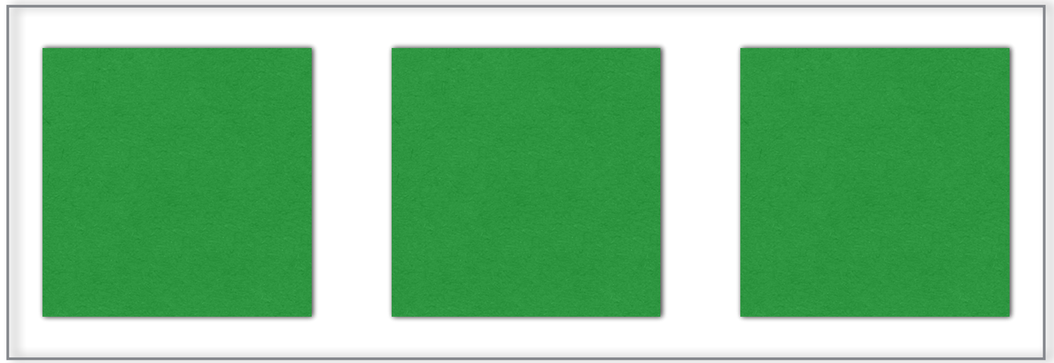
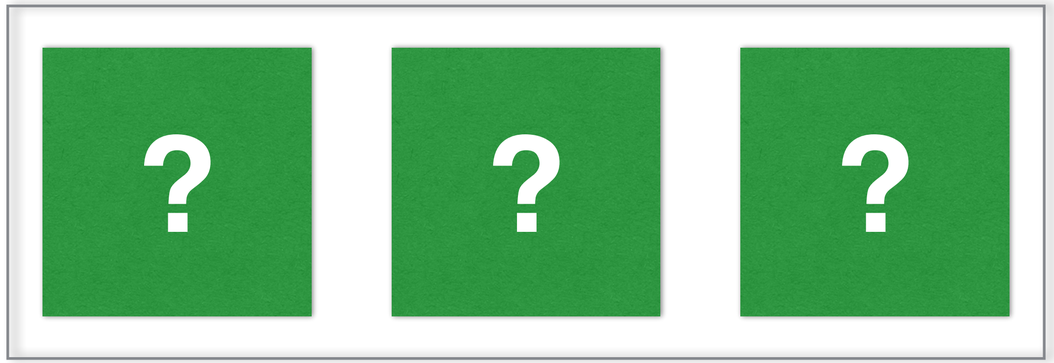


Figure out the rule





I T I V E B I A S C O D E X

ently based
xperienced

Tip of the tongue phenomenon
Google effect
Next-in-line effect
Testing effect
Absent-mindedness
Levels of processing effect
Suffix effect
Serial position effect
Part-list cueing effect
Recency effect
Primacy effect

We notice things already primed in memory or repeated often

Availability heuristic
Attentional bias
Illusory truth effect
Mere exposure effect
Context effect
Cue-dependent forgetting
Mood-congruent memory bias
Frequency illusion
Baader-Meinhof Phenomenon
Empathy gap
Omission bias
Base rate fallacy

Bizarre, funny, visually-striking, or anthropomorphic things stick out more than non-bizarre/unfunny things

Bizarreness effect
Humor effect
Von Restorff effect
Picture superiority effect
Self-relevance effect
Negativity bias

We notice when something has changed

Anchoring
Conservatism
Contrast effect
Distinction bias
Focusing effect
Framing effect
Money illusion
Weber-Fechner law

Too Much Information

We are drawn to details that confirm our own existing beliefs

Confirmation bias
Congruence bias
Post-purchase rationalization
Choice-supportive bias
Selective perception
Observer-expectancy effect
Experimenter's bias
Observer effect
Expectation bias
Ostrich effect
Subjective validation
Continued influence effect
Semmelweis reflex

We notice flaws in others more easily than than we notice flaws in ourselves

Bias blind spot
Naïve cynicism
Naïve realism

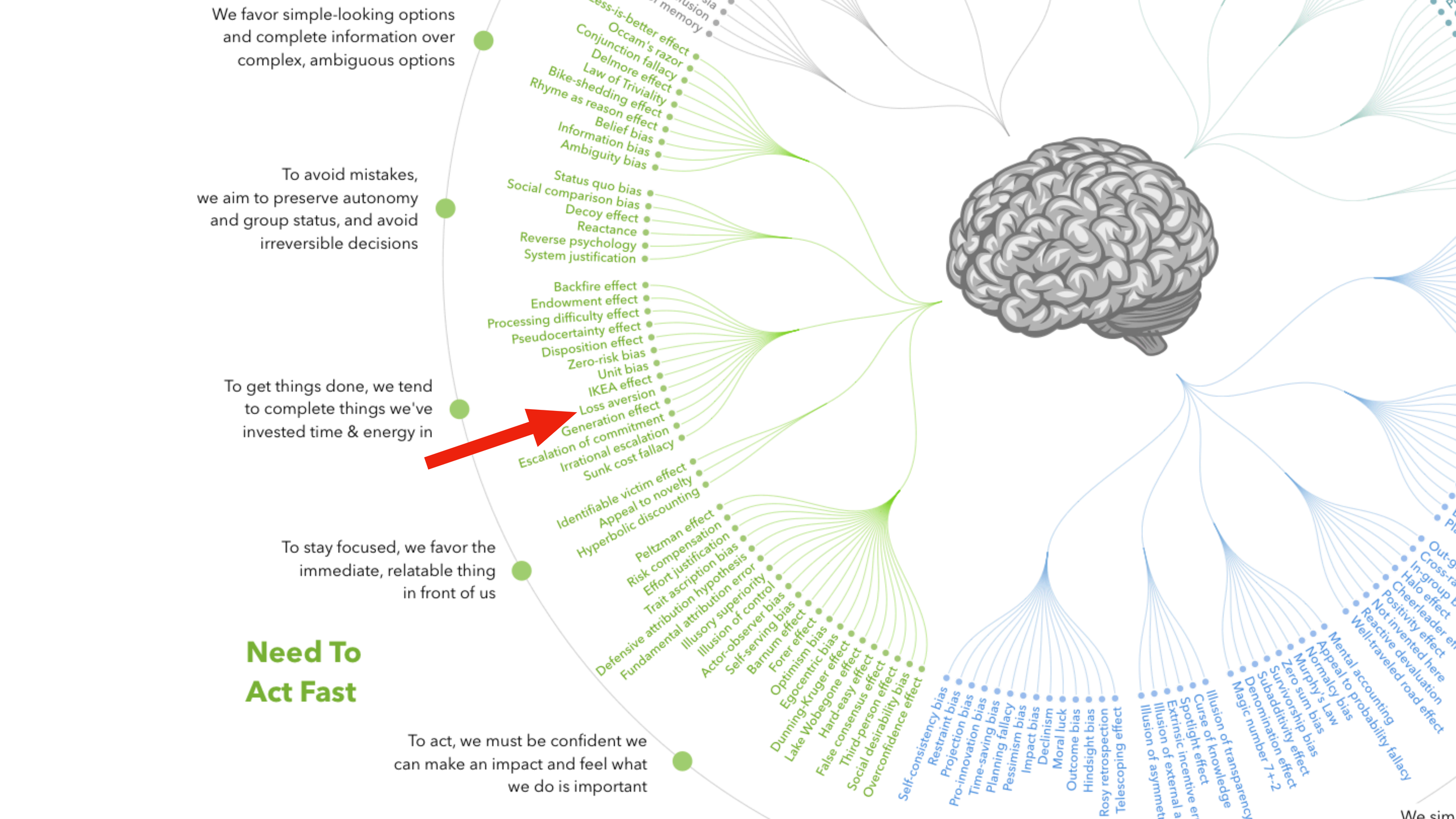
We tend to find stories and patterns even when looking

Confabulation
Clustering illusion
Insensitivity to sample size
Neglect of probability
Anecdotal fallacy
Illusion of validity
Masked man fallacy
Recency illusion

Confirmation bias

The only way to show you're right is to try to show you're wrong!

Confirmation bias…
and programming?


We favor simple-looking options and complete information over complex, ambiguous options
To avoid mistakes, we aim to preserve autonomy and group status, and avoid irreversible decisions
To get things done, we tend to complete things we've invested time & energy in
To stay focused, we favor the immediate, relatable thing in front of us
Need To Act Fast
To act, we must be confident we can make an impact and feel what we do is important
Less-is-better effect
Occam's razor
Conjunction fallacy
Delmore effect
Law of Triviality
Bike-shedding effect
Rhyme as reason effect
Belief bias
Information bias
Ambiguity bias
Status quo bias
Social comparison bias
Decoy effect
Reactance
Reverse psychology
System justification
Backfire effect
Endowment effect
Processing difficulty effect
Pseudocertainty effect
Disposition effect
Zero-risk bias
Unit bias
IKEA effect
Loss aversion
Generation effect
Escalation of commitment
Irrational escalation
Sunk cost fallacy
Identifiable victim effect
Appeal to novelty
Hyperbolic discounting
Peltzman effect
Risk compensation
Effort justification
Trait ascription bias
Defensive attribution hypothesis
Fundamental attribution error
Illusory superiority
Illusion of control
Actor-observer bias
Self-serving bias
Barnum effect
Forer effect
Optimism bias
Egocentric bias
Dunning-Kruger effect
Lake Wobegone effect
Hard-easy effect
False consensus effect
Third-person effect
Social desirability bias
Overconfidence effect
Self-consistency bias
Restraint bias
Projection bias
Pro-innovation bias
Time-saving bias
Planning fallacy
Pessimism bias
Impact bias
Declinism
Moral luck
Outcome bias
Hindsight bias
Rosy retrospection
Telescoping effect
Illusion of asymmetric
Illusion of external a
Extrinsic incentive er
Spotlight effect
Curse of knowledge
Illusion of transparency
Magic number 7+-2
Denomination effect
Subadditivity effect
Survivorship bias
Zero sum bias
Murphy's Law
Normalcy bias
Appeal to probability fallacy
Mental accounting
Well-traveled road effect
Reactive devaluation
Not invented here
Positivity effect
Halo effect
In-group b
Cross-ra
Out-g

Should I try base jumping? It could be fun!

Loss aversion

If you tell someone they have a 99.5% of surviving they think it's fine

…but tell them 1 in 200 people die and they think it’s too scary

- Bias blind spot
- Naïve cynicism
- Naïve realism

We notice flaws in others more easily than than we notice flaws in ourselves

- Confabulation
- Clustering illusion
- Insensitivity to sample size
- Neglect of probability
- Anecdotal fallacy
- Illusion of validity
- Masked man fallacy
- Recency illusion
- Gambler's fallacy
- Hot-hand fallacy
- Illusory correlation
- Pareidolia
- Anthropomorphism

We tend to find stories and patterns even when looking at sparse data

- Group attribution error
- Ultimate attribution error
- Stereotyping
- Essentialism
- Functional fixedness
- Moral credential effect
- Just-world hypothesis
- Argument from fallacy
- Authority bias
- Automation bias
- Bandwagon effect
- Placebo effect

We fill in characteristics from stereotypes, generalities, and prior histories

- Out-group homogeneity bias
- Cross-race effect
- In-group bias
- Halo effect
- Cheerleader effect
- Positivity effect
- Not invented here
- Reactive devaluation
- Well-traveled road effect

We imagine things and people we're familiar with or fond of as better

- Mental accounting
- Appeal to probability fallacy
- Normalcy bias
- Murphy's Law
- Zero sum bias
- Survivorship bias
- Subadditivity effect
- Denomination effect
- Magic number 7+-2

We simplify probabilities and numbers to make them easier to think about

- Illusion of transparency
- Curse of knowledge
- Spotlight effect
- Extrinsic incentive error
- Illusion of external agency
- Illusion of asymmetric insight

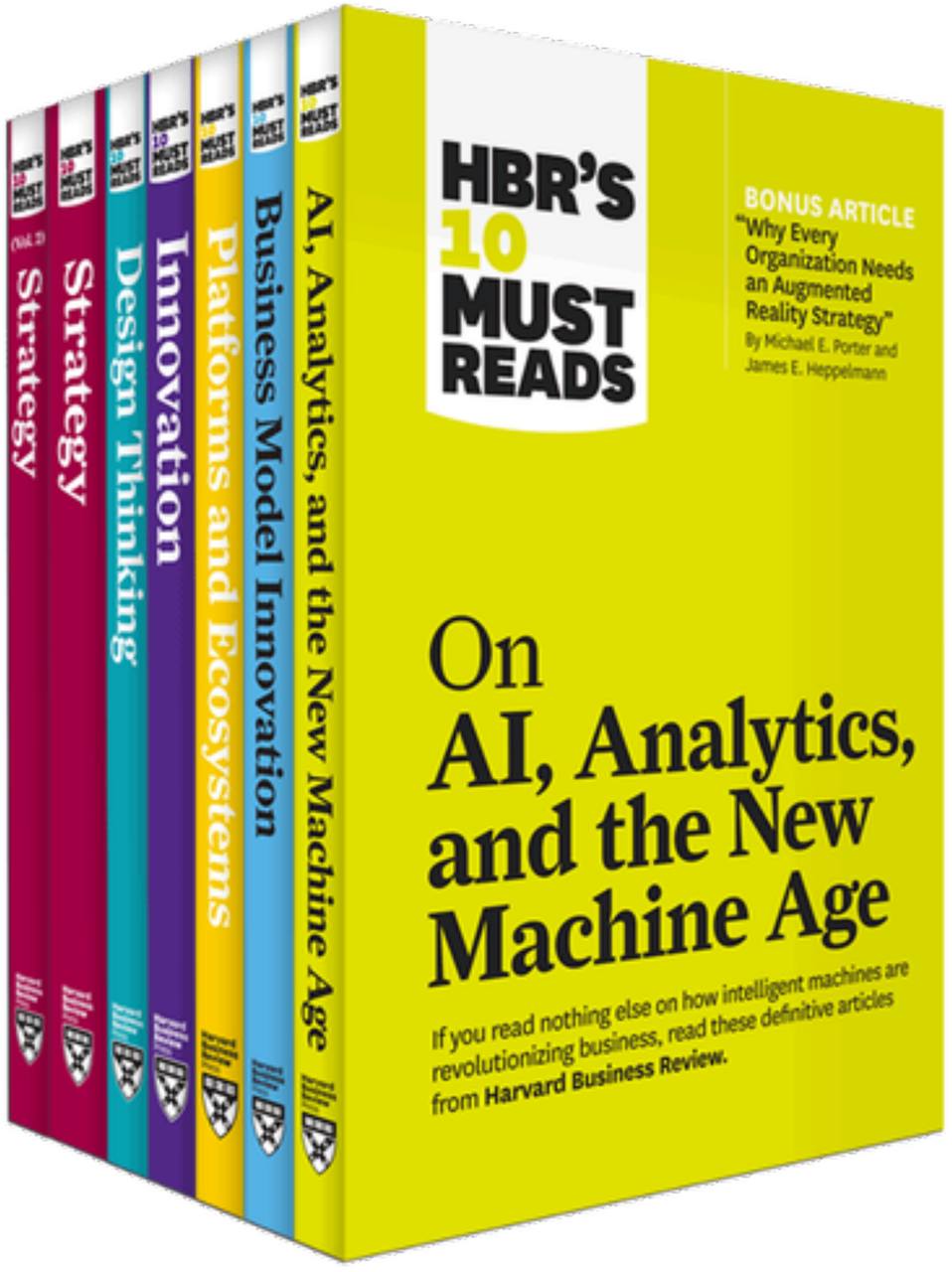
We think we know what other people are thinking

- Self-consistency bias
- Restraint bias
- Projection bias
- Pro-innovation bias
- Time-saving bias
- Planning fallacy
- Pessimism bias
- Impact bias
- Declinism
- Moral luck
- Outcome bias
- Hindsight bias
- Rosy retrospection
- Telescoping effect

We project our current mindset and assumptions onto the past and future

- Peltzman effect
- Risk compensation
- Effort justification
- Trait ascription bias
- Fundamental attribution error
- Illusory superiority
- Illusion of control
- Actor-observer bias
- Self-serving bias
- Barnum effect
- Forer effect
- Optimism bias
- Egocentric bias
- Dunning-Kruger effect
- Lake Wobegone effect
- Hard-easy effect
- False consensus effect
- Third-person effect
- Social desirability bias
- Overconfidence effect

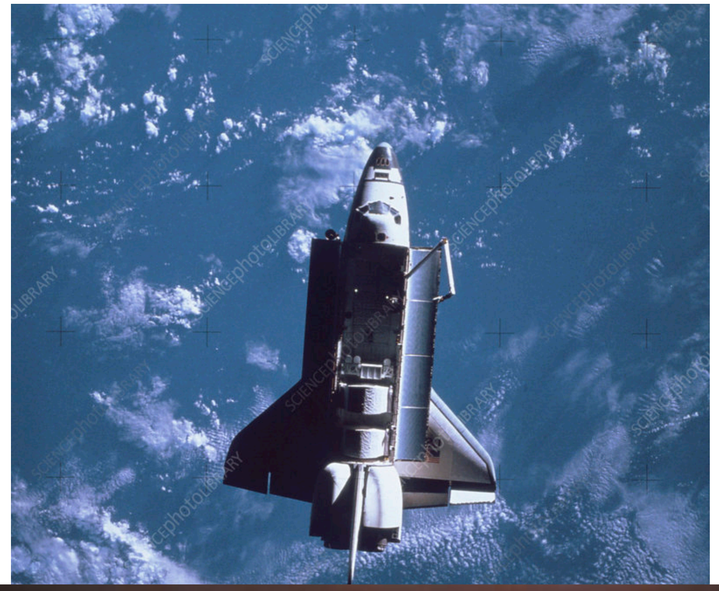
Not Enough Meaning



Anecdata

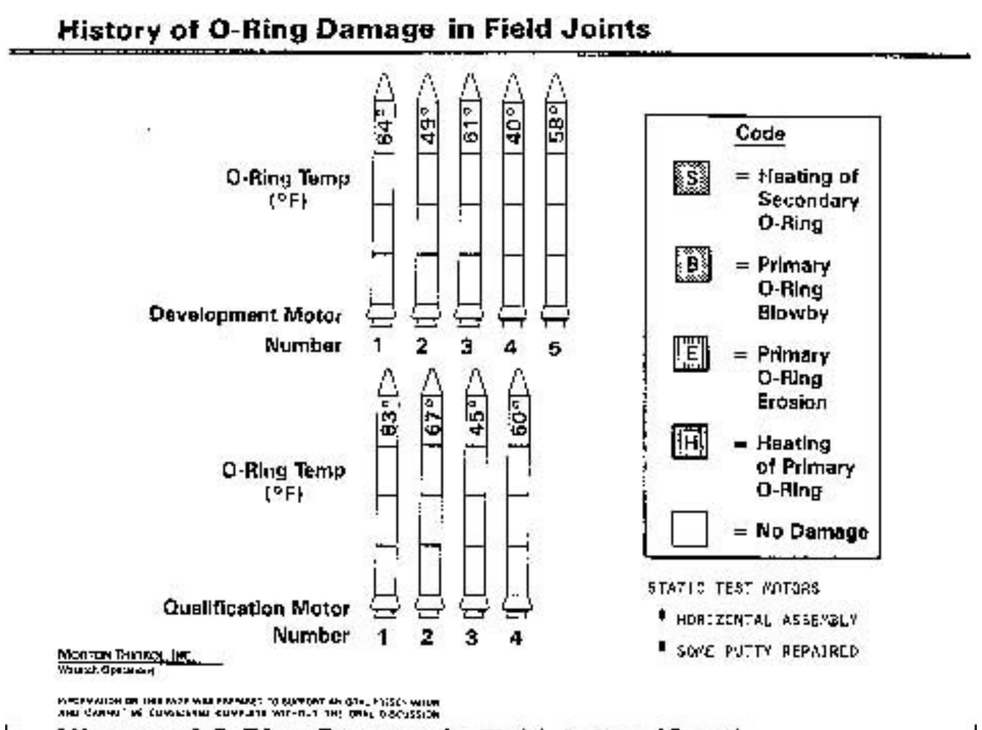
Rigorous analysis supported by anecdote

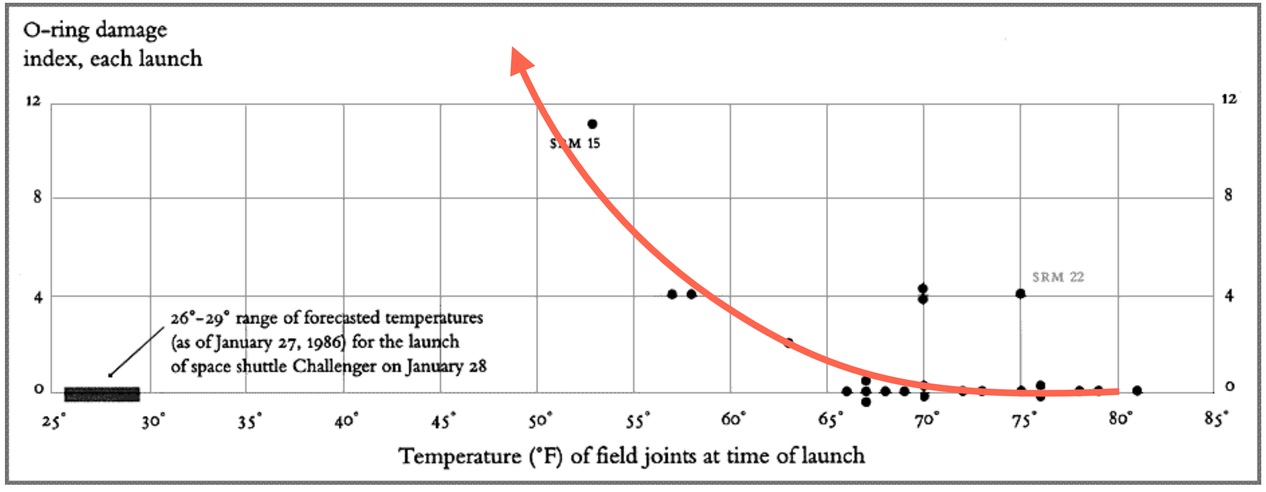
Errors of communication



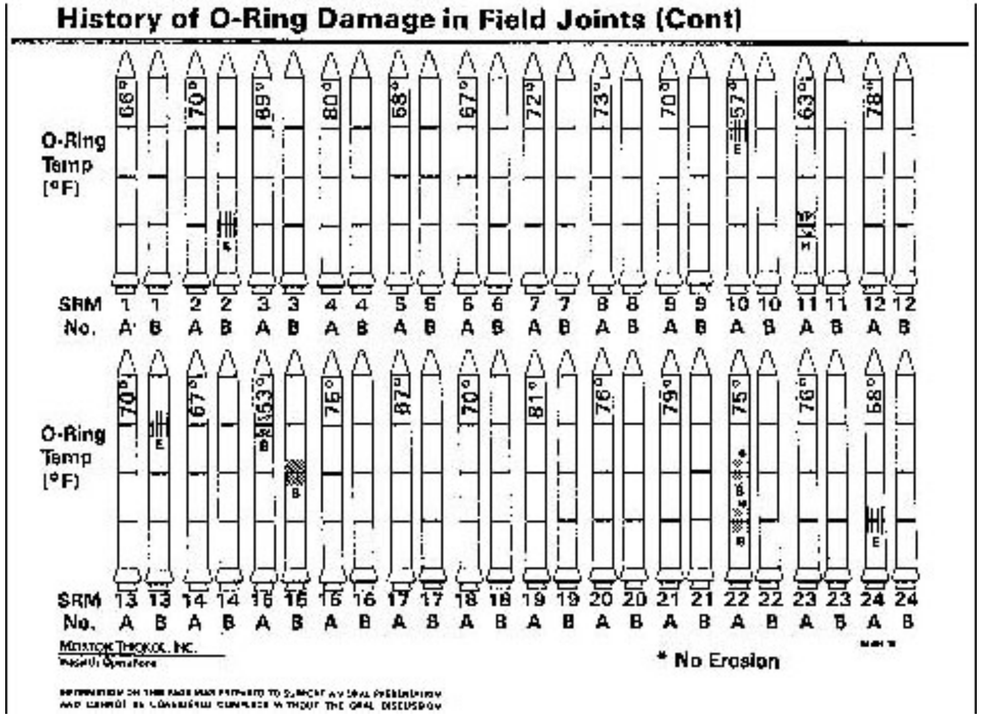
Jan 28, 1986

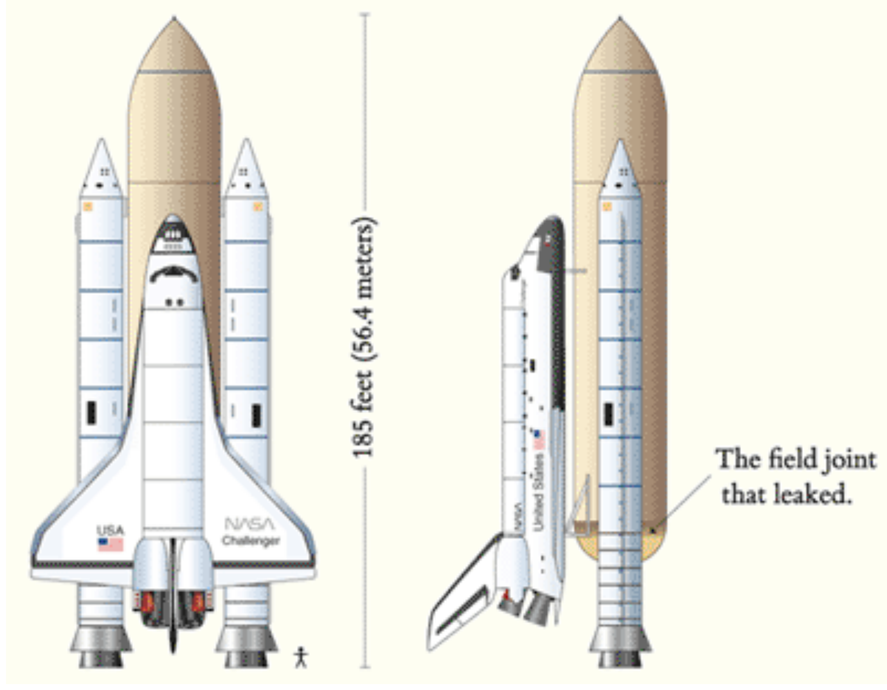
Feb 1, 2003





Images and graphs from Edward Tufte





On this one Columbia slide, a PowerPoint festival of bureaucratic hyper-rationalism, 6 different levels of hierarchy are used to display, classify, and arrange 11 phrases:

Level 1	Title of Slide
Level 2	● Very Big Bullet
Level 3	– big dash
Level 4	◆ medium-small diamond
Level 5	• tiny square bullet
Level 6	( ) parentheses ending level 5

The analysis begins with the dreaded Executive Summary, with a conclusion presented as a headline: "Test Data Indicates Conservatism for Tile Penetration." This turns out to be unmerited reassurance. Executives, at least those who don't want to get fooled, had better read far beyond the title.

The "conservatism" concerns the *choice of models* used to predict damage. But why, after 112 flights, are foam-debris models being calibrated during a crisis? How can "conservatism" be inferred from a loose comparison of a spreadsheet model and some thin data? Divergent evidence means divergent evidence, not inferential security. Claims of analytic "conservatism" should be viewed with skepticism by presentation consumers. Such claims are often a rhetorical tactic that substitutes verbal fudge factors for quantitative assessments.

As the bullet points march on, the seemingly reassuring headline fades away. Lower-level bullets at the end of the slide undermine the executive summary. This third-level point notes that "Flight condition [that is, the debris hit on the Columbia] is significantly outside of test database." How far outside? The final bullet will tell us.

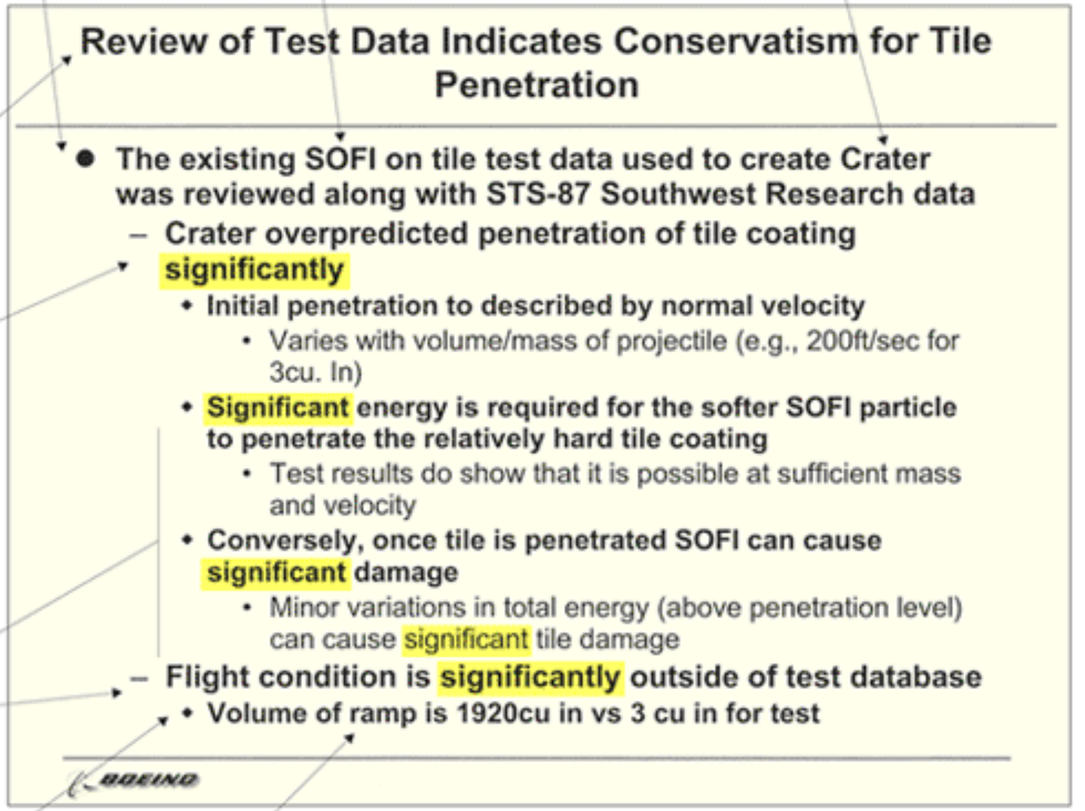
This fourth-level bullet concluding the slide reports that the debris hitting the Columbia is estimated to be 1920/3 = 640 times larger than data used in the tests of the model! The correct headline should be "Review of Test Data Indicates Irrelevance of Two Models." This is a powerful conclusion, indicating that pre-launch safety standards no longer hold. The original optimistic headline has been eviscerated by the lower-level bullets.

Note how close readings can help consumers of presentations evaluate the presenter's reasoning and credibility.

The Very-Big-Bullet phrase fragment does not seem to make sense. No other VBB's appear in the rest of the slide, so this VBB is not necessary.

Spray On Foam Insulation, a fragment of which caused the hole in the wing

A model to estimate damage to the tiles protecting flat surfaces of the wing



Here "ramp" refers to foam debris (from the bipod ramp) that hit Columbia. Instead of the cryptic "Volume of ramp," say "estimated volume of foam debris that hit the wing." Such clarifying phrases, which may help upper level executives understand what is going on, are too long to fit on low-resolution bullet outline formats. PP demands the shorthand of acronyms, phrase fragments, and clipped jargon in order to get at least some information into the tight format.

Edward Tufte

Our models are irrelevant

Debris hitting the wing was 640x larger than the experimental data used to build these models

We have no clue what will happen on re-entry

Communication is key

Identify audience & setting

Identify key insight, main points of evidence, and assumptions

Organize into a story focussed on ⬆️

Create supporting visualizations

Revise to be as precise and concise as possible

Errors of measurement - are we measuring what we think we are?

Errors of analysis - did we use the right methods to address the question?

Errors of borked tools - choosing the wrong tools or using them poorly leads to bad results

Errors of human cognition - data science is a human endeavor with all the usual frailties and foibles

Errors of communication - sometimes you get everything right, but the group and the decision makers never understand properly

Lecture #22

Your future in DS

Jason G. Fleischer, Ph.D.
Asst. Teaching Professor
Department of Cognitive Science, UC San Diego

jfleischer@ucsd.edu

@jasongfleischer

https://jgfleischer.com

Slides in this presentation are from material kindly provided by
Shannon Ellis and Brad Voytek

Courses in DS and ML at UCSD

- DS
- CSE
- CS
- ECE
- COGS
- But also many other departments like ECON, MATH, LING, BENG, etc

My list of '20-21 ML (and ML adjacent) courses

Some job titles and what they do

- Analytics or statistician: data handling, analysis
- Data scientist: programming, data handling, analysis
- Data engineer: programming, databases, management
- Data architect: programming, databases, design
- Data manager: databases, design, management
- *OPs (eg, devOPs, dataOPs, full stack): programming, tool development, mangagement concentrating on end to end process
- ML Engineer: programming, tool development, management of infrastructure
- ML researcher: programming, algorithm design and testing

Glut of new data scientists

First, let's talk about the oversupply of junior data scientists. The continuing media hype cycle around data science has enormously exploded the amount of junior talent available on the market over the past five years.

This is purely anecdotal evidence, so take it with a large grain of salt. But, based on my own participation as a resume screener, mentor to data scientists leaving boot camps, interviewer, interviewee, and from conversations with friends and colleagues in similar positions, I've developed an intuition that the number of candidates per any given data science position, particularly at the entry level, has grown from 20 or so per slot, to 100 or more. I was talking to a friend recently who had to go through 500 resumes for a single opening.

This is not abnormal. More anecdotal evidence comes from job openings like this one, from machine learning's godfather, Andrew Ng, whose AI startup demanded 70-80 hours a week. He was flooded with applications, after blithely noting that previously many people had tried to volunteer for free. As of this latest writing, they ran out of space in their current office.

It's very, very hard to estimate the true gap between market demand and supply, but here's a starting point.

https://veekaybee.github.io/2019/02/13/data-science-is-different/

Advice from Vicki Boykis

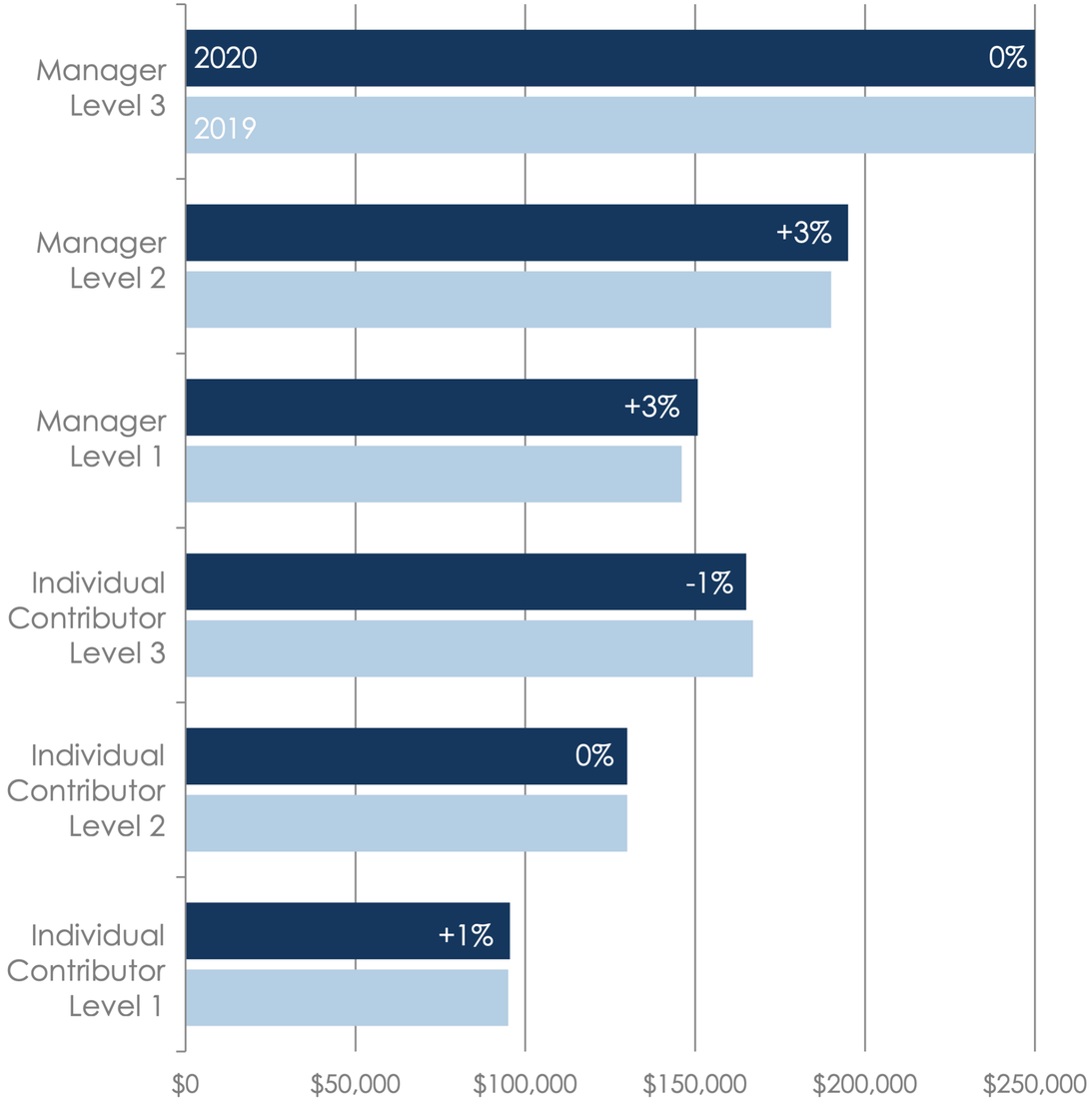
Sr. Manager, Data Science + Engineering at CapTech Ventures, Inc

1. Learn SQL
2. Learn a programming language extremely well and learn programming concepts.
3. Learn how to work in the cloud.
4. This stuff is really hard for everyone, and there are a million things it seems like you have to know. Don’t get discouraged.

https://veekaybee.github.io/2019/02/13/data-science-is-different/

Burtchworks annual predictions and report on DS hiring

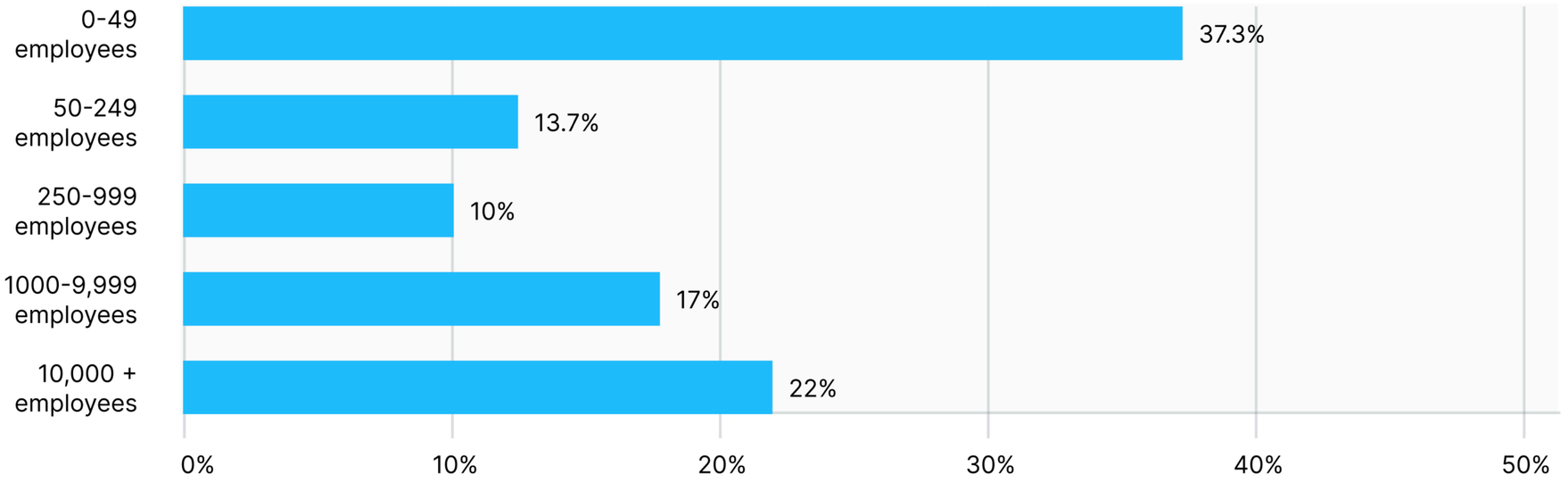
Figure 2 Comparison of **Data Scientists'** Median Base Salaries by Job Category



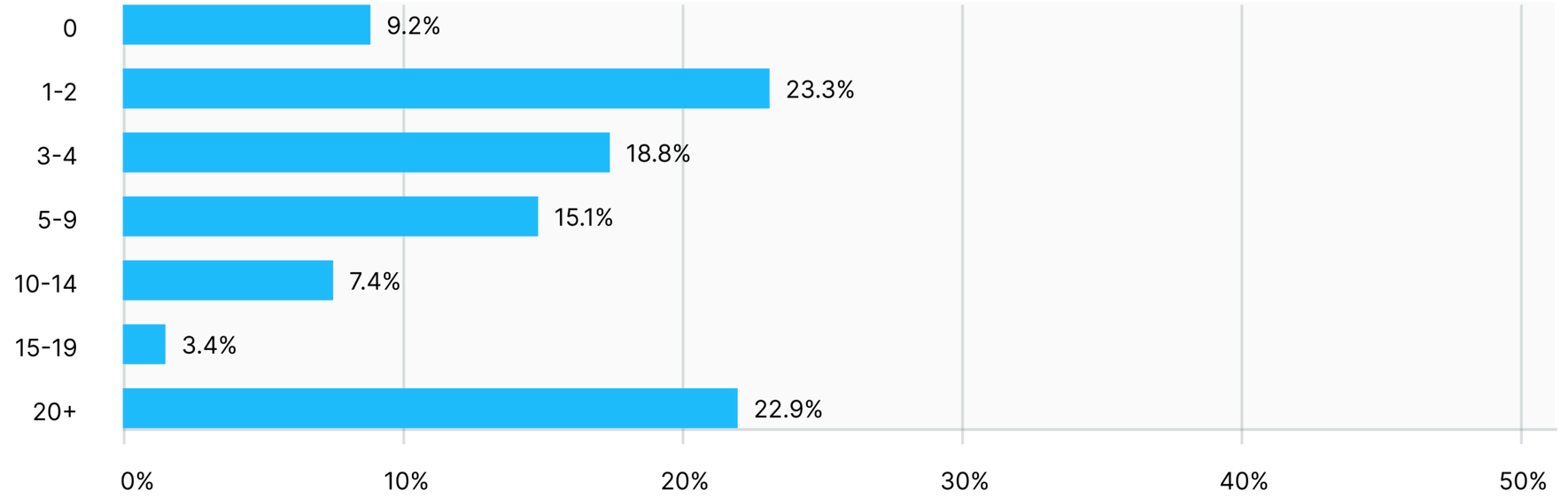
- Salary remained strong, pandemic may change that
- Concerns that supply + demand for DS may be narrowing at entry level
- WFH becomes normal, people move out of hot cities
- Current hot industries: Health, Supply chain

Kaggle 2020 State of ML & DS

COMPANY SIZE (# OF EMPLOYEES)



DATA SCIENCE TEAMS (# OF EMPLOYEES)

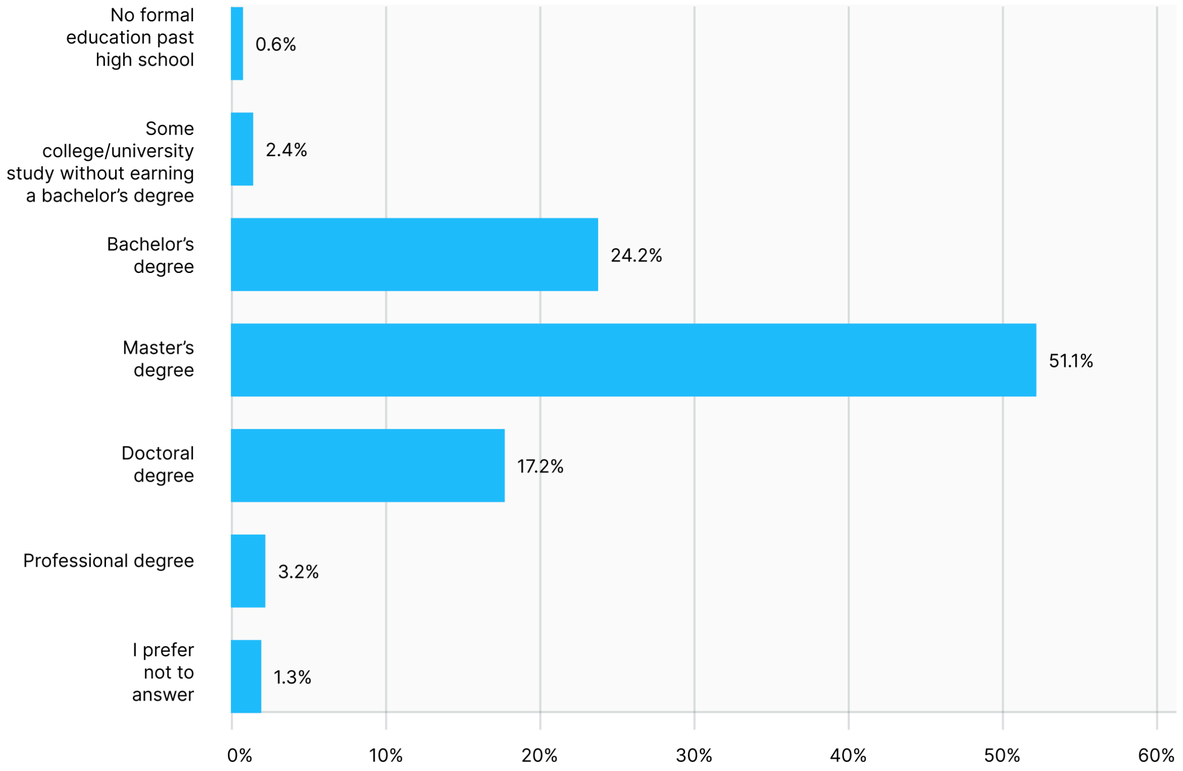


Ongoing Learning

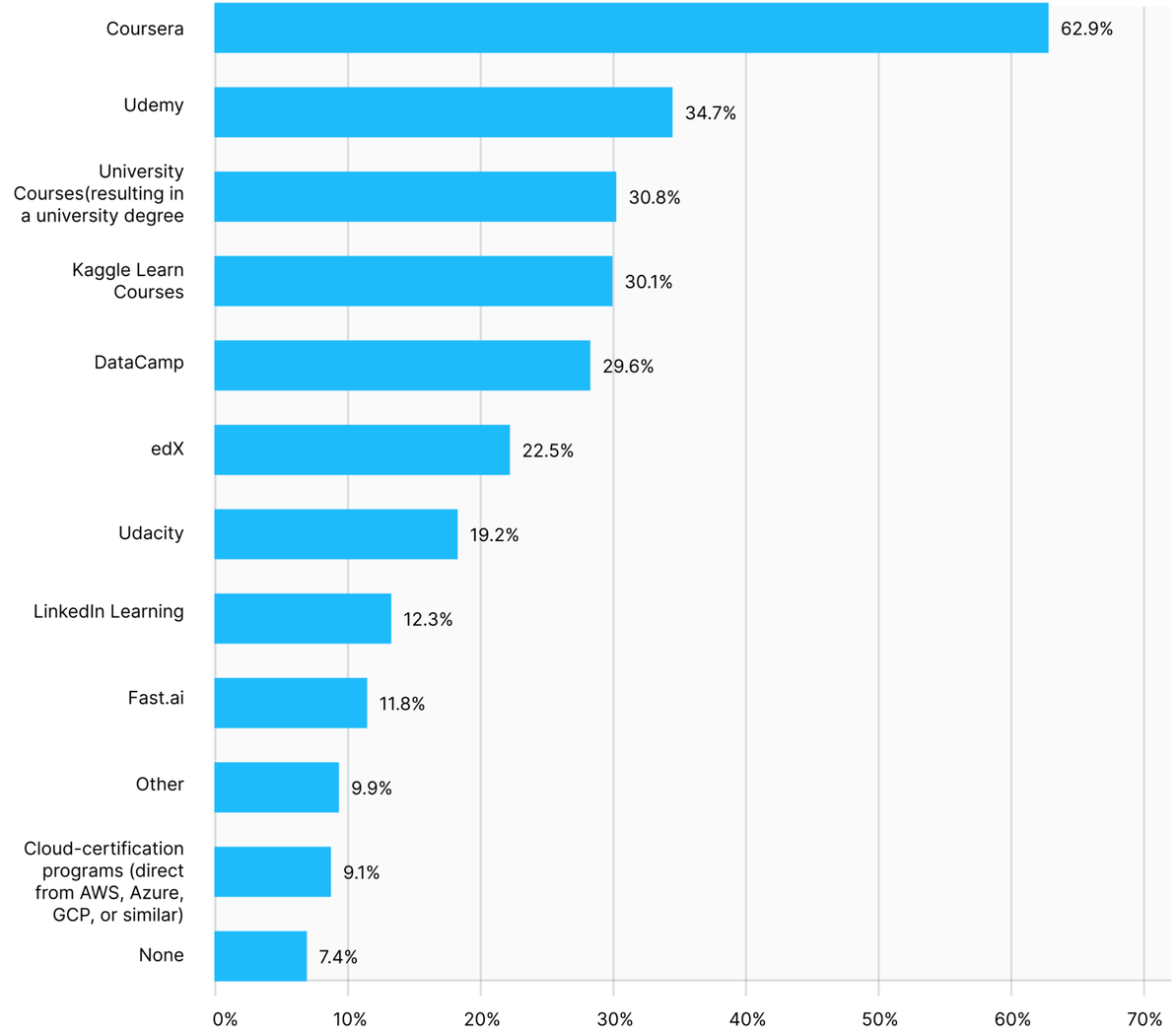
Data science and machine learning are quickly changing, so it's no surprise over 90% of Kaggle data scientists maintain ongoing education. While about 30% take traditional higher education courses, many more learn through online materials.

Coursera, Udemy, and Kaggle Learn top the most common mediums in our survey. Unsurprisingly, many Kaggle data scientists chose multiple resources in the survey, with an average of 2.8 mediums selected.

EDUCATION LEVEL OF KAGGLE DATA SCIENTISTS

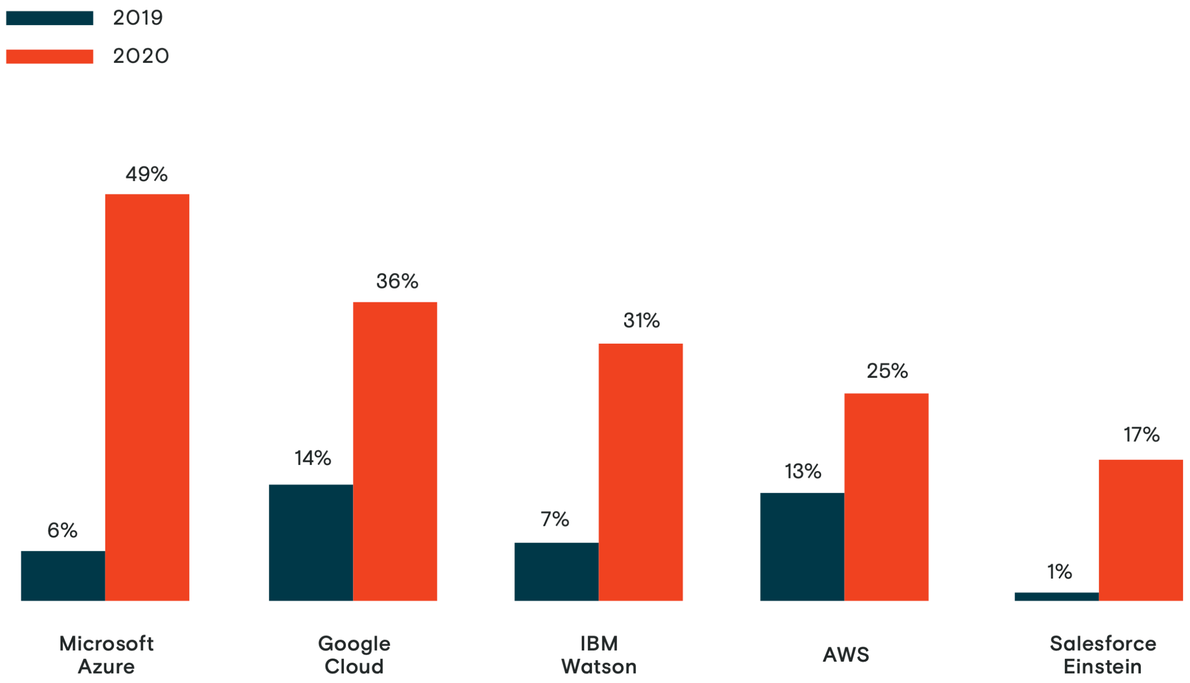


POPULAR ONGOING LEARNING RESOURCES



Appen (aka Figure-Eight aka Crowdflower) State of AI report

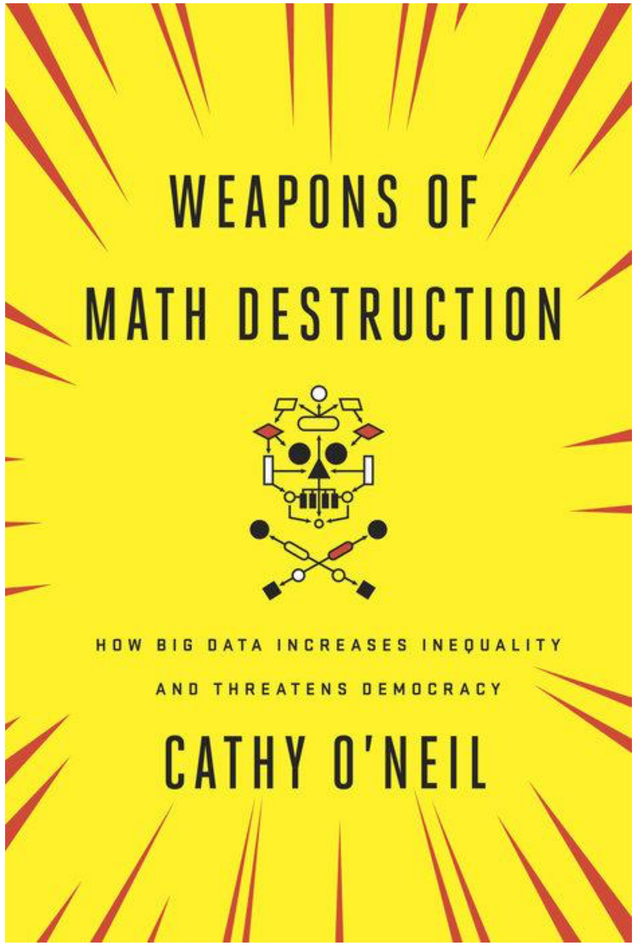
Figure 7: What data science and machine learning tools/frameworks do you use?



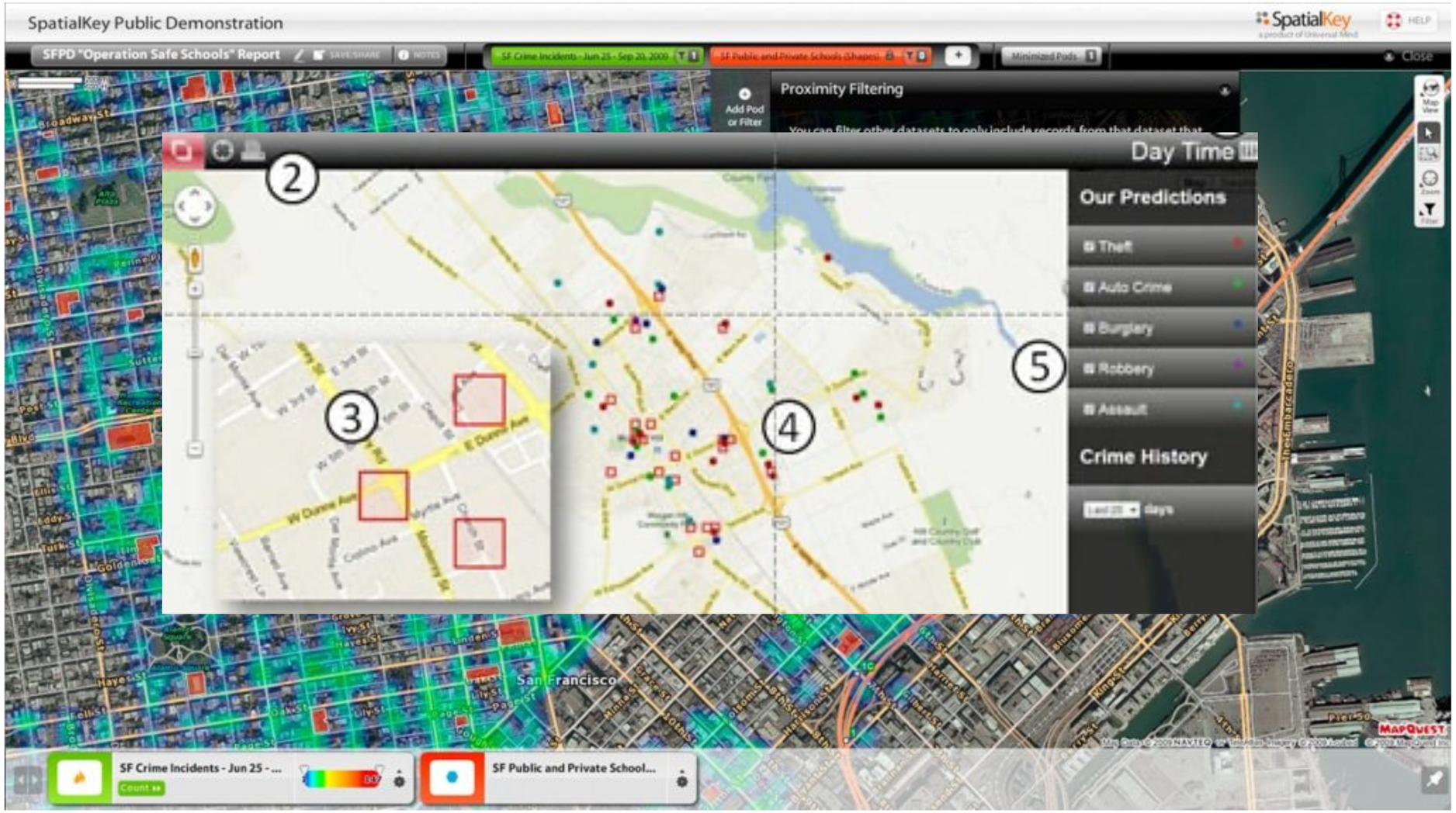
- AI/ML is a big deal at corporate level
- Everything is moving to the cloud (accelerating from WFH?)
- Lots of love for Azure, slowing growth for AWS

Don’t be a tool for creating WMDs

- Algorithms (and DS!) implement our biases, yet look objective
- Can implement our biases at scale
- Can have huge impacts on people’s lives
- Are not transparent or accountable to the people being impacted



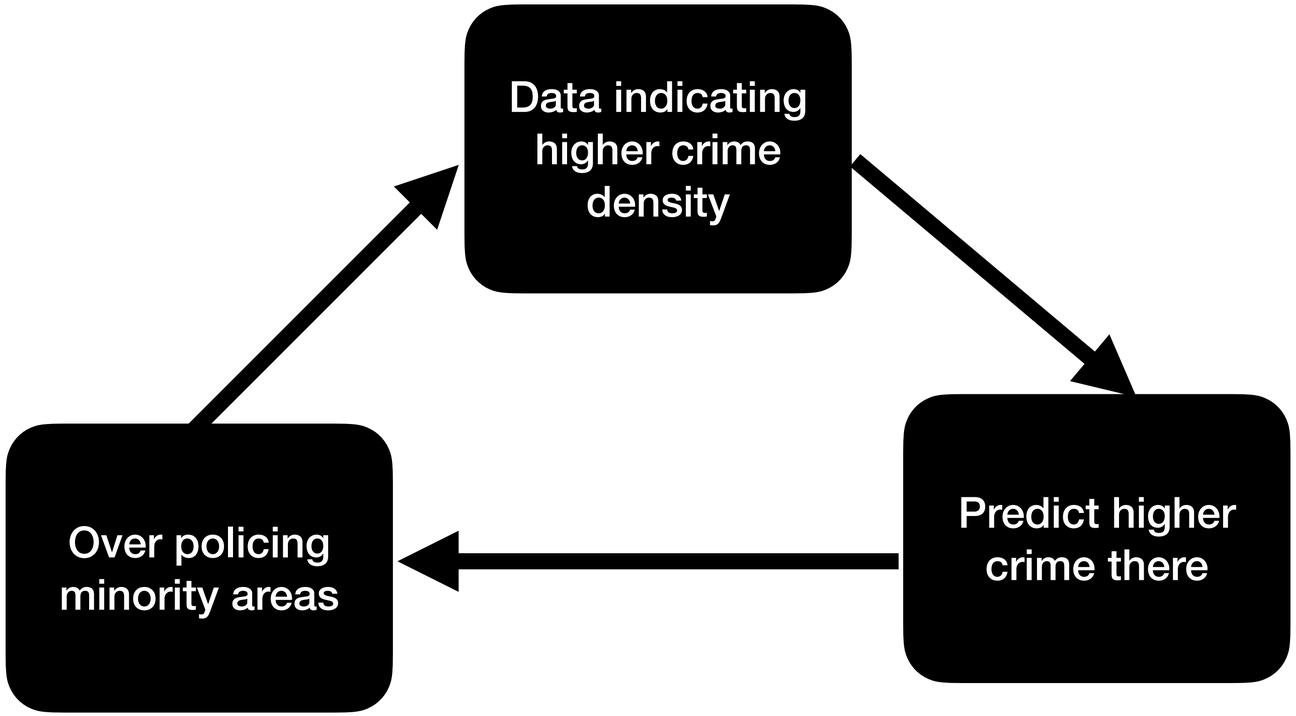
Predictive policing & sentencing



https://americanpoliceofficersalliance.com/police-tech-predictive-technology/#prettyPhoto

Predictive policing & sentencing

Blacks arrested for possession at 4x the rate of whites
Usage rates the same



https://norml.org/marijuana/fact-sheets/racial-disparity-in-marijuana-arrests/

https://rss.onlinelibrary.wiley.com/doi/full/10.1111/j.1740-9713.2016.00960.x

https://themarkup.org/prediction-bias/2021/12/02/crime-prediction-software-promised-to-be-free-of-biases-new-data-shows-it-perpetuates-them

“A lot of times, people are talking about bias in the sense of equalizing performance across groups. They’re not thinking about the underlying foundation, whether a task should exist in the first place, who creates it, who will deploy it on which population, who owns the data, and how is it used?”

-Timnit Gebru

Thank you!

Teaching Assistants:

- **Tyler Chang**
- **Mia Lucio**
- **Pooja Pathak**
- **Areeb Syed**

Instructional Assistants:

- **Scott Yang**
- **Harrison Ma**
- **Richard Duong**
- **Viki Zhao**

And thanks to YOU!