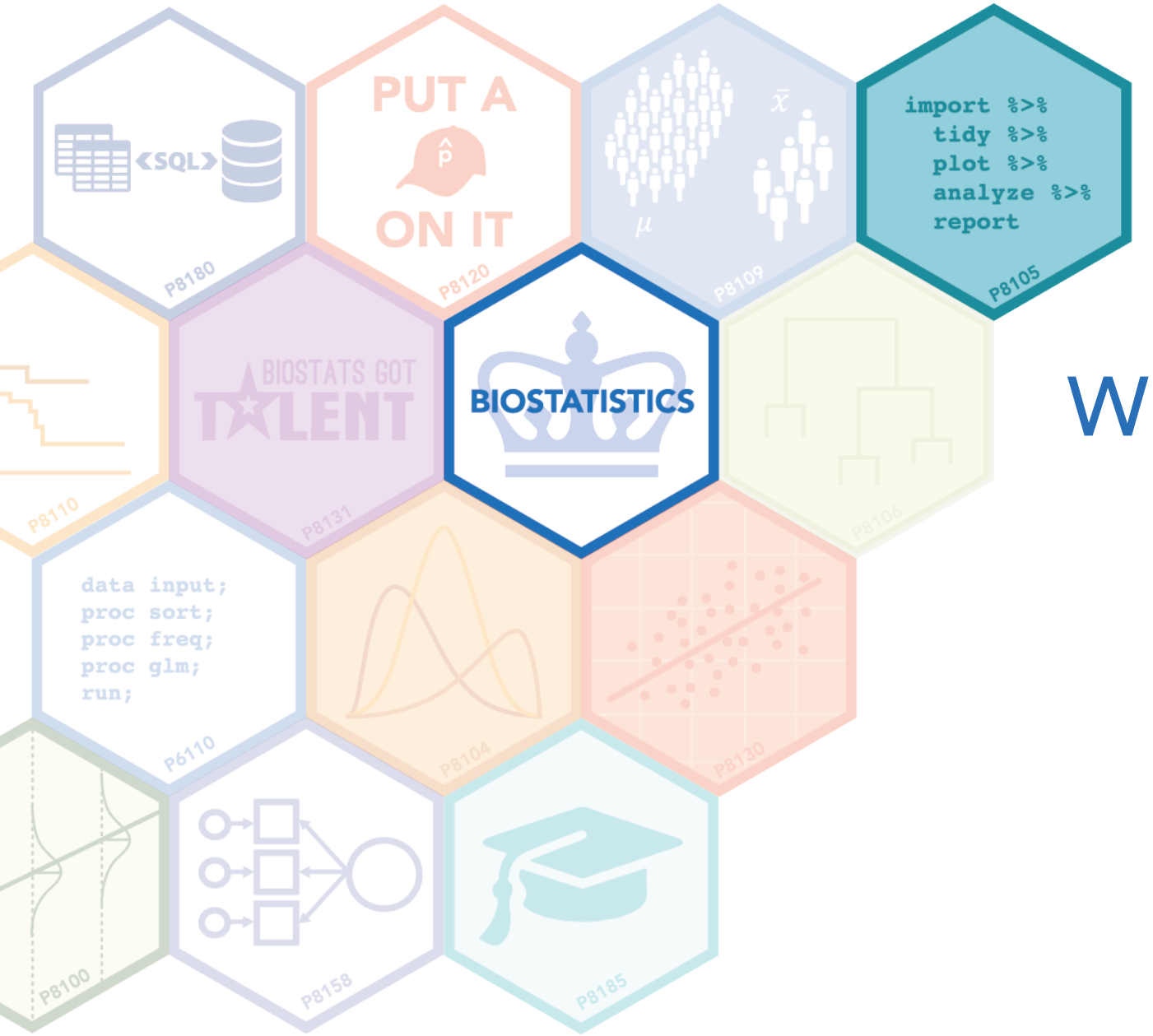

WHAT IS DATA SCIENCE?

Jeff Goldsmith, PhD
Department of Biostatistics

Data science is pretty new

Source: Google Trends

Some not great definitions

- Data science = statistics
- Data science = computer science
- Data science = machine learning
- Data science = statistics + computer science + machine learning
- Data scientists are big data wranglers
- “A data scientist is just a sexier word for statistician.” –Nate Silver
- “A data scientist is a better computer scientist than a statistician and is a better statistician than a computer scientist.”
- “A data scientist is a statistician who is useful” – Hadley Wickham
- A data scientist is a good statistical analyst
- A data scientist is a statistician who codes in python

Some not great definitions

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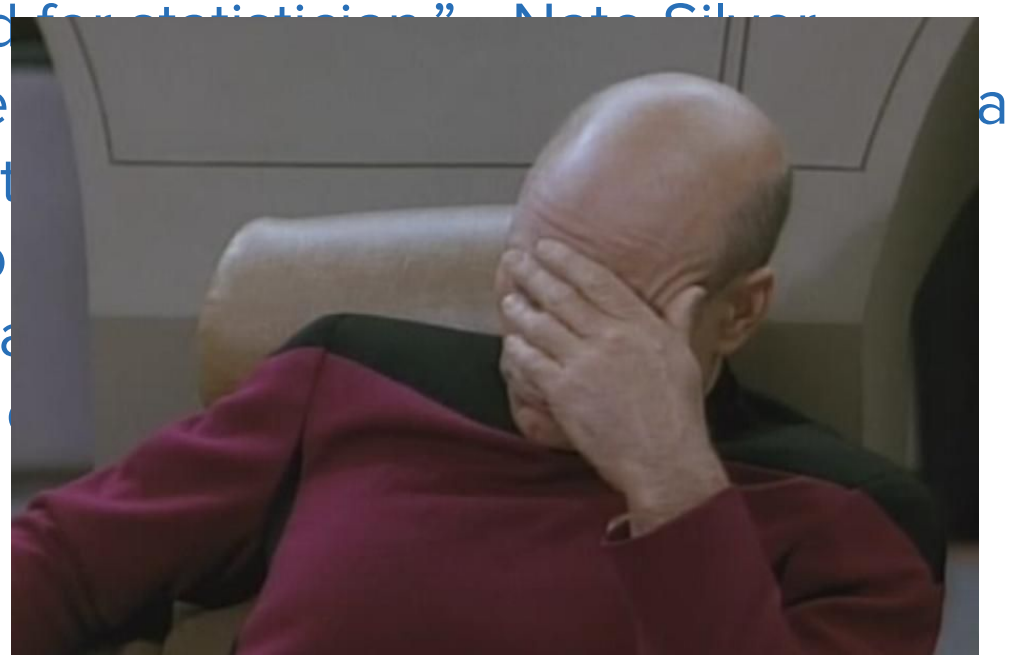

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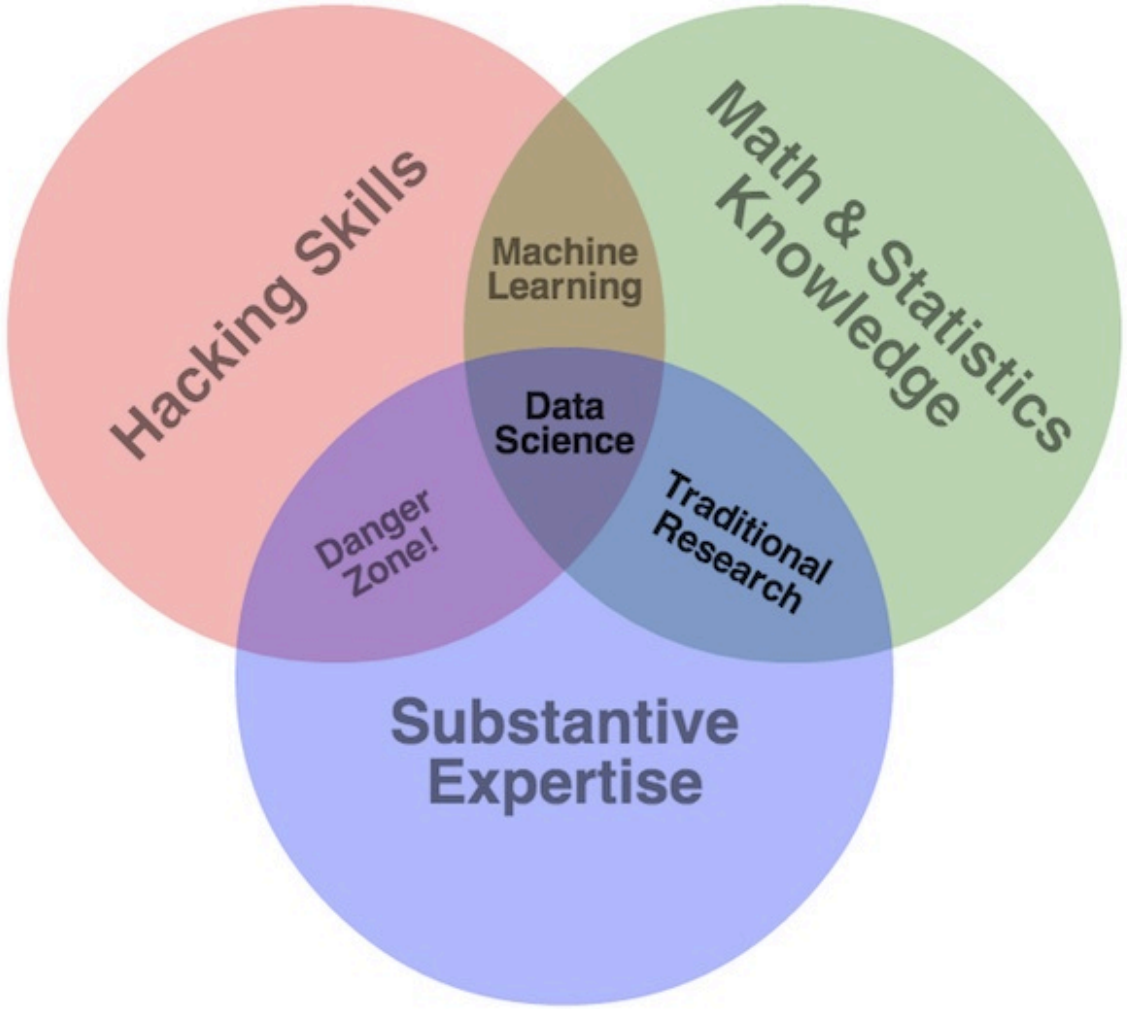

Image from Drew Conway

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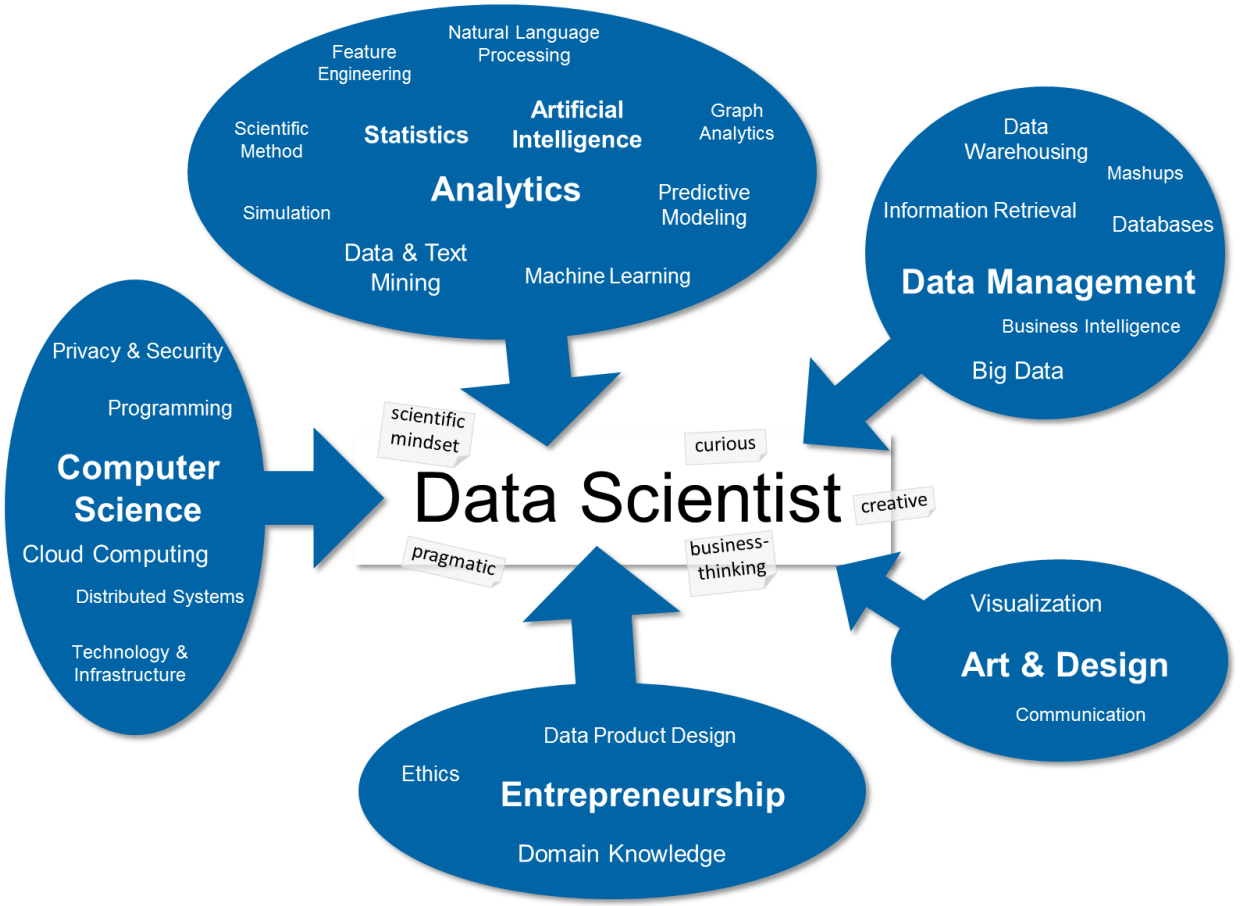

https://blog.zhaw.ch/datascience/the-data-science-skill-set/

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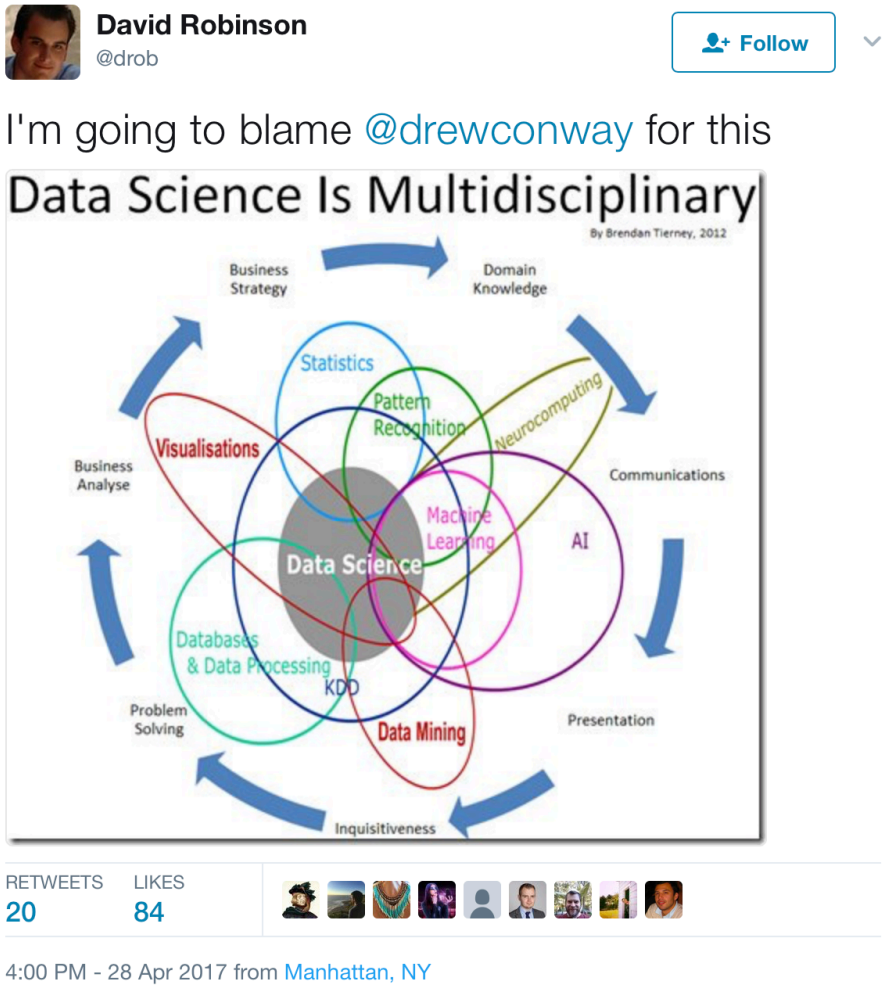

From twitter

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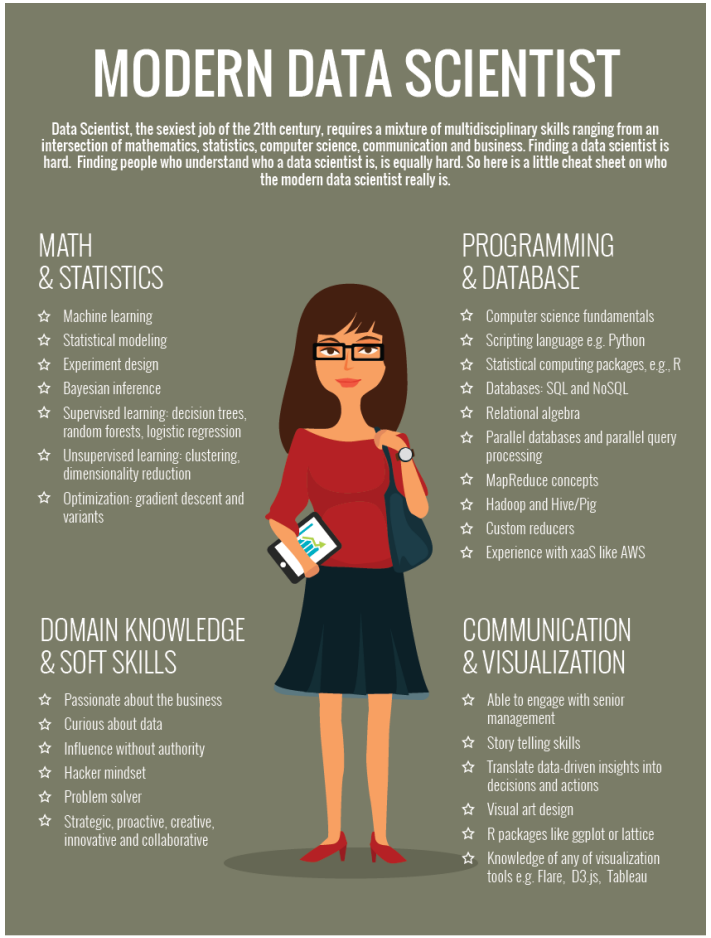
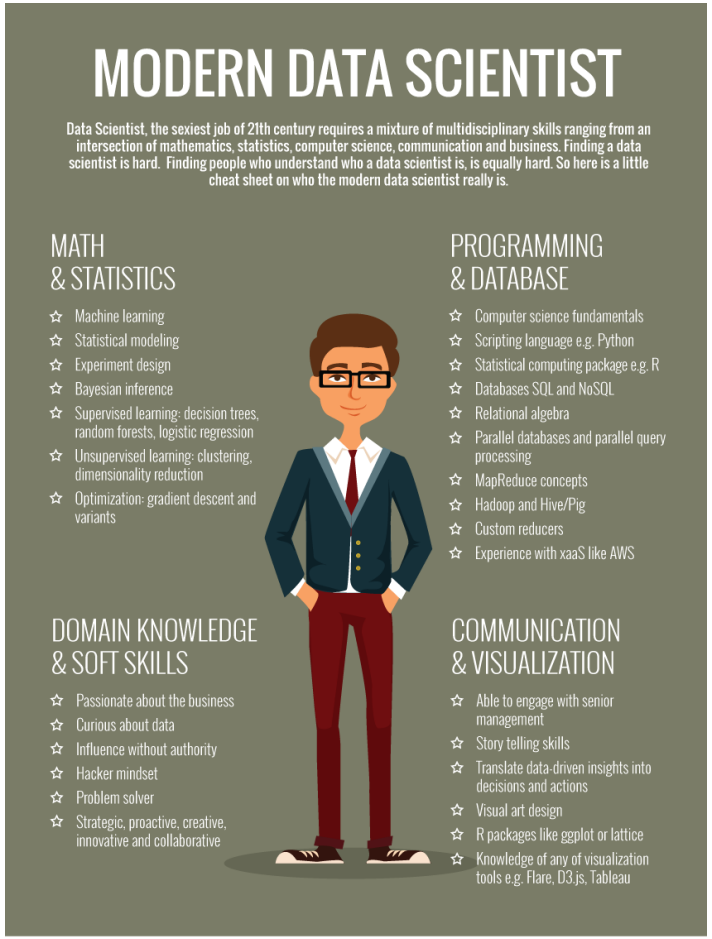




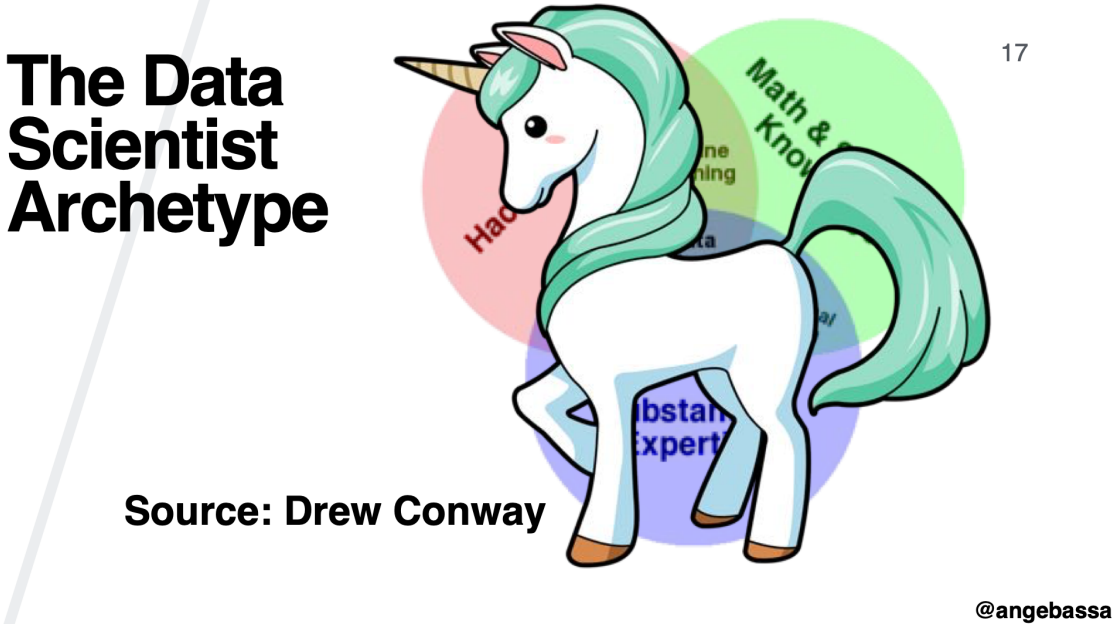
Why these definitions are bad

- "Data science is just …" definitions miss the point
  - If data science is just statistics (or machine learning, or computer science, or engineering) we wouldn't need a new term, let alone a new discipline
  - The popularity of "data science" suggests that there's a newly recognized need

- "A data scientist is a good " whatever definitions aren't helpful
  - They're almost deliberately judgmental
  - A good definition doesn't depend on opinions
  - There are "data scientists" in each discipline, but some very good statisticians / computer scientists / etc aren't "data scientists"

Why these definitions are bad

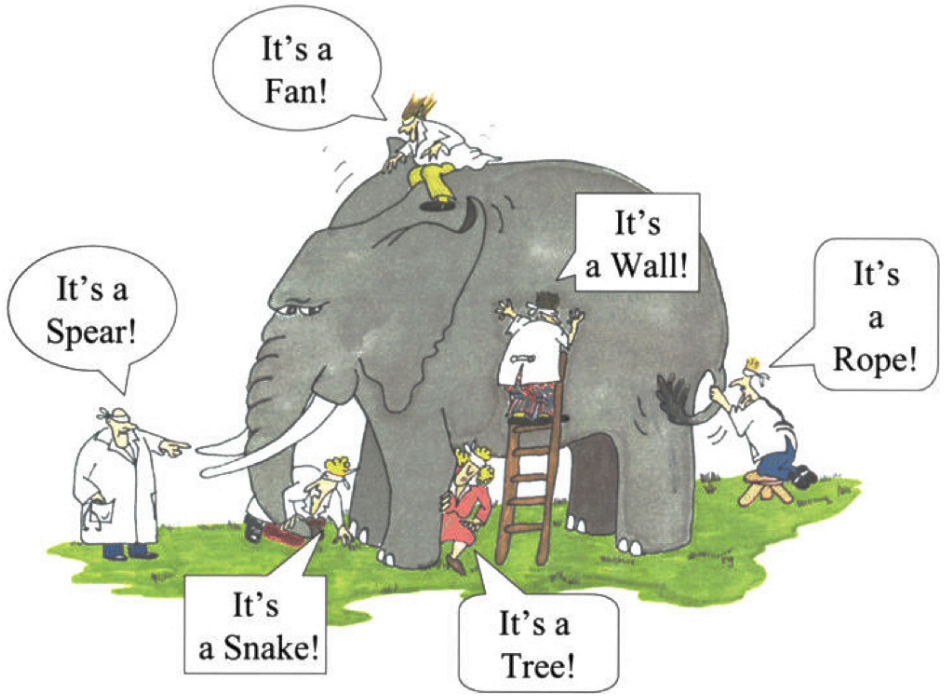
- "Data science is the combination of these 40 skills …" are unrealistic



https://www.youtube.com/watch?v=b9ZLXwAuUyw&app=desktop

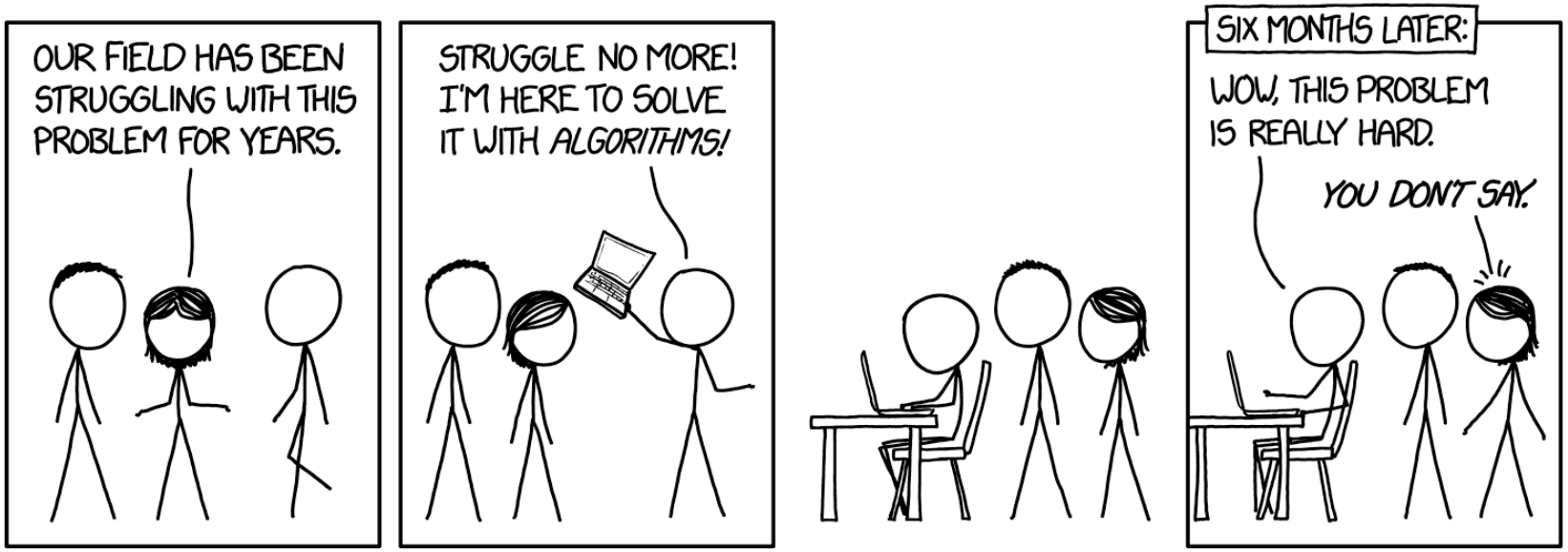
Why these definitions are good

- Kinda like the blind men and the elephant – no one perspective is completely right or completely wrong, but piling them all up isn't right either
- They give a sense of what is valued by the data science community – using data in a principled way and coding well



Why these definitions are good

- Data science is interdisciplinary
  - You do need a breadth of skills
  - You also need a particular mindset – curiosity and engagement is critical
  - You need some domain knowledge to be successful



https://www.xkcd.com/1831/

Is “data science” a buzzword?

- It is used to describe a frustratingly wide collection of ideas
- It is also used in different (sometimes contradictory) ways by different people

- Nonetheless, the popularity of “data science” reflects an increasingly data-centric reality
- Dismissing “data science” ignores this reality, and blinds people to the usefulness of a new perspective across disciplines

Reproducibility

- One concrete emphasis of data science is reproducibility
- Given the same data and the same code, anyone should be able to produce the same results
  - Openness is valuable – identify errors early and fix them quickly
  - Code is an important means of communication
  - New tools encourage reproducibility, but the concept is not platform-dependent

Replication

- Reproducibility is one part of replication …

Replication

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Replication

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Replication

- Reproducibility is one part of repli

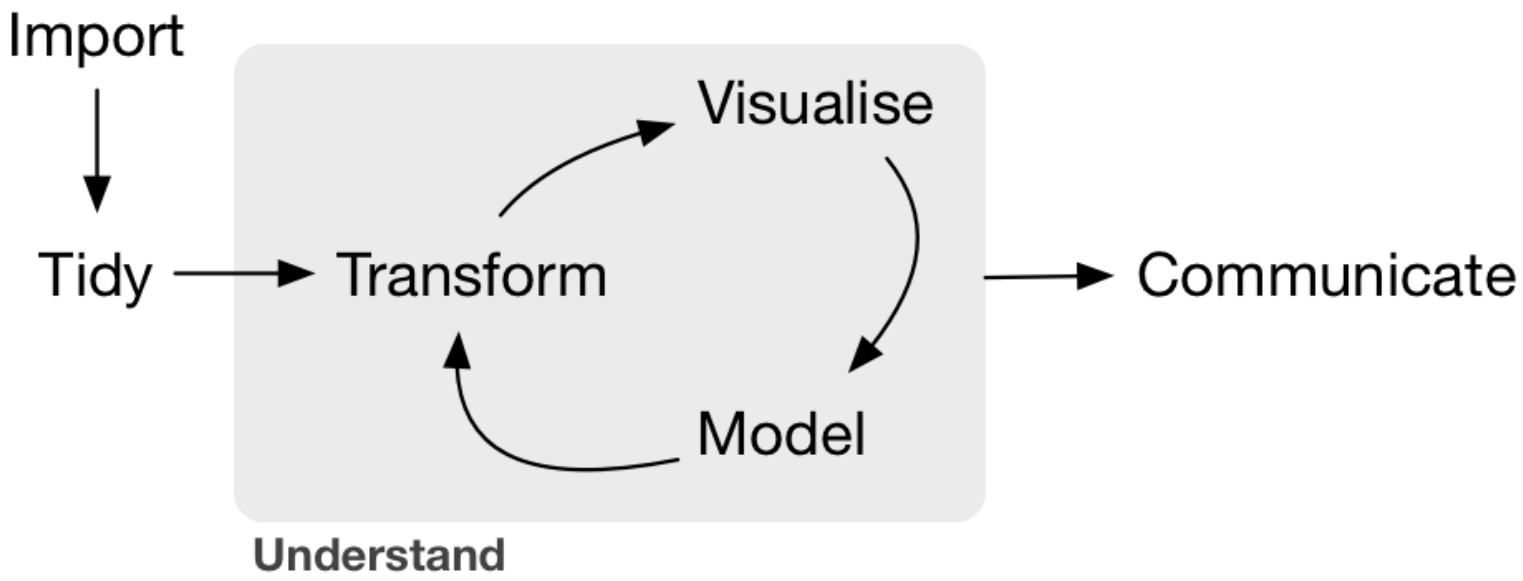
Patil, Peng, and Leek 2016

For the purpose of this class:

Data science is the use of data to formulate and rigorously answer questions in a process that emphasizes clarity, reproducibility, and collaboration, and that recognizes code as a primary means of communication.

- We'll focus mostly on process; how to answer questions through analyses are the focus of other courses

A data exploration diagram



R for Data Science

How to learn data science

- Build a broad knowledge base
- Don't be embarrassed by what you don't know
  - Corollary: don't be a jerk to people who don't know what you know
- Ask questions (well) and keep learning

- Pretty much the same as learning anything, but hard because people don't like to show their code

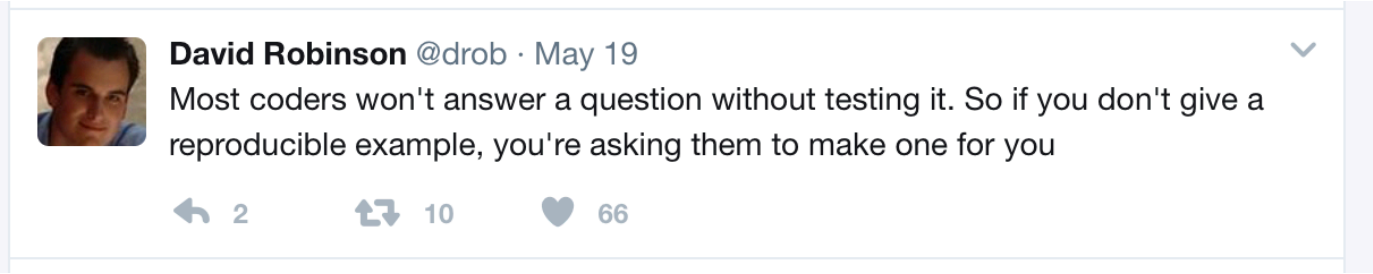
How to learn data science

- Build a broad knowledge base
- Don't be embarrassed by what you don't k
  - Corollary: don't be a jerk to people who
- Ask questions (well) and keep learning

- Pretty much the same as learning anything
  don't like to show their code

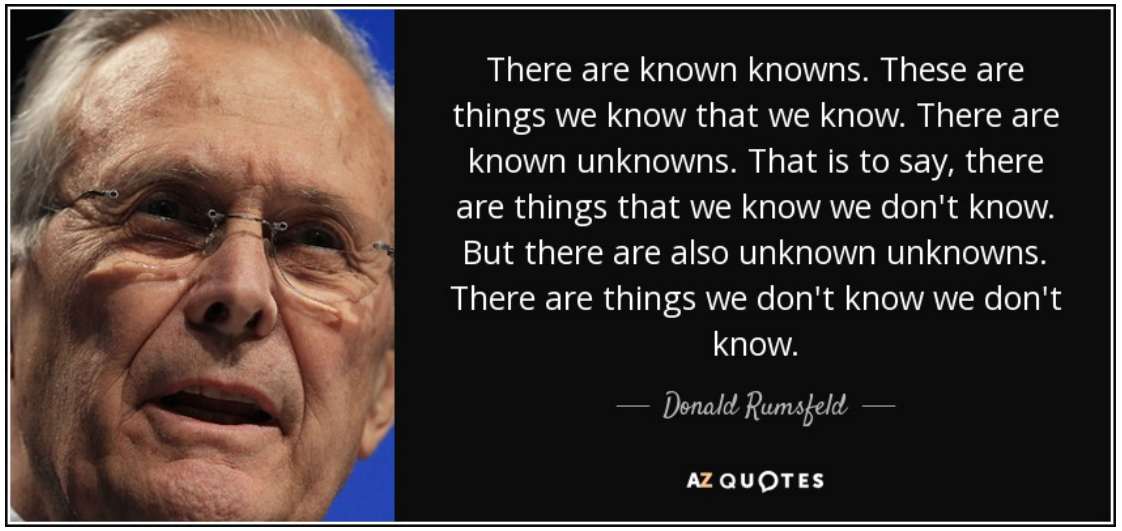
How to learn data science

- All questions are good questions, but sometimes good questions aren't asked well
- Think through what you're trying to ask
- If your code is broken, come up with a simple example that illustrates what's broken



How to learn data science

- Be on the lookout for cool stuff!



How to learn data science

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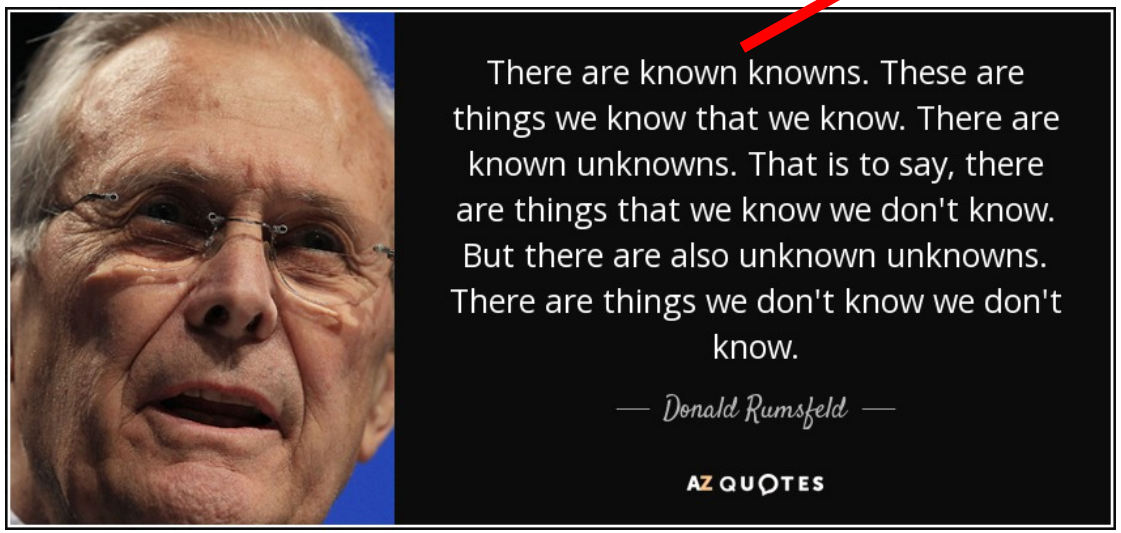
Knowledge base! :-D



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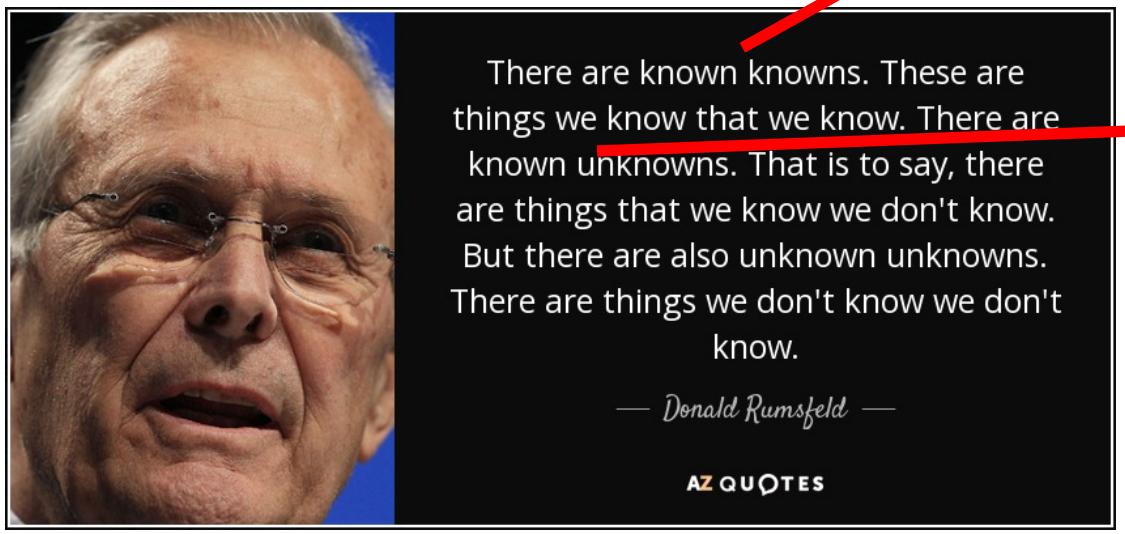
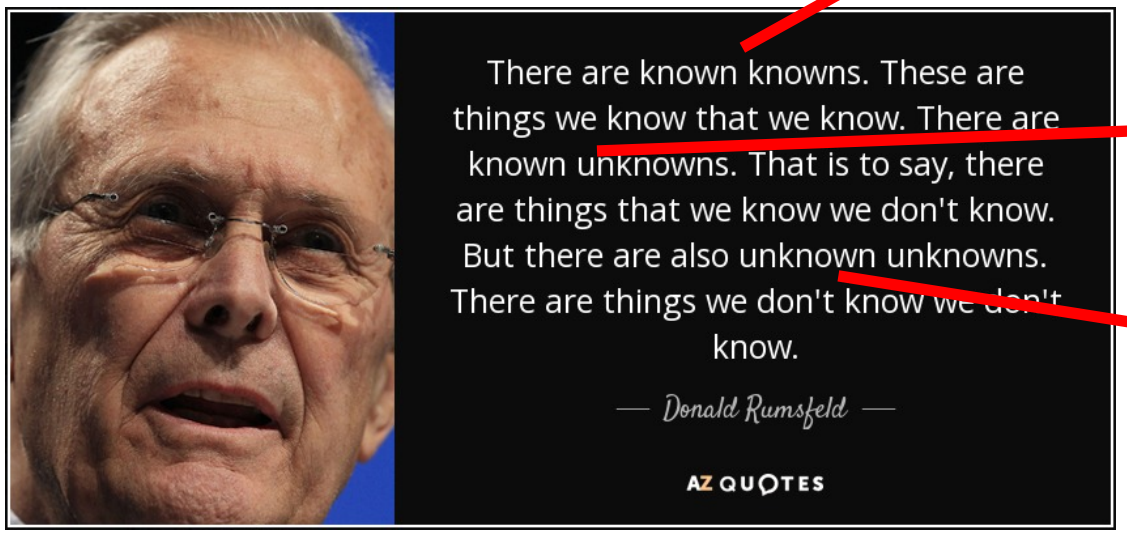


Knowledge base! :-D

Things you know exist and can learn how to do :-)

How to learn data science

- Be on the lookout for cool stuff!



Knowledge base! :-D

Things you know exist and can learn how to do :-)

Things you don't know exist and can't use :-(

DS twitter starter pack

- Follow these people to add some “knowns” to your repertoire

- @AmeliaMN
- @dataandme
- @drewconway
- @drob
- @hadleywickham
- @hmason
- @hspter
- @_inundata
- @jennybryan
- @johnmyleswhite
- @juliasilge
- @jtleek
- @kara_woo
- @kwbroman
- @rdpeng
- @robinson_es
- @seanjtaylor
- @sgrifter
- @statpumpkin
- @xieyihui

- #rstats
- #tidytuesday

Data as a resource

The world's most valuable resource is no longer oil, but data

The data economy demands a new approach to antitrust rules

Data as a resource

The world's most valuable resource is no longe

The data economy d

Sections ☰ The Washington Post

wp BrandStudio ⓘ Content from **IBM Power Systems**

Why big data is "the new natural resource"

Data as a resource

The world's most valuable resource
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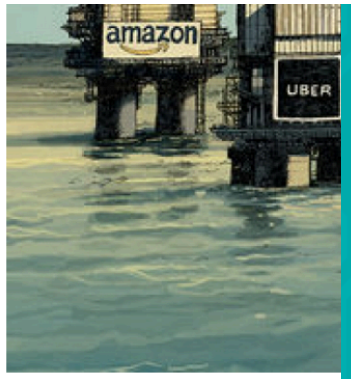
Is Data The New Oil? How One Startup Is Rescuing The World's Most Valuable Asset



"the new natural resource"

Data as a resource

The world's most valu
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The data economy d

Opinion

Streaming Video Will Soon Look Like the Bad Old Days of TV

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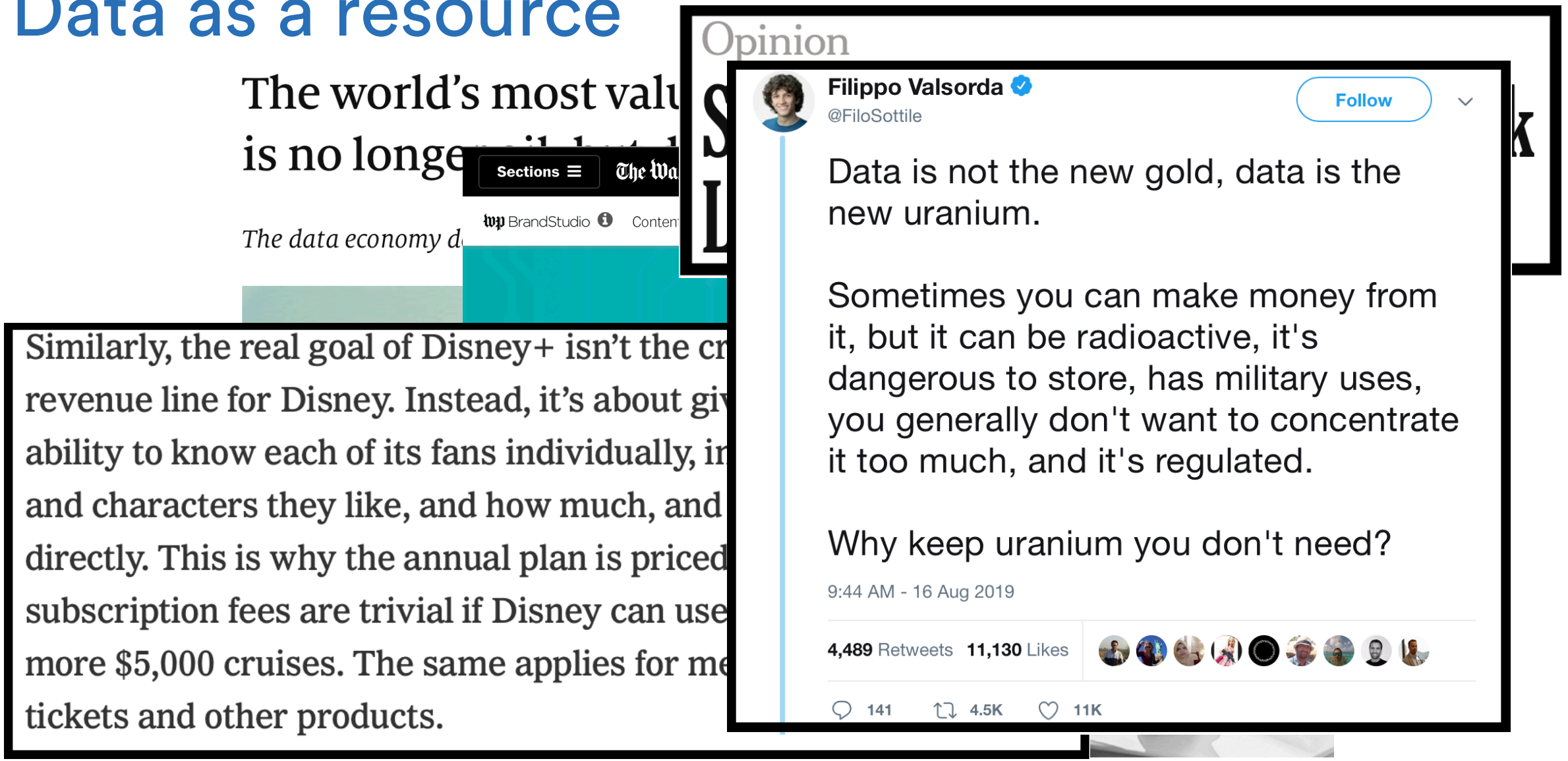
Similarly, the real goal of Disney+ isn't the creation of a new revenue line for Disney. Instead, it's about giving the company the ability to know each of its fans individually, including what content and characters they like, and how much, and to sell to them directly. This is why the annual plan is priced at only $70. Monthly subscription fees are trivial if Disney can use the service to sell more $5,000 cruises. The same applies for merchandise, movie tickets and other products.

Data as a resource



Data in health and medicine

- Data are everywhere

- Clinical trials
- Observational studies
- Genomics
- Medical imaging
- Microbiome

Data in health and medicine

- Data are everywhere

- Clinical trials
- Observational studies
- Genomics
- Medical imaging
- Microbiome

- Electronic health records?
- Mobile health technologies?
- Twitter posts?
- Search terms?
- Social networks?

A public health lens

How can we use these data to improve health?

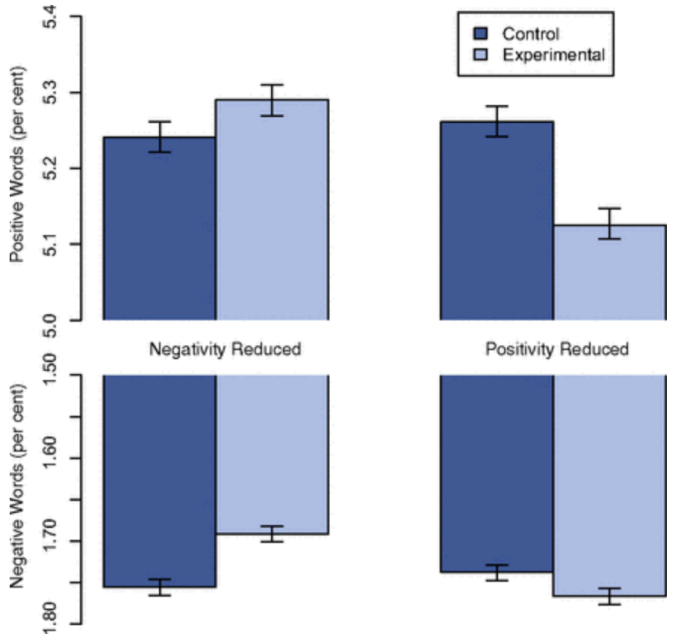
- Improve surveillance, leading to better prevention efforts?
- Better understanding of mechanisms?
- More precise and more effective outreach?

- Doing something simple and useful is better

Facebook experiments

PNAS

Experimental evidence of massive-scale emotional contagion through social networks

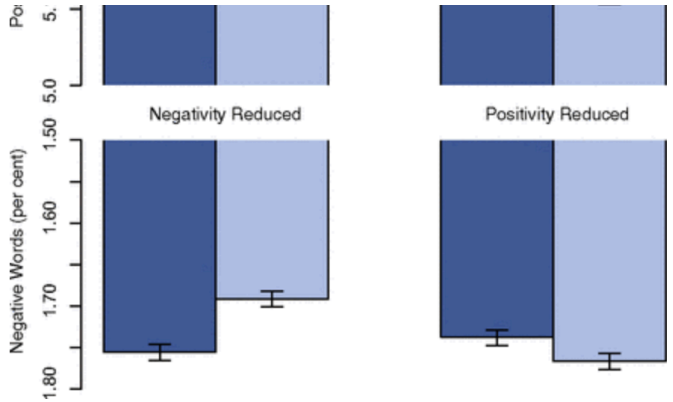


Facebook experiments

PNAS

Significance

We show, via a massive (*N* = 689,003) experiment on Facebook, that emotional states can be transferred to others via emotional contagion, leading people to experience the same emotions without their awareness. We provide experimental evidence that emotional contagion occurs without direct interaction between people (exposure to a friend expressing an emotion is sufficient), and in the complete absence of nonverbal cues.



Face xperiments

BBC NEWS

Facebook admits failings over emotion manipulation study

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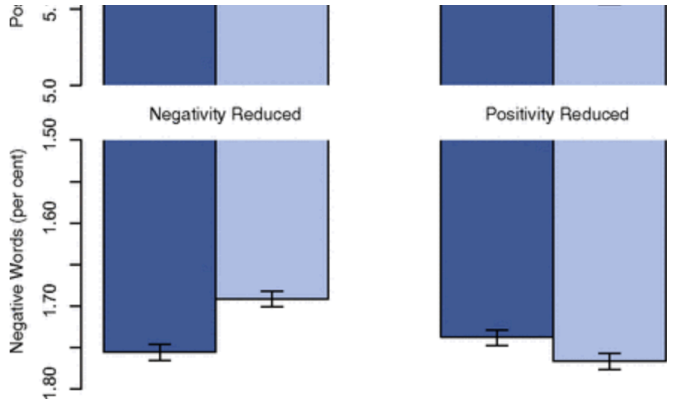

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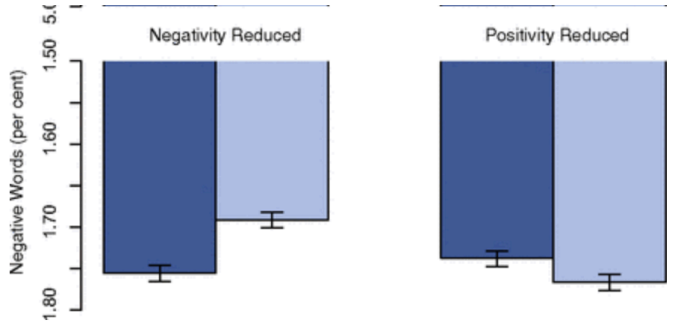

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Forbes / Tech

Facebook Manipulated 689,003 Users' Emotions For Science

Face xperiments

BBC NEWS

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On Facebook, you may be a guinea pig and not know it.

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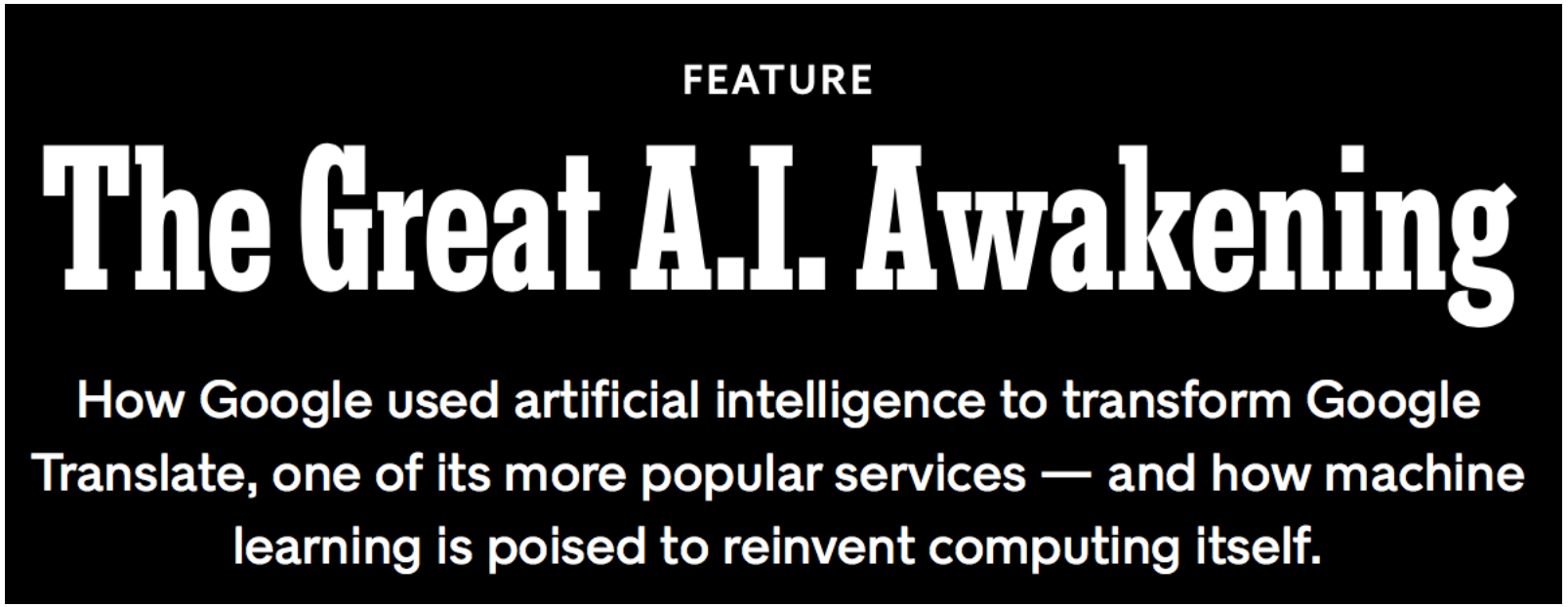
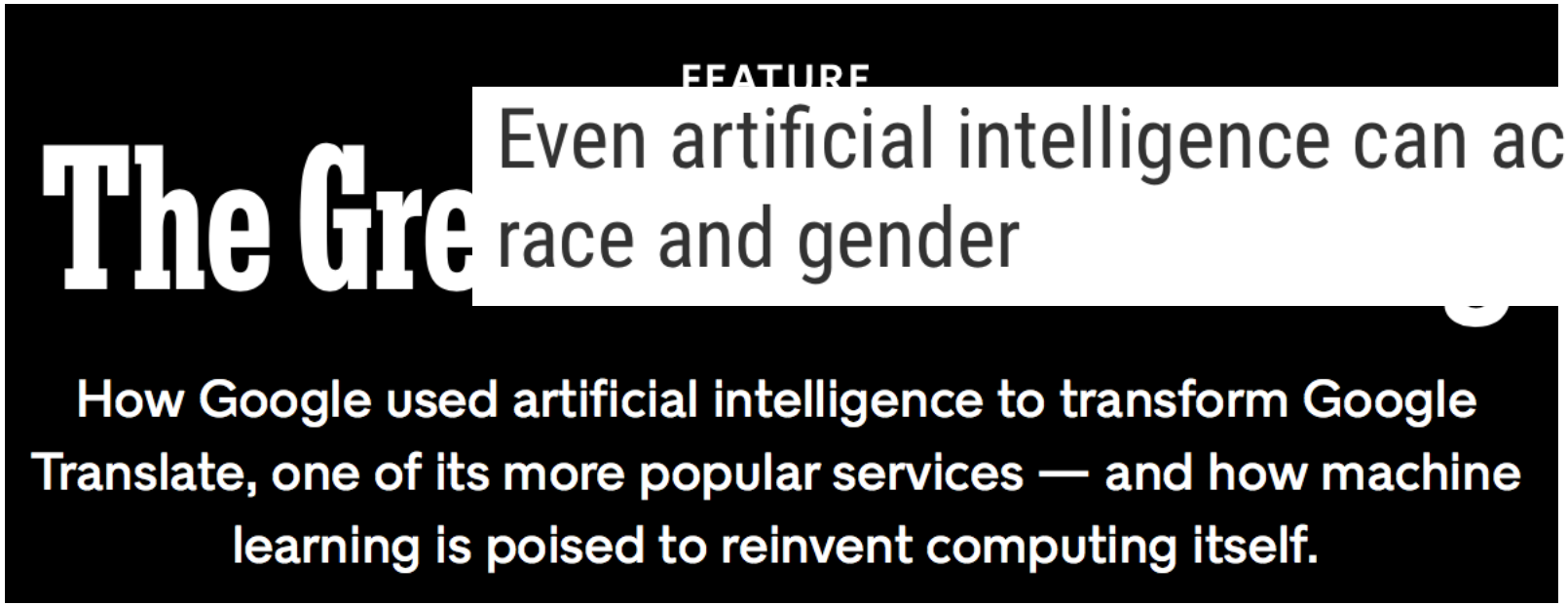
AI for Translation



AI for Translation



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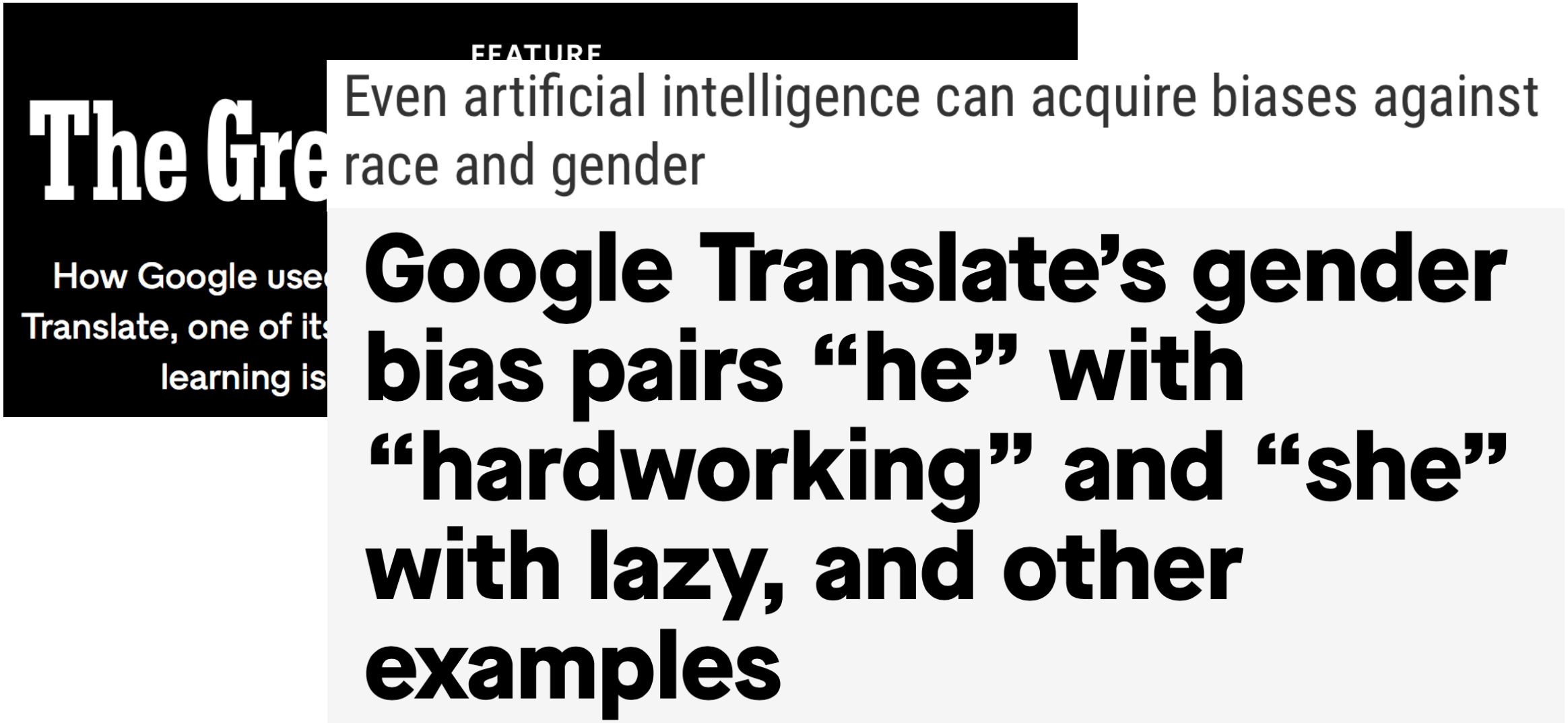

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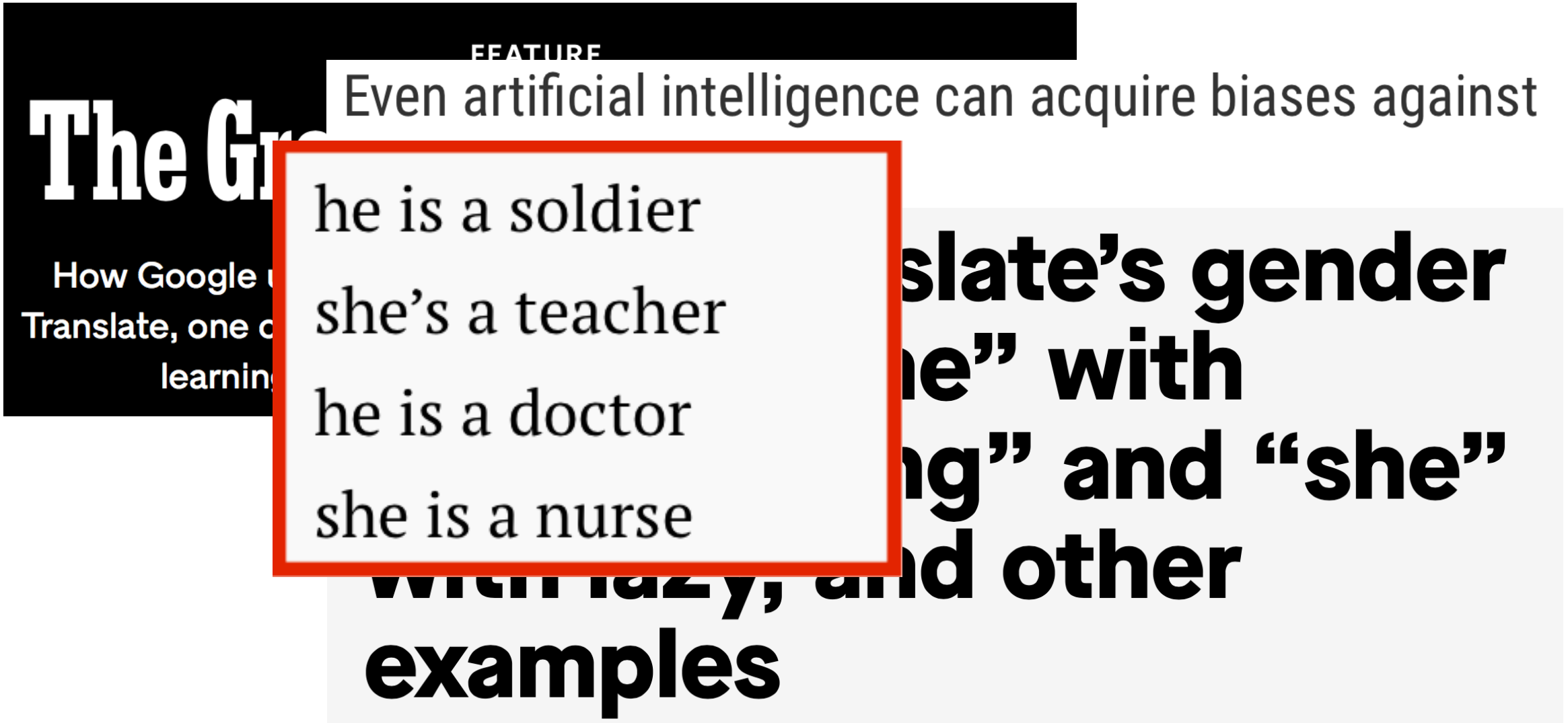
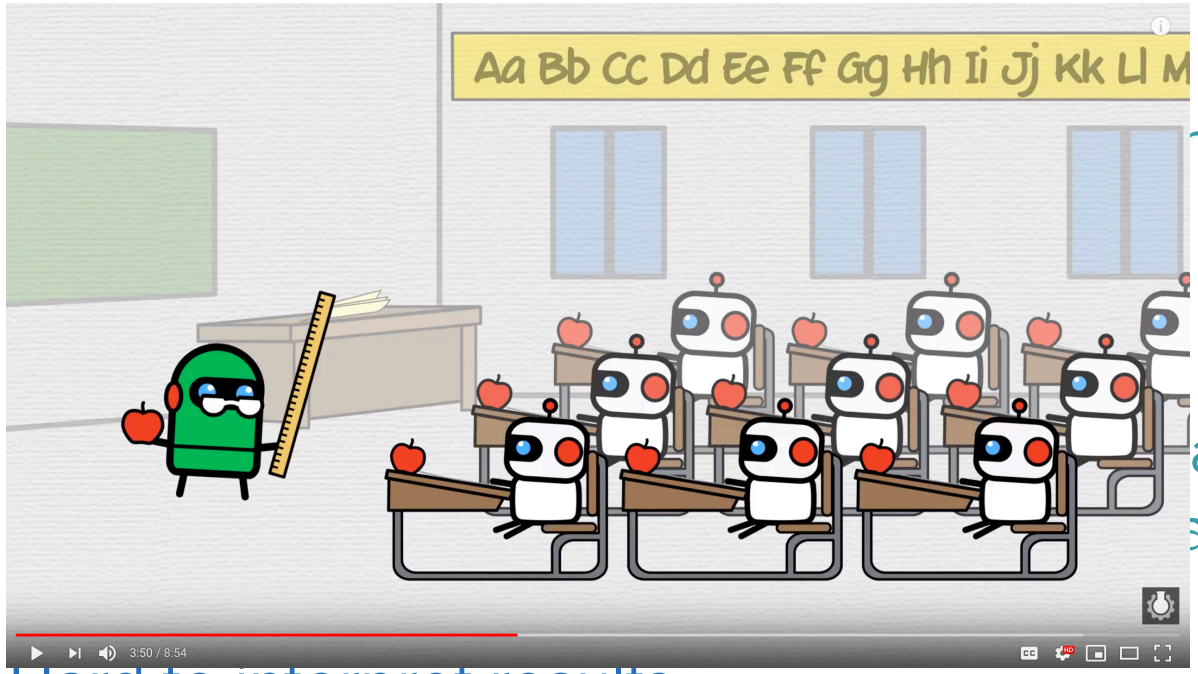


AI and deep learning

- Not a “magic bullet”
  - Predictions can be very different from the truth, even when advanced techniques are used
- Often requires massive training databases
  - Results are only as good as training data
  - Results also depend on what methods are trained to optimize
- Hard to interpret results…

Stills from “How machines learn” by CGP Grey

AI and deep learning

- 

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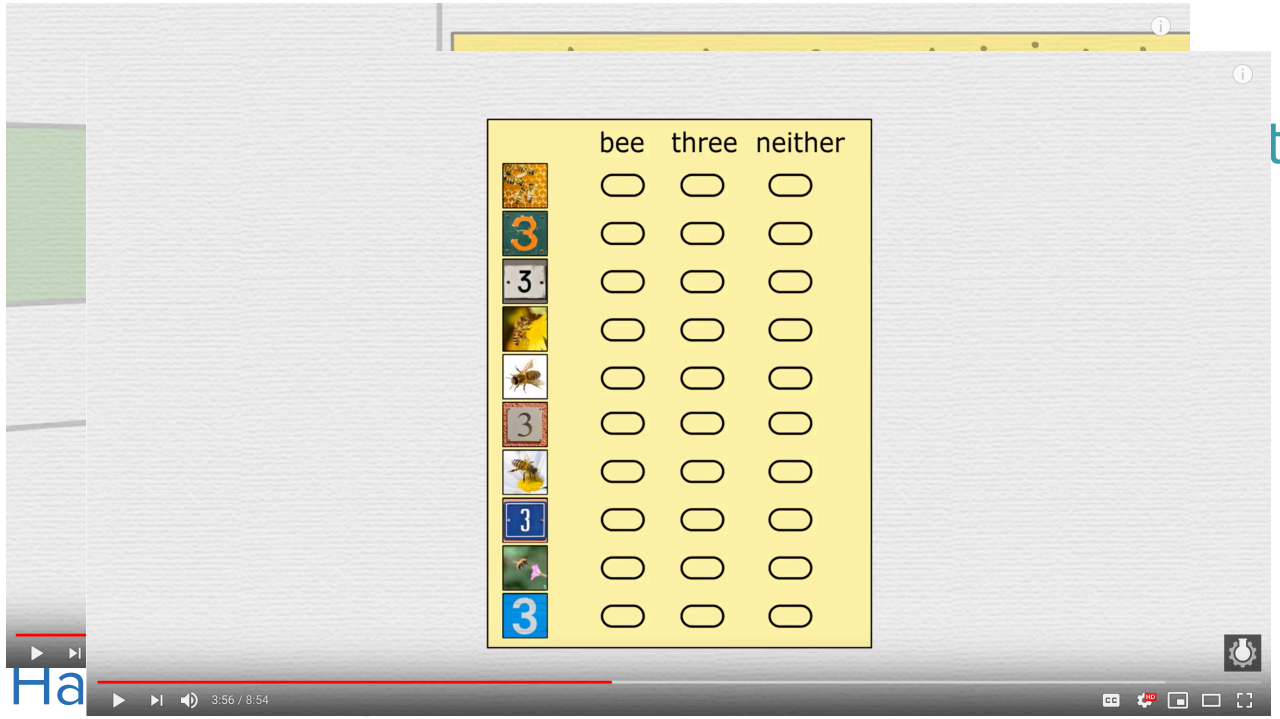
- 

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AI and deep learning

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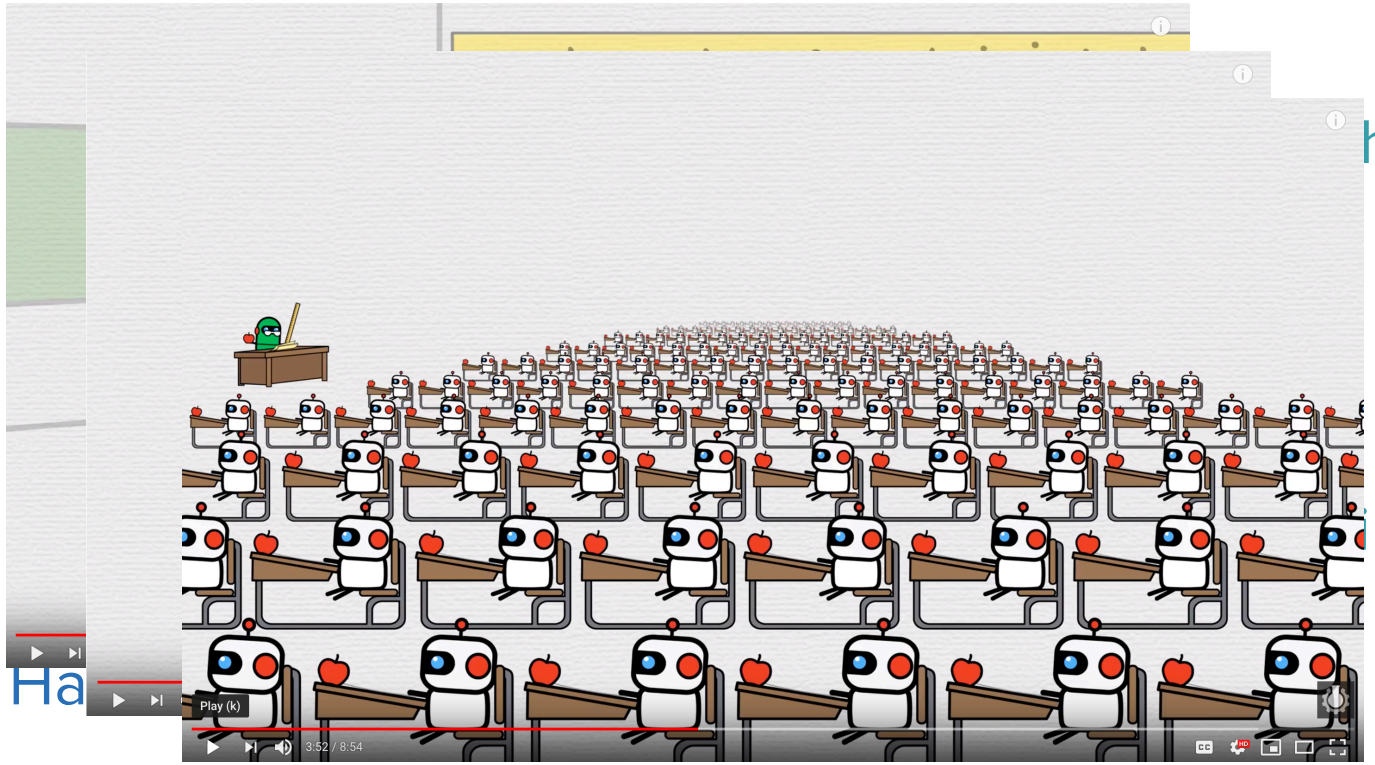

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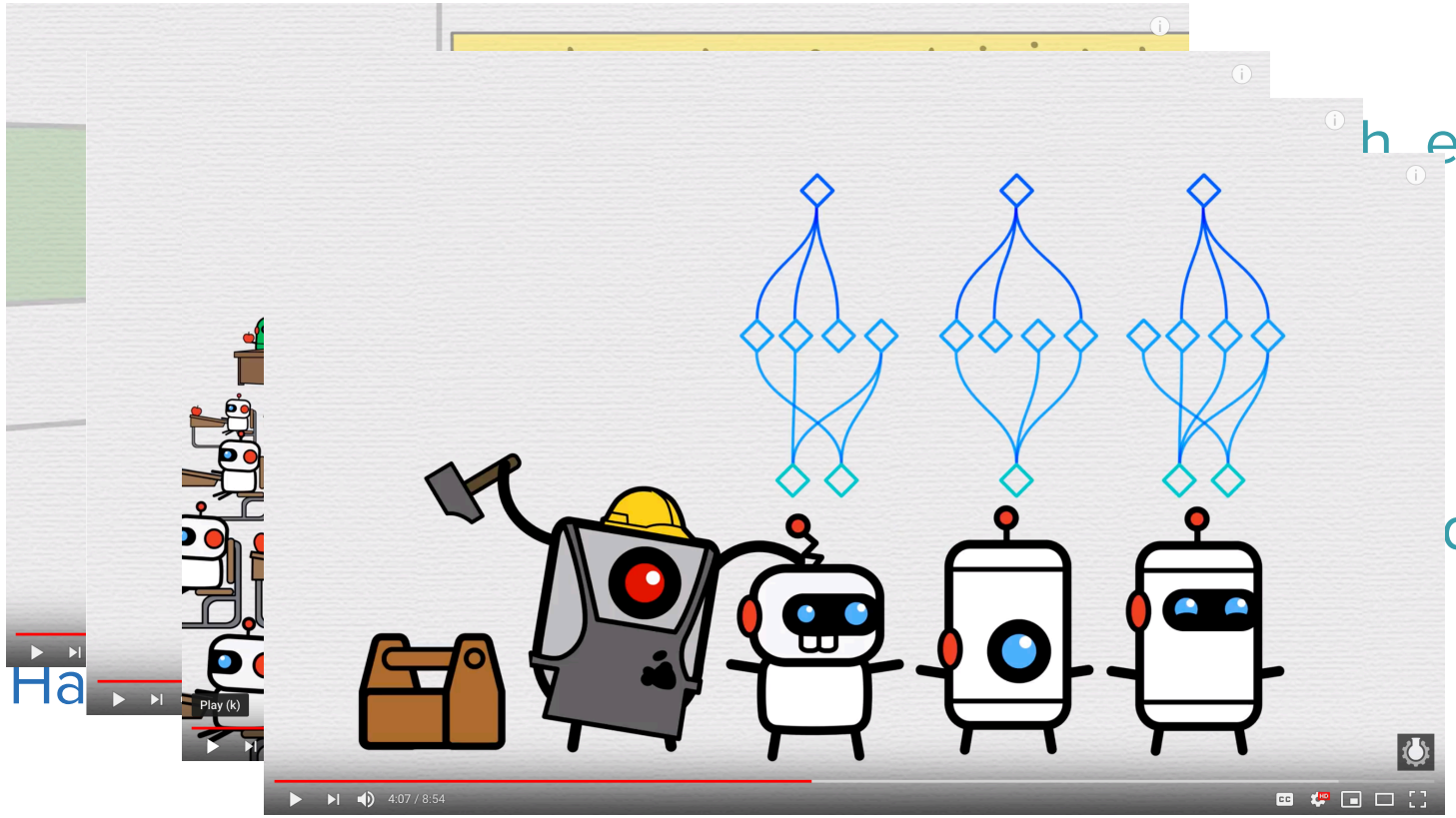

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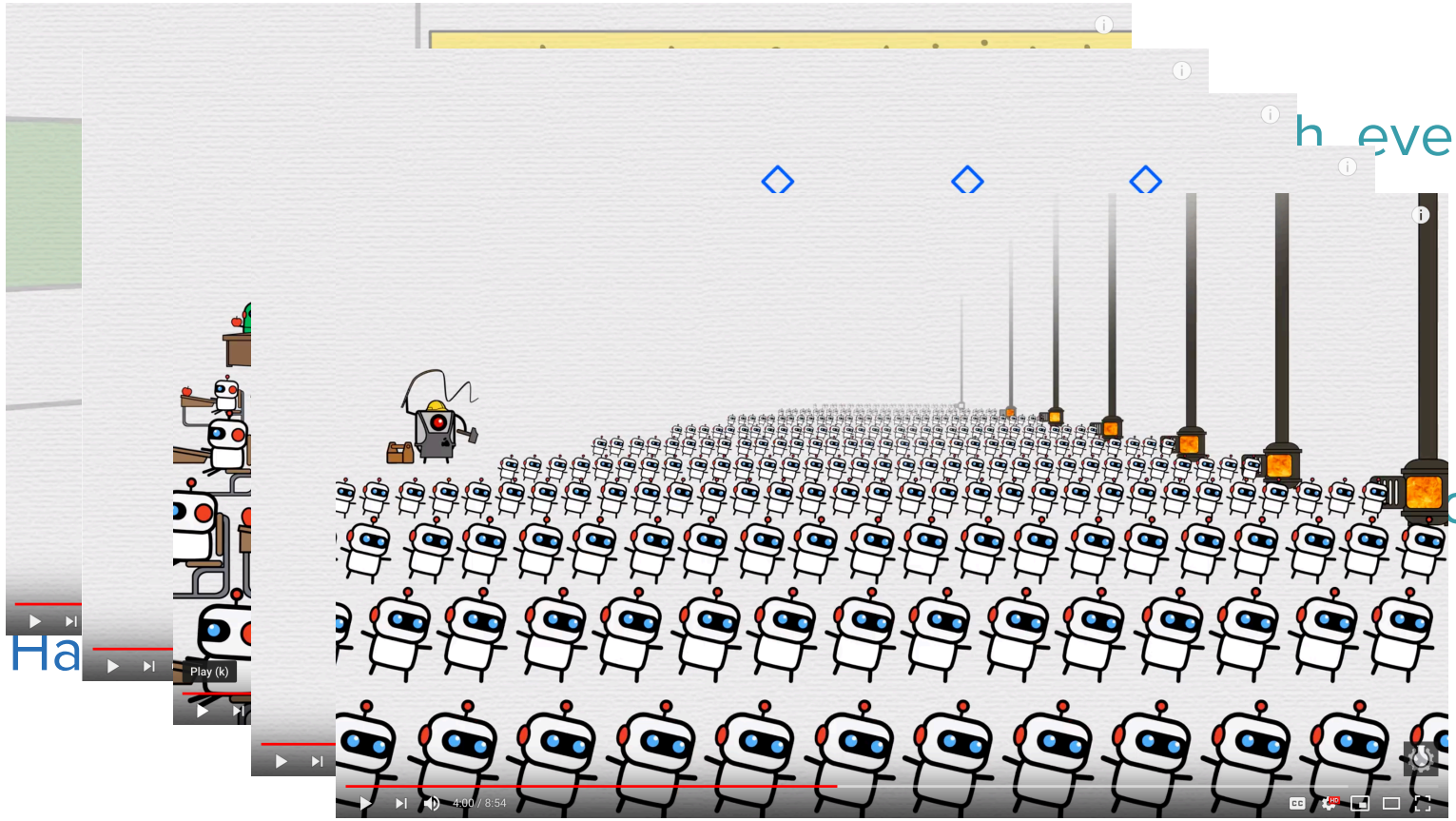

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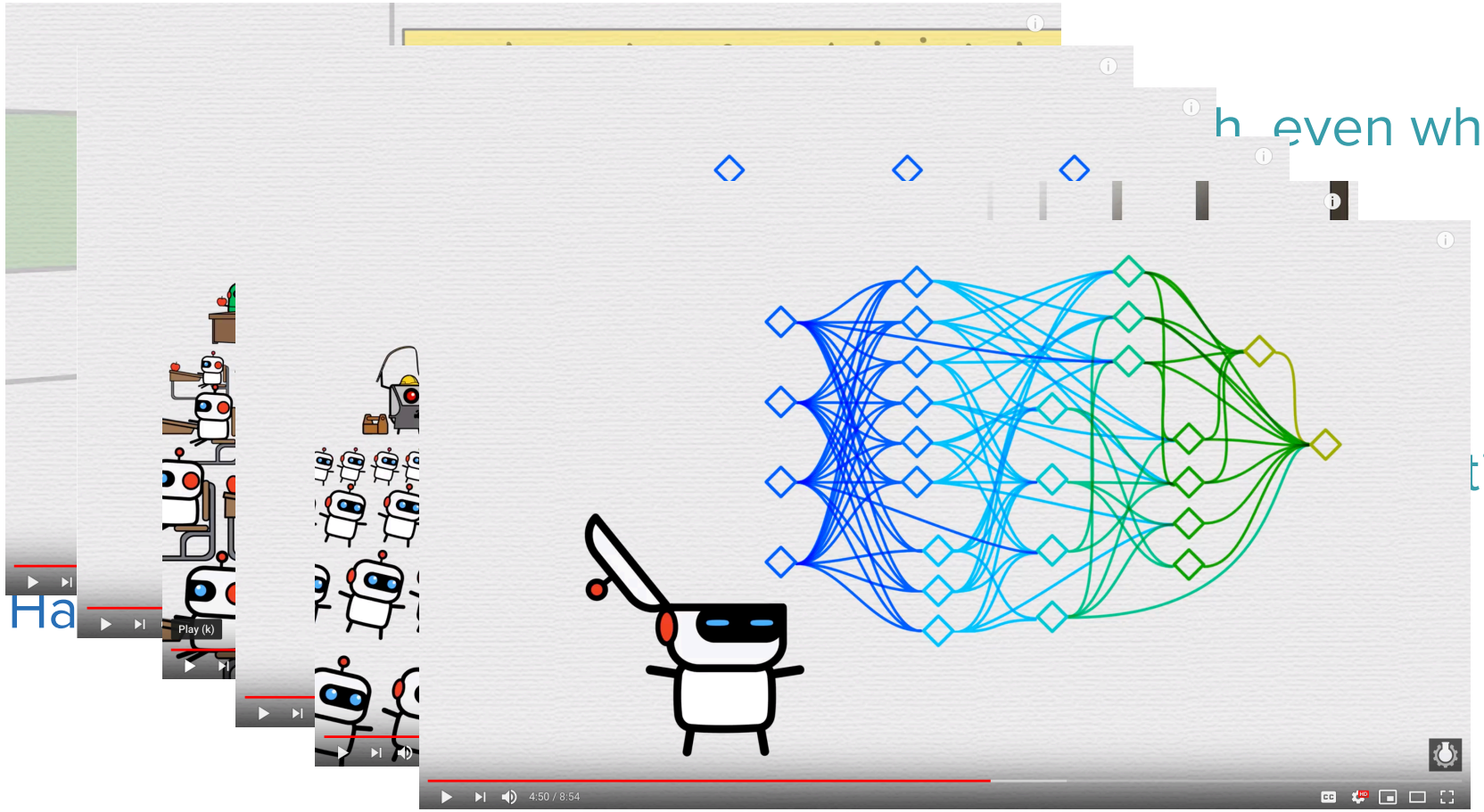

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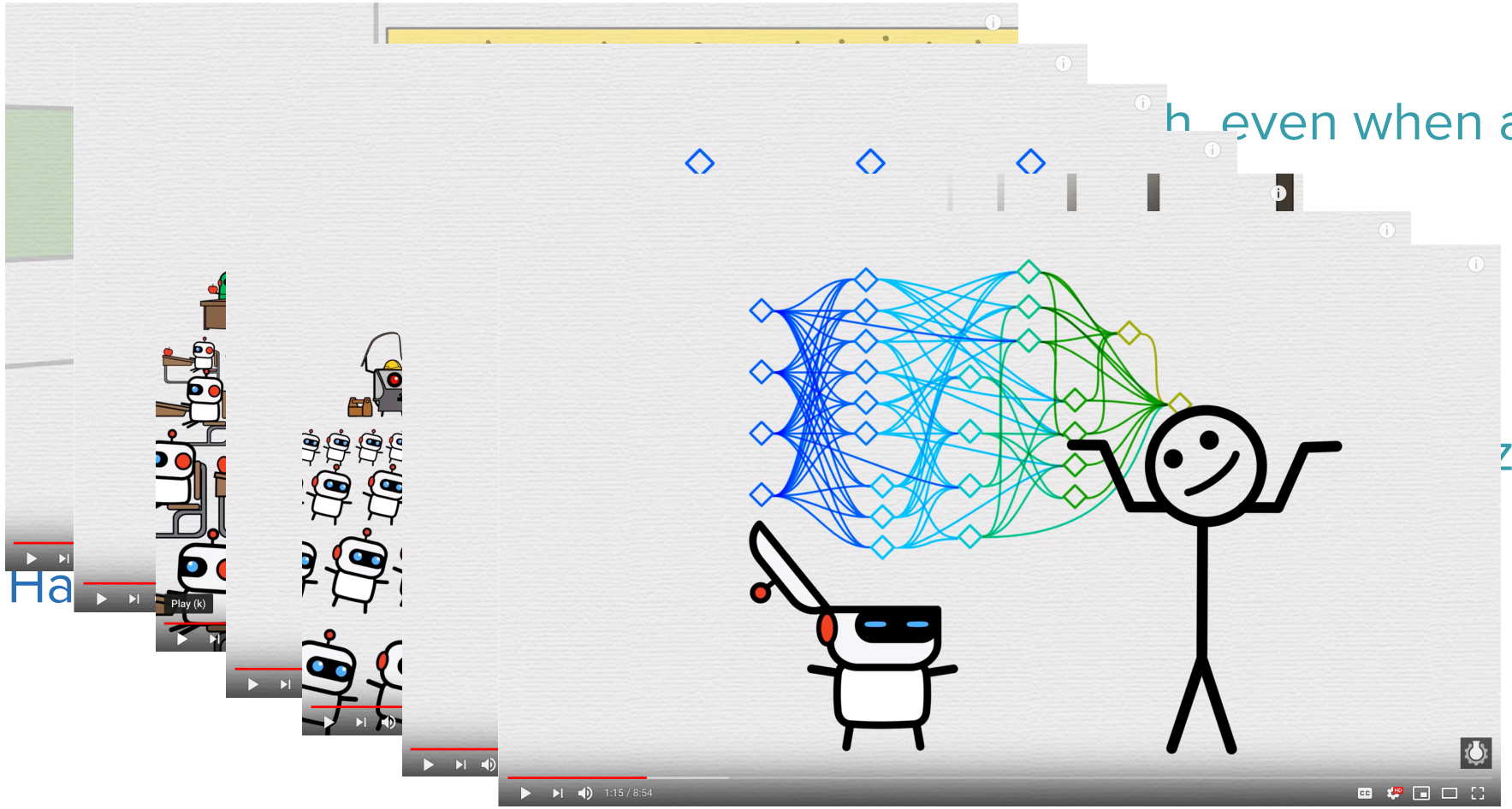


Stills from “How machines learn” by CGP Grey

Limitations of data

- Not trying to gang up on Google, Facebook etc
  - There's a lot to say there …
  - But in each case, these are smart people doing interesting (maybe even important) things with cool data

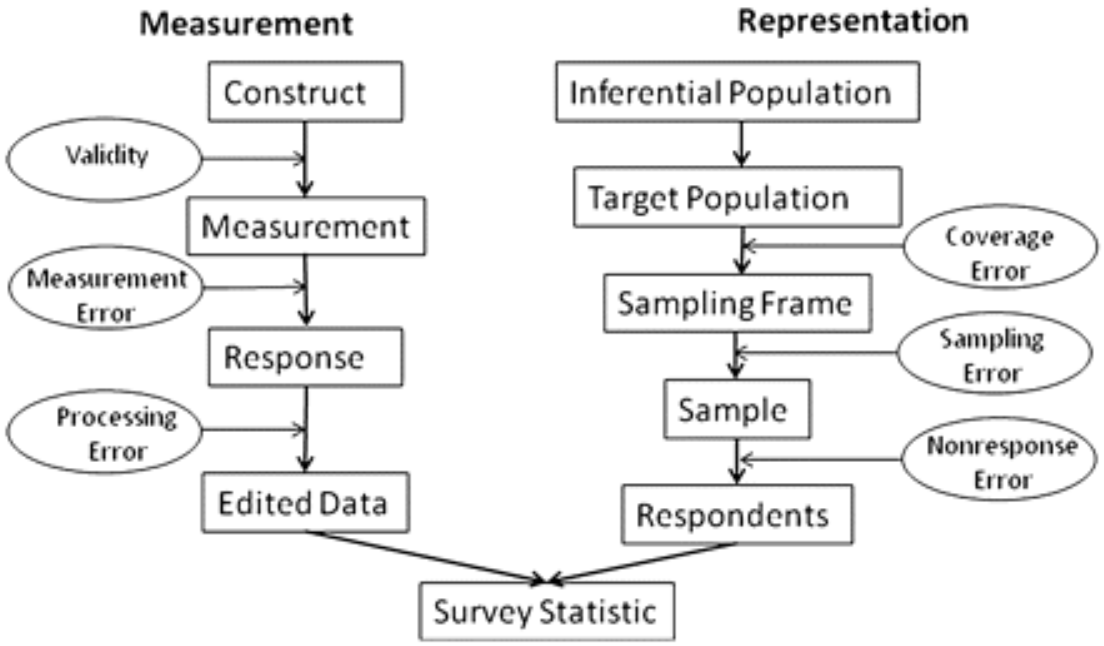
- These cases point to challenges to be overcome, and are important opportunities
  - How can public health practitioners engage with non-traditional partners in a beneficial way?
  - How can tech be used or evaluated as a public health tool when it changes so rapidly?
  - How can big data overcome issues of selection bias and access?

A public health lens

How can we use these data to improve health?

- Who is represented?
- What do measurements mean? Can they be trusted?
- Will I uncover associations? Causes?
- Can I develop new hypotheses or confirm existing ones?
- Can I design an intervention, or evaluate the success of one?

Be skeptical about data



From "Total Survey Error: Past, Present, and Future" (Groves and Lyberg)
via "Data Alone Isn't Ground Truth" by Angela Bassa

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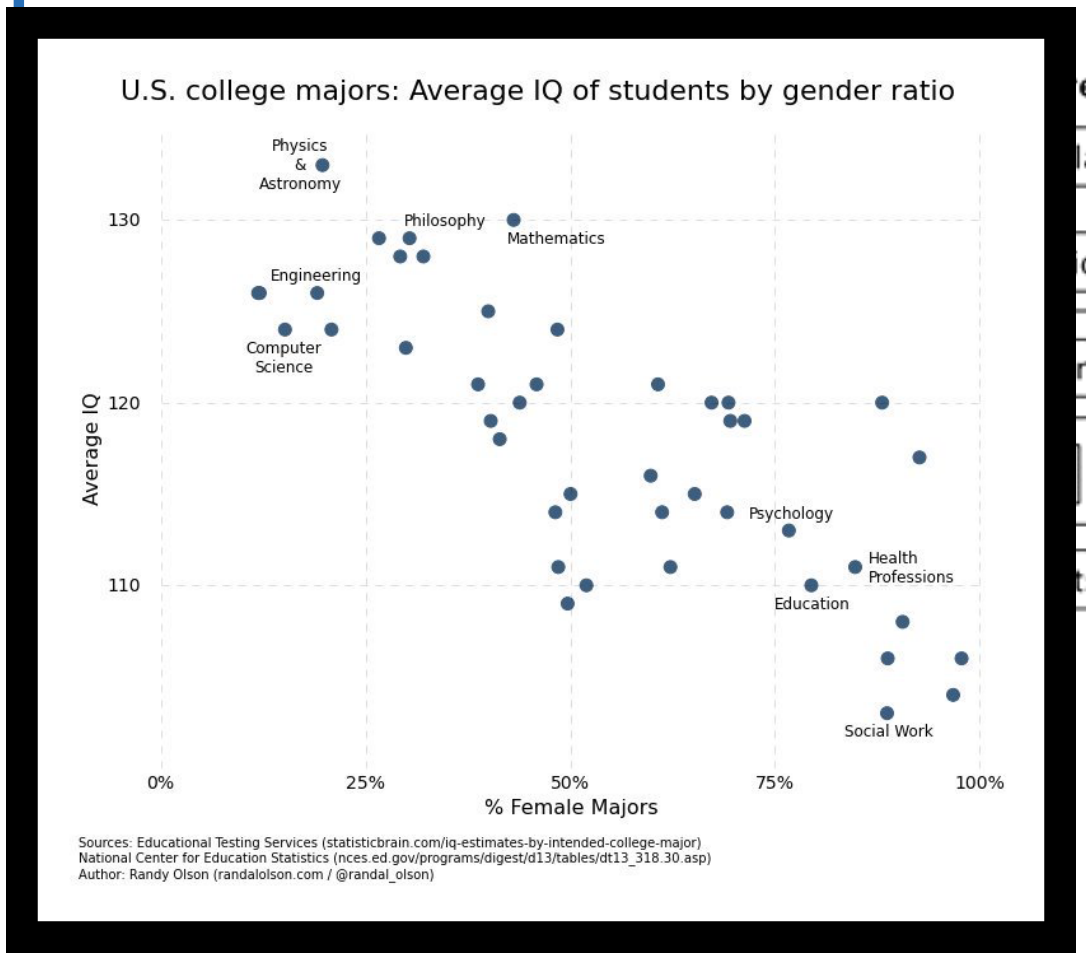

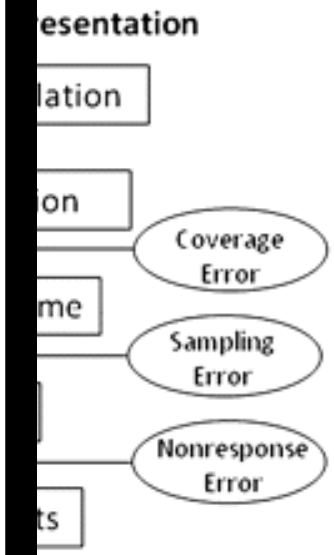

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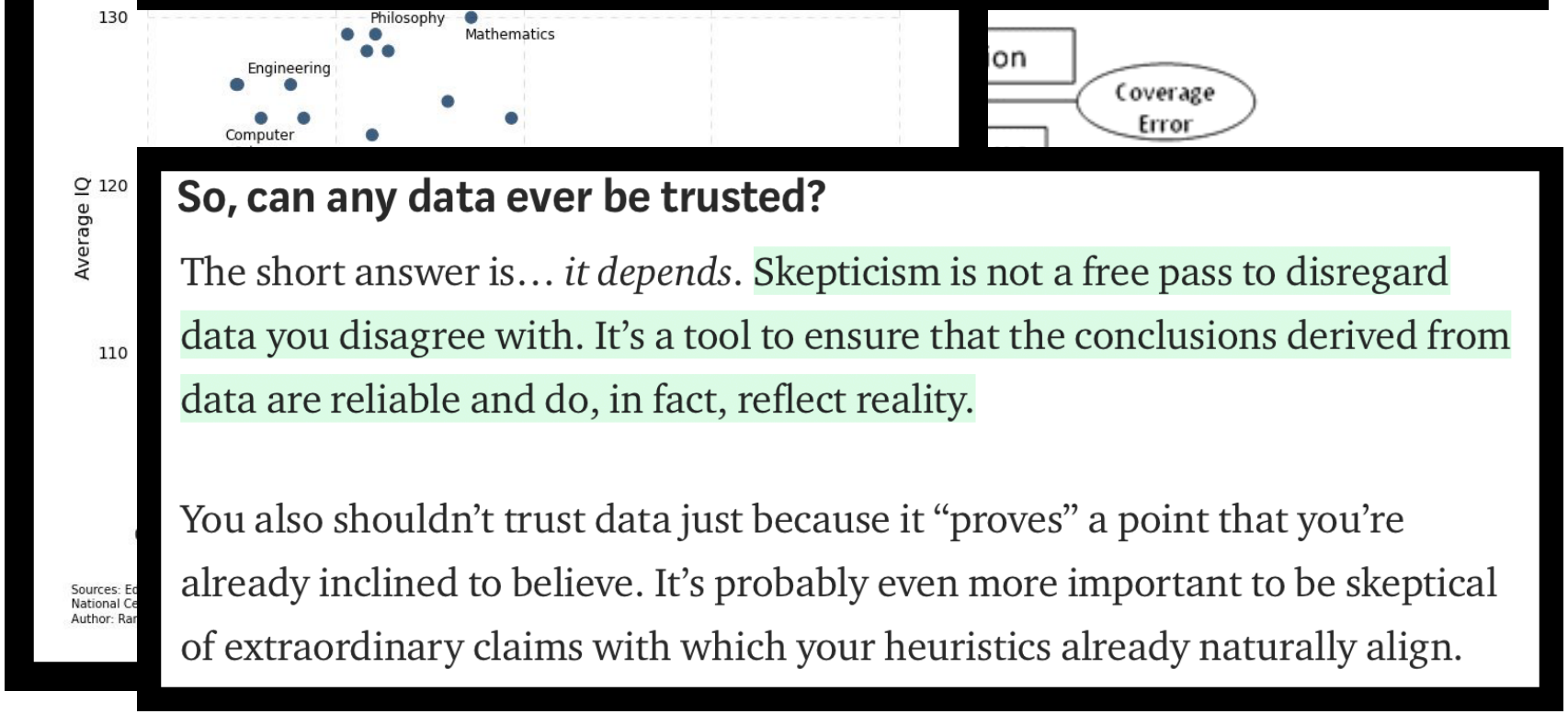
Be skepti

Untrustworthy Data Will Lead to Poor Conclusions

Trusting all data as if it were fact is a dangerous proposition.



So, can any data ever be trusted?

The short answer is… *it depends*. Skepticism is not a free pass to disregard data you disagree with. It's a tool to ensure that the conclusions derived from data are reliable and do, in fact, reflect reality.

You also shouldn't trust data just because it "proves" a point that you're already inclined to believe. It's probably even more important to be skeptical of extraordinary claims with which your heuristics already naturally align.

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A caveat before starting …

People sometimes confuse fancy methods for data science.

Don't Do That.

A simple method applied to good data and clearly communicated

is **much** better than

a fancy method that no one understands applied to bad data.