Title: Mind Over Data: One Thing You Know that Machines (and some Statisticians) Donâ€™t

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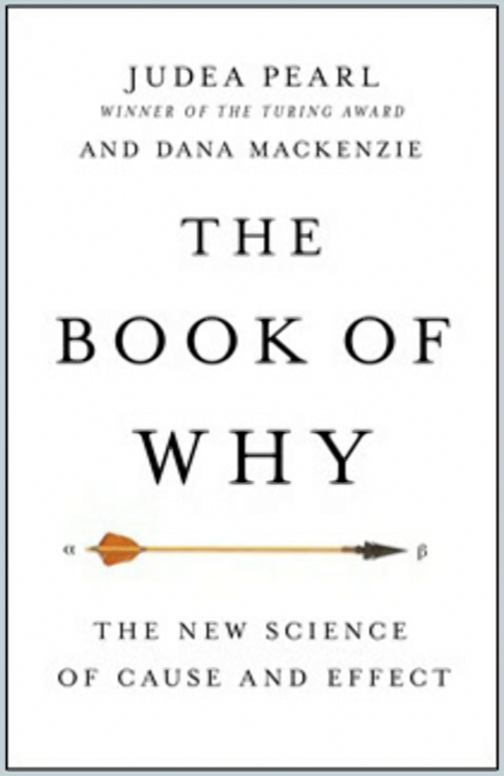
Abstract: <p>From earliest infancy, we live in and learn to function in a world of causes and effects. Yet science has had an ambivalent, even hostile attitude toward causation for more than a century. Statistics courses teach us that â€œcorrelation is not causation,â€• yet they are strangely silent about what is causation.</p>

<p>A central reason for this silence is that causation does not reside in data alone, but in the process that generates the data. In order to answer causal questions, like â€œWhat would happen if we lowered the price of toothpaste?â€• or â€œShould I brake for this object?â€• we need a model of causes and effects. Judea Pearl has developed a simple calculus for expressing our cause-effect knowledge in a diagram and using that diagram to tell us how to interpret the data we gather from the real world. His methods are already transforming the practice of statistics and could equip future artificial intelligences with causal reasoning abilities they currently lack.</p>

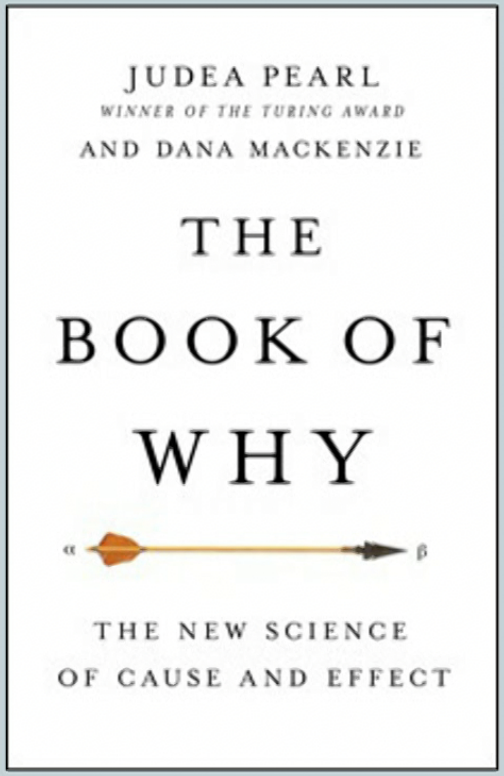
<p>This talk is largely based on Mackenzieâ€™s book co-written with Pearl, The Book of Why.</p>

Three Claims …



- Machines do not understand questions about cause and effect.
- The human brain is still an unmatched technology for answering such questions.
- If we want to create "strong AI," we must emulate the way humans think about causal processes.

... and a Fourth



- Causal blindness has in fact been pervasive in a variety of sciences, not just **AI**. Many scientists think of "model-free" (i.e., non-causal) reasoning as a virtue, when in fact the opposite is true.

My Co-Author

"Judea Pearl has been the heart and soul of a revolution in artificial intelligence and in computer science more broadly."
-- Eric Horvitz, Director of Microsoft Research

Correlation and Causation

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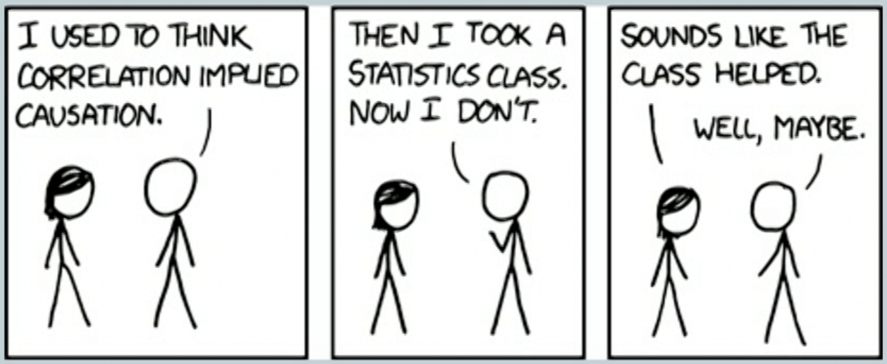

http://xkcd.com/552

Correlation and Causation

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Examples:

Will lowering cholesterol reduce my risk of heart attack?

If I raise the price of toothpaste in my store, what will happen to the store's revenues?

Did Company X's hiring practices discriminate against women?

Causal Diagrams (or Directed Acyclic Graphs)

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IT DEPENDS!

Causal Diagrams (or Directed Acyclic Graphs)

Observed data. Revenue higher when price of toothpaste is higher.	**Observed data.** Revenue higher when price of toothpaste is higher.
Market Price ↗ ↘ Store Price → Customer Behavior ↘ ↙ Revenue	Market Price ↙ ↘ Store Price → Customer Behavior ↘ ↙ Revenue
Model 1. Other stores historically set their prices in response to ours.	**Model 2.** We historically set our prices to match other stores.
Conclusion 1. Intervening to raise our price will raise our revenue.	**Conclusion 2.** Intervening to raise our price will decrease our revenue.

Causal Diagrams (or Directed Acyclic Graphs)

Some lessons:

- Data alone don't tell us which model to use.
- Experience and insight add value to data.
- Interventions (*do* X = *x*) alter the causal diagram.
- Data collected prior to intervention (*see* X = *x*) may not directly answer our question.
- Nevertheless, such data may *indirectly* answer our question.

Simpson's Paradox

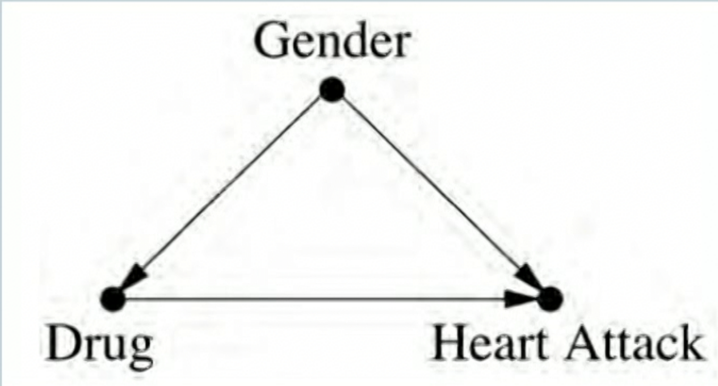
TABLE 6.4. Fictitious data illustrating Simpson's paradox.

	Control Group (No Drug)		Treatment Group (Took Drug)	
	Heart attack	*No heart attack*	*Heart attack*	*No heart attack*
Female	1	19	3	37
Male	12	28	8	12
Total	13	47	11	49

Summary:

- Drug A seems bad for women (heart attack risk 5% → 7.5%)
- Drug A seems bad for men (heart attack risk 30% → 40%)
- Drug A seems good for people (heart attack risk 22% → 18%)

Simpson's Paradox



- Gender is a *confounder* of treatment (drug) and outcome (heart attack)
- Causal effect can be found by *controlling* for gender. (Stratify by gender, average the results, re-weighting according to prevalence of genders.)
- Result: Drug increases risk of heart attack from 17.5% to 23.75%.
- Drug A is bad for women, bad for men, bad for people.

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Simpson's Paradox

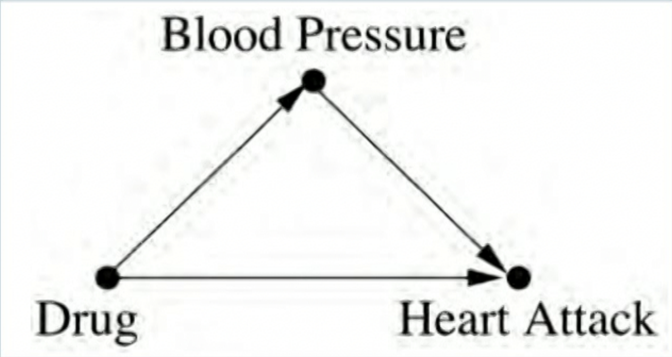
Table 6.6. Fictitious data for blood pressure example.

	Control Group (No Drug)		Treatment Group (Took Drug)	
	Heart attack	*No heart attack*	*Heart attack*	*No heart attack*
Low blood pressure	1	19	3	37
High blood pressure	12	28	8	12
Total	13	47	11	49

Same data as before!

- Drug B seems bad for people with low blood pressure
- Drug B seems bad for people with high blood pressure
- Drug B seems good for people.

Simpson's Paradox



- Blood pressure is a *mediator* between treatment (drug) and outcome (heart attack)
- It is important to *not control* for blood pressure.
- Result: Drug B reduces heart attack risk from 22% to 18%.
- In fact, it moves people from the high-risk to low-risk category. (Those that stay in the high-risk category were probably sicker to begin with.)

My Favorite Example

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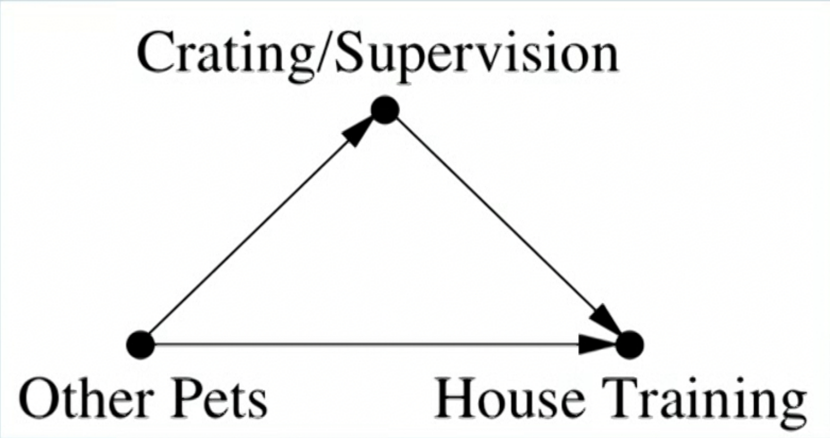
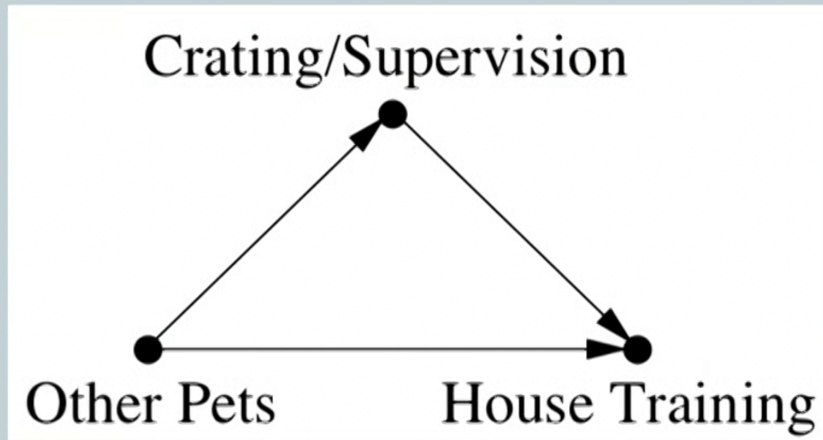


Direct Effect: Kittens directly change Daisy's behavior.

Indirect Effect: Kittens indirectly change Daisy's behavior because we supervise her more carefully.

My Favorite Example



Experiment: Remove the kittens (intervention 1) and supervise the dog as we would have if kittens were present (intervention 2)

Requires us to know a counterfactual!

Another Example (Confounding)

- Honolulu Heart Program
- Observational study, 707 men of Japanese descent
- Over a 12-year period, death rate among intense walkers (>2 miles/day) was two times lower than for casual walkers (<1 mile/day)

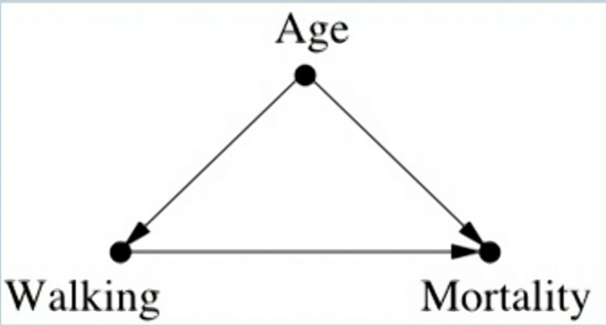
- Does 2 miles/day of walking increase lifespan?

(Abbott et. al., *New Engl. Jour. Medicine*, 1998)

Another Example (Confounding)

Does 2 miles/day of walking increase lifespan?

This is a causal question. To answer it, we need a causal model.



Problem: The intense walkers could be younger to start with than the casual walkers.

Solution: Control for confounding variables (like age).

Another Example (Confounding)

Does 2 miles/day of walking increase lifespan?

Authors: "Of course, the effects … of intentional efforts to increase the distance walked per day… cannot be addressed in our study."

Pearl and Mackenzie: Of course we can address the question! And should!

The C-Word

Journal of the American Medical Association (2017): "If it isn't [a randomized clinical trial] and is a report of an observational study, then all cause-and-effect language must be replaced."

Miguel Hernan, *Am. Jour. Public Health* (2018): "Arguably, the biggest disservice of traditional statistics to science was to make 'causal' into a dirty word, the C-word that researchers have learned to avoid."

The C-Word

PERSPECTIVE

SPECIAL SECTION

Control of Confounding and Reporting of Results in Causal Inference Studies

Guidance for Authors from Editors of Respiratory, Sleep, and Critical Care Journals

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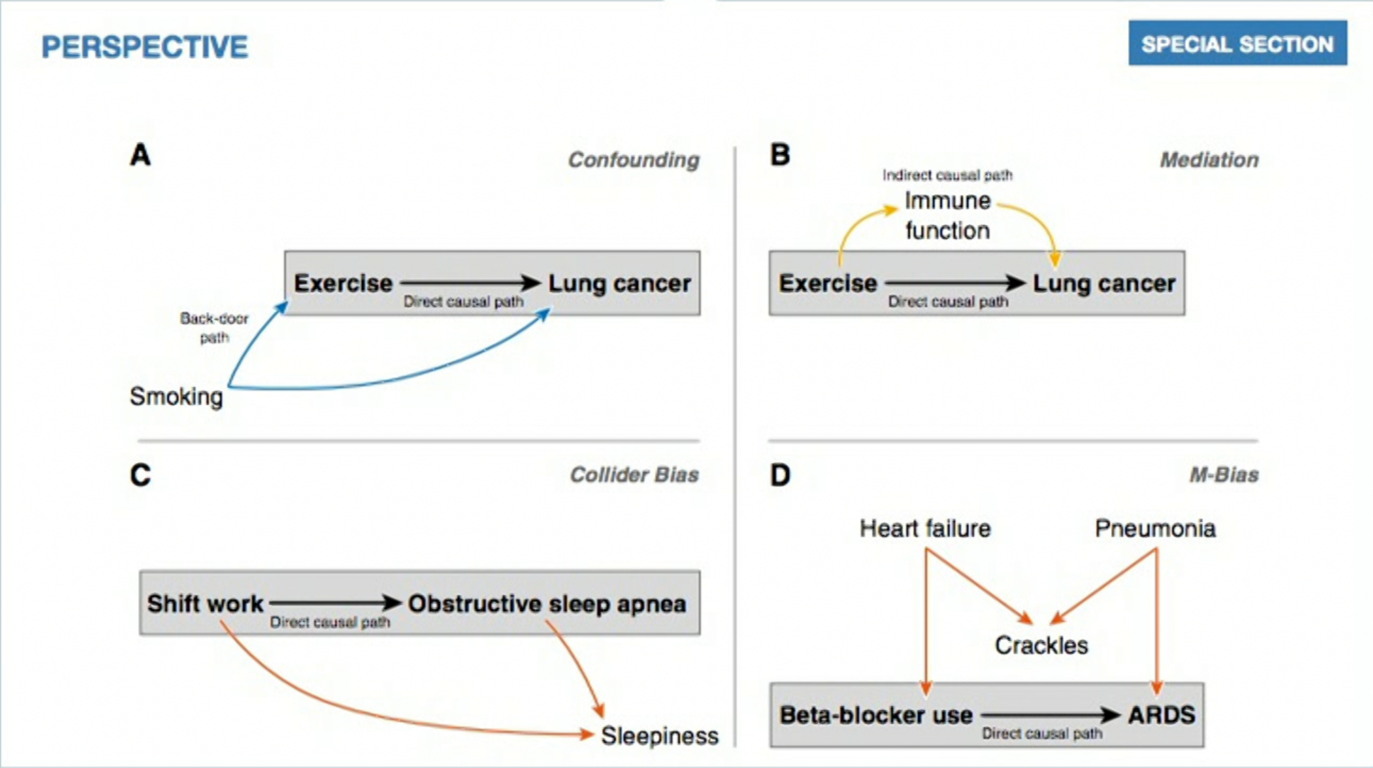
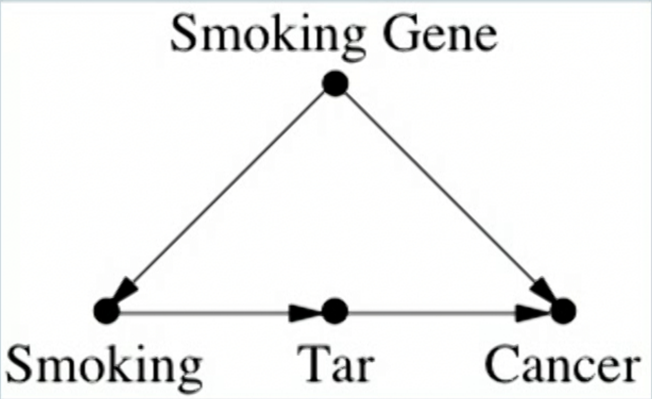
47 Authors, *Annals of the American Thoracic Society* (2019): "We urge authors to consider using causal models when testing causal associations. The scientific, mathematical, and theoretical underpinnings of causal inference... have evolved sufficiently to permit the everyday use of causal models."

Times Change!



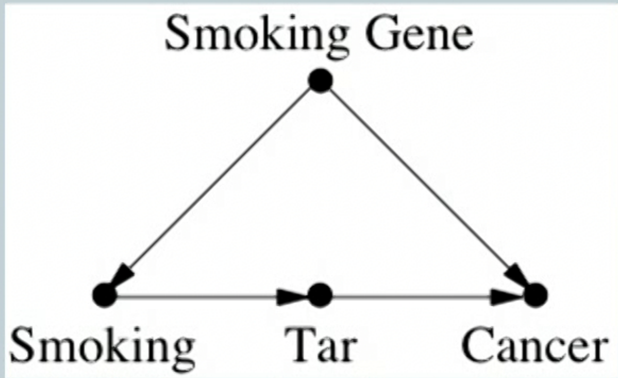
Another Favorite Example

- Does smoking cause lung cancer?
- Vigorously disputed by R.A. Fisher and others
- "Constitutional hypothesis" – a confounder



Another Favorite Example

Same procedure works any time we have:



- Two variables (X and Y)
- Unobservable confounder (Z)
- Intermediate variable (M) that is "shielded" from the effect of Z.

Front-door adjustment: Invented by Judea (1993), proved using causal diagrams.

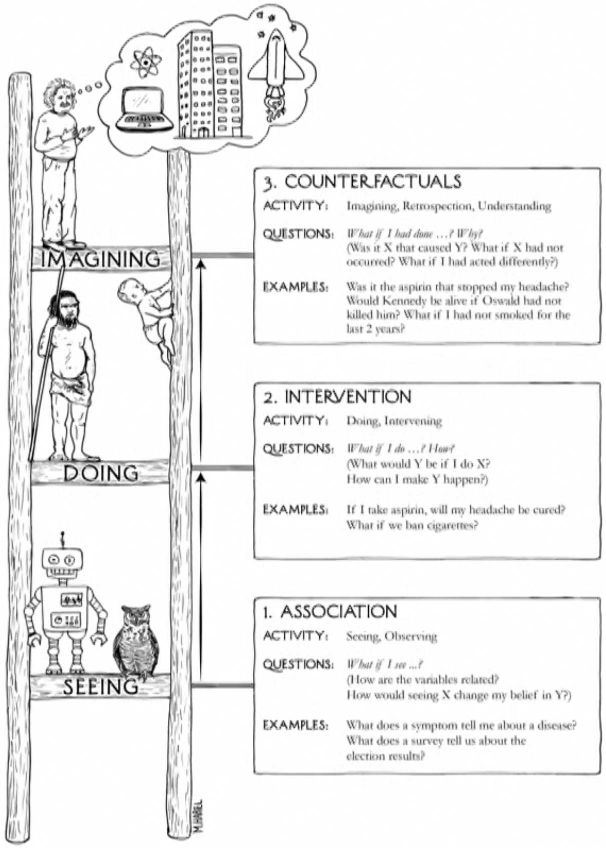
What Causal Diagrams Can Do For Us

- Tell us what experiments to conduct (or emulate)
- Tell us how to interpret existing data
- Cure the fear of confounding
- Give us new ways to extract causation from association

But What Does This Have to Do with AI?

National Transportation Safety Board

The Ladder of Causation

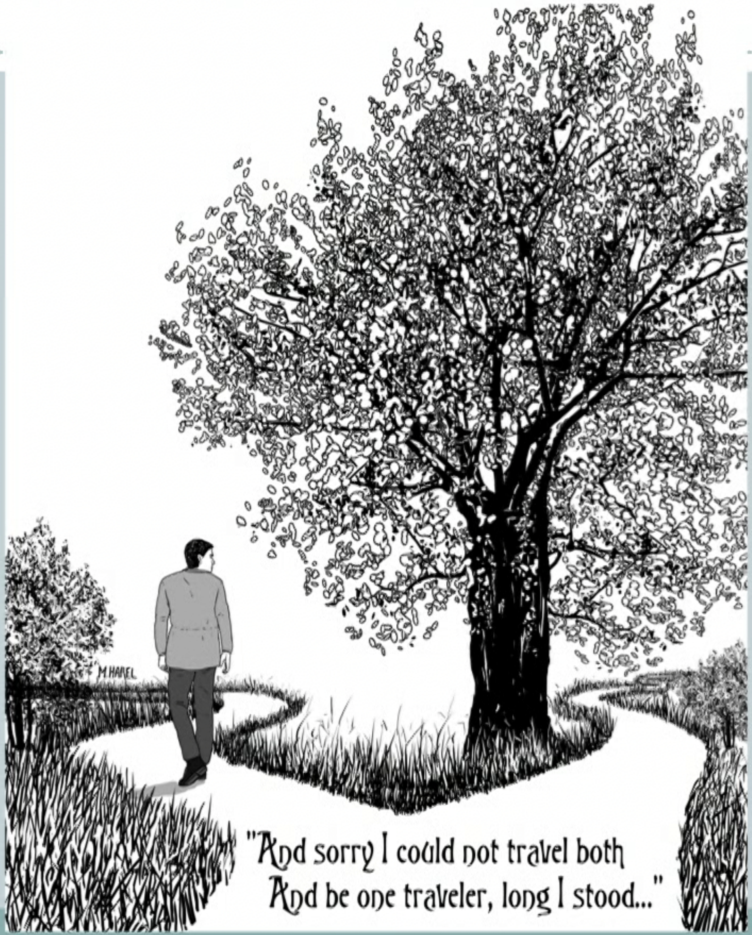


<<Any organism that can build a causal model or "theory" of its environment, imagine the results of actions not taken, and be capable of introspection and retrospection, is on the third rung.

<< Tool users, any organism that can plan an action without having seen such an action before is on the second rung.

<< Deep learning, neural nets, Big Data, all "model-free" statistical methods are on the first rung.

My Other Favorite Picture from the Book



In the End, the Bunnies Always Win

Amazon Top 100 List, 5/19/2018

#93. The Book of Why >>>>>>

#94. Cute baby bunnies! >>>>>>>>>>>>

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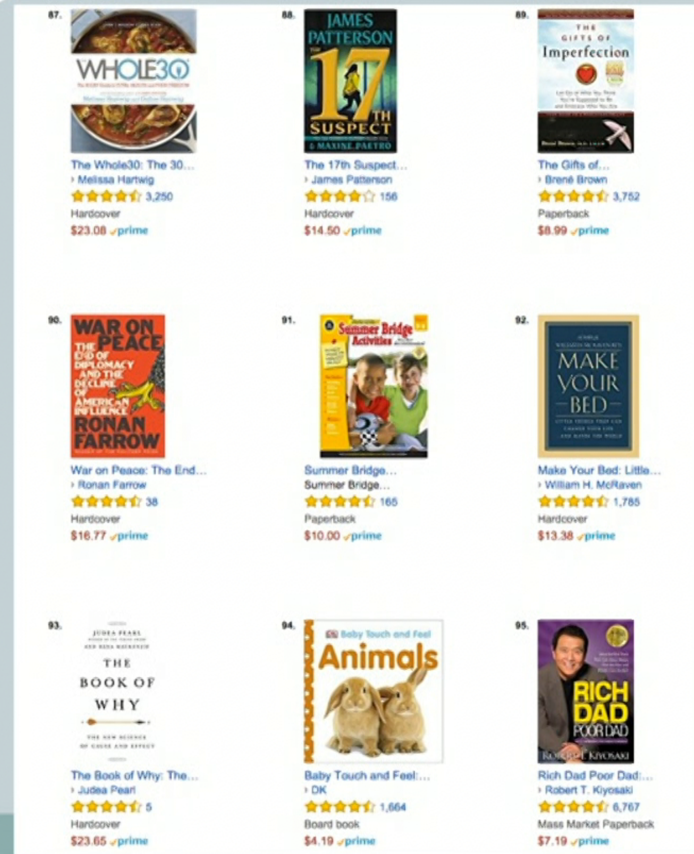

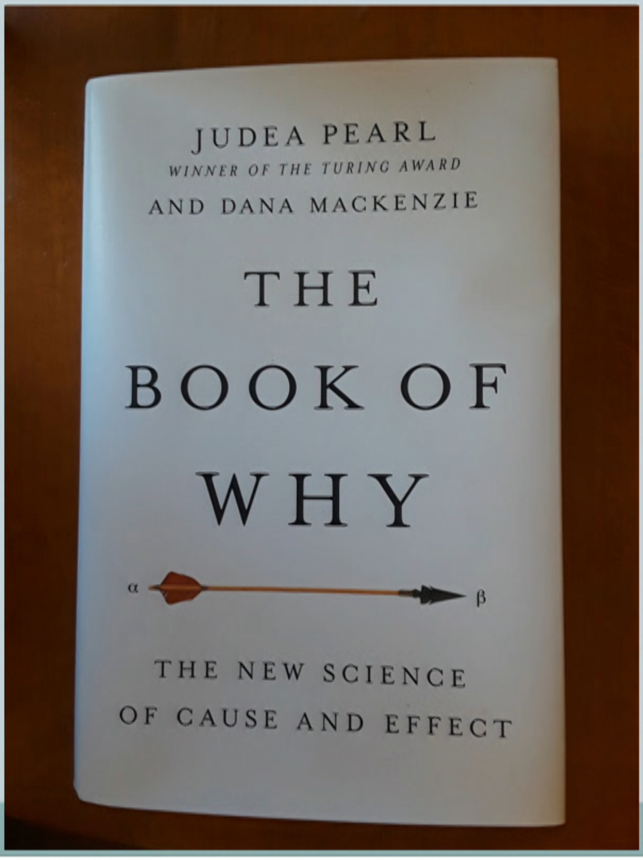
JUDEA PEARL
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BOOK OF
WHY
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THE NEW SCIENCE
OF CAUSE AND EFFECT