From Causes to Actions

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Photo by Chona Kasinger

COMMENTARY

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A Framework for Reducing Alarm F

Anaesthesia, 2006, 6

Learnab equipm

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Summary

Melodic alarms tested for learnal alarms over two than 30% of par Confusions persi (p = 0.011). Par medium priority alarms as soundi training identifie and found the t alarms are neede

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KEY WORDS
alarm fatigue, c physiologic mo

ABBREVIATIC
ECG: electrocar

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Alarm Fatigue

A Patient Safety Concern

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ABSTRACT

Research has demonstrated that 72% to 99% of clinical alarms are false. The high number of false alarms has led to alarm fatigue. Alarm fatigue is sensory overload when clinicians are exposed to an excessive number of alarms, which can result in desensitization to alarms and missed alarms. Patient deaths have been attributed to alarm fatigue. Patient safety and regulatory agencies have focused on the issue of alarm fatigue, and it is a 2014 Joint Commission National Patient Safety Goal. Quality improvement projects have demonstrated that strategies such as daily electrocardiogram electrode changes, proper skin preparation, education, and customization of alarm parameters have been able to decrease the number of false alarms. These and other strategies need to be tested in rigorous clinical trials to determine whether they reduce alarm burden without compromising patient safety.

Keywords: alarm fatigue, patient safety, regulatory agencies

What doctors and patients actually want to know: why is this happening and what can they do about it?

Can we learn..

risk factors for heart failure

Kleinberg & Elhadad (2013) AMIA

what leads to an individual's hyperglycemic episodes Heintzman & Kleinberg (2016) JBI

causes of secondary brain injury

Claassen et al. (2016) PLoS ONE

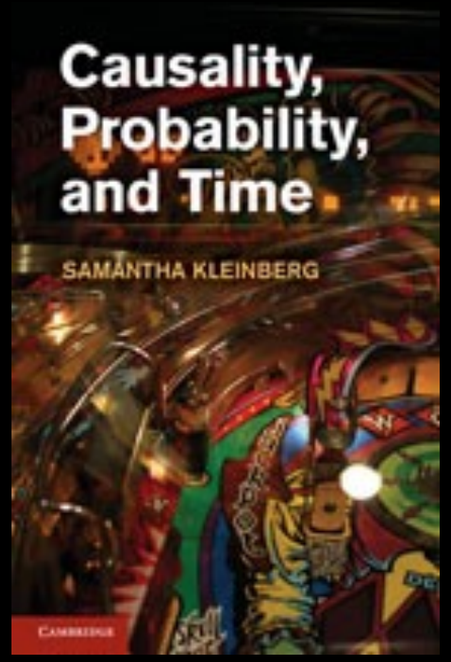
from observing people?

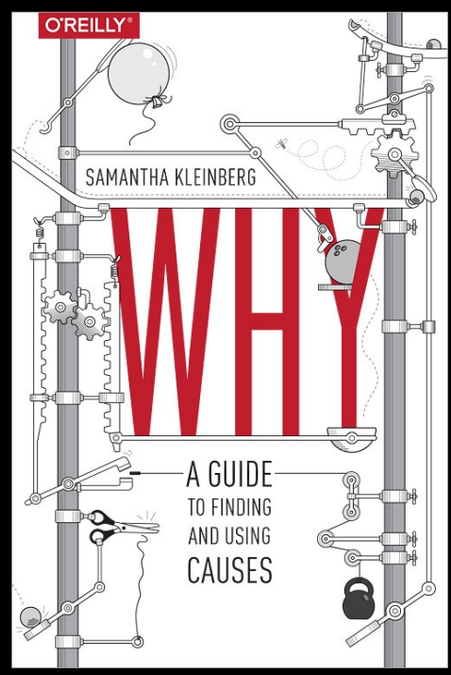
Logic-based causal inference

Complex, temporal relationships

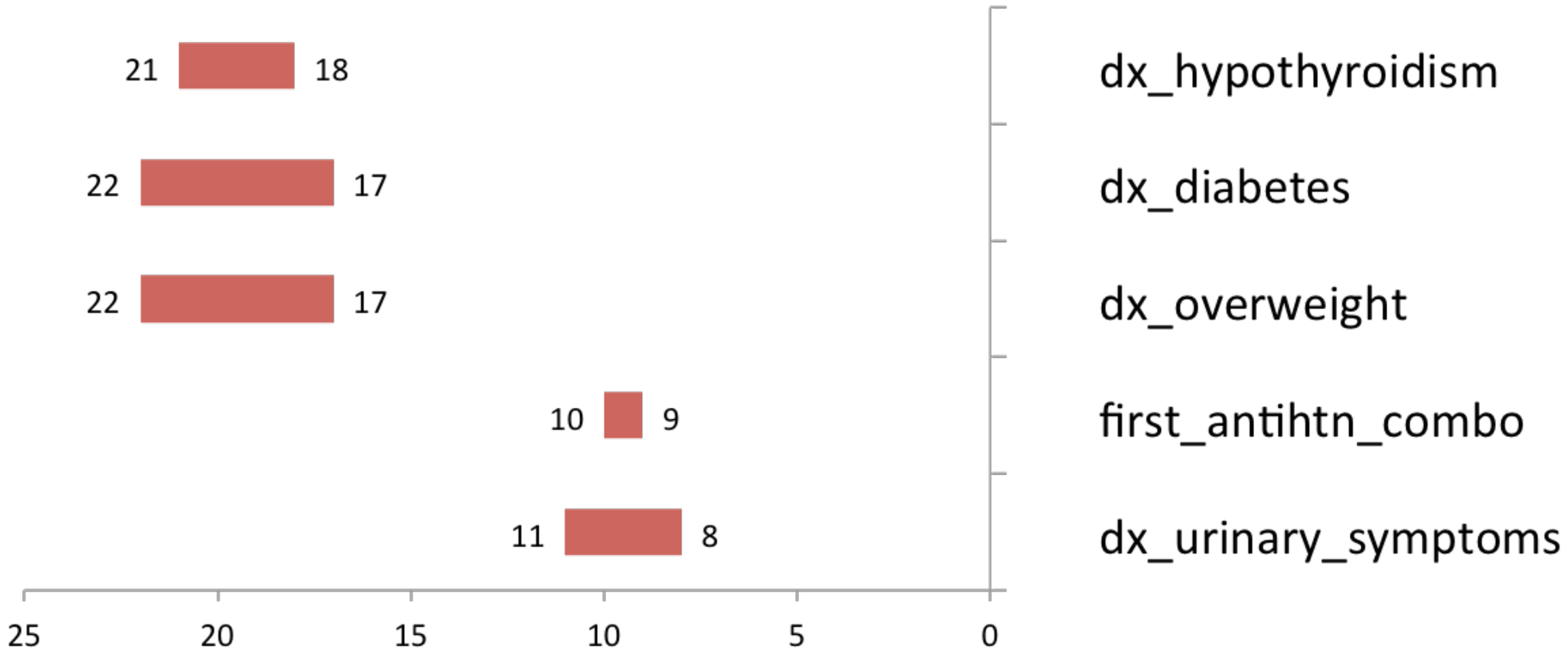
$$\nu \overset{\geq 15, \leq 40}{\underset{\geq 0.4}{\rightsquigarrow}} g$$

(PCTL + some additions)





Congestive heart failure



Months before CHF diagnosis

Kleinberg S, Elhadad N (2013) Lessons Learned in Replicating Data-Driven Experiments in Multiple Medical Systems and Patient Populations. In: AMIA Annual Symposium.

Can we trust the data?

FDA guidance

95% of fingerstick BG values must be within 15% of the actual value

A value of 150 could be [128, 172]

A value of 70 could be [60,81]

CGM accuracy is also a function of time

Visit	Number of Readings / Unique Patients	Mean Absolute Relative Difference 95% Confidence Interval	Percentage of Readings within 15 mg/dL or 15%[a]
Day 1	2,665 / 35	11.6% (10.0, 13.1)	79%
Day 7	2,926 / 35	9.8% (7.9, 11.7)	86%

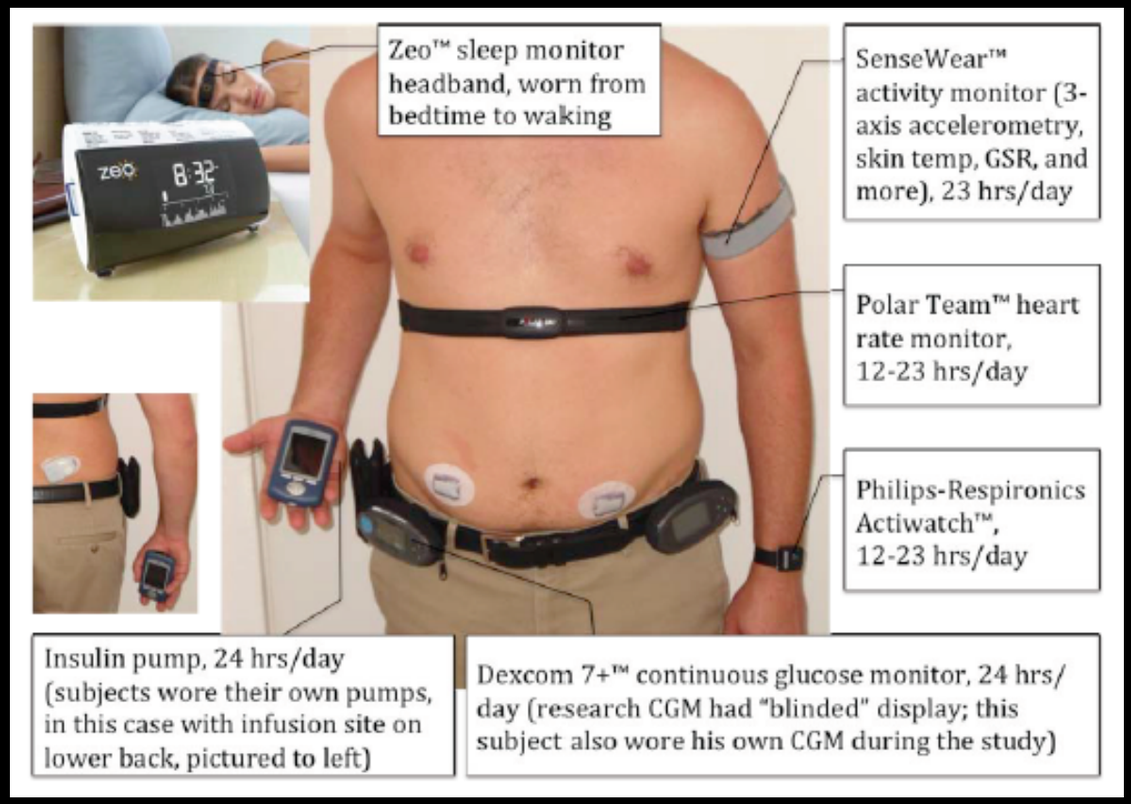
https://www.fda.gov/media/112142/download

17 subjects with T1DM, sensor data (collected for >72 hours)

Used causal inference methods + body-worn sensors to find cause of changes in glycemia

- intense activity leads to hyperglycemia in 5-30min

only found when modeling uncertainty



N. Heintzman and S. Kleinberg. Using Uncertain Data from Body-Worn Sensors to Gain Insight into Type 1 Diabetes. Journal of Biomedical Informatics (2016)

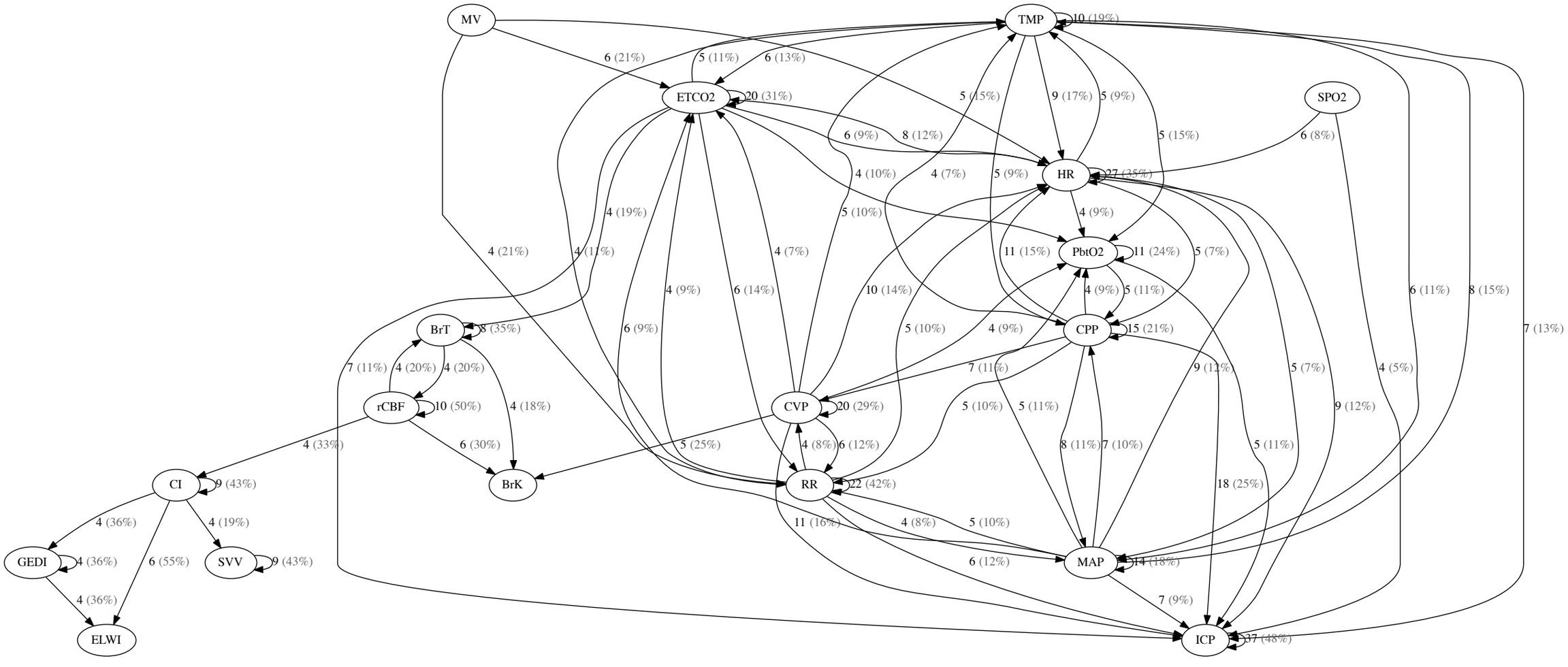
Latent variables are not always latent

- Leverage prior knowledge (experts, other experiments)
- Be robust to wrong/inapplicable knowledge
- Reconstruct time series
- Identify inconsistencies
- Iterate

We can use knowledge of the effect of meals on glucose to recover latent meals and their effects

We find: exercise causes meal in 60-85min, moderate exercise causes hypo in 70-90min, 67 meals recovered
tsFCI: 1 latent variable, and hypo/hyper cause themselves

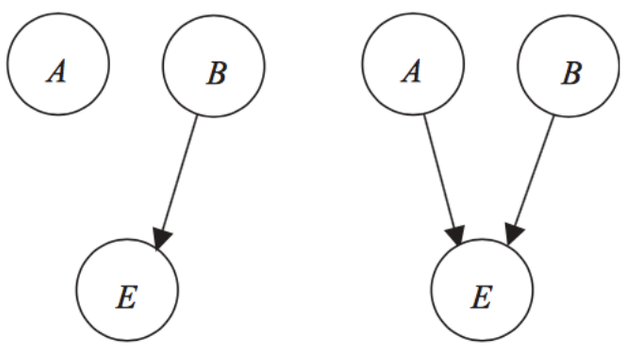
M. Zheng, and S. Kleinberg. (2019) Using Domain Knowledge to Overcome Latent Variables in Causal Inference from Time Series. Machine Learning for Healthcare.



Claassen J, Rahman SA, Huang Y, Frey H, Schmidt M, Albers D, Falo CM, Park S, Agarwal S, Connolly ES, Kleinberg S (2015) Causal structure of brain physiology after brain injury. PLoS ONE.

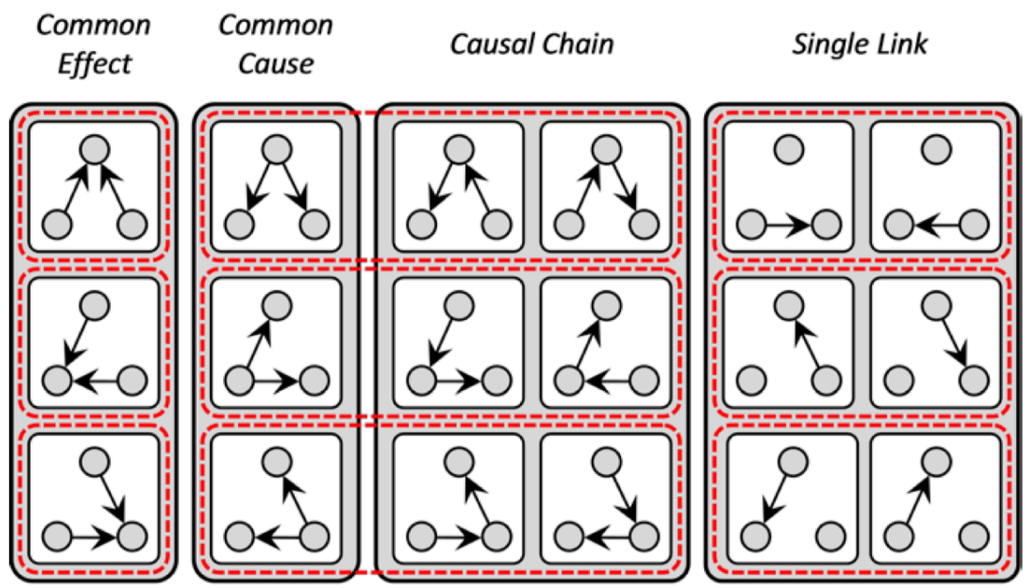
Does this actually help people make decisions?

- Should I have oatmeal or a fruit salad?
- When is the best time to run?
- How should I invest my retirement savings?



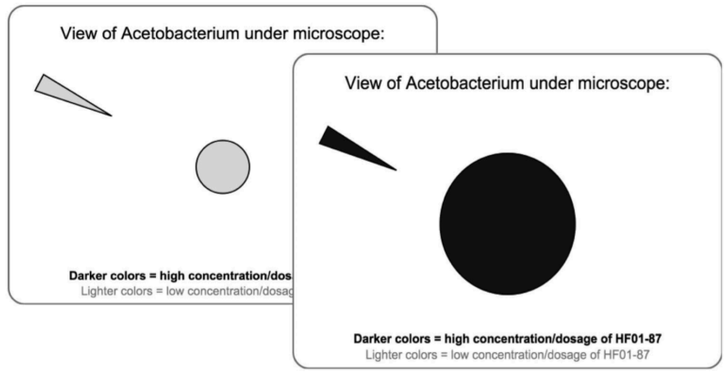
Super pencils/
Blicket detector

Griffiths et al. 2011



Mind-reading aliens

Mayrhofer & Waldmann 2011



Drug+microorganism size

Soo & Rottman 2018

Can causal information aid decision-making in familiar scenarios?

Are people doing worse
because they have
experience with the domain?

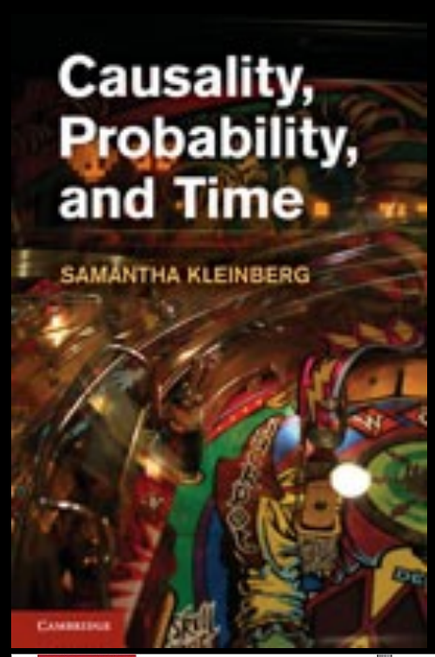
Action requires causality

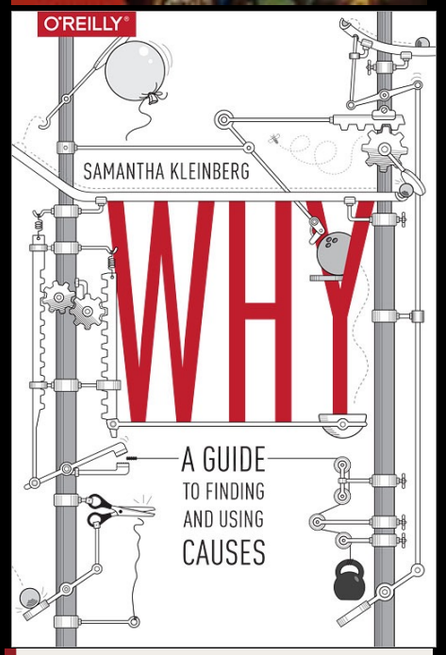
But causality alone isn’t enough

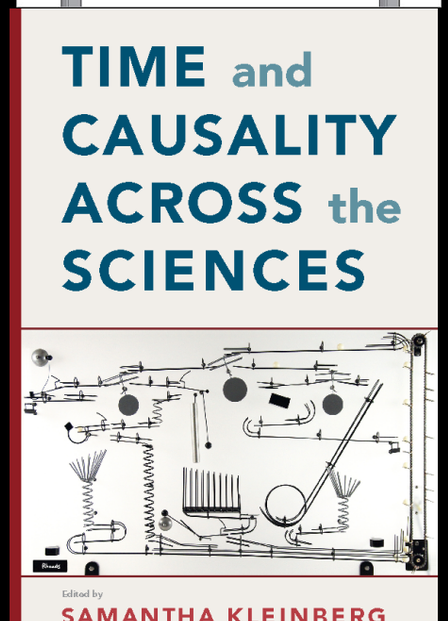
We need evaluations of utility of algorithms (not just accuracy)

Explainable AI → **Usable** AI

Information must be personalized







Thanks! Teams at @ Columbia, Stevens, Lehigh

Health +AILab

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