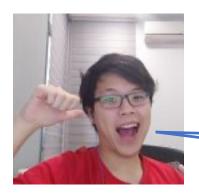
Solving problems using imperfect advice

Davin Choo 24 March 2023

$$66 = 2 \times 3 \times 11$$

$$66 = 2 \times 3 \times 11$$
 101291

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 101291



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 101291

Idea: Let's just output the smaller factor

- sqrt(101291) = 318.262470298
- Brute force:
 - Is 2 a factor? X
 - Is 3 a factor? X
 - Is 4 a factor? X
 - •

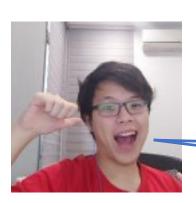


$$66 = 2 \times 3 \times 11$$
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Idea: Let's just output the smaller factor

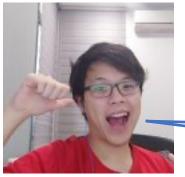
- sqrt(101291) = 318.262470298
- Brute force:
 - Is 2 a factor? X
 - Is 3 a factor? X
 - Is 4 a factor? X
 - •
- Smarter: Sieve of Eratosthenes

(If you can generically solve this efficiently, you can break RSA)



$$66 = 2 \times 3 \times 11$$
 101291





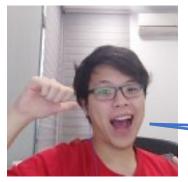
Let me help you!

(If you can generically solve this efficiently, you can break RSA)

$$66 = 2 \times 3 \times 11$$
 101291

(goes undercover)





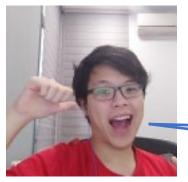
Let me help you!

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$$66 = 2 \times 3 \times 11$$
 101291

(goes undercover)





One of the factors is ≈500

(If you can generically solve this efficiently, you can break RSA)

 $66 = 2 \times 3 \times 11$ 101291

(goes undercover)



 $101291/500 = 202.582 \Rightarrow X$



(If you can generically solve this efficiently, you can break RSA)



 $66 = 2 \times 3 \times 11$ 101291

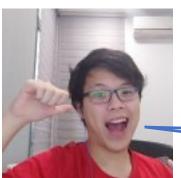
(goes undercover)



 $101291/500 = 202.582 \Rightarrow X$ $101291/501 = 202.177644711 \Rightarrow X$



(If you can generically solve this efficiently, you can break RSA)



 $66 = 2 \times 3 \times 11$ 101291

(goes undercover)



$$101291/500 = 202.582 \Rightarrow X$$

 $101291/501 = 202.177644711 \Rightarrow X$
 $101291/499 = 202.987975952 \Rightarrow X$



One of the factors is ≈500

(If you can generically solve this efficiently, you can break RSA)

 $66 = 2 \times 3 \times 11$ $101291 = 199 \times 509$

(goes undercover)



 $101291/500 = 202.582 \Rightarrow X$ $101291/501 = 202.177644711 \Rightarrow X$ $101291/499 = 202.987975952 \Rightarrow X$

101291/509 = 199 ⇒ Found it! $\sqrt{\ }$



(If you can generically solve this efficiently, you can break RSA)



$$66 = 2 \times 3 \times 11$$

 $101291 = 199 \times 509$

Advice can help solve hard problems, especially if advice is high quality!

 $101291/509 = 199 \Rightarrow$ Found it! $\sqrt{ }$



One of the factors is ≈500

(If you can generically solve this efficiently, you can break RSA)

Searching sorted array

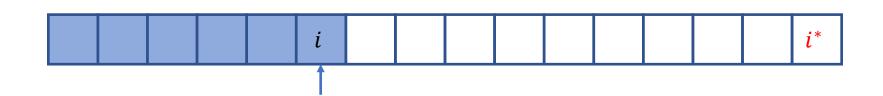
- Problem Given a sorted array A on n numbers, locate $x^* \in A$
- Solution

Binary search: $O(\log n)$ queries Without further assumptions, $\Omega(\log n)$ queries

- Advice: index $i \in [n]$



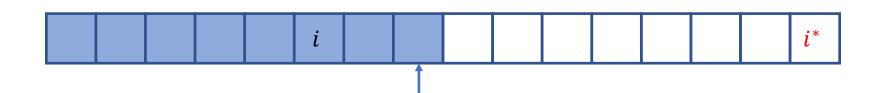
- Advice: index $i \in [n]$
- Linear probe



- Advice: index $i \in [n]$
- Linear probe



- Problem
 - Given a sorted array A on n numbers, locate $x^* \in A$
- Advice: index $i \in [n]$
- Linear probe



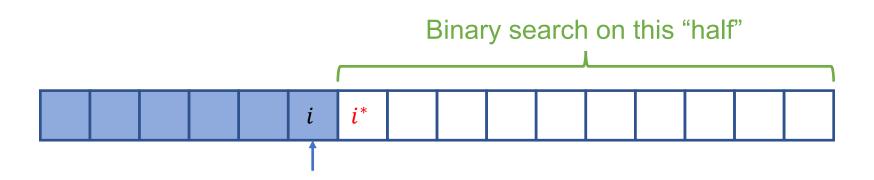
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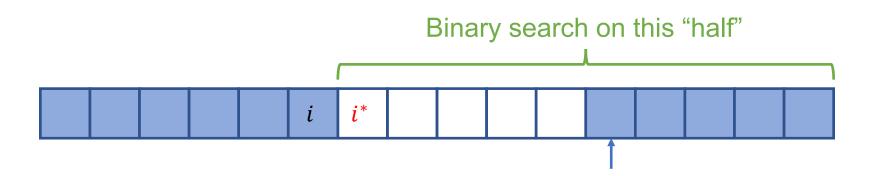
- Problem
 - Given a sorted array A on n numbers, locate $x^* \in A$
- Advice: index $i \in [n]$
- Linear probe: Good when $i \approx i^*$; $\mathcal{O}(n)$ worst case



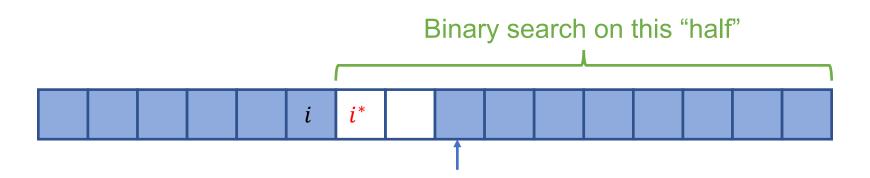
- Problem Suppose $A[i^*] = x^*$
 - Given a sorted array A on n numbers, locate $x^* \in A$
- Advice: index $i \in [n]$
- Linear probe: Good when $i \approx i^*$; $\mathcal{O}(n)$ worst case
- Prune then binary search



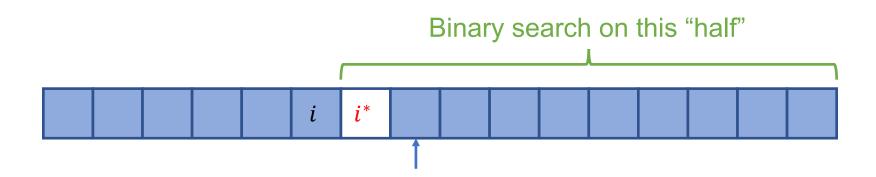
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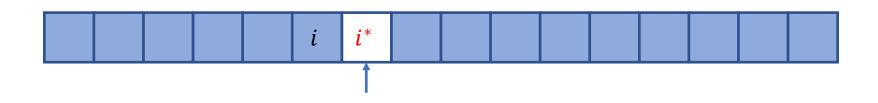
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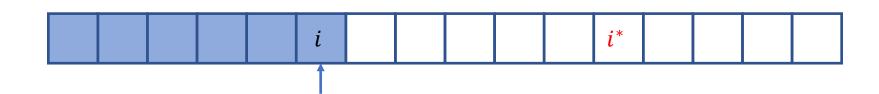
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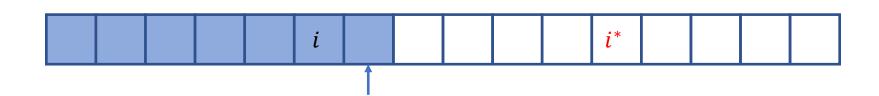
- Problem
 - Given a sorted array A on n numbers, locate $x^* \in A$
- Advice: index $i \in [n]$
- Linear probe: Good when $i \approx i^*$; $\mathcal{O}(n)$ worst case
- Prune then binary search: Doesn't exploit $i \approx i^*$ (Still worst case $\mathcal{O}(\log n)$)



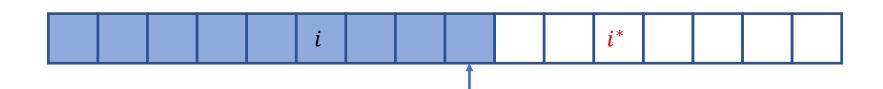
- Problem
 - Given a sorted array A on n numbers, locate $x^* \in A$
- Advice: index $i \in [n]$
- Idea: Exponential search from A[i], then binary search within bounds



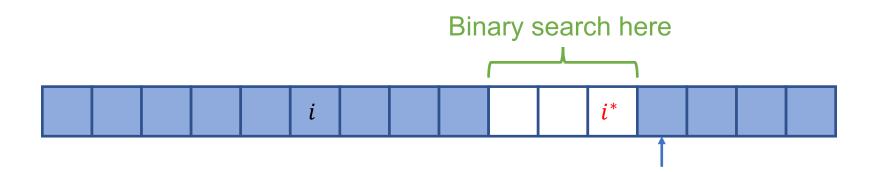
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- Problem
 - Given a sorted array A on n numbers, locate $x^* \in A$
- Advice: index $i \in [n]$
- Idea: Exponential search from A[i], then binary search within bounds $O(\log |i i^*|)$ suffices!





1. When advice is "perfect"

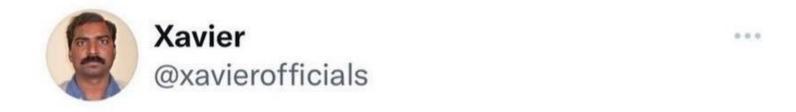
Perform as well as just the oracle

2. When advice is "garbage"

Perform as well as state-of-the-art without advice

3. Provable guarantees and "efficient"

Cute idea... but is it useful?

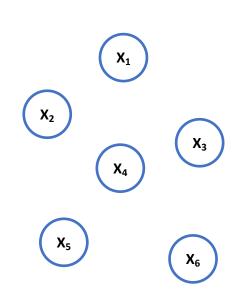


be useless, so nobody can use you

Case study: Causal graph discovery via interventions

Health factors

How are they related?





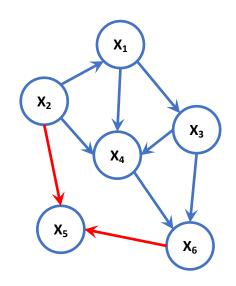
Example:

 X_2 = Blood glucose

 X_6 = Blood pressure

Health factors

How are they related?





Example: $X_a = Blood$

 X_2 = Blood glucose

 X_6 = Blood pressure

acyclic **causal** relationships

Arrows denote

Example scenario:

Low levels of X_2 and X_6 leads to low levels of X_5 (say, cancer cell counts)

Suppose high levels of X_5 is known to cause disease Y but there is no available treatment to suppress X_5 . Then, given the above causal relationships, a possible treatment is to suppress the levels of X_2 and X_6

Modelling causal relations

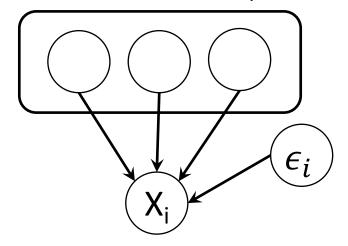
"We may regard the present state of the universe as the effect of its past and the cause of its future..." — Pierre Simon Laplace, A Philosophical Essay on Probabilities, 1814



$$X_i = f_i(pa_i, \epsilon_i)$$

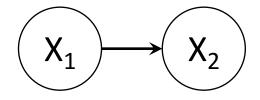
The value of each variable X_i is function f_i of the values taken by its parents pa_i and some noise ϵ_i

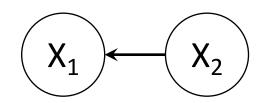




Which model generated this data?

X ₁	-0.27	0.29	0.37	-0.09	0.34	0.33	0.30	-1.34	0.68
X ₂	-0.10	1.65	0.47	1.92	2.04	1.67	0.11	-3.58	1.97





•
$$X_1 = \epsilon_1$$

•
$$X_2 = a \cdot X_1 + \epsilon_2$$

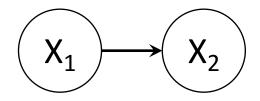
•
$$X_1 = b \cdot X_2 + \epsilon_3$$

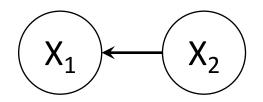
•
$$X_2 = \epsilon_4$$

Simple linear relationship between variables a and b are (hidden) positive constants ϵ 's are independent Gaussian terms with mean 0

Two equivalent causal models

X ₁	-0.27	0.29	0.37	-0.09	0.34	0.33	0.30	-1.34	0.68
X ₂	-0.10	1.65	0.47	1.92	2.04	1.67	0.11	-3.58	1.97





- $X_1 = \epsilon_1 \sim N(0, 1)$
- $X_2 = X_1 + \epsilon_2 \sim N(0, 2)$
- $\epsilon_1 \sim N(0,1)$
- $\epsilon_2 \sim N(0,1)$

•
$$X_1 = \frac{1}{2} \cdot X_2 + \epsilon_3 \sim N(0, 1)$$

•
$$X_2 = \epsilon_4 \sim N(0,2)$$

•
$$\epsilon_3 \sim N\left(0, \frac{1}{2}\right)$$

• $\epsilon_4 \sim N(0,2)$

Two equivalent causal models

-0.27	0.29	0.37	-0.09	0.34	0.33	0.30	-1.34	0.68
-0.10	1.65	0.47	1.92	2.04	1.67	0.11	-3.58	1.97



So what? Who cares?

•
$$X_1 = \epsilon_1 \sim N(0,1)$$
 • $X_1 = \overline{-\cdot X_2 + \epsilon_1}$

•
$$X_2 = X_1 + \epsilon_2 \sim N(0, 2)$$

•
$$\epsilon_1 \sim N(0, 1)$$

•
$$\epsilon_2 \sim N(0, 1)$$

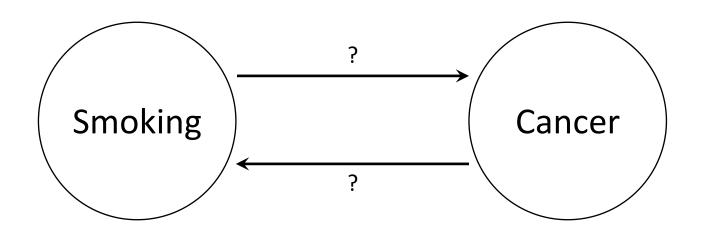
•
$$X_1 = \frac{1}{2} \cdot X_2 + \epsilon_3 \sim N(0, 1)$$

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$$X_2 = \epsilon_4 \sim N(0,2)$$

•
$$\epsilon_3 \sim N\left(0, \frac{1}{2}\right)$$

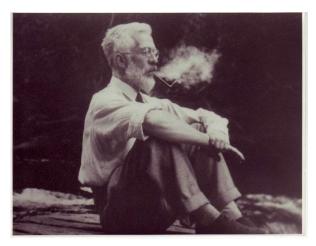
•
$$\epsilon_4 \sim N(0,2)$$

Smoking	Yes	Yes	Yes	No	No	No	
Cancer	No	Yes	Yes	No	No	Yes	•••

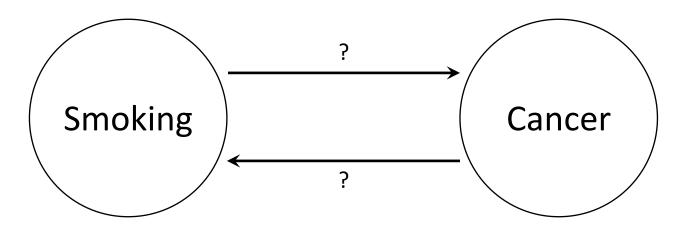


Fisher's letter to Nature, 1958:

"The curious associations with lung cancer found in relation to smoking habits do not, in the minds of some of us, lend themselves easily to the simple conclusion that the products of combustion reaching the surface of the bronchus induce, though after a long interval, the development of a cancer... Such results suggest that an error has been made, of an old kind, in arguing from correlation to causation..."

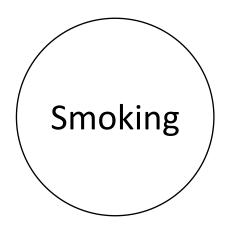


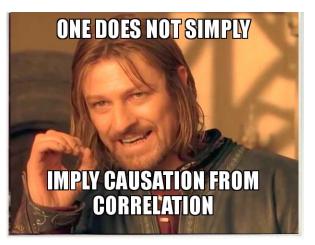
Ronald Fisher



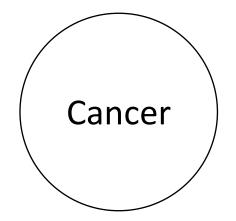
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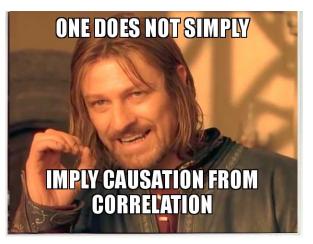


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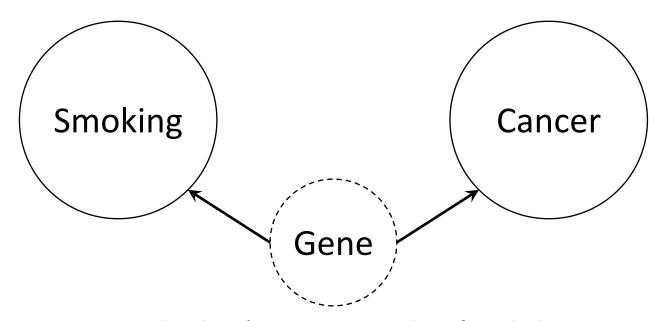


Fisher's letter to Nature, 1958:

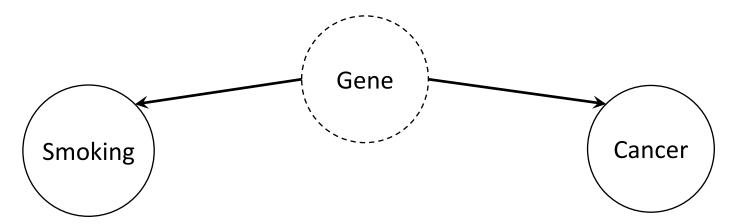
"... Such results suggest that an error has been made, of an old kind, in arguing from correlation to causation, and that the possibility should be explored that the different smoking classes, non-smokers, cigarette smokers, cigar smokers, pipe smokers, etc., have adopted their habits partly by reason of their personal temperaments and dispositions, and are not lightly to be assumed to be equivalent in their **genotypic composition**..."

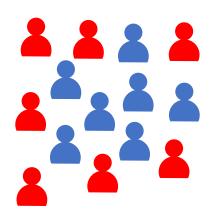


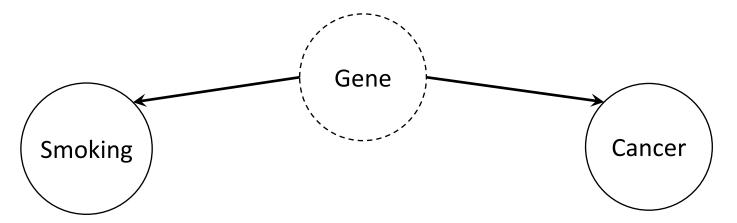
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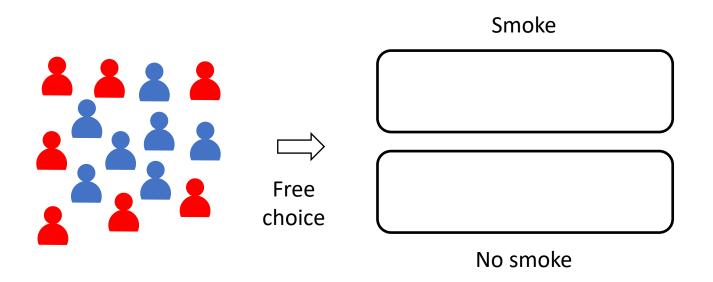


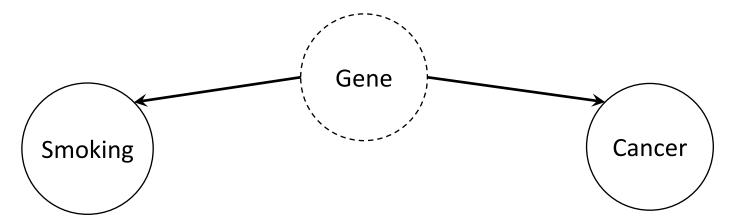
Maybe there's an unmeasured confounder?

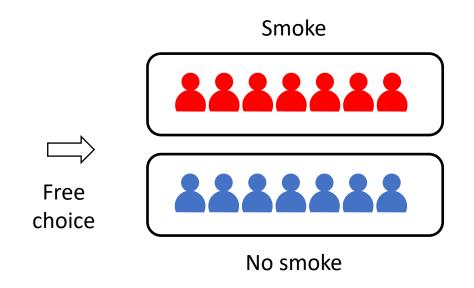


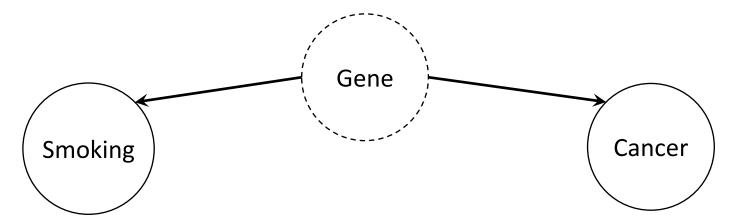


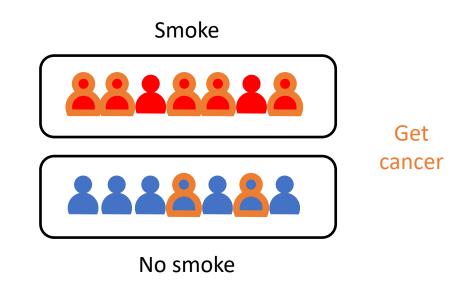




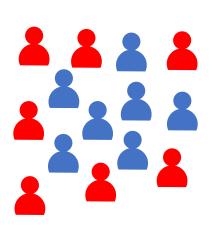


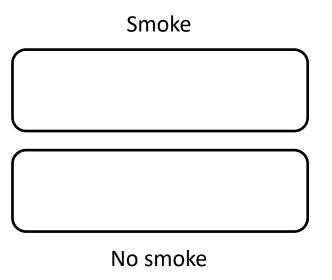




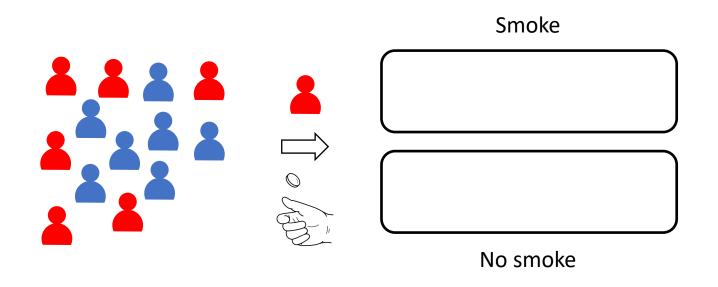


- Gold standard in scientific exploration
- RCTs ≡ Interventions in causality

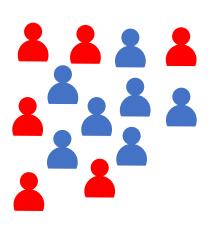


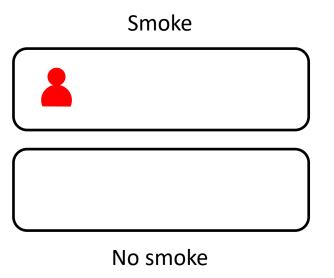


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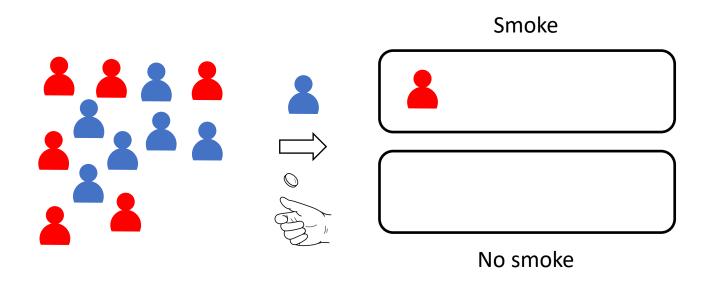


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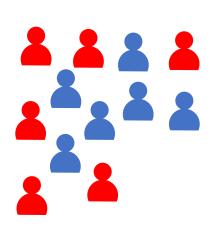


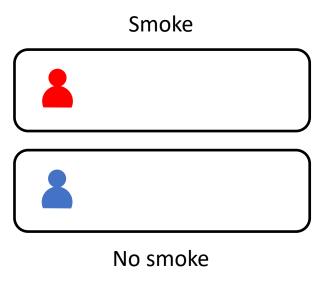


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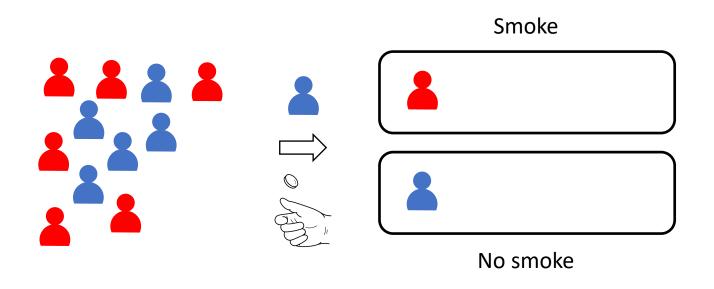


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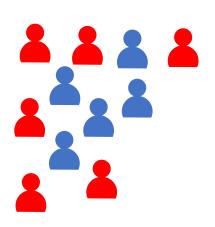


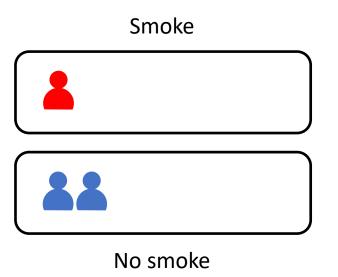


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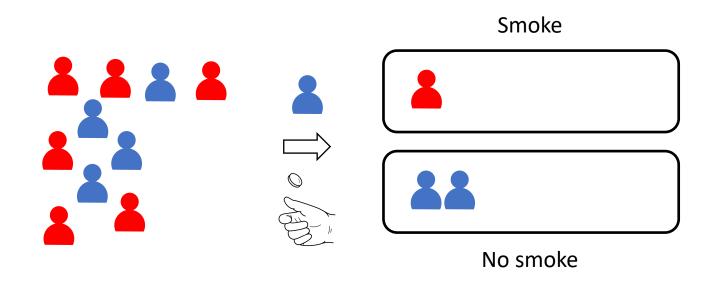


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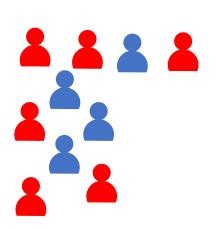


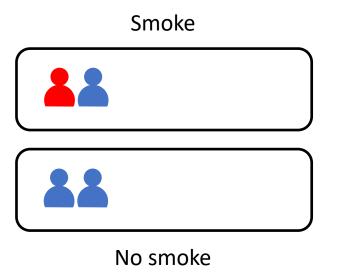


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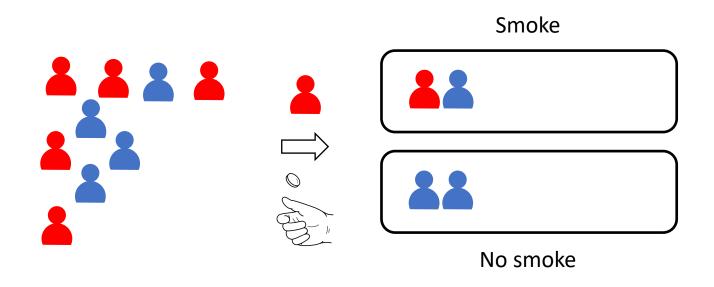


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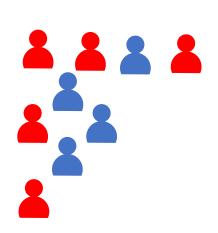


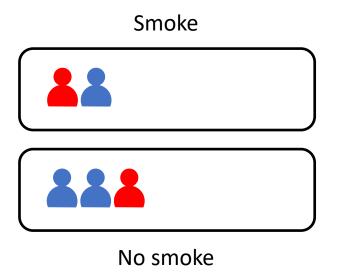


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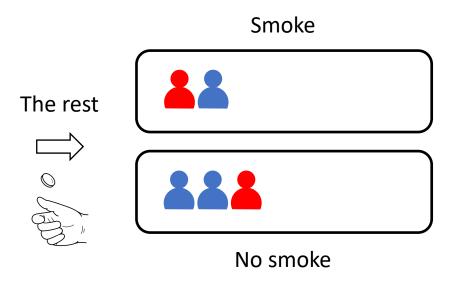


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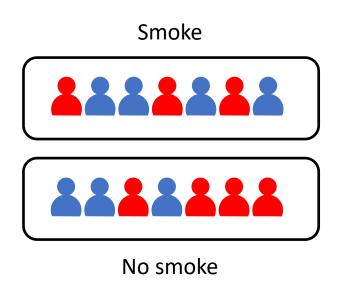




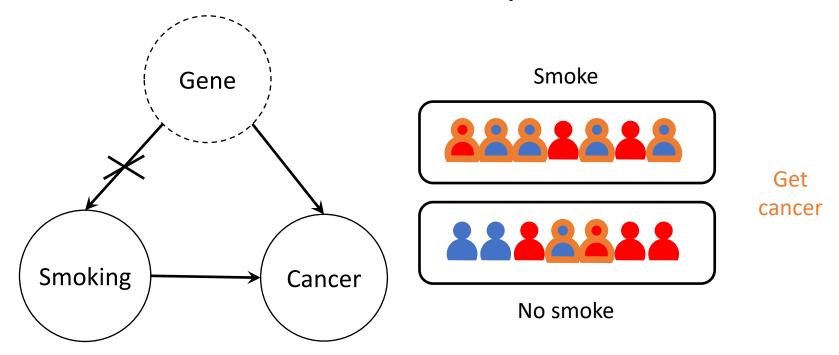
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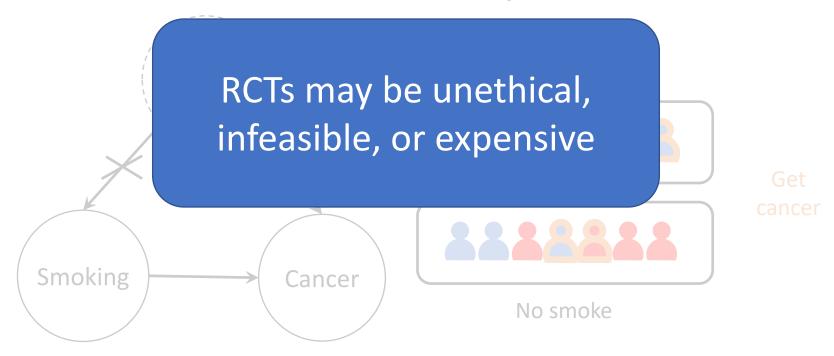
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RCT removed causal link from "gene" to "smoking"

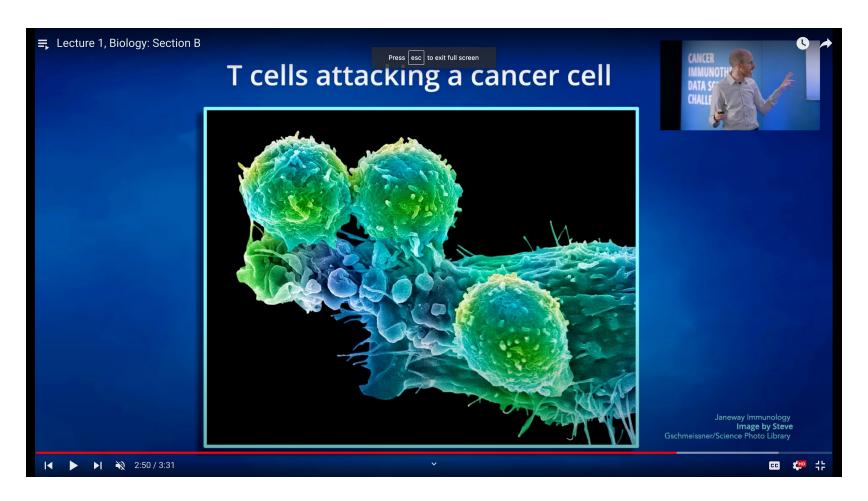
If smoking and cancer still highly correlated, then smoking causes cancer

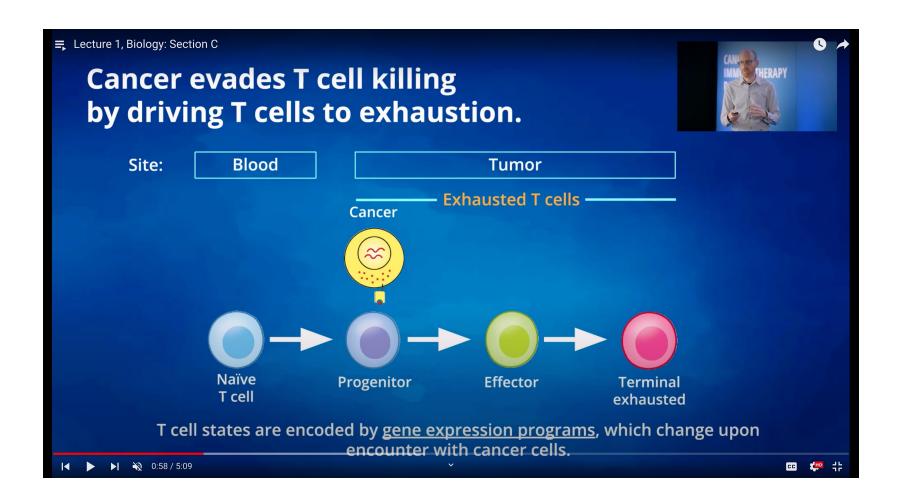
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RCT removed causal link from "gene" to "smoking"

If smoking and cancer still highly correlated, then smoking causes cancer

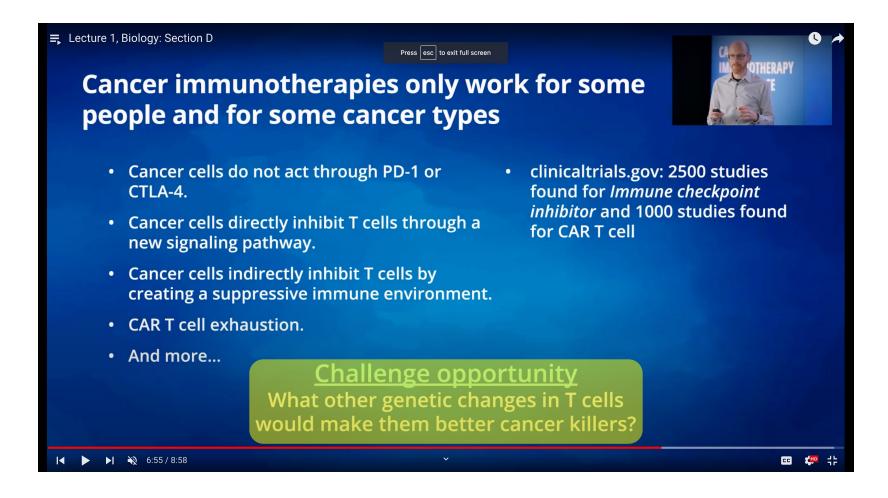


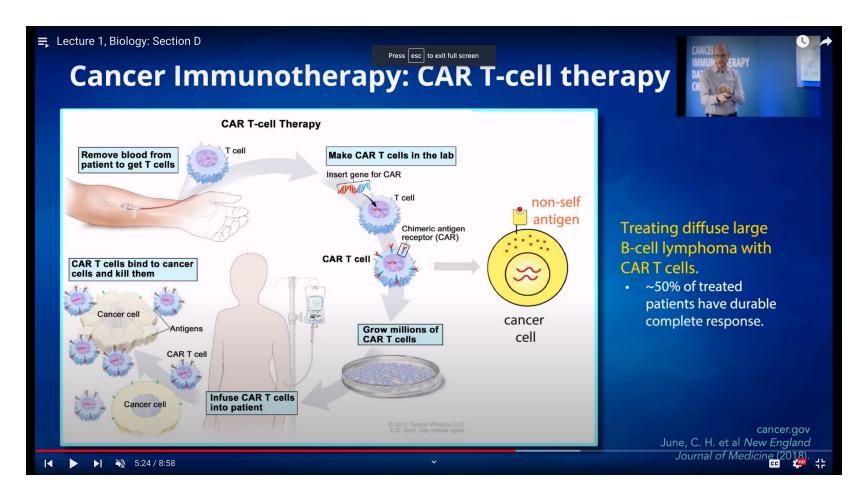




CANCER IMMUNOTHERAPY DATA SCIENCE GRAND CHALLENGE

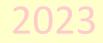


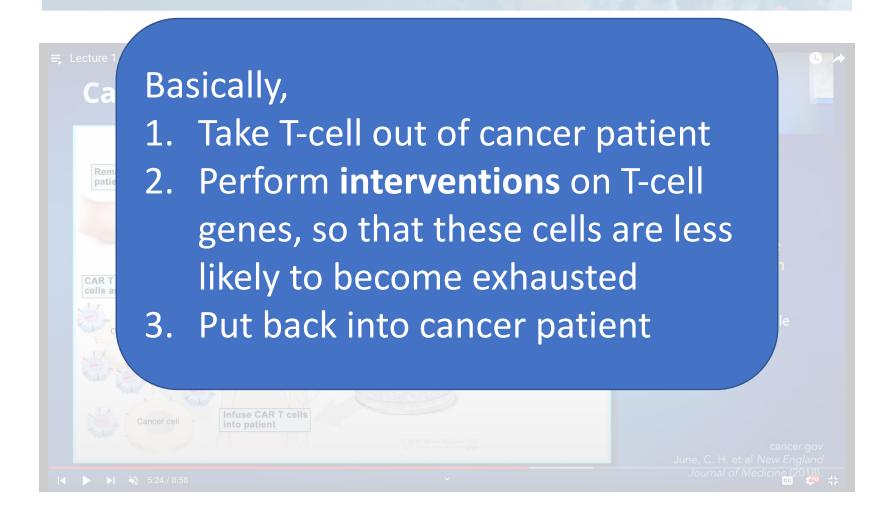






CANCER IMMUNOTHERAPY DATA SCIENCE GRAND CHALLENGE







07 October 2020

Pioneers of revolutionary CRISPR gene editing win chemistry Nobel

Emmanuelle Charpentier and Jennifer Doudna share the award for developing the

precise genome-editing technology.



Heidi Ledford & Ewen Callaway







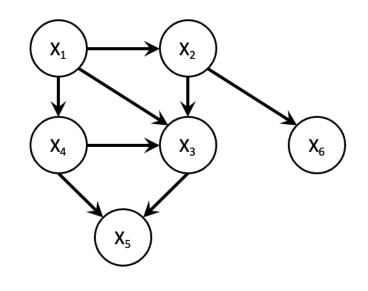


Jennifer Doudna and Emmanuelle Charpentier share the 2020 Nobel chemistry prize for their discovery of a game-changing gene-editing technique. Credit: Alexander Heinel/Picture Alliance/DPA



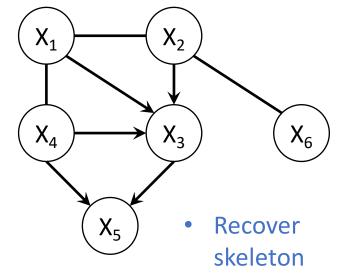
Structure learning (simplified)

This represents an equivalence class of graphs



Get samples



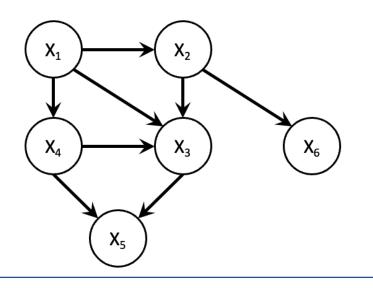


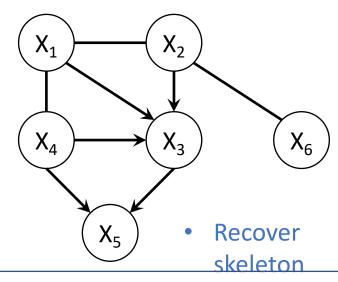


	X ₁	X ₂	X ₃	X ₄	X ₅	X ₆
Sample 1	0.22	0.04	0.84	0.48	0.98	0.82
Sample 2	0.87	0.17	0.61	0.67	0.67	0.23
Sample 3	0.55	0.54	0.67	0.86	0.93	0.23
Sample M	0.12	0.95	0.79	0.47	0.05	0.92

Structure learning (simplified)

This represents an equivalence class of graphs





Get samples

Orient somedges

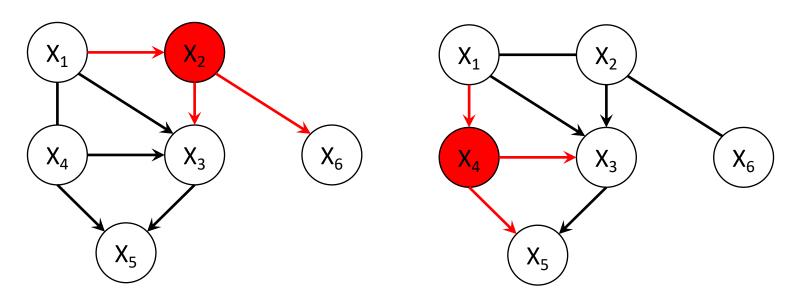
How to recover all the other arc orientations? Use interventions!

Sample M 0.12 0.95 0.79 0.47 0.05 0.92

What do interventions give us?

(*Under some causal assumptions)

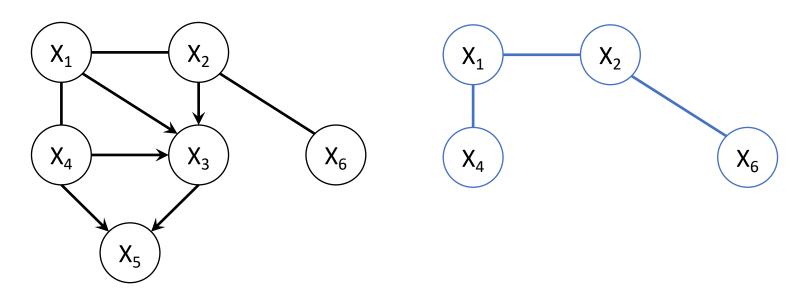
 When we intervene on a vertex, we recover the orientations of edges incident to the vertex



What do interventions give us?

(*Under some causal assumptions)

 When we intervene on a vertex, we recover the orientations of edges incident to the vertex

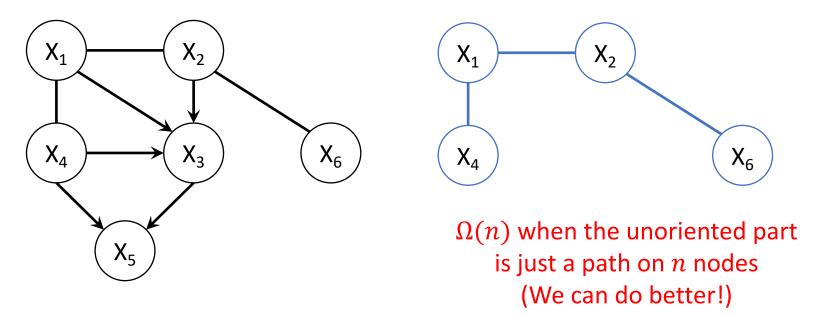


 Naïve: Compute minimum vertex cover on subgraph induced by unoriented arcs

What do interventions give us?

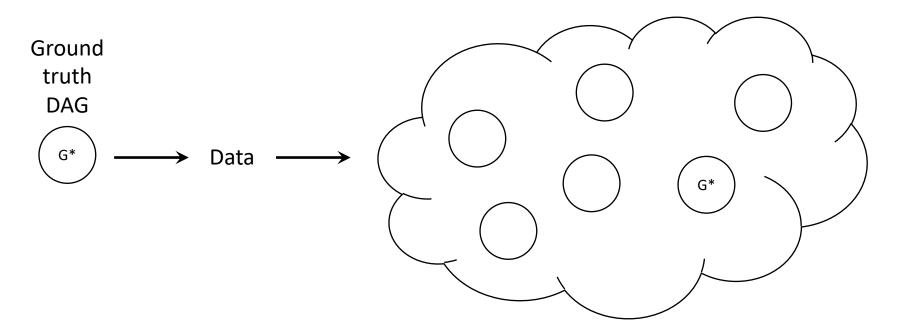
(*Under some causal assumptions)

 When we intervene on a vertex, we recover the orientations of edges incident to the vertex



 Naïve: Compute minimum vertex cover on subgraph induced by unoriented arcs

Identify G*

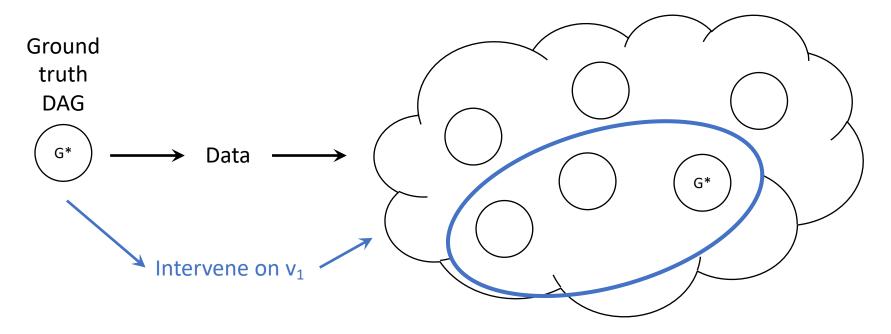


Equivalence class of causal graphs.

Can be represented by a partially

oriented causal graph

Identify G* using interventions

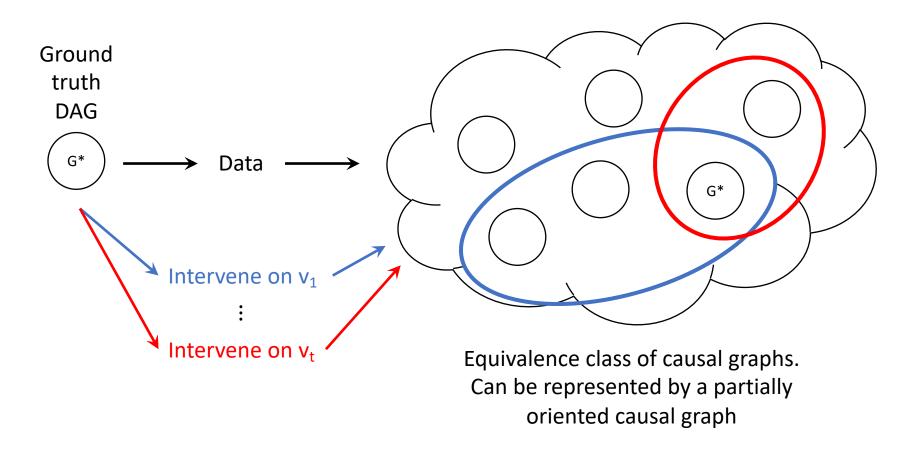


Equivalence class of causal graphs.

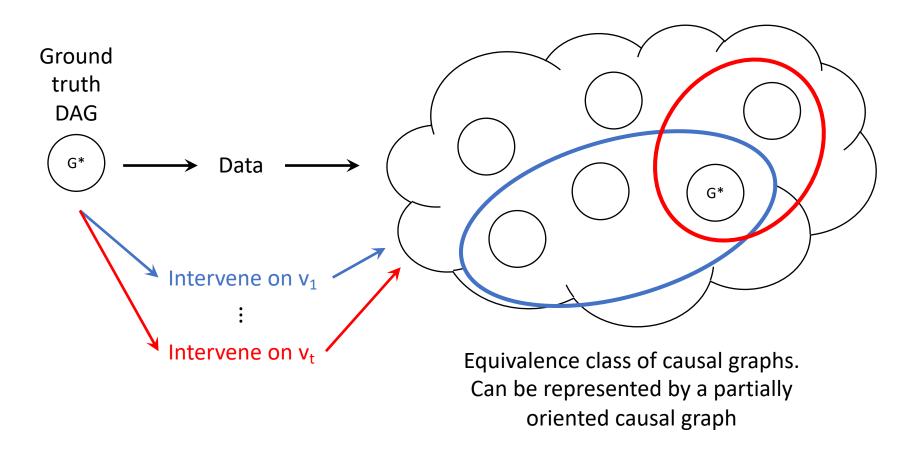
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Identify G* using interventions



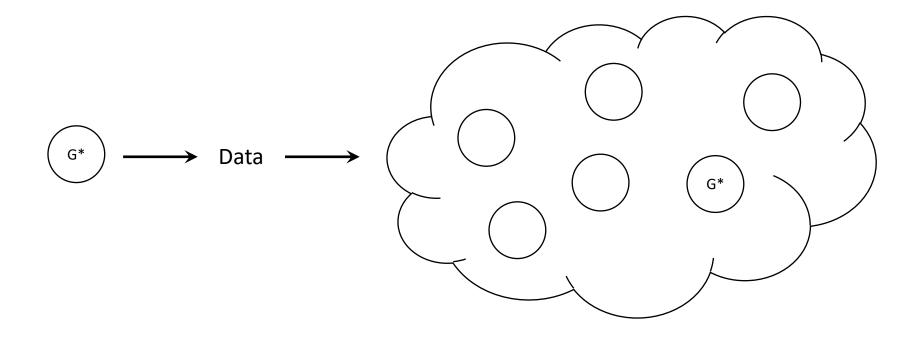
Identify G* using as few interventions as possible (minimize t)

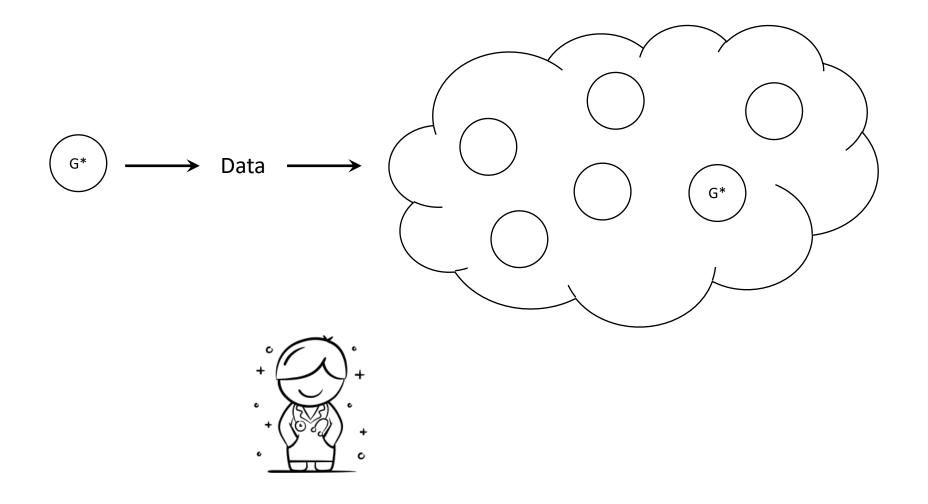


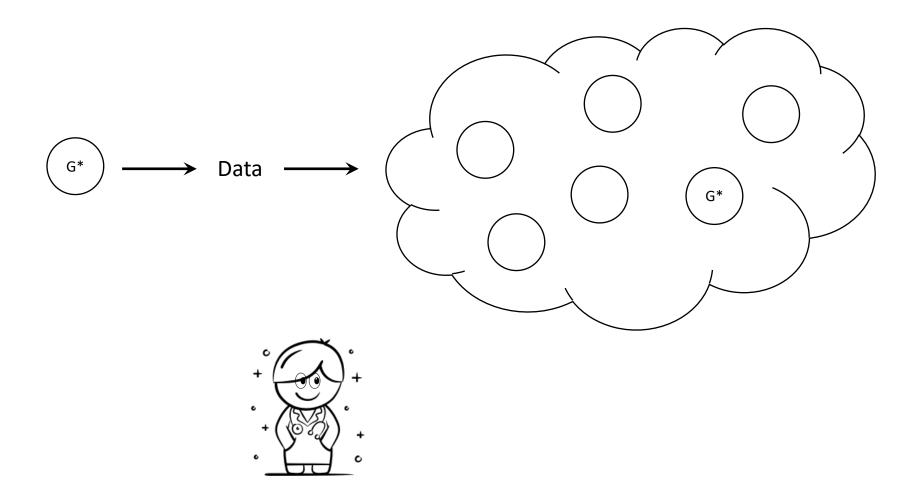
What is known

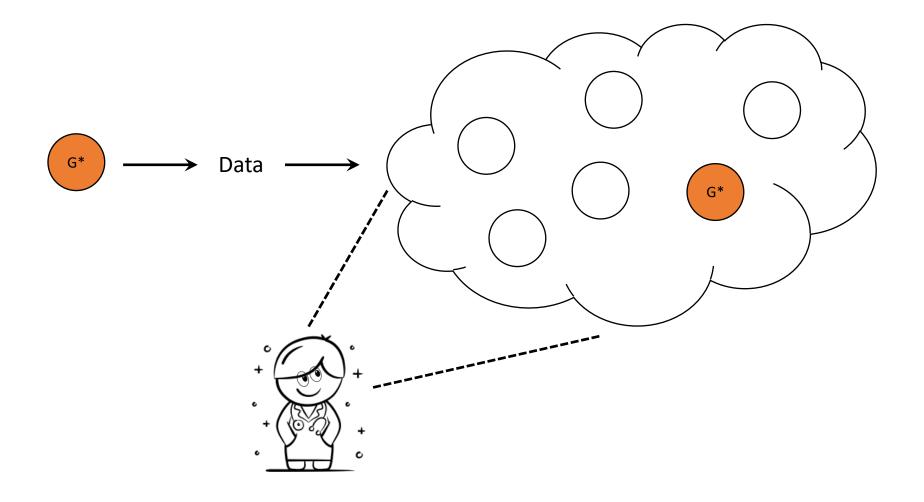
- Let $\nu(G^*)$ be the minimum number of interventions that an oracle (that knows G^*) needs to fully orient G^* from the partially oriented graph
- Known [Choo, Shiragur, Bhattacharyya 2022]
 - $\mathcal{O}(\log n \cdot \nu(G^*))$ interventions suffice
 - $\Omega(\log n \cdot \nu(G^*))$ interventions worst case necessary
- If we only care about arc orientations within a node-induced subgraph $H \subseteq G^*$ [Choo, Shiragur 2023]
 - $\mathcal{O}(\log |V(H)| \cdot \nu(G^*))$ interventions suffice

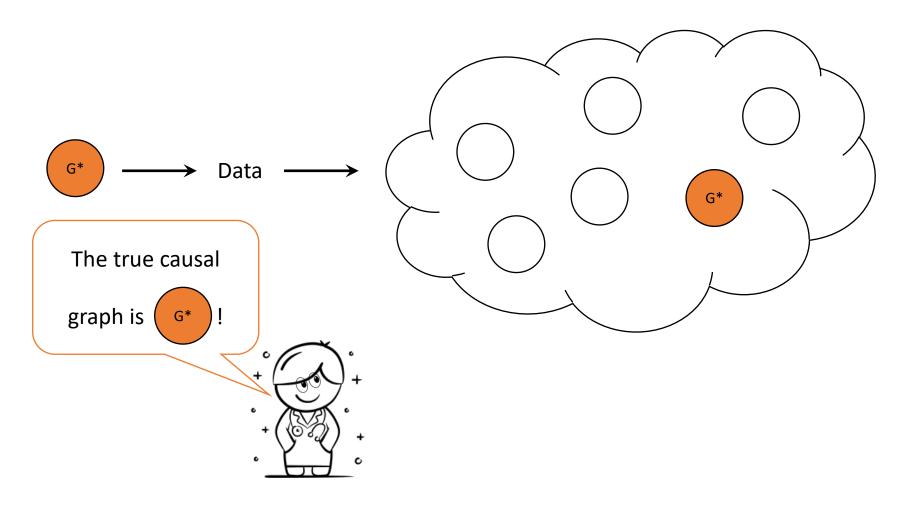
In many problem domains...

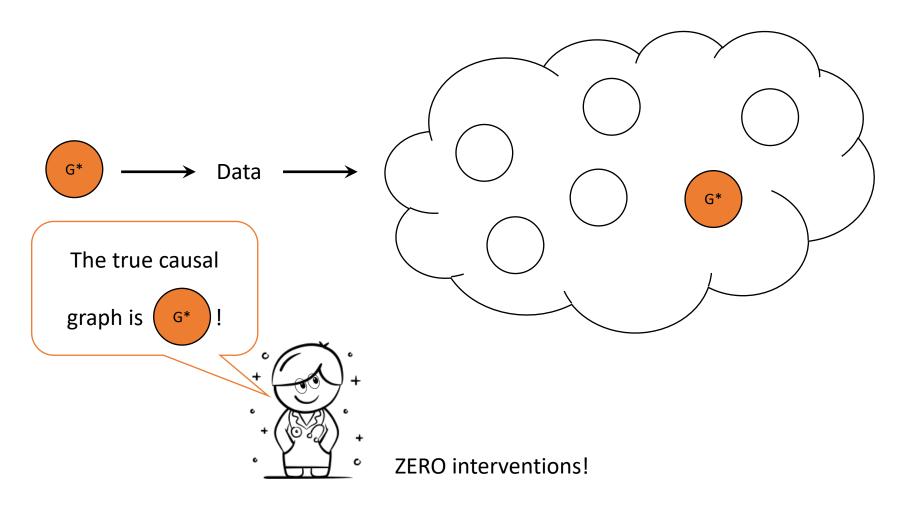


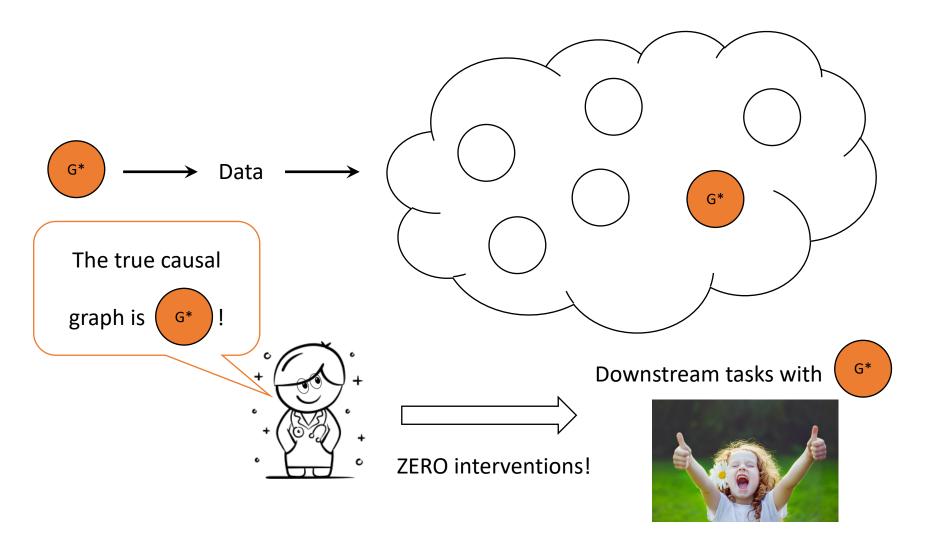




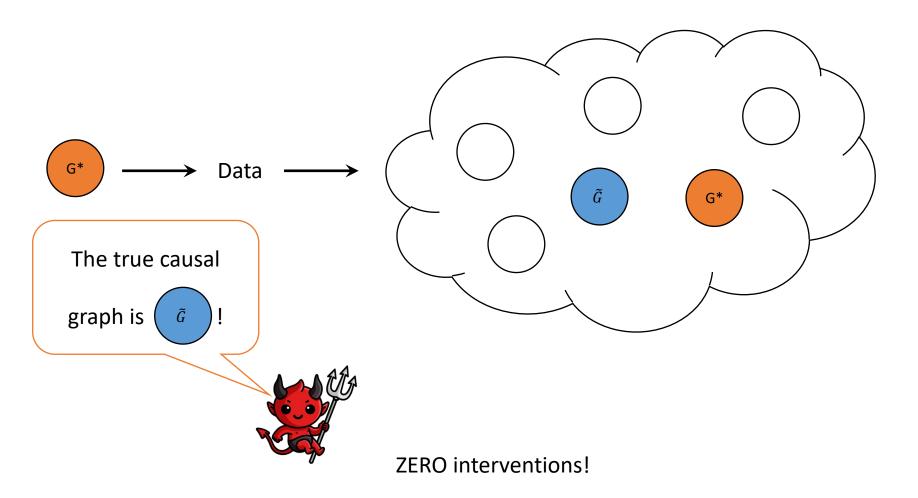




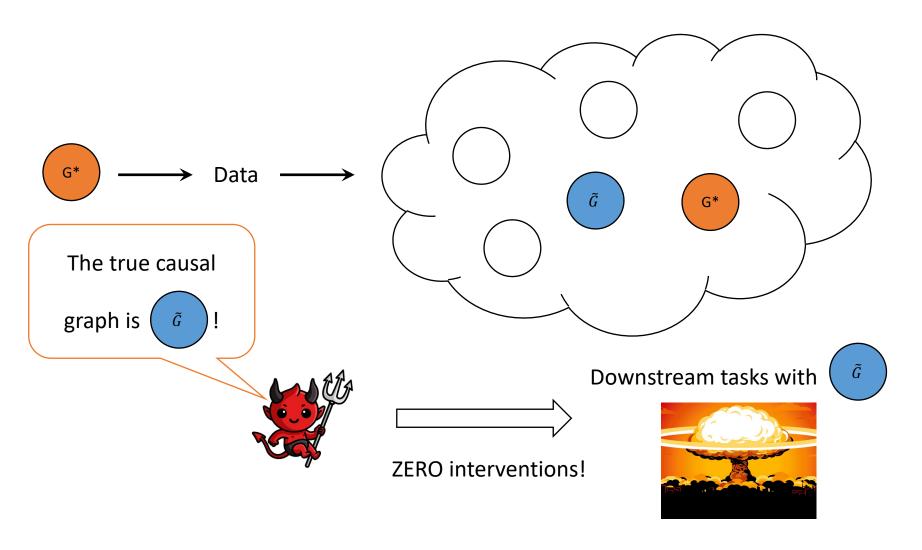




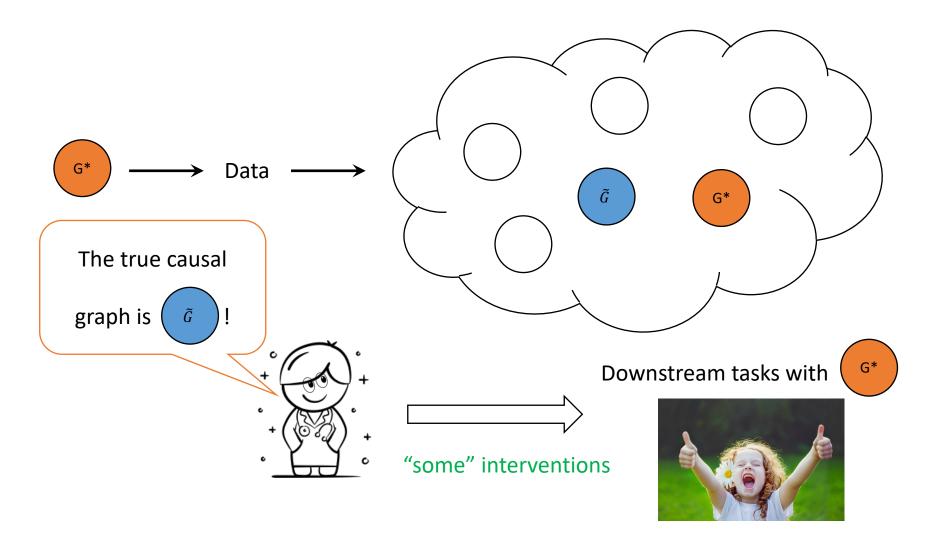
But... experts can be wrong



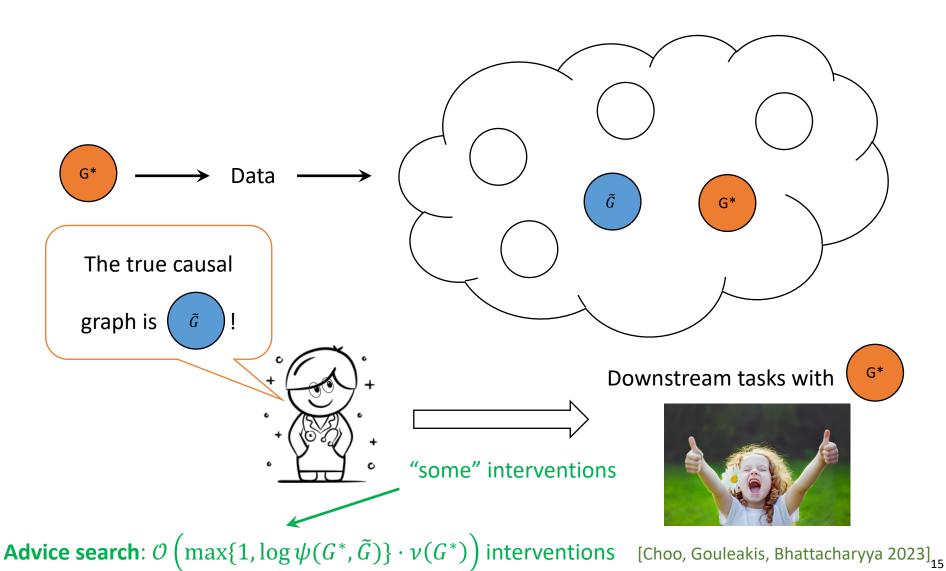
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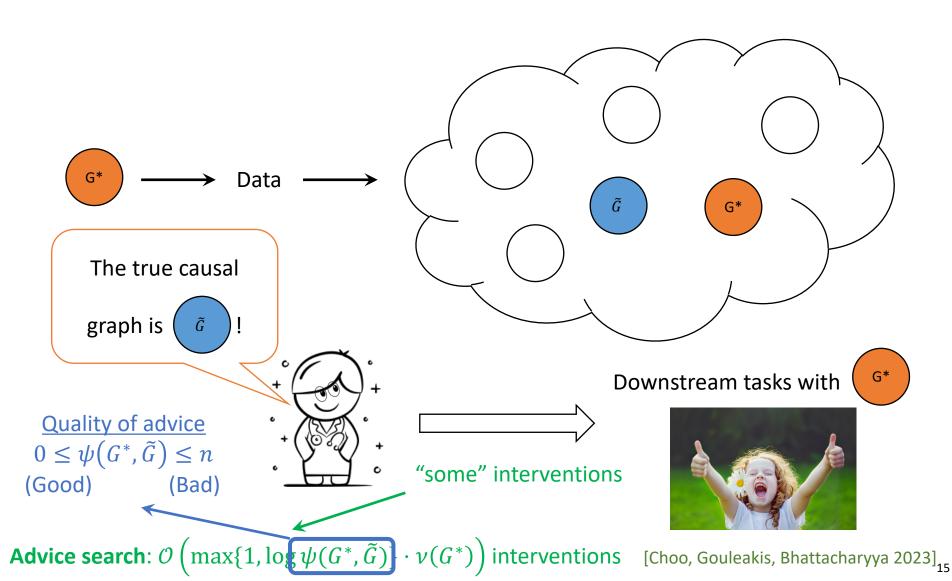
How to use imperfect advice?



How to use imperfect advice?



How to use imperfect advice?



Other problem settings (beyond causality)

Estimating Gaussians

- Given: i.i.d. Gaussian s samples from $N(0, \Sigma)$
- Output: $\hat{\Sigma}$ such that $\hat{\Sigma} \approx \Sigma$
- Goal: Minimize s required for "up to ϵ " closeness
- Known: $\widetilde{\Theta}\left(\frac{n^2}{\epsilon}\right)$ samples
- Known: What if Σ is sparse?
- Known: What if Σ^{-1} is sparse?
 - Requires dependency on condition number





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- Known: What if Σ is sparse?
- Known: What if Σ^{-1} is sparse?
 - Requires dependency on condition number
- Can we remove/weaken this dependency if we know a good guess of the sparsity pattern of Σ^{-1} ?

Online bipartite matching

- Given: Bipartite graph G = (U, V, E)
 - Offline nodes *U* fixed in advance
 - Online nodes V appear one by one, with edges incident to it
- When $v \in V$ arrives, decide irrevocably whether to match v to some unmatched neighbor
- Goal: Maximize size of matching at the end
- Maximal matching: $(\frac{1}{2})$ -approximation to OPT offline
- RANKING algorithm: $(1 \frac{1}{e})$ -approximation

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- RANKING algorithm: $(1 \frac{1}{e})$ -approximation
- NeurIPS'22: "Final degree of $u \in U$ " as advice
 - Doesn't achieve the desiderata that I mentioned earlier
 - I believe more can be done

https://www.mit.edu/~tgoule/

Distributed computing

- Setting: Broadcast networks (*Simplified variant)
- Problem: When > 1 device speak, all hear garbage
- Standard solution: Exponential backoff
 - Discrete time steps
 - Each device does the following:
 - Initialize i = 1. Send message.
 - If detect collision
 - Pick a random delay time t between $[0,2^i-1]$
 - Wait t steps before trying to send again.
 - When $i = \log n$, everyone starts succeeding
- Performance measure: "Throughput"

Distributed computing

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- Standard solution: Exponential backoff



What if we have a good guess of how many devices are in the network?

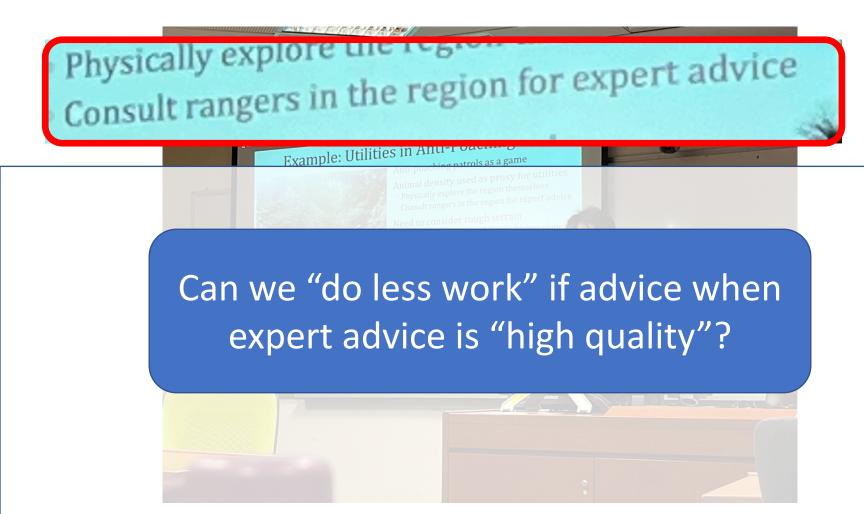
We thought about it back in 2021 (along with some other distributed computing problems where imperfect advice may make sense), had some partial ideas, but did not manage to work out all the details... 🖰

(Let us know if you have ideas and are keen on working out the details together)

Inverse game theory



Inverse game theory



The results mentioned in this talk are based on joint work with



Arnab Bhattacharyya



Themis Gouleakis



Kirankumar Shiragur

Let's talk!

What other problems are amenable to imperfect advice in your problem domain?