

# Lecture 9:

## Incentive Design: Financial Incentives

Instructor: Chien-Ju (CJ) Ho

# Logistics: Assignments

- Assignment 2: Due this Friday
- Assignment 3: Due Oct 13 (Wed)
- You are encouraged to discuss with others
  - However, you **MUST** write down the solution entirely on your own
- I'll stay after each lecture for questions

# Logistics: Project

- Project proposal:
  - Every person should be able to see **comments** on Gradescope as long as you include all teammates in the interface as required
  - Most comments are about what I expect to see for milestone 1
  - I ask some groups to update the proposal or come talk to me.
    - Please do so within this week

# Logistics: Project

- Project milestone 1: Due Oct 15 (Fri)
  - Initial literature survey (know what other works are out there)
    - At least 3~5 papers
  - A plan on what you want to do for the remaining of the semester
    - Formalize your research question and approaches, e.g.,
      - Theory/simulation project: formalize your models
      - Data-analysis project: figure out where and how to get data and what you plan to do with it
      - Experiment/application project: have a prototype design and an evaluation plan
- Include a **timeline** (weekly or biweekly) on what you plan to do
  - Nov 2: Midterm project pitch and discussion
  - Nov 5: Milestone 2

# Logistics: Peer Review

- The link to the peer review form is on the course website

Sep 28     Incentive Design: Financial Incentives

Presenter:  
Riwen, Dhruva, Charles  
[\[Student Slides\]](#) [\[Additional Slides\]](#)

[Peer Review Form](#)

- The comments are not anonymous to me but will be to the presenters
- Please try to provide constructive suggestions
- Please try to submit them **before 6pm**
  - might make sense to get it done during the lecture

# Student Presentation

# Additional Lecture

# Financial Incentive in Crowdsourcing

- Fixed payment
  - Post a price for the task, workers can choose to accept it or not
- Contract: Performance-based payments (PBP)

1: Nearly every group of animals has its giants, its species which tower above  
2: their fellows as Goliath of Gath stood head and shoulders above the Philistines  
3: hosts; and while some of these are giants only in comparison with their  
4: fellows, belonging to families whose members are short of stature, others are  
5: sufficiently great to be called giants under any circumstances. Some of these  
6: giants live to-day, some have but recently passed away, and some ceased to  
7: long ages before man trod this earth. The most gigantic of mammals—the  
8: whales—still survive, and the elephant of to-day suffers but little in  
9: comparison with the mammoth of yesterday; the monstrous Dinosaurs, greatest of  
10: all reptiles—greatest, in fact, of all animals that have walked the  
11: earth—flourished thousands upon thousands of years ago. As for birds, some of  
12: the giants among them are still living, some existed long geologic periods ago,  
13: and a few have so recently vanished from the scene that their memory still  
14: lingers amid the haze of tradition. The best known among these, as well as the  
15: most recent in point of time, are the Moas of New Zealand, first brought to  
16: notice by the Rev. W. Colenso, later on Bishop of New Zealand, one of the many  
17: missionaries to whom Science is under obligations.  
18: Colenso, while on a missionary visit to the East Cape  
19: natives of Waiaapu tales of a monstrous bird, called  
20: man, that inhabited the mountain-side some eighty  
21: the last of his race, was said to be attended by two  
22: kept guard while he slept, and on the approach of  
23: immediately rushed upon the intruders and trampled them to death. None of the  
24: Maoris had seen this bird, but they had seen and somewhat irreverently used for  
25: making parts of their fishing tackle, bones of its extinct relatives, and these  
26: bones they declared to be as large as those of an ox.

Proofread this text, earn \$0.50


Earn an extra bonus \$0.10  
for every typo found

Requester's goal:


Maximize “work quality minus payment”



# Static Contract Design


 Requester		Contract	
	Task value	Bad Outcome worth \$1	Good Outcome worth \$5
	Payment	\$1	\$3

Set payments to maximize [expected task value – expected payment]

 Worker		Bad Outcome	Good Outcome	
	High effort	Prob: 0.1	Prob: 0.9	Cost: \$1
	Low effort	Prob: 0.8	Prob: 0.2	Cost: \$0

Choose effort to maximize [ expected payment – cost ]


# Static Contract Design



Requester

	Contract	
Task value	Bad Outcome worth \$1	Good Outcome worth \$5
Payment	\$1	\$3

- Expected payoff:  $\underbrace{0.1 \times \$1 + 0.9 \times \$5}_{\text{expected value}} - \underbrace{0.1 \times \$1 + 0.9 \times \$3}_{\text{expected payment}} = \$1.8$





Worker

	Bad Outcome	Good Outcome	
High effort	Prob: 0.1	Prob: 0.9	Cost: \$1
Low effort	Prob: 0.8	Prob: 0.2	Cost: \$0

- Expected payoff of high effort:  $\underbrace{0.1 \times \$1 + 0.9 \times \$3}_{\text{Expected payment}} - \underbrace{\$1}_{\text{cost}} = \$0.18$
- Expected payoff of low effort:  $\underbrace{0.8 \times \$1 + 0.2 \times \$3}_{\text{Expected payment}} - \underbrace{\$0}_{\text{cost}} = \$0.14$

# Static Contract Design

		Contract	
Requester	Task value	Bad Outcome worth \$1	Good Outcome worth \$5
	Payment	\$1	\$3
			
worker		Bad Outcome	Good Outcome
	High effort	Prob: 0.1	Prob: 0.9
	Low effort	Prob: 0.8	Prob: 0.2
			Cost: \$1
			Cost: \$0

## Contract Design:

- How to find the **optimal** payment that maximizes the requester's payoff?
- In the **full information** setting, i.e., we know everything about the worker
  - Well-studied principal-agent problem in economics

# Contract Design in Crowdsourcing



Requester

Task value

Payment

Contract

Bad Outcome worth \$1	Good Outcome worth \$5
?	?



- **Multiple** workers
- **Unknown** parameters
- **Unknown** distributions
- Interact with one worker at a time
- Workers are i.i.d. drawn

# Contract Design in Crowdsourcing



Contract

Task value

Bad Outcome  
worth \$1

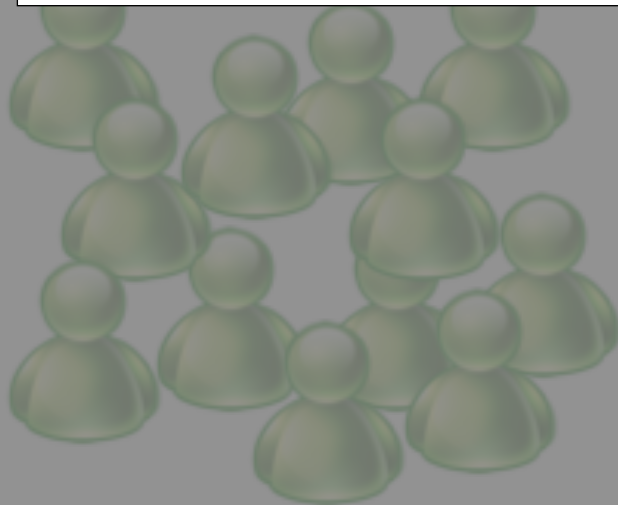
Good Outcome  
worth \$5

Payment

?

?

Can we **adaptively** update contracts to maximize the requester's expected payoff over time



Multiple workers

- **Unknown** parameters
- **Unknown** distributions
- Interact with one worker at a time
- Workers are i.i.d. drawn

# Adaptive Contract Design in Crowdsourcing Markets

joint work with



Alex Slivkins  
Microsoft Research, NYC

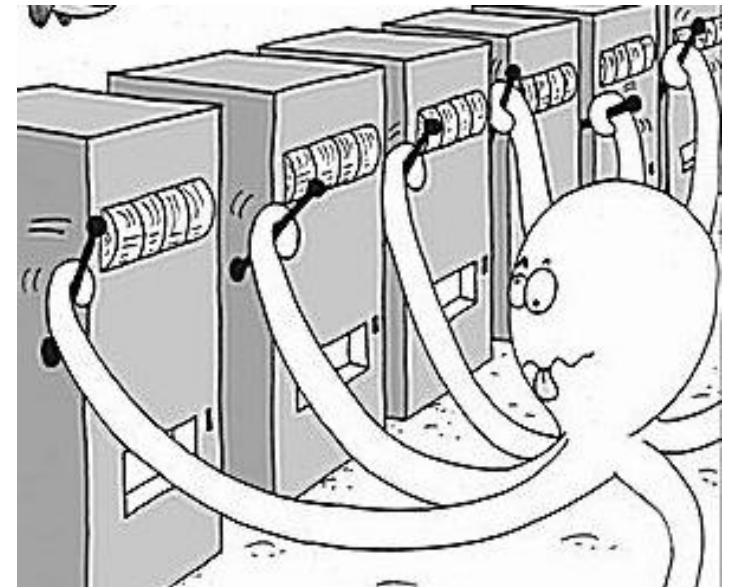


Jenn Wortman Vaughan  
Microsoft Research, NYC

Appeared In ACM EC'14 and JAIR'16

# Adaptive Contract Design as A Machine Learning Problem

- At each time step
  - the requester posts a contract
  - a worker completes the task and returns the result
  - the requester observes the result and updates the contract
- An online learning problem (**bandit learning**)
  - exploring the payoff of each contract
  - exploiting the optimal contract
  - **exploration/exploitation tradeoff**
- Challenge:
  - An infinite number of possible contracts (arms)!
  - **Bandits with infinitely many arms**

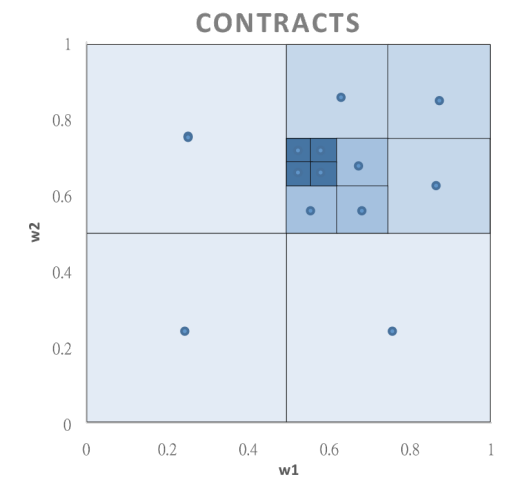


# Dealing with Infinitely Many Contracts

- Make assumptions on worker behavior
  - Workers are **rational**: workers exert effort that maximizes their payments minus costs
  - Workers are **myopic**: worker arrive only once and/or won't try to "game" the system
- When posting a PBP (performance-based payments), we learn the payoffs of the **posted payment** and **similar payments**



# Algorithm and Result



- Agnostic Zooming Algorithm:
  - Adaptively refine the search space and “zoom in” into more promising regions of PBPs
- Main theorem  
If workers are rational and myopic,  
we can learn the optimal payment efficiently!

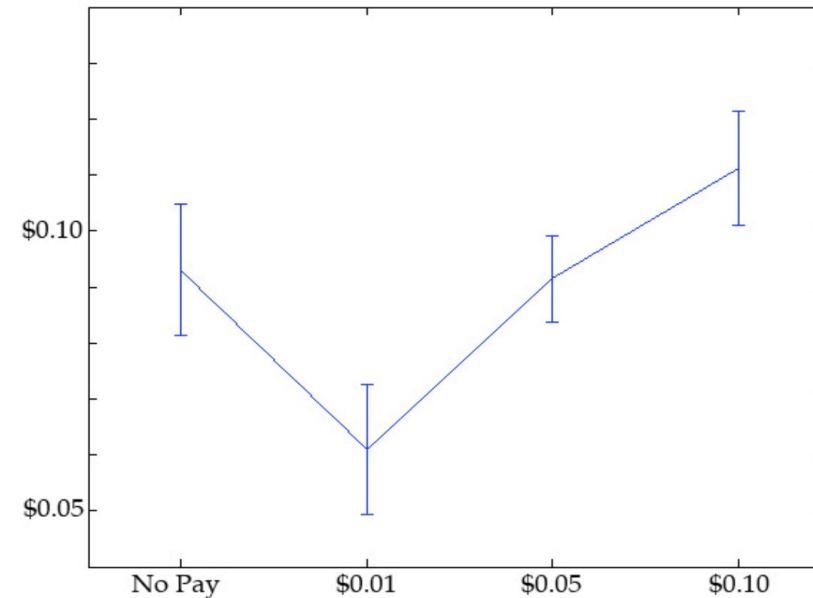
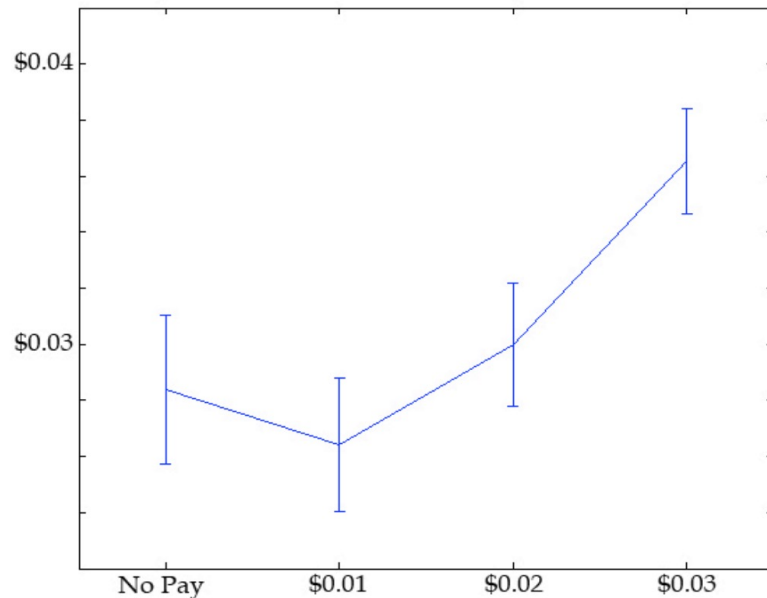
The average difference of running our algorithm for  $T$  rounds and running the optimal algorithm for  $T$  rounds is bounded by  $O(1 / T^\alpha)$ , where  $\alpha > 0$  indicates the difficulty of learning.

# Discussion

- The two main assumptions made in this paper
  - Rational: crowd workers want to maximize their payments minus cost
  - Myopic: crowd workers only care about the payoff “now” at this round
- How comfortable are you with these two assumptions? What are the example scenarios these assumptions break? How can you examine empirically that these assumptions hold or not? Are there alternatives for the modeling choices?
- Are there other implicit/explicit assumptions out these?

# Anchoring effect: Workers' Perceptions of Fair Payments

- When asked how much do they think the payment should be after tasks



X-axis: the payment they receive

Y-axis: the payment they think it should be

# Incentivizing High Quality Crowdwork

joint work with



Alex Slivkins  
Microsoft Research



Sid Suri  
Microsoft Research

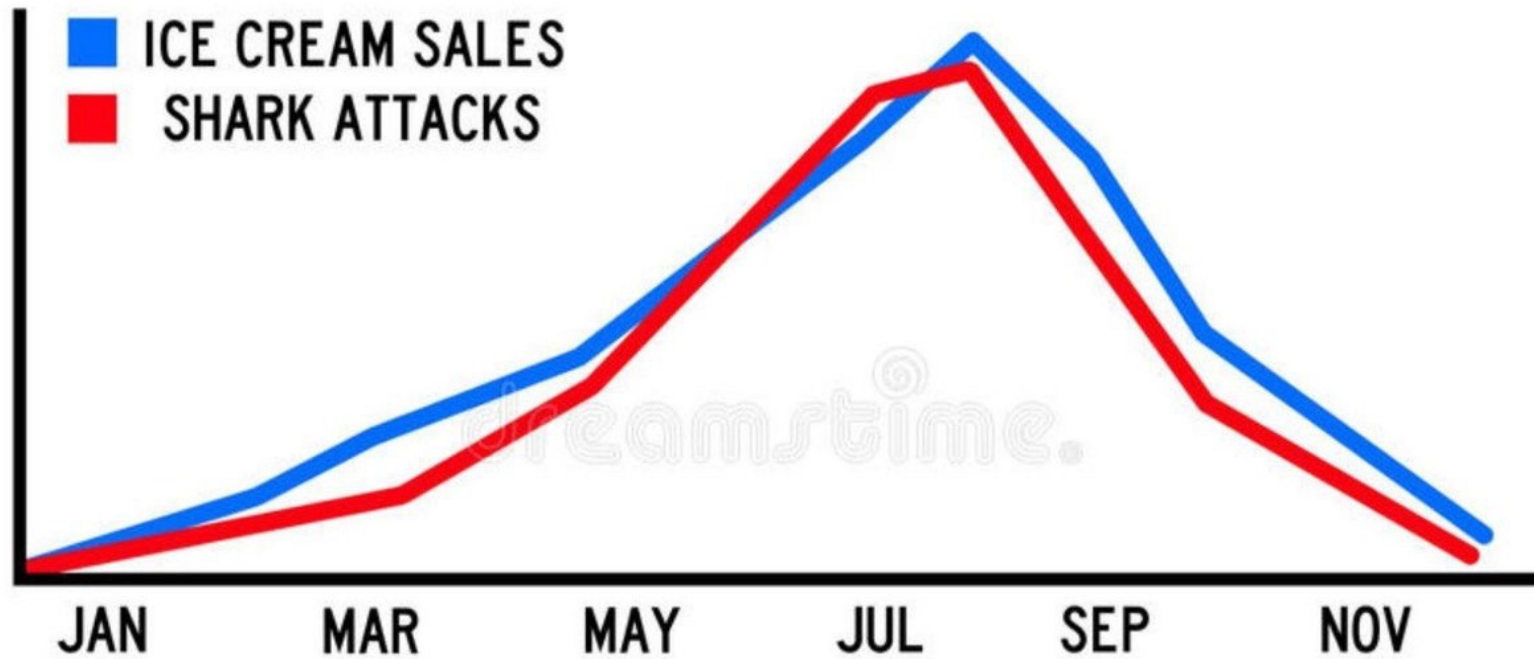


Jenn Wortman Vaughan  
Microsoft Research

Are workers really *rational*?

Goal: Investigate the **casual effects** of  
financial incentives on the quality of crowdwork.

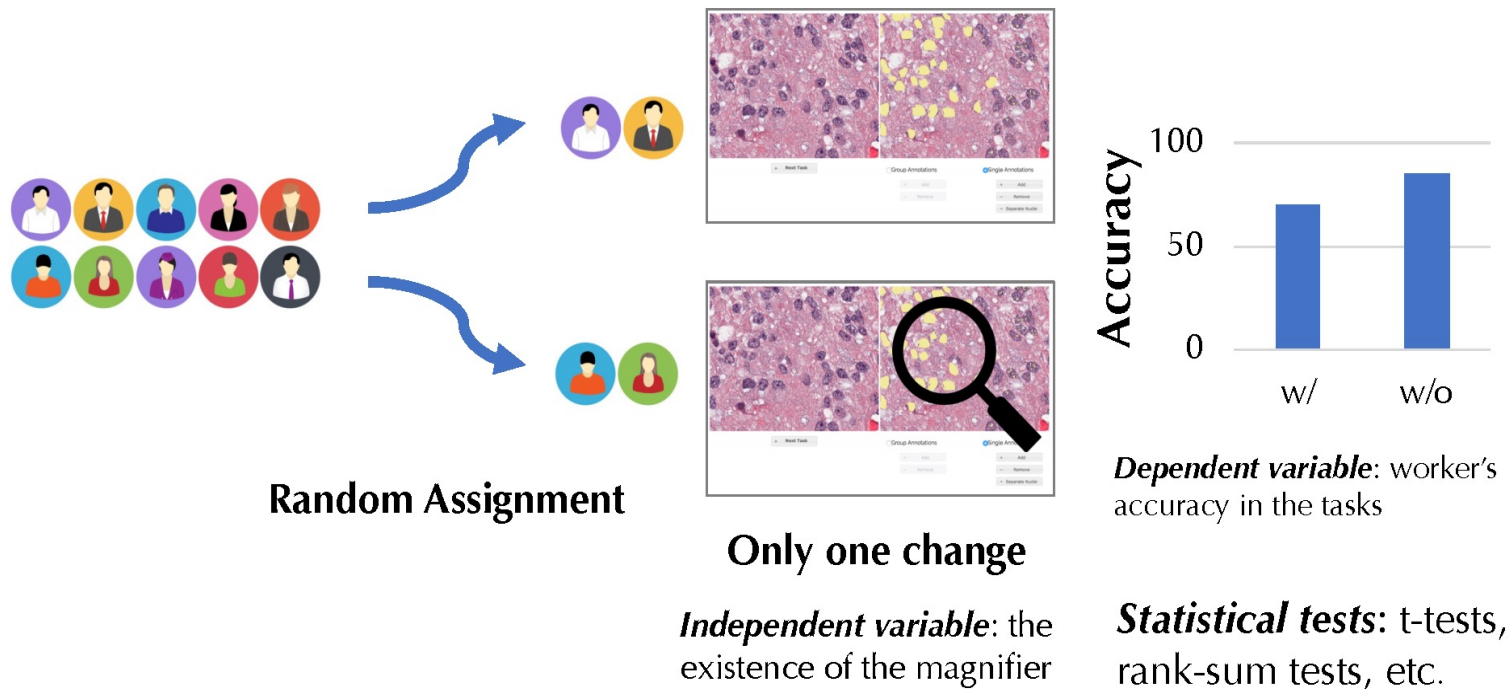
# Correlation $\neq$ Causality



<https://twitter.com/kiabms5/status/1288685777866506240>

# Correlation $\neq$ Causality

- To infer causality (whether A causes B), randomized experiment is the gold solution at the moment



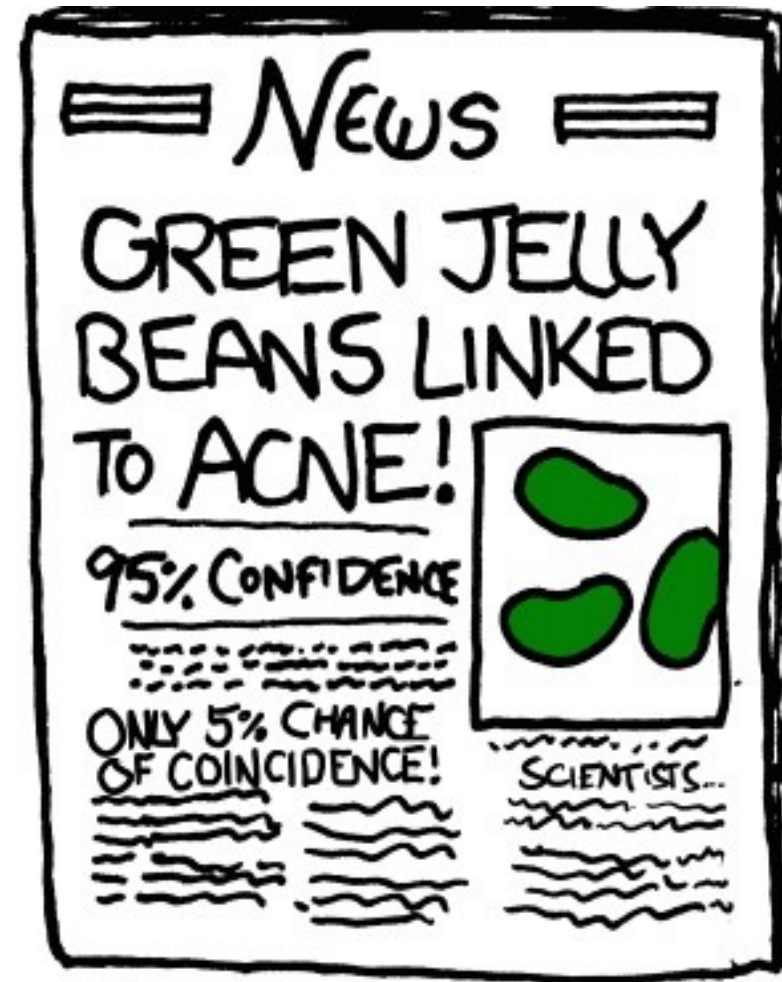
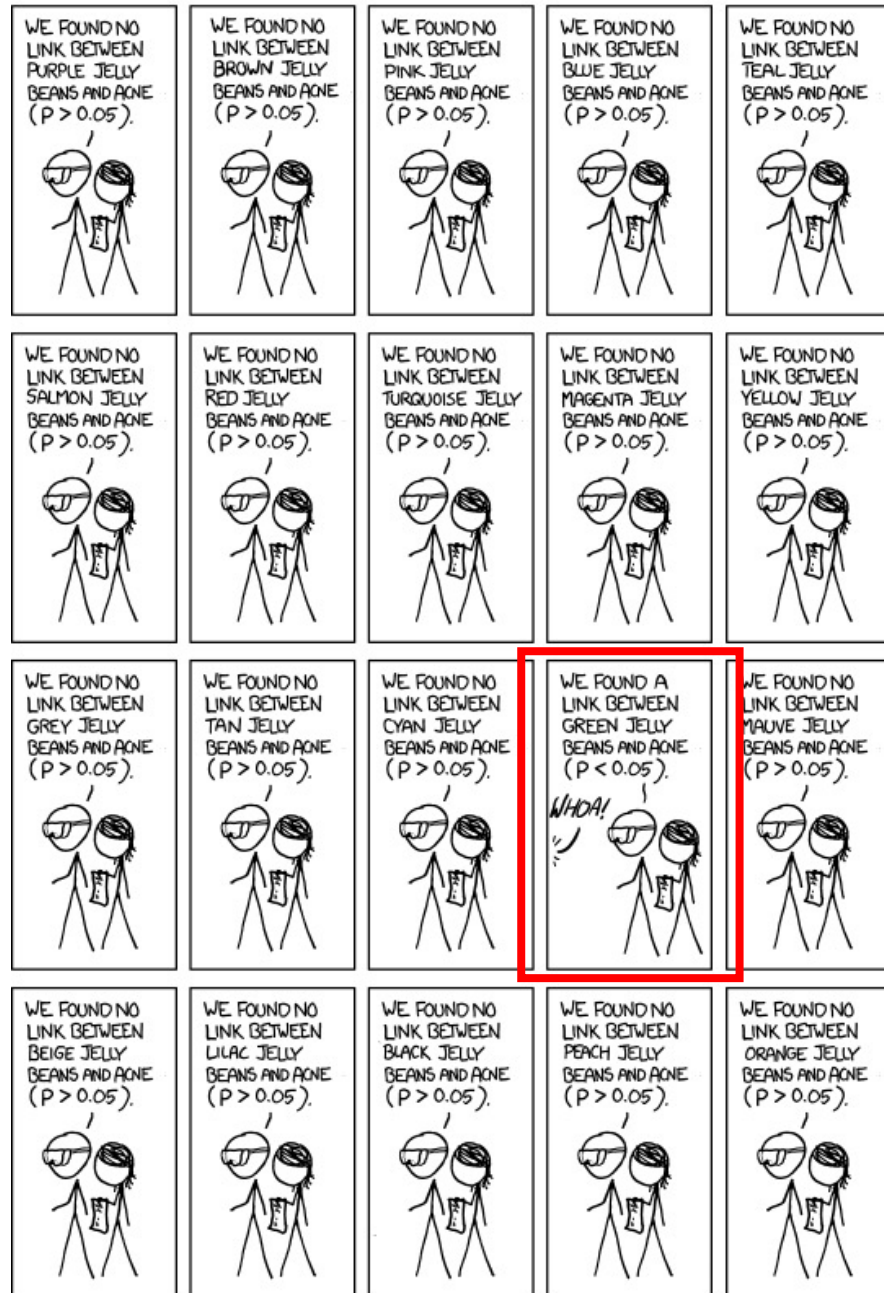
There have been studies on inferring causality using observational data, but they require some assumptions.

# A bit more notes...

- How do we know whether a COVID-vaccine works?
  - Randomized experiments
    - Control: people receiving placebo
    - Treatment: people receive the vaccine
  - Measure their immunity afterwards
- Need principled way of conducting the experiments
  - Pre-registered hypothesis
  - Don't peek at the data before it finalizes (or deal with it appropriately)
    - In the COVID vaccine experiments, a common protocol allows the company to “peek” at the data a few times before the experiment ends, so there is a chance to end the experiment early
    - Need to take care of this effect in the statistical analysis







# Discussion

- We have read several papers so far and they have made various assumptions about humans. What assumptions do you think might be questionable (maybe just in some particular applications)?
- Can you think of ways to examine the assumption, for example, by designing behavioral experiments or crawling data from the Web for analysis?