Lecture 8:
Incentive Design: Financial Incentives

Instructor: Chien-Ju (CJ) Ho

Logistics: Assignment 2 and Project Proposal

- Assignment 2
  - Due: Feb 28 (Wed)
  - 3 long-ish math questions that extend the lecture today

- Project Proposal
  - <u>Tentative</u> due: Mar 1 (Friday)
  - Requirement
    - 1~2 paragraph description of the project
    - Identify at least one research paper on the topic

Logistics: Presentation

- For presenters:
  - Give a **55~60 min** presentation
    - Based on the **required reading** and **N-optional reading** for N-person groups
    - The papers are the "backbone" of the presentation
  - Prepare **2 reading questions** for the required reading
  - Prepare around **~2 discussion sessions**
  - Lead the discussion for the discussion sessions
  - Template format (if you are not sure what to do):
    - Discussion on the required reading (10~15 min)
    - Discussion session (5~10 min)
    - Discussion on the optional reading (15 min)
    - Another discussion session (5~10 min)
    - Another optional reading + summary (15 min)
    - Feel free to be creative and include materials outside of the papers

Logistics: Presentation

- For presenters:
  - You do not need to submit the review for the lecture of your presentation
  - Talk to me **one week before your presentation**
    - Default time: talk to me after class
  - You need to be ready for the following before meeting with me
    - Finish reading the papers
    - A structure of your presentation (no need to show me the completed slides)
    - Topics for the discussion sessions
    - Two reading questions for the required reading

Logistics: Presentation

- The schedule is posted on Piazza

Date	Topic	Presenters
Feb 12	Incentive Design: Financial Incentives	CJ
Feb 14	Incentive Design: Badges and Attention	CJ
Feb 26	Workflow Design for Crowdsourcing	CJ
Feb 28	Learning in the Presence of Disagreements	Kai Ang, Sangwook Suh
Mar 4	LLM as a Proxy for Humans	Yifan Yuan, Ilan Barr, Nancy Patel
Mar 6	Adapting Crowdsourcing Techniques for LLM	Oscar Ortiz, Zhiyuan He
Mar 18	Fairness in AI	CJ
Mar 20	Human Perceptions of Fairness	Oen McKinley, Kyle Stein
Mar 25	Ethical Decision Making and Participatory Design	Garrett Kearney, Jake Valentine, Leib Malina
Mar 27	Human Trust in AI-Assisted Decision Making	Vincent Siu, Arpit Jain
Apr 1	Designing AI for AI-Assisted Decision Making	Joshua Tang, Sunny Yuan, Meichuan Yin
Apr 3	Explainable Machine Learning	Kaitlin Day, Micah Benson, Victoria Black
Apr 10	Human-Centered Explainable Machine Learning	Tory Farmer, Stuart Aldrich
Apr 15	Designing Collaborative AI in Human-AI Teams	CJ

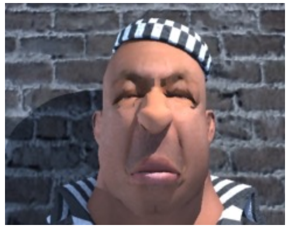
No class next Wed.
Please talk to me after class next Monday, or schedule a time with me.

Recap

Game Theory Basics

- Key elements of game theoretical models
  - Players, strategies, payoffs

- Normal-form game



B

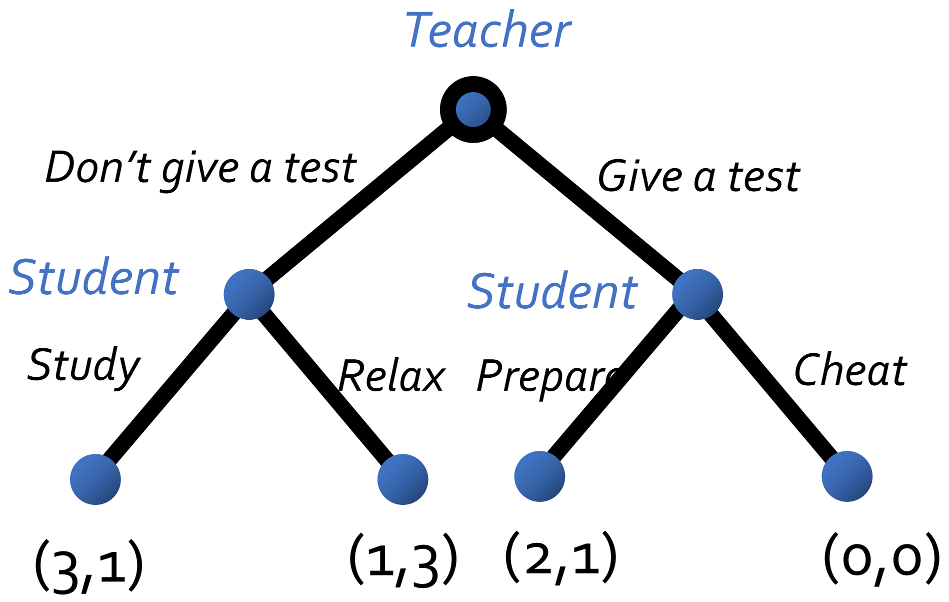
A

	Stay Silent	Confess
Stay Silent	A: 6 months B: 6 months	A: 10 years B: free
Confess	A: free B: 10 years	A: 5 years B: 5 years

Game Theory Basics

- Key elements of game theoretical models
  - Players, strategies, payoffs

- Extensive-form game



Solutions Concepts

- Informally, predictions of what rational agents will do given the game

- Nash equilibrium
  - If everyone else follows Nash equilibrium, it's your best interest to follow

B

A

	Movie	Bar
Movie	(2, 1)	(0, 0)
Bar	(0, 0)	(1, 2)

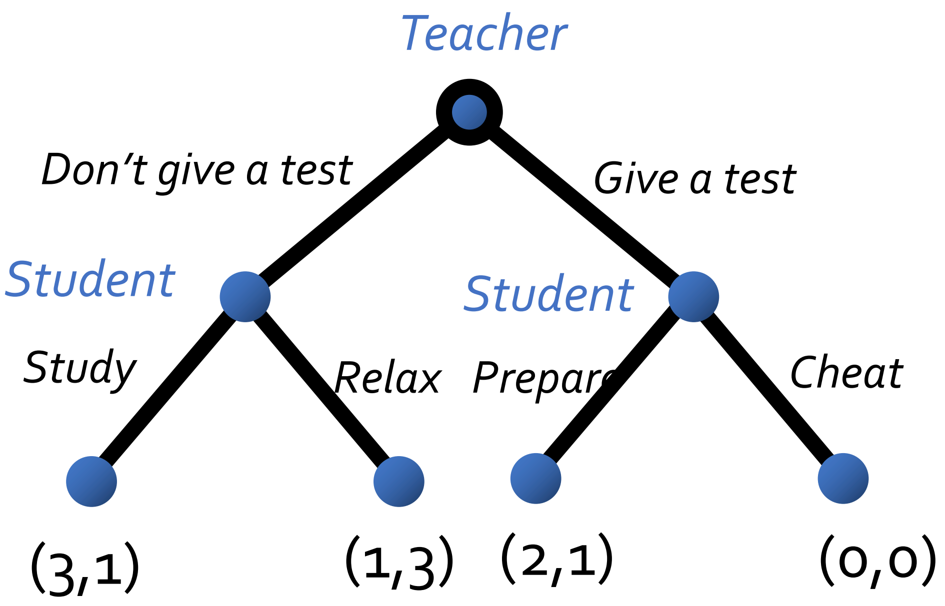
(Movie, Movie) and **(Bar, Bar)** are pure strategy Nash equilibria

Generally speaking, finding a Nash is hard, but verifying whether it's a Nash is easy

Solutions Concepts

- Informally, predictions of what rational agents will do given the game

- Subgame perfect equilibrium
  - Play in each ”subgame” is a Nash equilibrium



- Subgame perfect equilibrium
  - Teacher chooses “Give a test”
  - Student chooses (“Relax”, “Prepare”)

Mechanism Design

- Game theoretical analysis
  - Given the game, analyze what rational agents will do

- Mechanism design (reverse game theory)
  - Give a goal of what you want rational agents do, design the game rules (e.g., what payoffs agents can receive) such that agents choose the actions you want them to choose.

Lecture Today

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 Philistine
3: hosts; and while some of these are giants only in comparision with their
4: fellows, belonging to families whose members are short of stature, others are
5: sufficently 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 elphant 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 missonary visit to the East Cap
19: natives of Waiapu 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 attened by two e
22: kept guard while he slept, and on the approach of n
23: imediately 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

	Bad Outcome worth $1	Good Outcome worth $5
Task value		
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

	Bad Outcome worth $1	Good Outcome worth $5
Task value		
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: $\boxed{\underline{0.1\times\$1+0.9\times\$3}-\underline{\$1}=\$0.18}$
- Expected payoff of low effort: $\underline{0.8\times\$1+0.2\times\$3}-\underline{\$0}=\$0.14$

Expected payment - cost

Static Contract Design

Requester

Contract

	Bad Outcome worth $1	Good Outcome worth $5
Payment	$1	$3

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

- 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

Contract

	Bad Outcome	Good Outcome
Task value	worth $1	worth $5
Payment	?	?

- **Multiple** workers
- **Unknown** parameters
- **Unknown** distributions

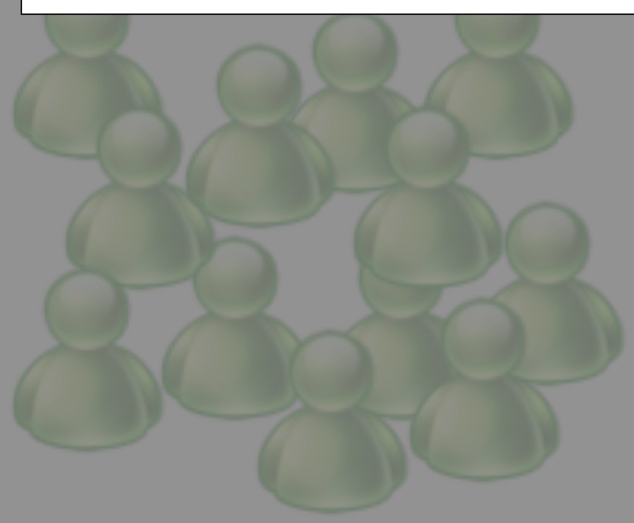
- Interact with one worker at a time
- Workers are i.i.d. drawn

Contract Design in Crowdsourcing

Contract

	Bad Outcome worth $1	Good Outcome worth $5
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

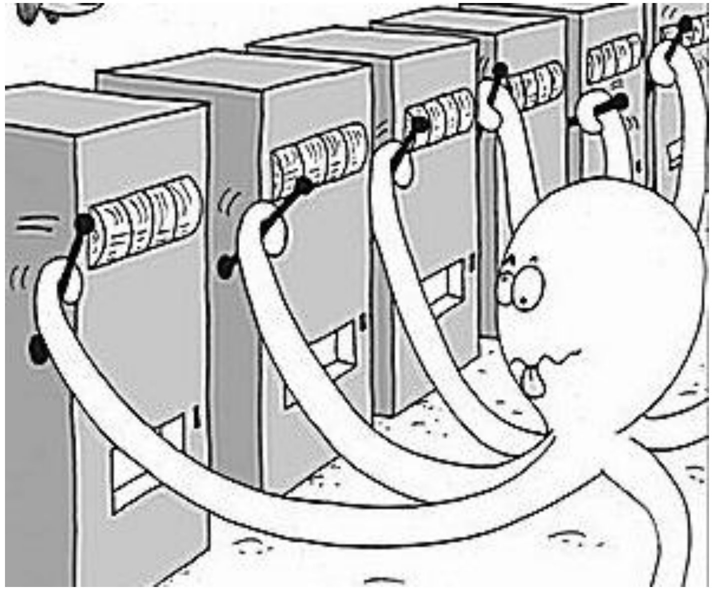
Alex Slivkins
Microsoft Research

Jenn Wortman Vaughan
Microsoft Research

Appeared In ACM EC'14 and JAIR'16

Contract Design as A Machine Learning Problem

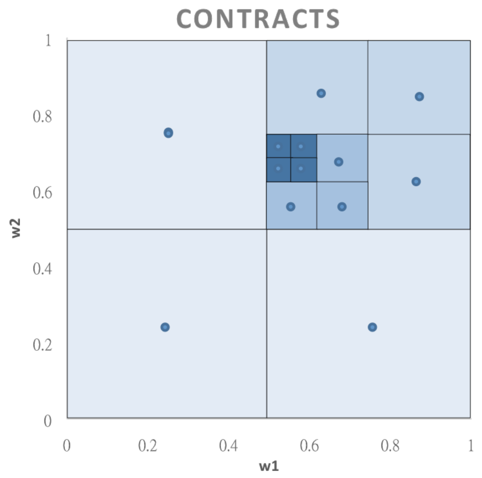
- At each time step
  - the requester posts a payment
  - a worker completes the task and returns the result
  - the requester observes the result and updates the payment
- An online learning problem (bandit learning)
  - exploring the payoff of each payment
  - exploiting the optimal payment
  - exploration/exploitation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



Dealing with Infinitely Many Payments

- 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 $\boxed{\text{workers are rational and myopic,}}$
  we can learn the optimal payment efficiently!

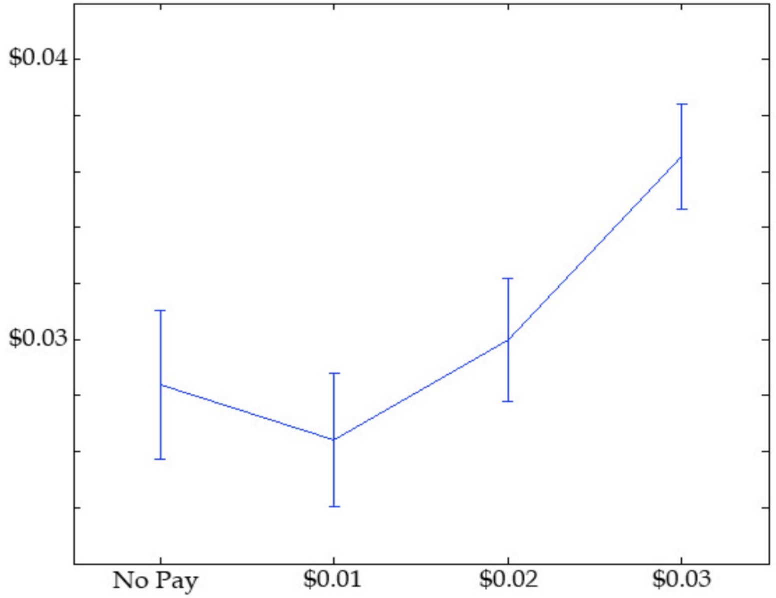
> The average difference of running our algorithm for T rounds and running the optimal algorithm for T rounds is bounded by $\boxed{O(1/T^{\alpha})}$, where $\alpha > 0$ indicates the difficulty of learning.

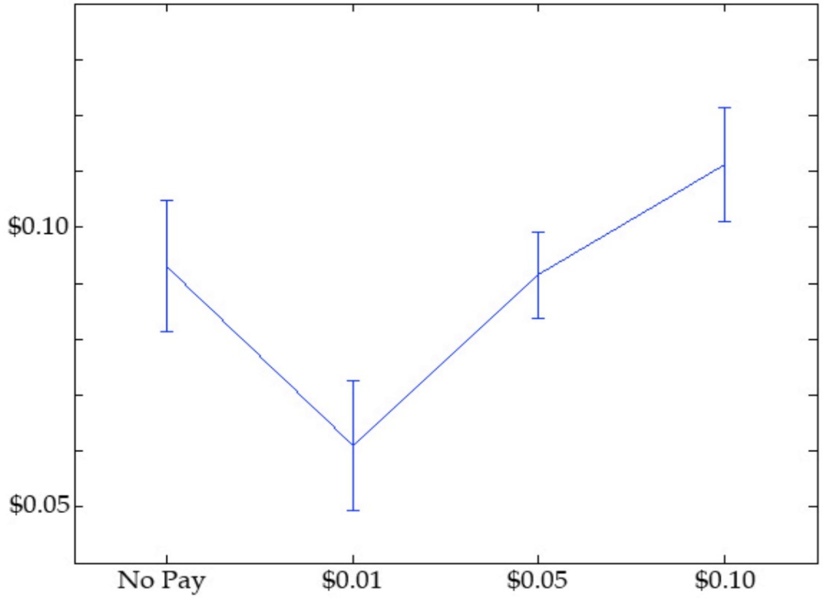
Discussion

- 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



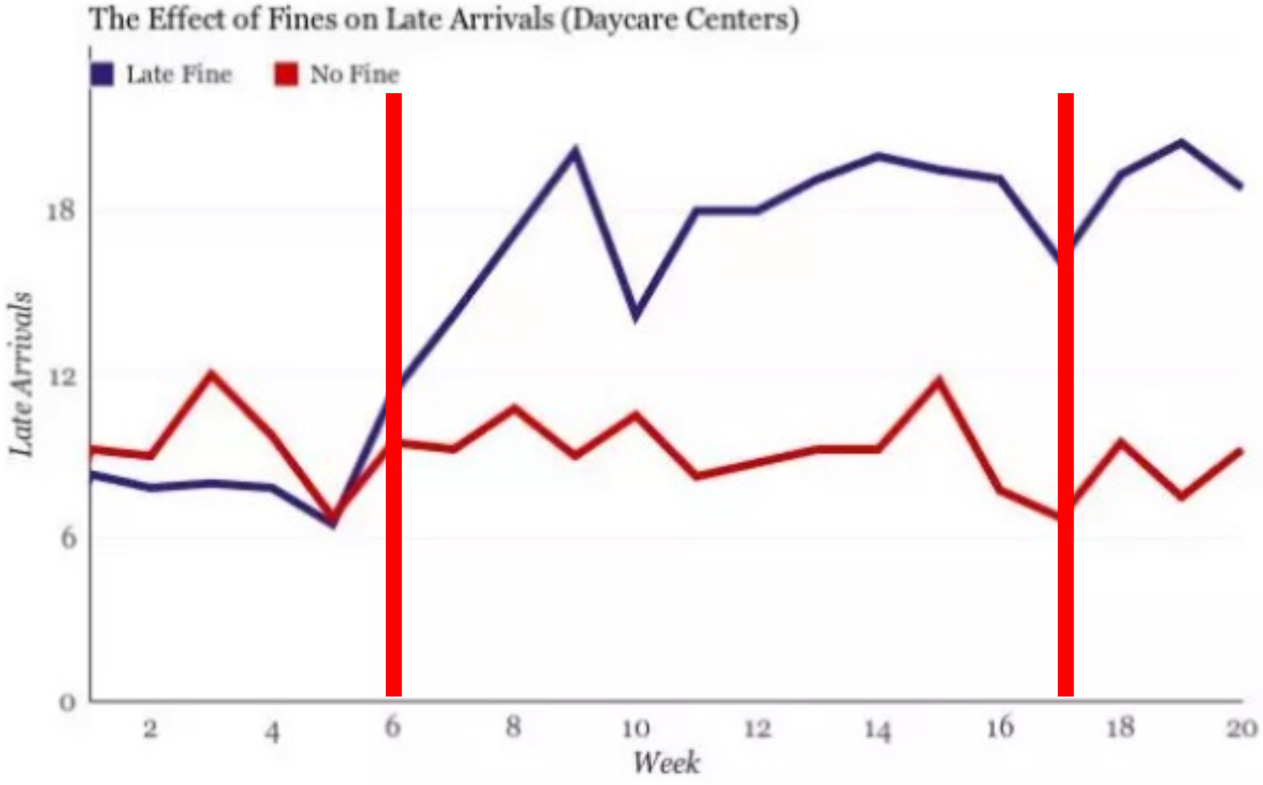


X-axis: the payment they receive
Y-axis: the payment they think it should be

Financial Incentives and the "Performance of Crowds”. Mason and Watts. HCOMP 2009.

Effectiveness of Fines for Late Pick-Up at Daycare Centers

Priceonomics



Are workers really *rational*?

Incentivizing High Quality Crowdwork

joint work with

Alex Slivkins
Microsoft Research

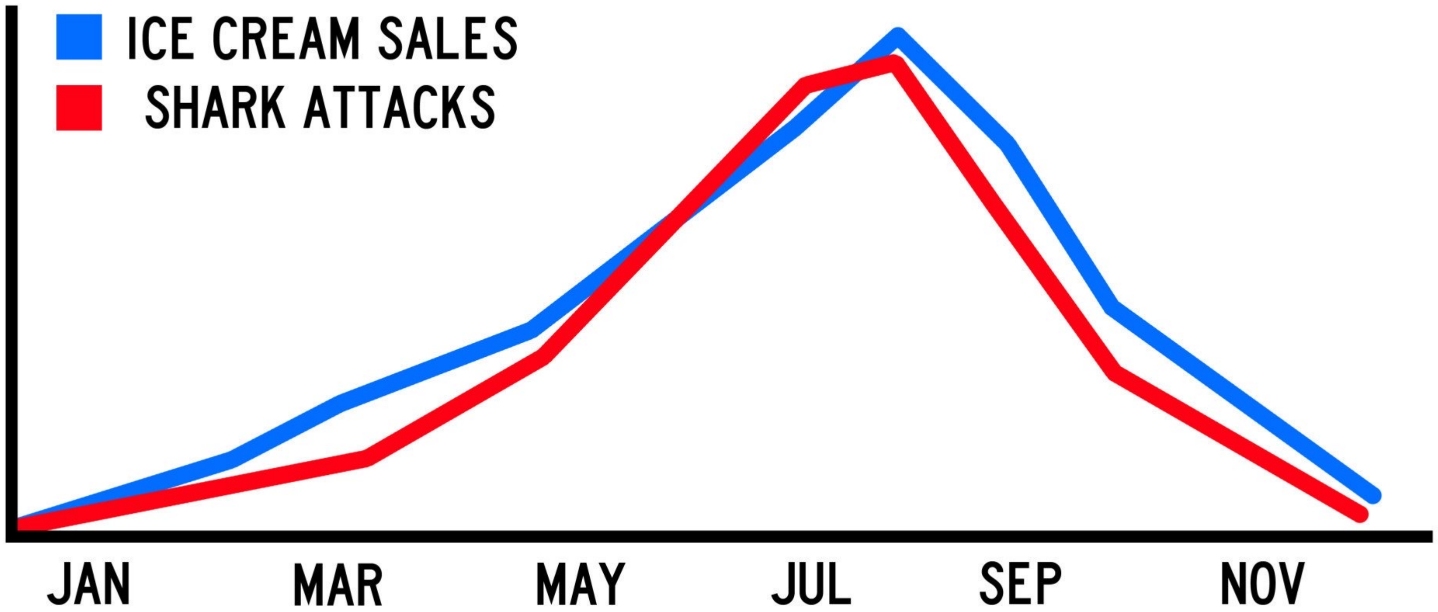
Sid Suri
Microsoft Research

Jenn Wortman Vaughan
Microsoft Research

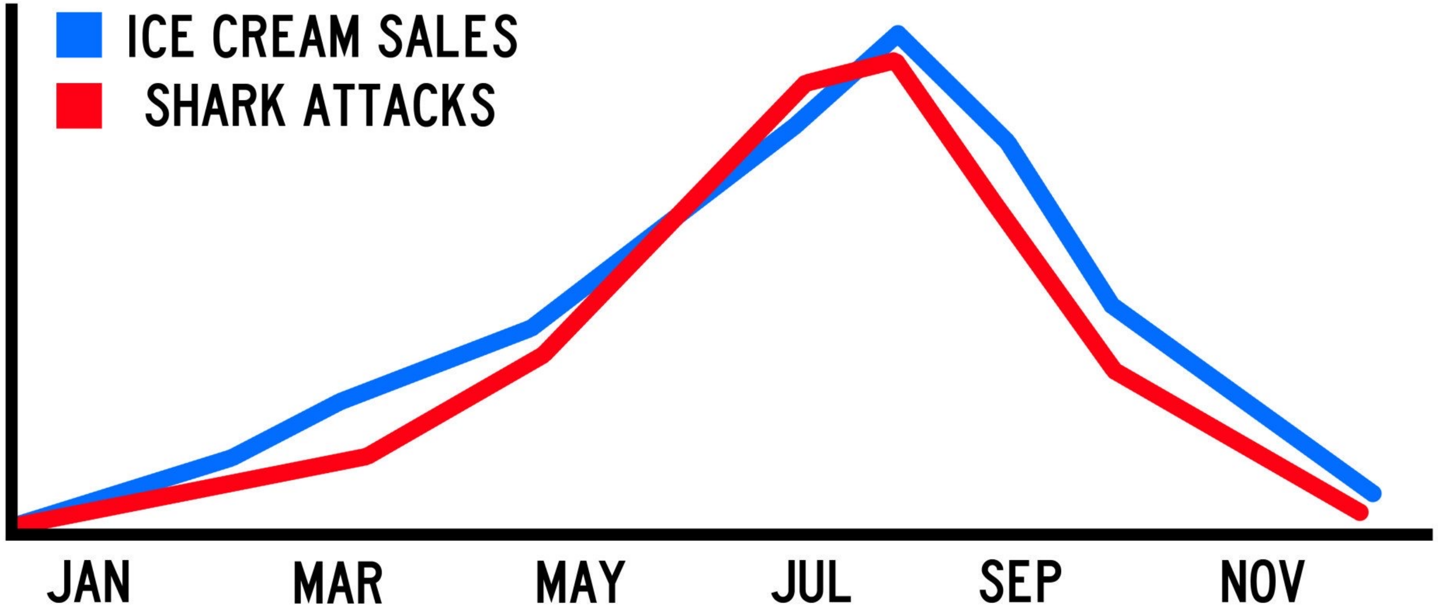
Are workers really *rational*?

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

Causality ≠ Correlation



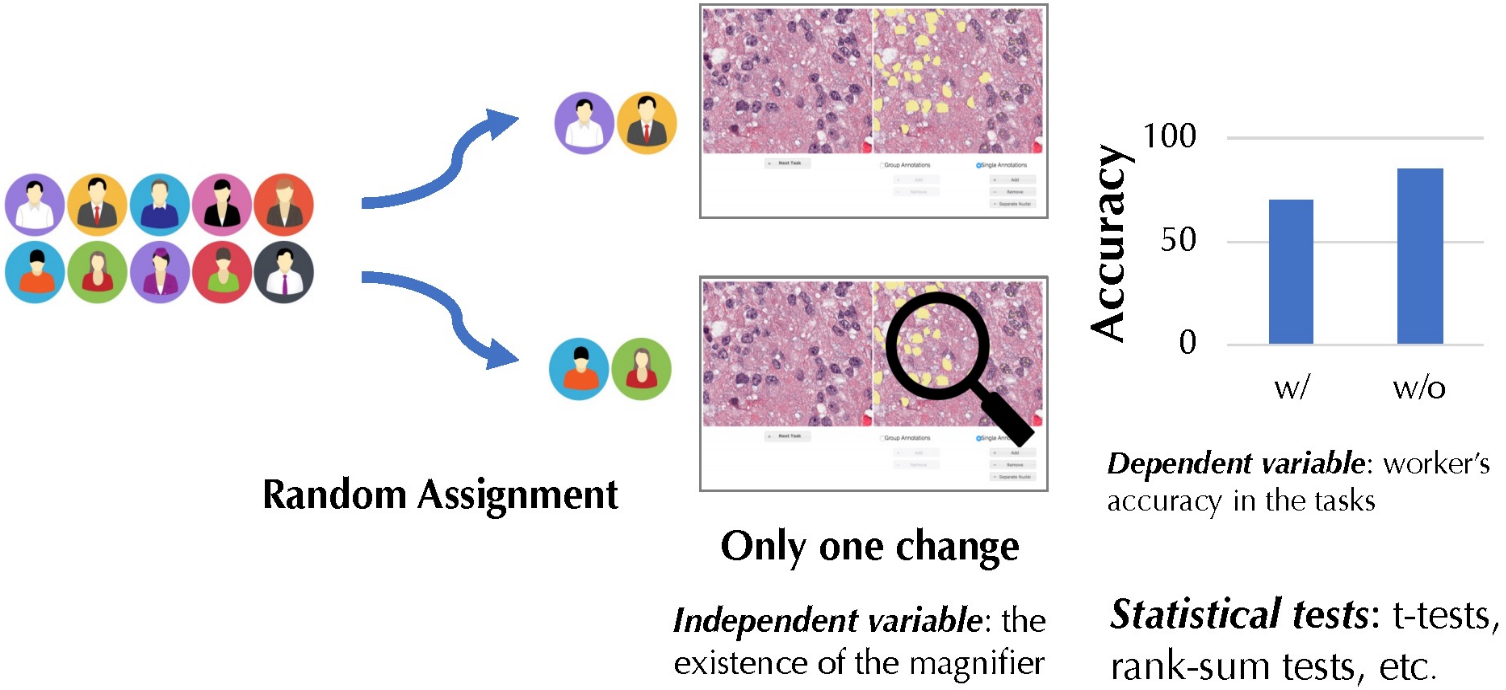
Causality ≠ Correlation



Both ice cream sales and shark attacks increase when the weather is hot and sunny, but they are not caused by each other (they are caused by good weather, with lots of people at the beach, both eating ice cream and having a swim in the sea)

Causality ≠ Correlation

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

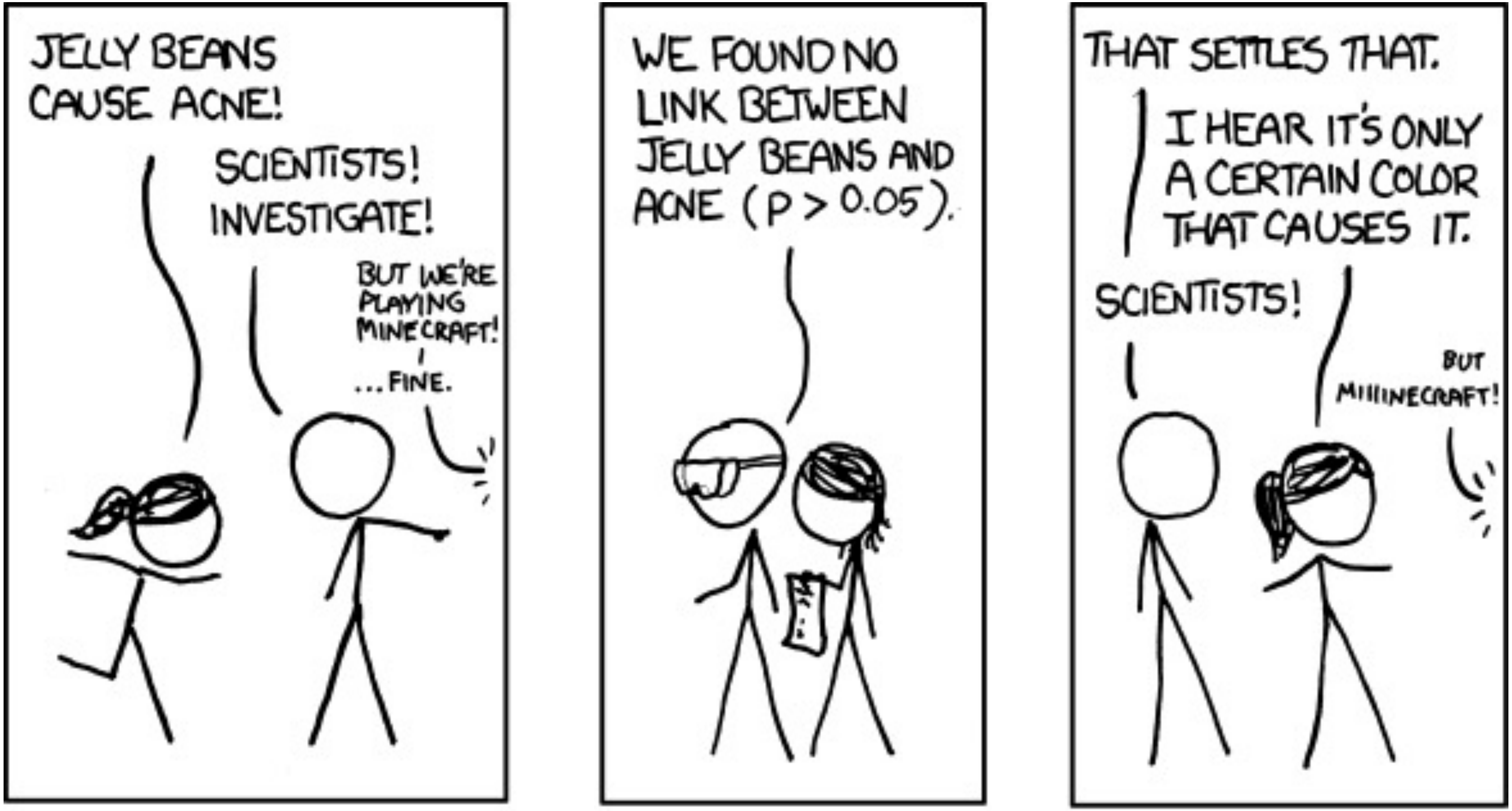


There have been studies on inferring causality using observational data, but they require some assumptions.

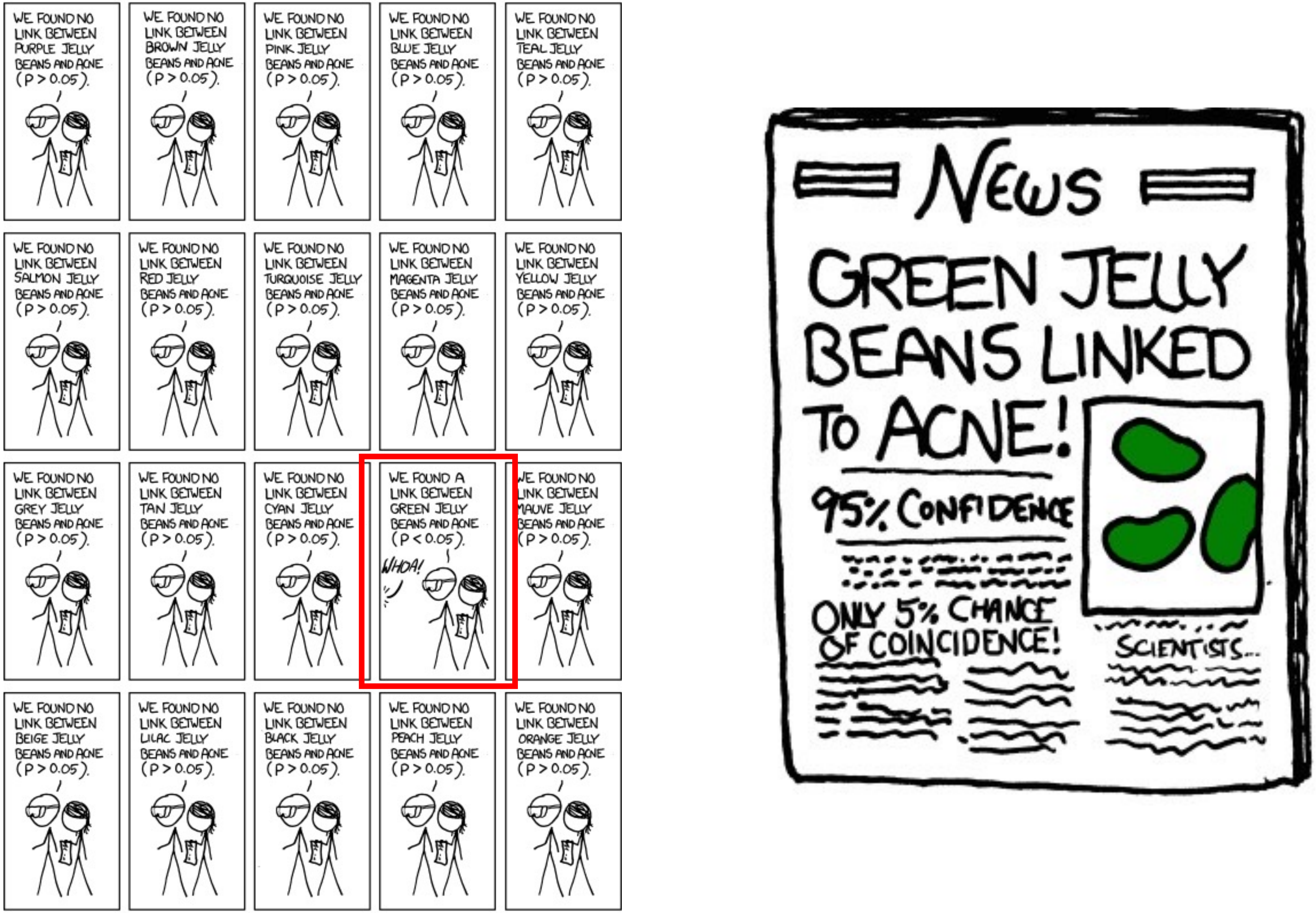
A bit more notes…

- 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



From xkcd, by Randall Munroe: http://xkcd.com/882



From xkcd, by Randall Munroe: http://xkcd.com/882

How do workers really react to performance-based payments (PBPs)?

In the economics literature...

- PBPs improve quality in lab experiments [CH99] and can help in real firms (observational study) [L00]

In crowdsourcing markets...

- Paying more increases the quantity of work, but not the quality [MW09, RK+11, BKG11, LRR14]
- Mixed results on whether PBPs help
  - PBPs improve performance [H11, YCS14]
  - PBPs do not improve performance [SHC11]
  - Bonus size does not matter [YCS13]

Which led to this work...

- We explore whether, when, why, and where performance-based payments (PBPs) improve the quality of crowdwork on Amazon Mechanical Turk.

- We propose a novel but simple worker model coherent with our empirical results.

Experiment 1: Does PBP work?

- Verify that performance-based payments (PBPs) can lead to higher quality crowdwork at least for some tasks.

- Determine if there exists an implicit PBP effect:
  workers have subjective beliefs on the quality of work they must produce to receive the base payment, and therefore already behave as if payments are (implicitly) performance-based.

Experiment 1: Does PBP work?

- Task: Proofread an article and find spelling errors.

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 Philistine
3: hosts; and while some of these are giants only in comparision with their
4: fellows, belonging to families whose members are short of stature, others are
5: sufficently 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 be
7: long ages before man trod this earth. The most gigantic of mammals—the
8: whales—still survive, and the elphant 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. Early in 1838, Bishop
18: Colenso, while on a missonary visit to the East Cape region, heard from the
19: natives of Waiapu tales of a monstrous bird, called Moa, having the head of a
20: man, that inhabited the mountain-side some eighty miles away. This mighty bird,
21: the last of his race, was said to be attened by two equally huge lizards that
22: kept guard while he slept, and on the approach of man wakened the Moa, who
23: imediately 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.
27:
28: About the same time another missionary, the Rev. Richard Taylor, found a bone
29: ascribed to the Moa, and met with a very similer traditition among the natives of
30: a near-by district, only, as the foot of the rainbow moves away as we move
31: toward it, in his case the bird was said to dwell in quite a diffrent locality
32: from that given by the natives of East Cape. While, however, the Maoris were

- We randomly insert 20 typos
  - sufficiently -> sufficently
  - existence -> existance
  - …
- Useful properties:
  - Quality is measurable
  - Exerting more effort leads to better results

Experiment 1: Does PBP work?

Base payment: \$0.50; Bonus payment: \$1.00

Three Bonus Treatments:

- *No Bonus:* no bonus or mention of a bonus
- *Bonus for All:* get the bonus unconditionally
- *PBP:* get the bonus if you find 75% of the typos found by others

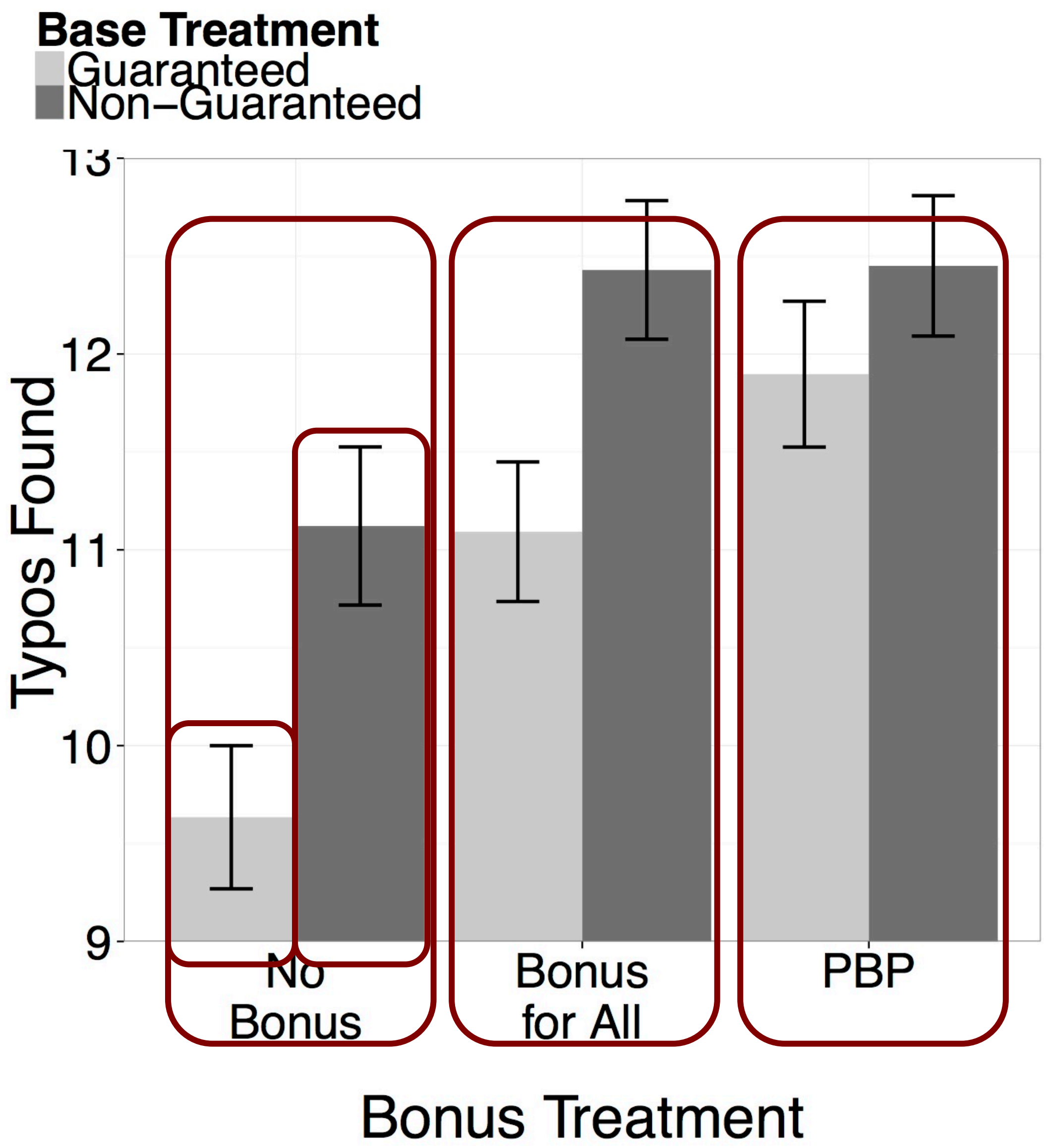
Two Base Treatments:

- *Guaranteed:* guaranteed to get paid
- *Non-Guaranteed:* no mention of a guarantee

Workers saw exactly the same description before accepting the task.

After accepting the task, they are randomly assigned to the treatments.

Experiment 1: Does PBP work?

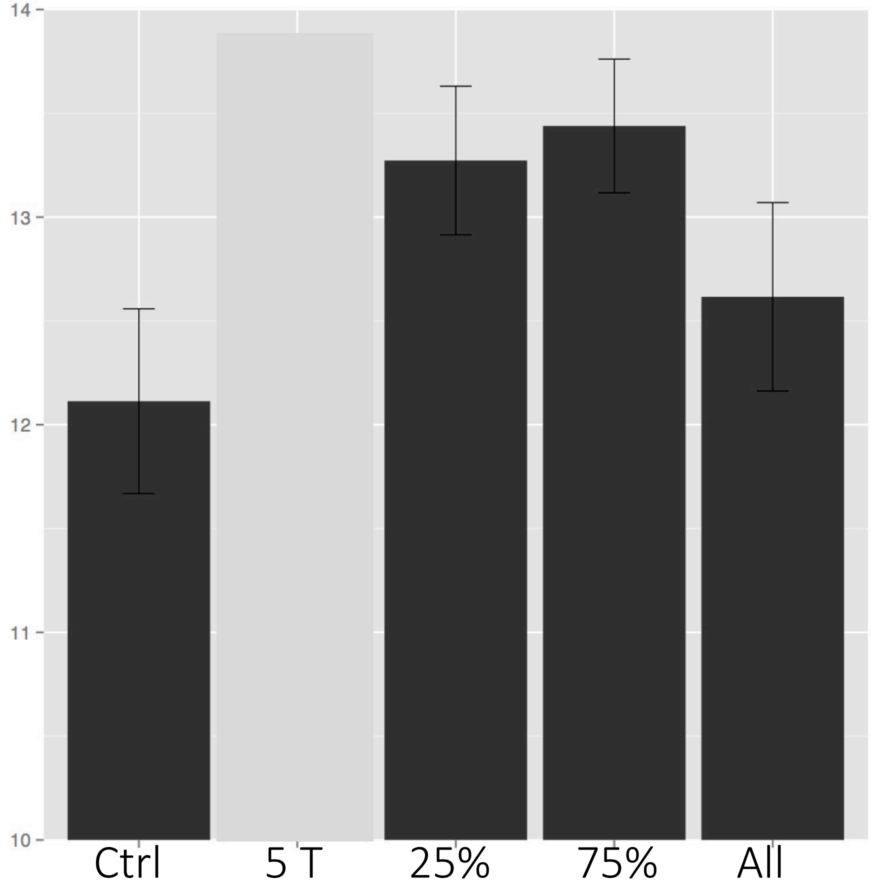


- Results from 1000 unique workers
- Guaranteed payments hurt (implicit PBP)
- PBP improves quality
- Paying more also improves quality

Experiment 2: When does PBP work?

Bonus threshold (585 unique workers)

- \$0.50 base + \$1.00 bonus for finding *X* typos

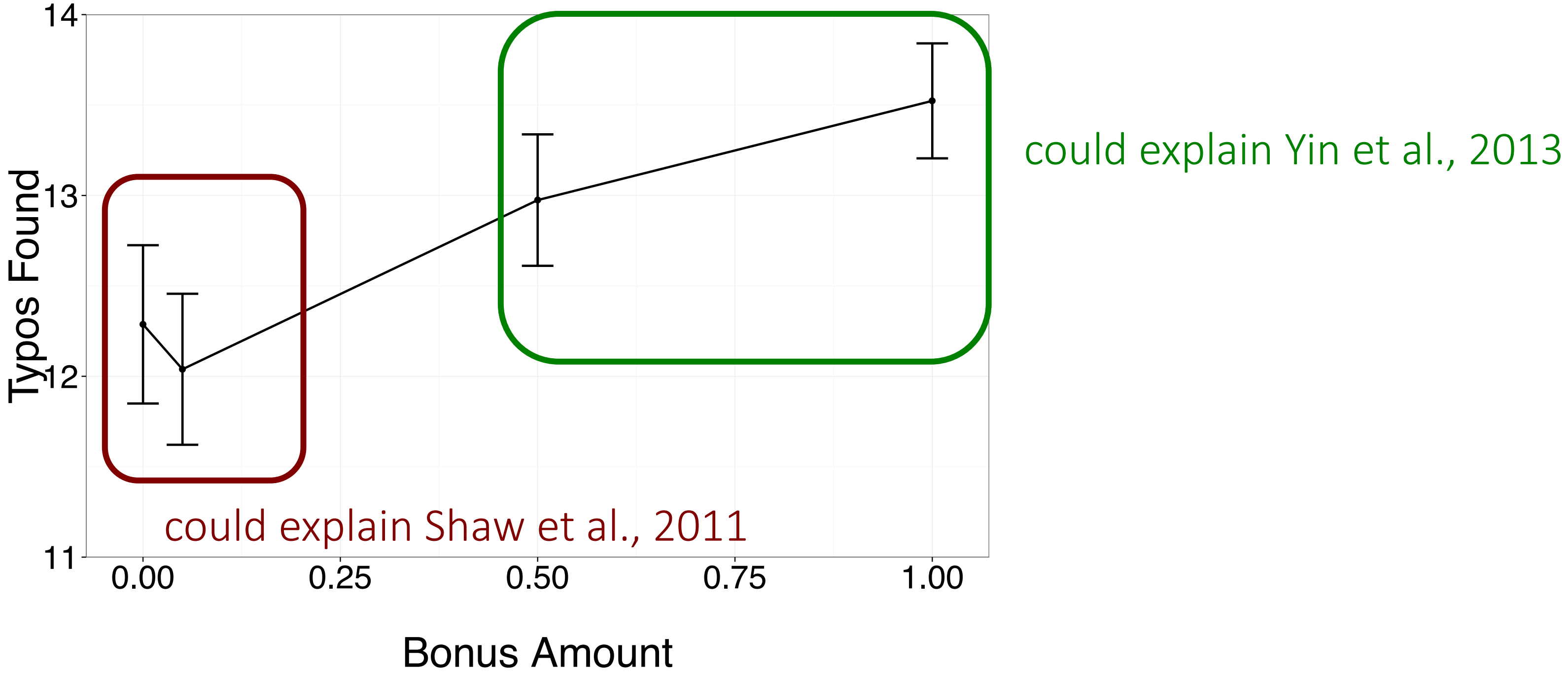


- PBPs work for a wide range of thresholds
- Subjective beliefs (5 typos vs. 25% of typos) can improve quality

Experiment 2: When does PBP work?

Bonus amounts (451 unique workers)

- \$0.50 base + \$*X* bonus for finding 75% of typos
- PBPs work as long as the bonus is large enough



Experiment 3: Why does PBP work?

Possible explanations:

- Workers are rational and aim to maximize their expected payoff (expected payment - cost)
- Workers work harder when being paid more
- Workers work harder when receiving unexpected bonuses for the work [G14]
    - To avoid selection bias, our bonus description is announced *after* a worker accepts the task.

Experiment 3: Why does PBP work?

Can we separate the unexpected bonus effects?

- Goal: Give workers full payment description before they accept our tasks while avoiding selection bias
- Use qualifications for random treatment assignment
    - Post recruitment tasks to recruit a pool of workers
    - Randomly assign workers to different treatments
    - Invite workers to complete tasks
    - Ensure workers cannot see other tasks using qualifications

Experiment 3: Why does PBP work?

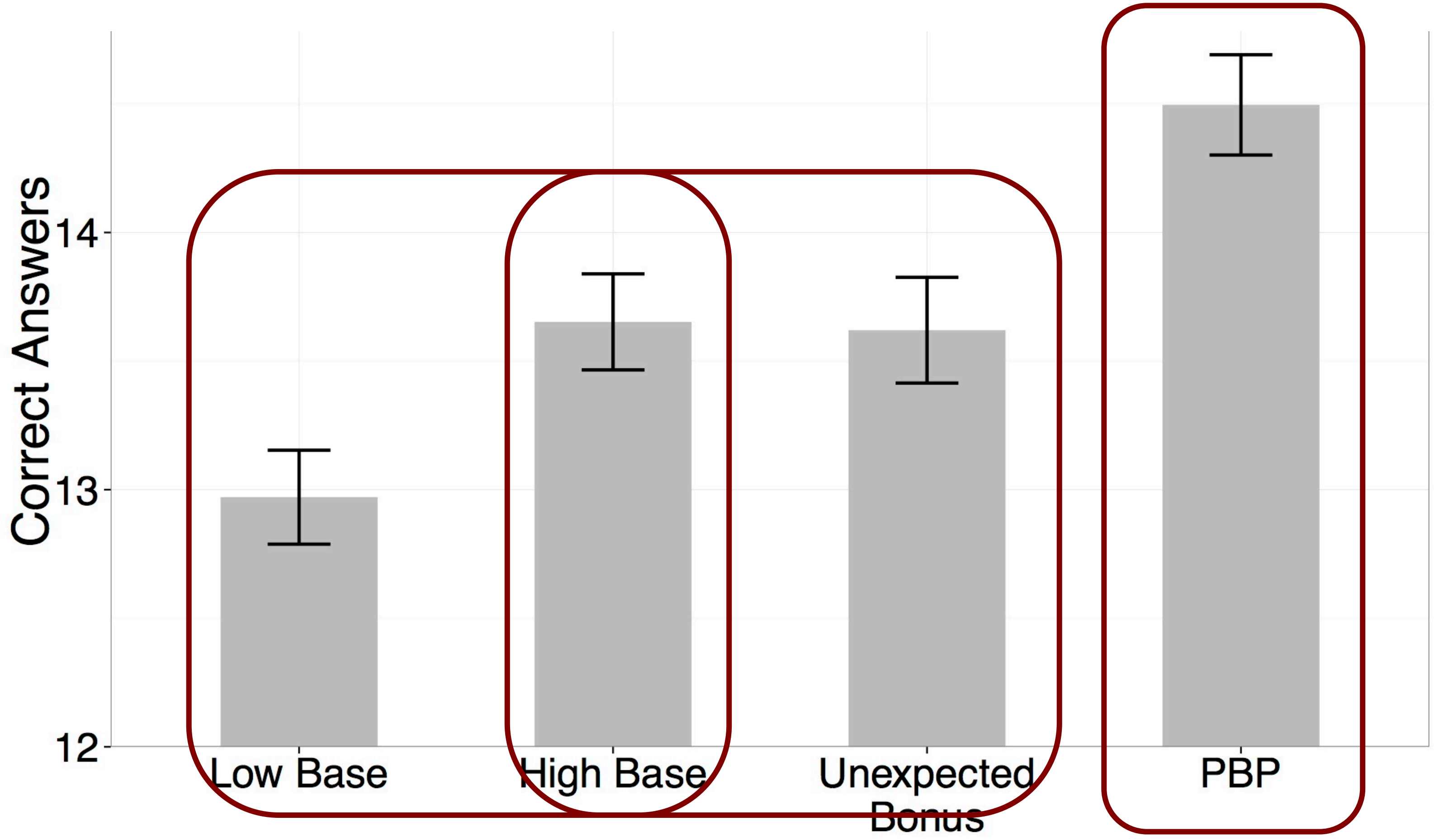
Task: Determining whether or not there are differences between 20 pairs of images [Y13]

Four treatments:

- *Low base*: $0.50 base payment
- *High base*: $1.50 base payment
- *Unexpected bonus*: $0.50 base + $1.00 unconditional (unexpected) bonus
- *PBP*: $0.50 base + $1.00 bonus if accuracy >= 80%

Experiment 3: Why does PBP work?

- **Results** (542 unique workers)



No unexpected bonus effects

Paying more works,
but PBP works even better

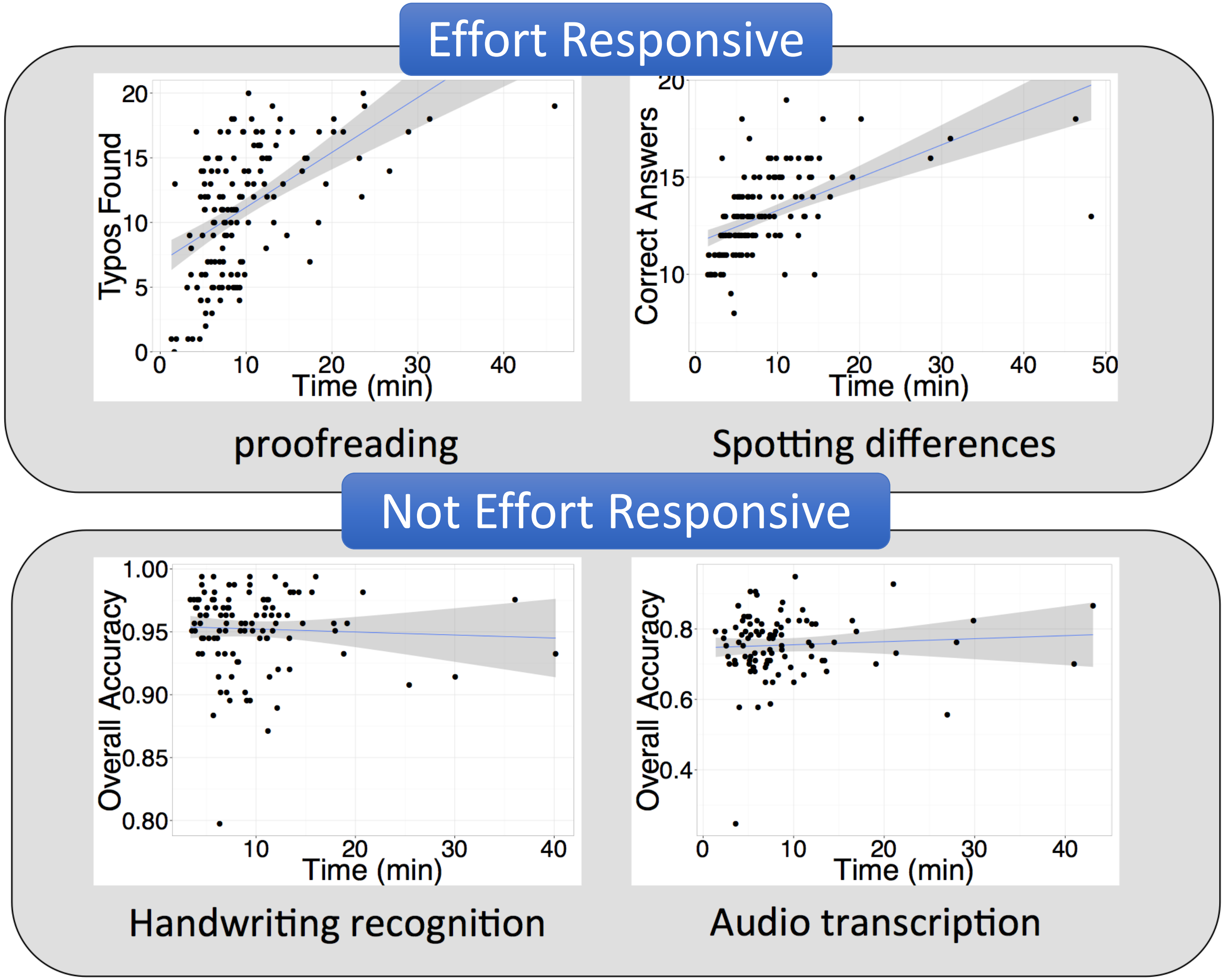
Experiment 4: Where does PBP work?

- What properties of a task allow PBP to improve quality?

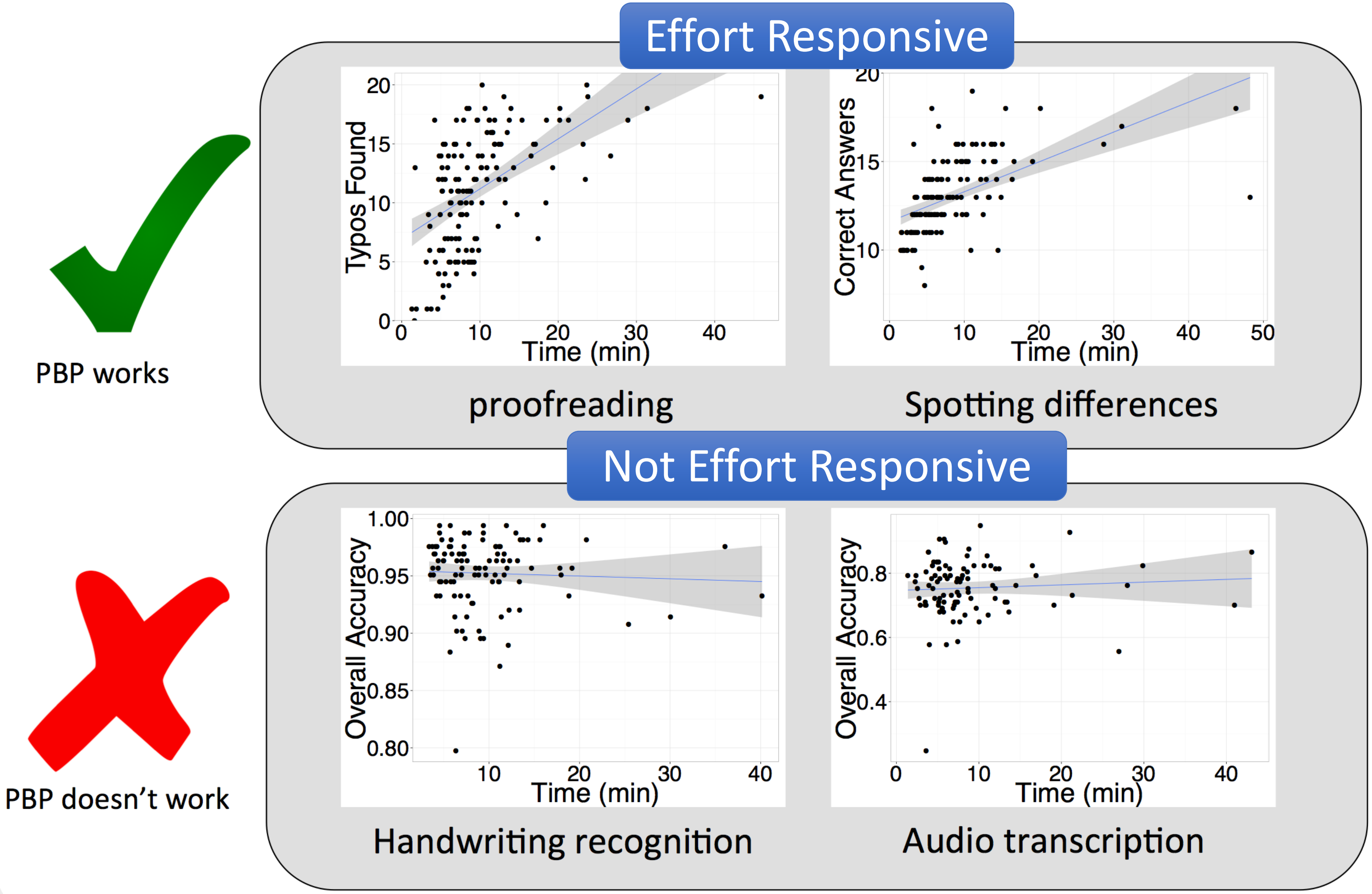
- Some pilot experiments suggested that
  - PBPs improve quality for effort-responsive tasks
  - It is not always straightforward to guess which tasks are effort-responsive.

- Examine the correlation between effort-responsiveness and whether PBPs work.
  - Use time as a proxy for effort

Experiment 4: Where does PBP work?



Experiment 4: Where does PBP work?



Worker Model

- Standard economic assumption (principal-agent model): each worker chooses to produce work of the quality q that maximizes their expected utility:

$$
\begin{aligned}
&\text{BasePayment} \\
&\quad + \text{BonusPayment} \times \Pr(\text{GetBonus} \mid q) \\
&\quad - \text{Cost}(q)
\end{aligned}
$$

true probability of receiving the bonus

(*positive or negative*) intrinsic cost of performing the work

Worker Model

- In our model, workers choose q to maximize:

subjective probability of receiving the base

$$\text{BasePayment} \times \Pr(\text{GetBase} \mid q)$$
$$+ \text{BonusPayment} \times \Pr(\text{GetBonus} \mid q)$$
$$- \text{Cost}(q)$$

subjective probability of receiving the bonus

Worker Model

This model can be used to explain key observations from our experiments:

- Subjective beliefs about acceptance increase quality.
- Higher payments increase quality. (Not true for PA!)
- Performance-based payments (significantly) increase quality when
  - the task is effort-responsive
  - there are no ceiling effects
  - the bonus payment is sufficiently high
  - the bonus is not too easy to obtain

Results from HSV14 still apply under this model!

Conclusion

- We explore whether, when, why, and where performance-based payments improve the quality of crowdwork and propose a novel but simple worker model coherent with our results.

- More in this line of research
  - Can we use empirical insights to inform the algorithmic theory of human computation?
  - What can this informed algorithmic theory give back to the crowdsourcing research?

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?

Social Networks and Incentives

The Small-World Experiment [Stanley Milgram, 1967]

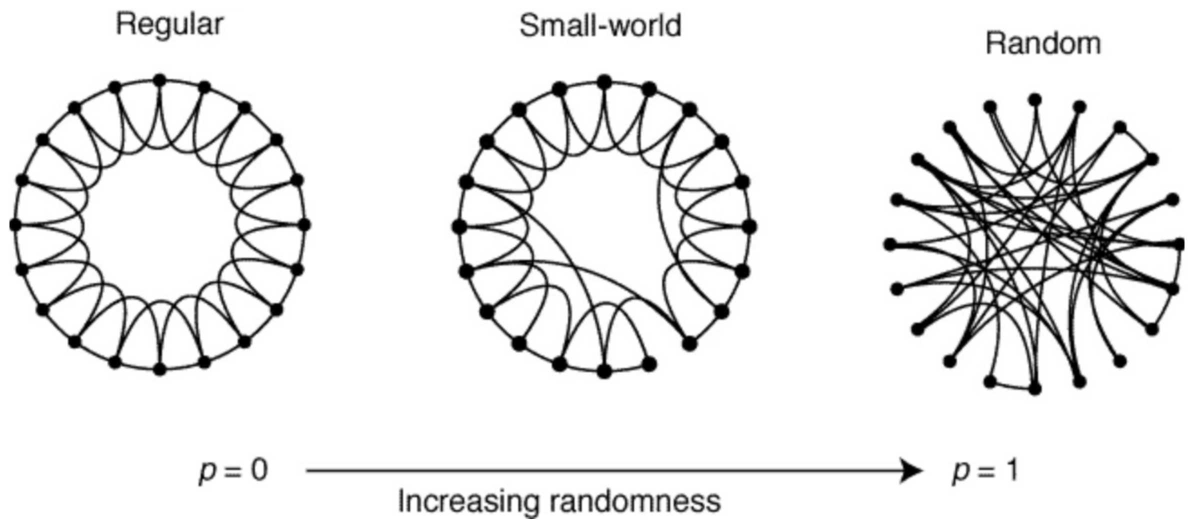
[The figure is from Wikipedia]

- How many hops does it take to deliver a mail from a person in Nebraska/Kansas to a person in Massachusetts?
- A person can only pass the mail to someone she/he knows in a first-name basis.
- Average: Around 5.5~6 hops
  - Six degrees of separation

There are criticisms on the methodology, but the results are still very impressive

Small-World Networks [Watts and Strogatz, Nature 1998]

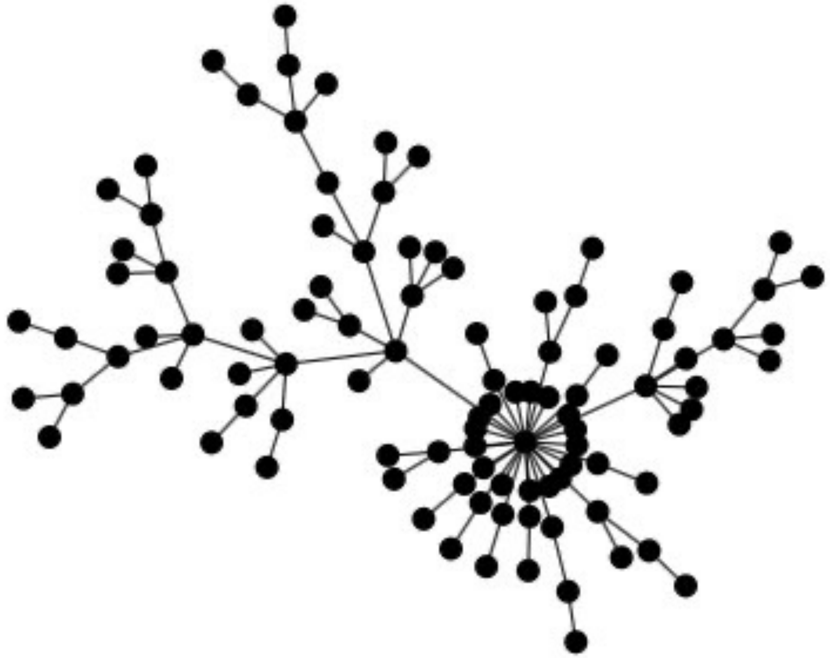
- Two characteristics
  - People form “cliques” (my friends are usually my friends’ friends)
  - There are some random links



- “One of the models” that explain the small world phenomenon

Another Social Network Model

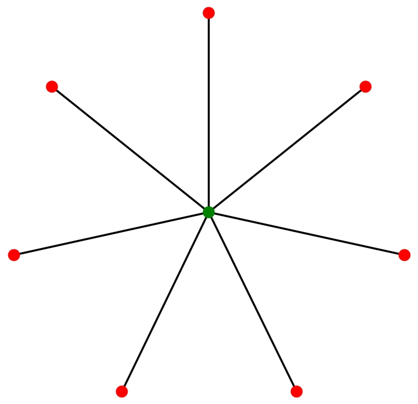
- Preferential Attachments (Barabási–Albert Model)
  - People join the network on by one
  - Attach (form edges) to existing members
  - Attach probability proportional to edges



- Explains the rich-gets-richer effect

Friendship Paradox [Scott L. Feld. 1991]

- On average, do your friends have more friends than you have?
  - Yes, if we take the average over everyone in the network.



Average # friends: $\frac{7*1+7}{8} = 1.75$

Average # friends a person's friends have: $\frac{7*7+1}{8} = 6.25$

- Local observations could be distorted by the network structure
  - One's friends are happier, wealthier, more popular…

Utilizing the Power of Networks

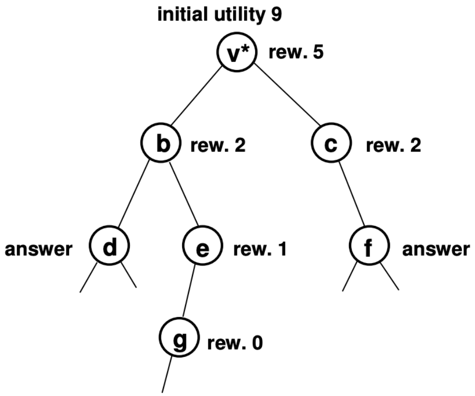
- Given we can reach most people in a small number of hops, can we utilize the people in networks to help with tasks.

- Not that trivial
  - A replication of the small world experiment using emails has faced a high-level of drop-out rate since people are not motivated in attending.

- Need proper incentives:
  - See more in the seminal paper of query incentive networks

Query Incentive Networks [Kleinberg and Raghavan, 2005]

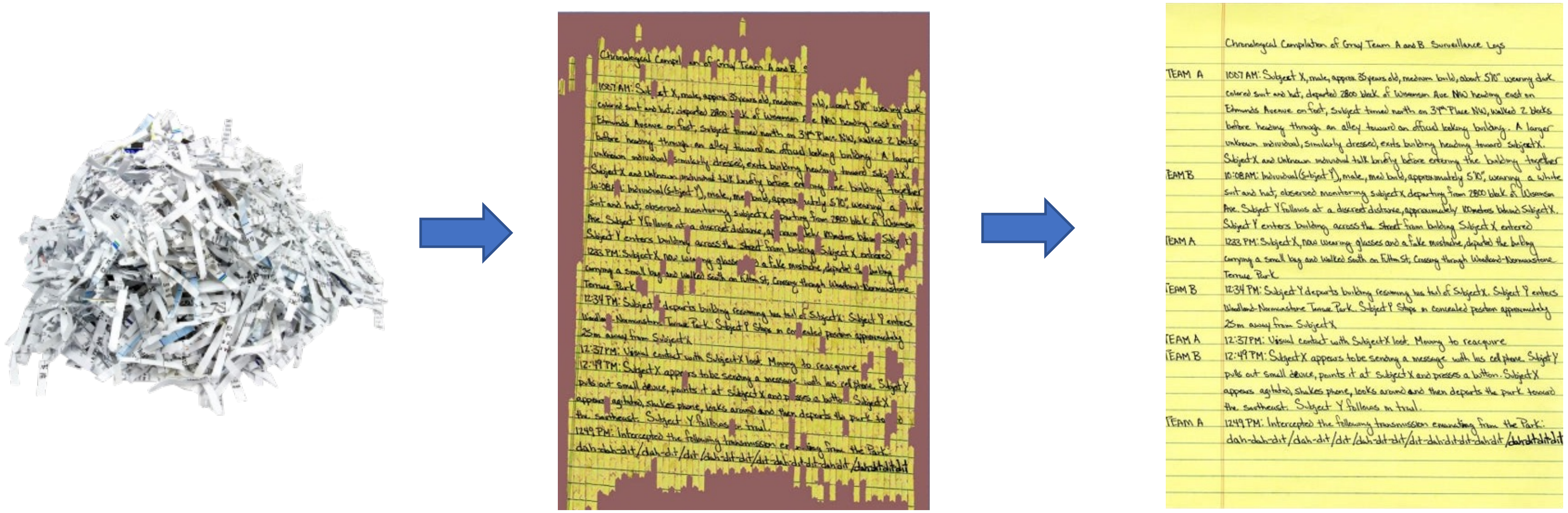
- Formalize the theoretical discussion on incentives in networks



- Successful example: DARPA network challenge

Generalize the Results from DARPA Network Challenge

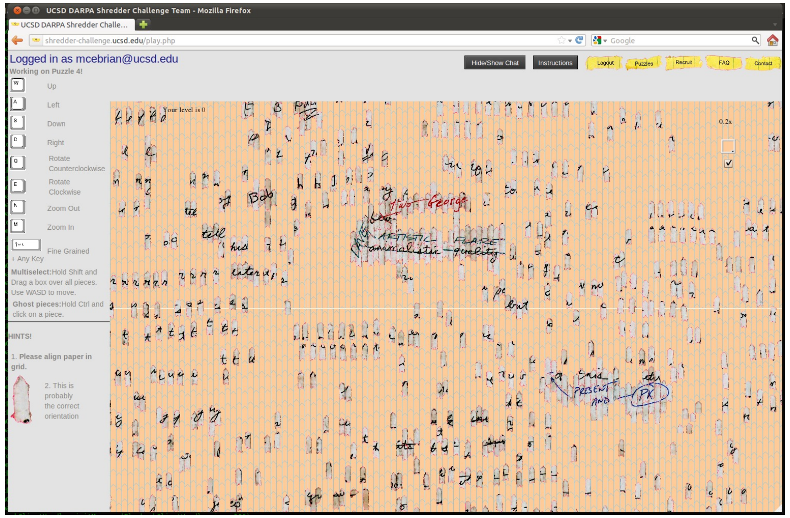
- DARPA shredder challenge, 2011
  - Goal: Piece together the information in shredded paper



  - First team to complete 5 puzzles win $50,000
  - Duration: October 27, 2011 to December 4, 2011

Generalize the Results from DARPA Network Challenge

- UCSD team tried the same method as MIT team did in network challenge



"However, the crowd was hopeless against a determined attacker. Before the first attack, our progress on the fourth puzzle had combined 39,299 moves by 342 users over more than 38 hours. Destroying all this progress required just 416 moves by one attacker in about an hour."

"creation took 100 times as many moves and about 40 times longer than destruction." [How Crowdsourcing Turned On Me](). Iyad Rahwan.

- Solved 3 (out of 5) puzzles in 5 days
- No progress after that
  - Too many sabotage attempts to ruin their results
  - Designing mechanisms **robust** to adversarial attacks is important but non-trivial

Utilizing the Power of Networks

- Influence maximization [Who should we start to ask questions?]
  - You can send products to K people to try on
  - Assume people who try the product will tell their neighbors with some probability
  - Who should you choose to send the products maximize the expected number of people knowing your product?

Generally a NP-hard question.

There exists efficient approximation algorithms, if you know the network structure.

What if you don’t know the network structure?

- Learning and sampling

Utilizing the Power of Networks

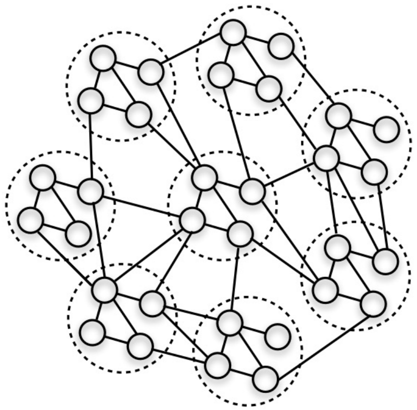
- AI for social good:
  Taking interventions to prevent HIV for homelessness youth [Wilder et al. 2021]

- Procedure
  - Recruit “peer leaders” in drop-in centers
  - Train the leaders and have them help disseminate the information
  - Adapt techniques from influence maximization to maximize the information spread

- Help reduce 31% chance of risk behavior

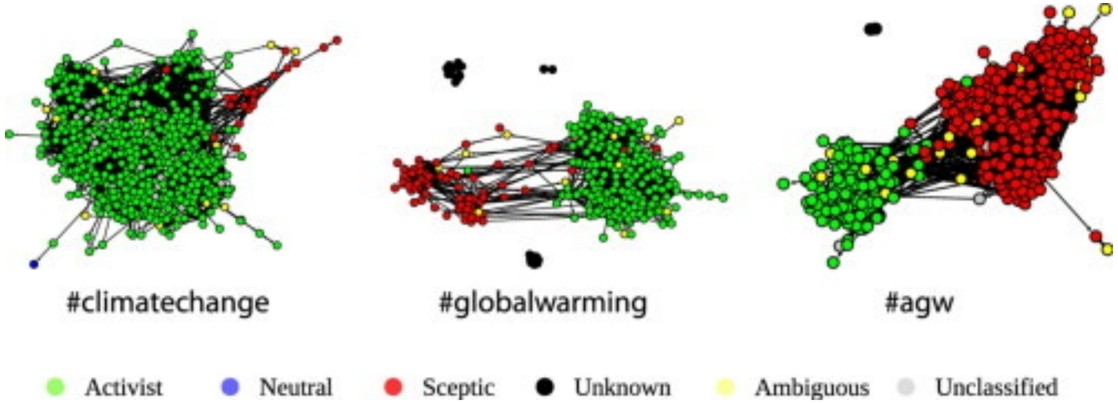
Other Challenges/Opportunities of Networks

- Network could create biases in data collection [Saveski et al. 2017]

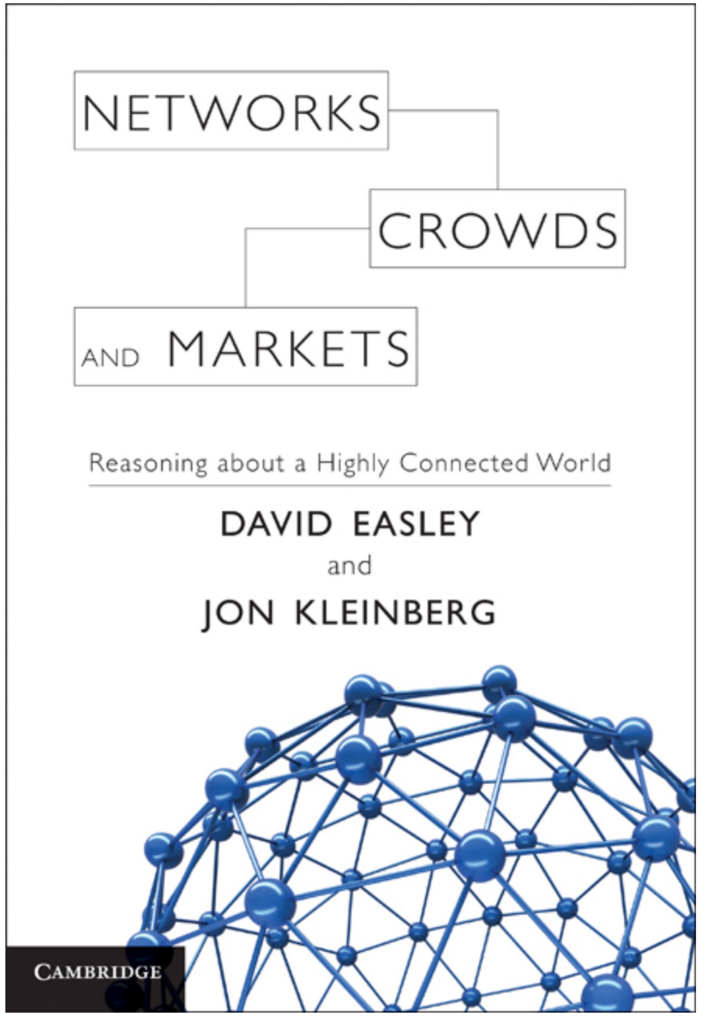


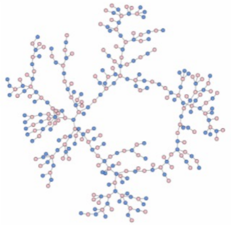
Neighbors might have similar opinions
Break the common “independence” assumption

- Opinion formation: Human opinions might be influenced by networks

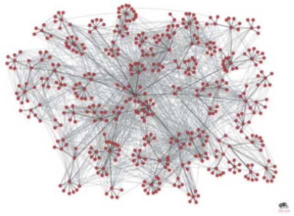


[Williams et al. 2015]



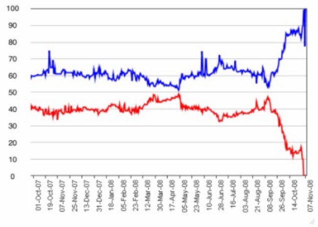


High School Dating
(Bearman, Moody, and Stovel, 2004)
(Image by Mark Newman)



Corporate E-Mail Communication
(Adamic and Adar, 2005)

Trails of Flickr Users
in Manhattan
(Crandall et al. 2009)



Prediction Market for the
2008 U.S. Presidential Election
(Iowa Electonic Markets, 2008)

Networks, Crowds, and Markets:

Reasoning About a Highly Connected World

By David Easley and Jon Kleinberg

https://www.cs.cornell.edu/home/kleinber/networks-book/