

Lecture 17

What's Next for Crowdsourcing

Instructor: Chien-Ju (CJ) Ho

Logistics: Project

- Milestone 2: Due Nov 20 (Friday)
- Midterm Project Pitch and Discussion: Nov 19 (Thu) in Lecture
 - A chance to get feedback or collect data from other students
 - Think about whether/how you can best utilize this time
- If you want to collect data from the entire class during the Nov 19 lecture, please let me know by [this Thursday \(Nov 12\)](#).

Logistics: Assignment 4

- No class on Nov 24, Tuesday (happy thanksgiving!)
- Instead, I'll give a list of talks/tutorials relevant to this course.
 - Choose one of them, watch the content, and write a report
 - The report needs to be no less than 2 pages, with any reasonable format
 - The report will serve as your assignment 4
- More details will be announced next week

Lecture Today

Recap of what we have discussed so far

Introduce what we will discuss in the next few lectures

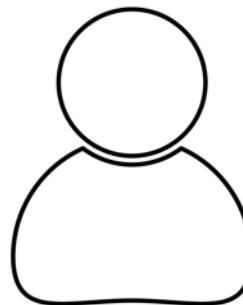
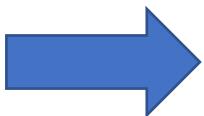
Discussion on related topics that are not covered in this course

What We Have Discussed So far

Human-in-the-Loop Computation:
From Task Solvers' Perspective

From Task Solvers' Perspective

Tasks



Output

Microtasks

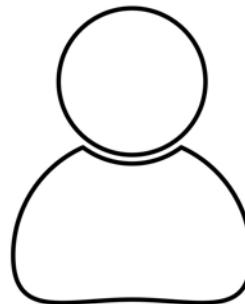


Flower
Dog
Cute

...

From Task Solvers' Perspective

Tasks



Output

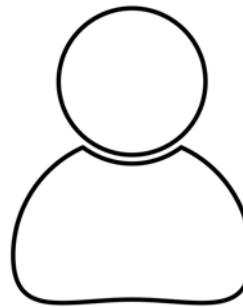
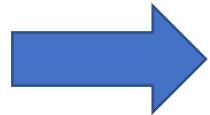
Key Challenge: How To Ensure Output Quality

Human as data sources:
Label aggregation
Probabilistic reasoning to aggregate noisy human data

Humans are “Humans”:
Incentive design
Game theoretical modeling of humans and incentive design

From Task Solvers' Perspective

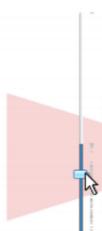
Tasks



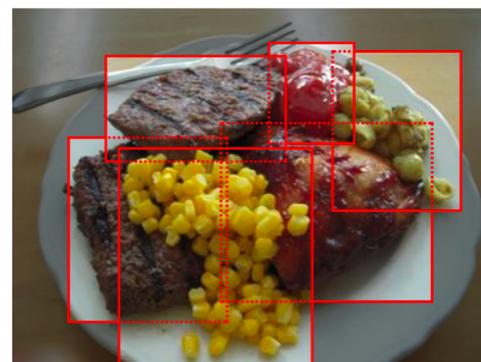
Output

Practical challenges: Real-time, non-independent work, complex tasks

Automatic clustering generally helps separate different kinds of records that need to be edited differently, but it isn't perfect. Sometimes it creates more clusters than needed, because the differences in structure aren't important to the user's particular editing task. For example, if the user only needs to edit near the end of each line, then differences at the start of the line are largely irrelevant, and it isn't necessary to split based on those differences. Conversely, sometimes the clustering isn't fine enough, leaving heterogeneous clusters that must be edited one line at a time. One solution to this problem would be to let the user rearrange the clustering manually, perhaps using drag-and-drop to merge and split clusters. Clustering and selection generalization would also be improved by recognizing common text structure like URLs, filenames, email addresses, dates, times, etc.

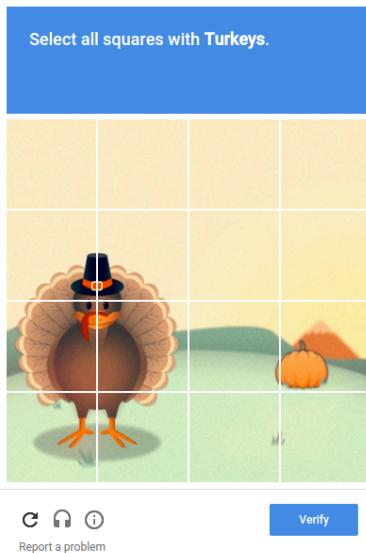


Automatic clustering generally helps separate different kinds of records that need to be edited differently, but it isn't perfect. Sometimes it creates more clusters than needed, because the differences in structure aren't relevant to a specific task. | Conversely, sometimes the clustering isn't fine enough, leaving heterogeneous clusters that must be edited one line at a time. One solution to this problem would be to let the user rearrange the clustering manually using drag-and-drop edits. Clustering and selection generalization would also be improved by recognizing common text structure like URLs, filenames, email addresses, dates, times, etc.



(From Lecture 1) What is this course about?

- Study the design and analysis of human-in-the-loop computation.



**Human as data sources:
Label aggregation**
Probabilistic reasoning to
aggregate noisy human data

**Practical challenges:
Real-time and complex tasks**
Studies on workflow and team
designs from HCI perspective

**Humans are “Humans”:
Incentive design**
Game theoretical modeling of
humans and incentive design

Crowdsourcing and Human Computation



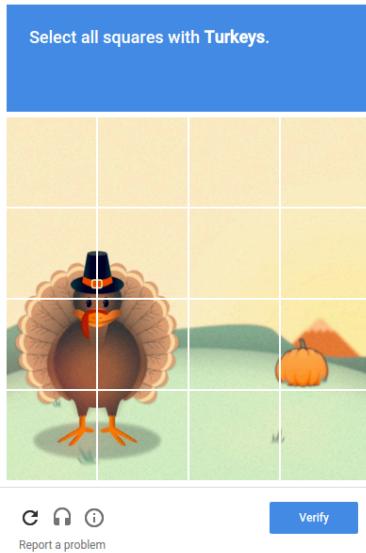
Human-in-the-Loop Computation

Remaining Lectures: Focus on Human-AI Interactions

- Ethical decision making (Nov 12)
 - Can we, and how can we, ask **humans** to help **AI** make "ethical" decisions
- Fairness in AI (Nov 17 and Dec 1)
 - Are the decisions made by **AI** *fair* to **humans** involved?
- Interpretable machine learning (Dec 3)
 - How to make the predictions by **AI** understandable by **humans**.
- Strategic machine learning (Dec 8)
 - What if **humans** who generated data are influenced by the outcome of **AI**?
- Human-AI Collaboration (Dec 10)
 - Can we team up **humans** and **AI** to solve tasks together?

(From Lecture 1) What is this course about?

- Study the design and analysis of human-in-the-loop computation.



Human as data sources: Label aggregation

Probabilistic reasoning to
aggregate noisy human data

Practical challenges: Real-time and complex tasks

Studies on workflow and team
designs from HCI perspective

Humans are “Humans”: Incentive design

Game theoretical modeling of
humans and incentive design

Selected recent topics:

Ethical issues of AI/ML, learning
with strategic behavior, Human-
AI collaborations.

The focus of the next six lectures!

An Emerging Research Agenda on AI/ML + Humans/Society

- WashU Division of Computational and Data Sciences
 - PhD program hosted by CSE, Political Science, Social Work, Psychology and Brain Science
- Stanford Institute for Human-Centered Artificial Intelligence
- MIT Institute for Data, Systems, and Society
- CMU Societal Computing
- USC Center for AI in Society

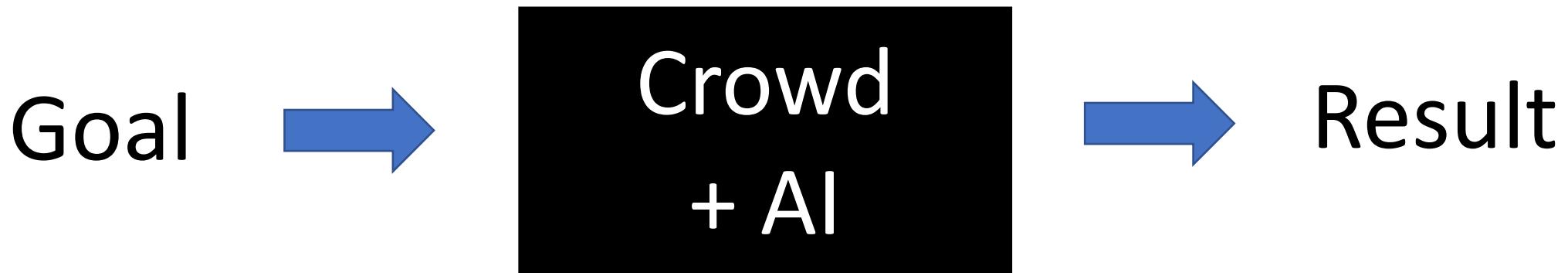
Before we move on...

Required Reading:

Mathematical Foundations For Social Computing.

Yiling Chen, Arpita Ghosh, Michael Kearns, Tim Roughgarden, Jennifer Wortman Vaughan.
Communications of the ACM. 2016

Crowdsourcing Compiler



- Understanding humans, developing realistic *human models*, and incorporating them into the *computation framework*.
- Multidisciplinary in nature



Warm-Up Discussion

- In computer science theory, we usually use time and space complexity to characterize how good an algorithm. Imagine you are now trying to develop a similar theory for algorithms that include humans in the loop, what do you think are the key factors that should be considered?
- What do you think are the top challenge(s) in designing/implementing the crowdsourcing compiler?

Brief Discussions on Topics that We Won't Cover

Beyond Solving Objective Tasks

- Fair division among the crowd
- Crowd research: open and scalable lab
- Crowdsourcing democracy
- Incentives in Blockchain

Fair Division (Resource Allocation)

- Classical example:
 - How to fairly split (fair: envy-free) the cake among two people?



- General research question:
 - How to design mechanisms to allocate resources with “good” properties
 - participants truthfully report their preferences
 - no one is envy of others

Fair Division

- Who should do the household chores



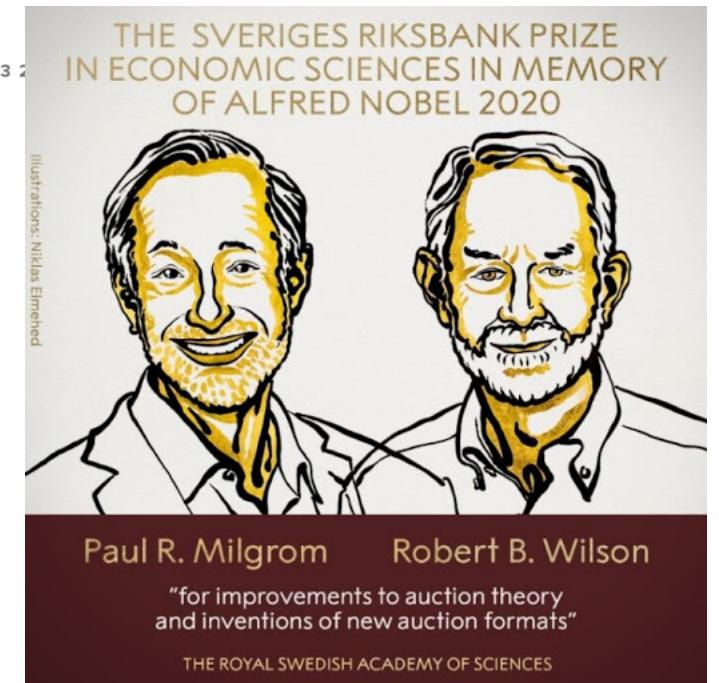
PERSONAL FINANCE

The Couple That Pays Each Other to Put Kids to Bed

PUBLISHED THU, FEB 13 2014 • 11:41 AM EST | UPDATED THU, FEB 13 2014

Essentially a **second-price auction**:

- Each “bid” how much she/he thinks the work is worth
- High bidder pays the amount the low bidder bids
- Low bidder does the work and gets paid



Fair Division

- Spliddit



Share Rent



Split Fare



Assign Credit



Divide Goods

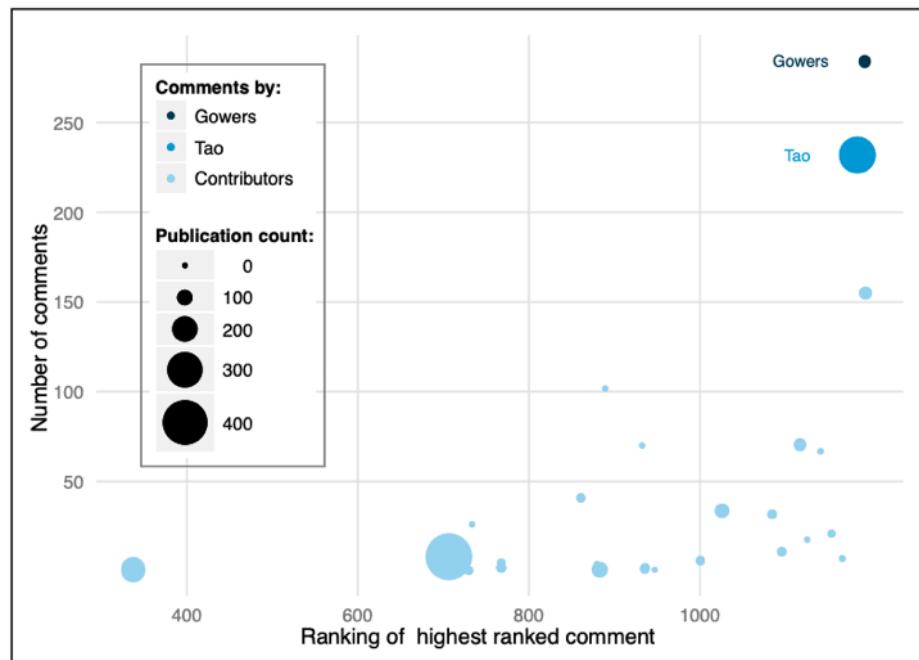


Distribute Tasks

- How do we allocate payments / credits to workers who work together for a complex task?
 - What are the "good" properties we want to achieve
 - How to design algorithms to achieve that?
- Fair division / resource allocation on societal issues
 - How do we allocate "donated organs" to patients who need them?
 - How do we allocate government resources to homeless people?
 - How do we allocate COVID vaccines to people.

Crowd Research: Scalable and Open Lab

- Most research projects are done by small groups of researchers
 - Can we scale up research as well?
 - Success story:
 - Polymath project: Collaborative Math Problem Solving
 - Published papers under the pseudonym **D.H.J. Polymath**.



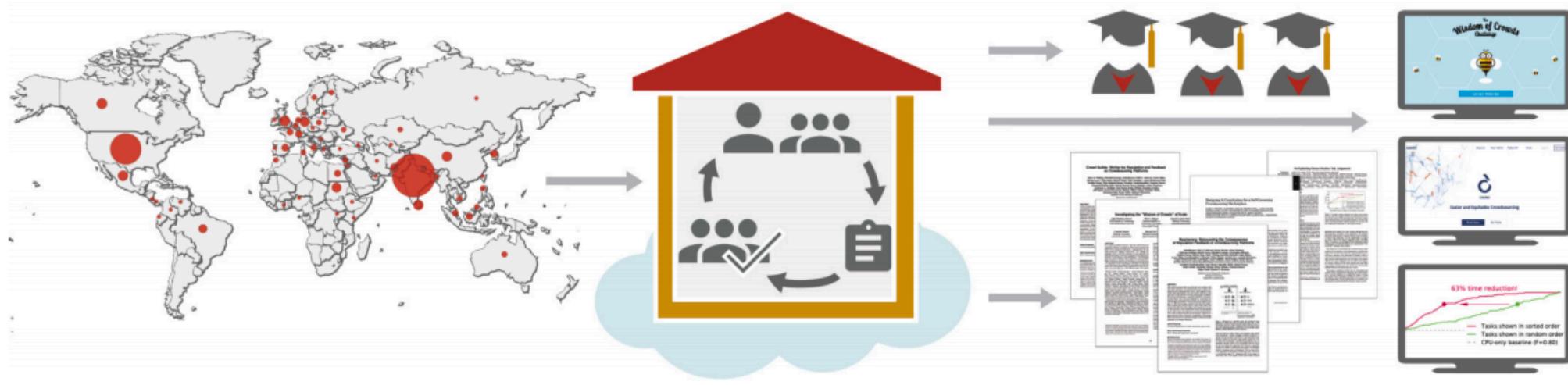
Majority of contributions are done by a few

- Timothy Gowers (U Cambridge)
- Terence Tao (UCLA)

Many have made solid contributions

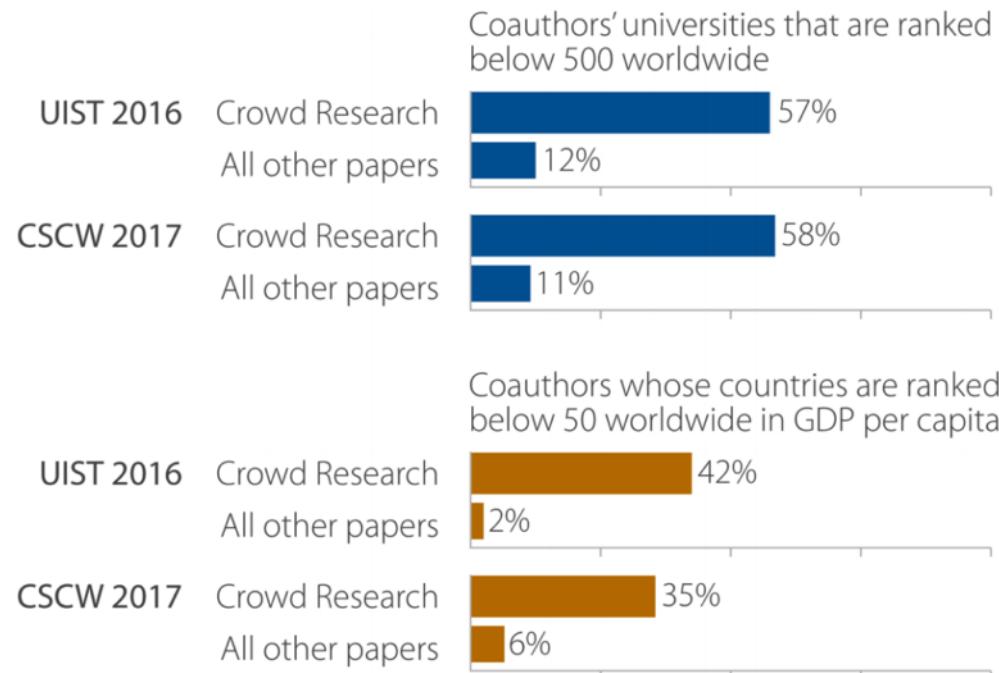
Crowd Research: Scalable and Open Lab

- Incorporating diverse thoughts / skills
 - 1500 participants from 62 countries for 3 research projects



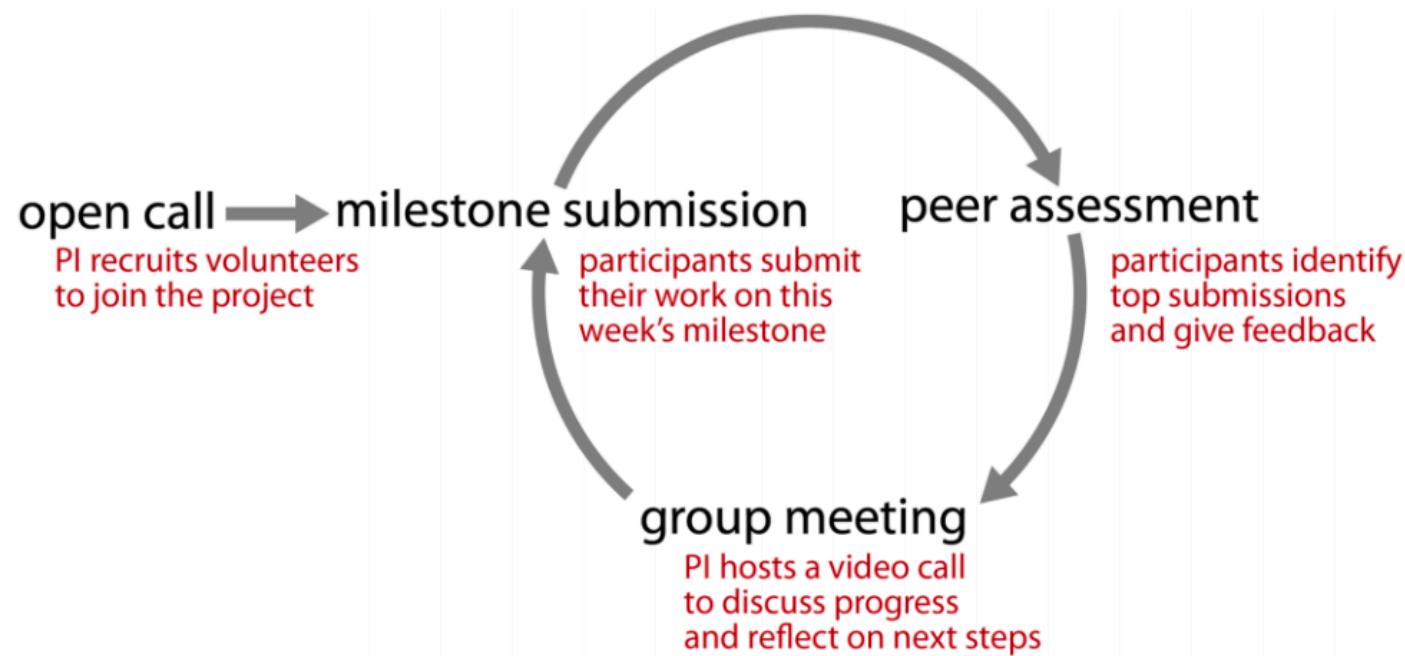
Crowd Research: Scalable and Open Lab

- Incorporating diverse thoughts / skills
 - 1500 participants from 62 countries for 3 research projects
- Enabling research opportunities to students in less resourceful institutions



Crowd Research: Scalable and Open Lab

- Challenges
 - How to maintain the research progress?
 - How to distribute the credits?



Crowd Research: Scalable and Open Lab

- Outcome:
 - A couple of work-in-progress reports
 - Two top-tier conference papers (UIST'16, CSCW'17)
 - Recommendations are given to participants with significant contributions for graduate school applications

Boomerang: Rebounding the Consequences of Reputation Feedback on Crowdsourcing Platforms

Snehal Kumar (Neil) S. Gaikwad, Durim Morina, Adam Ginzberg,
Catherine Mullings, Shirish Goyal, Dilrukshi Gamage, Christopher Diemert,
Mathias Burton, Sharon Zhou, Mark Whiting, Karolina Ziulkoski, Alipta Ballav,
Aaron Gilbee, Senadhipathige S. Niranga, Vibhor Sehgal, Jasmine Lin, Leonardy Kristianto,
Angela Richmond-Fuller, Jeff Regino, Nalin Chhibber, Dinesh Majeti, Sachin Sharma,
Kamila Mananova, Dinesh Dhakal, William Dai, Victoria Purynova, Samarth Sandeep,
Varshine Chandrakanthan, Tejas Sarma, Sekandar Matin, Ahmed Nasser,
Rohit Nistala, Alexander Stolzoff, Kristy Milland, Vinayak Mathur,
Rajan Vaish, Michael S. Bernstein

Stanford Crowd Research Collective
Stanford University
daemo@cs.stanford.edu

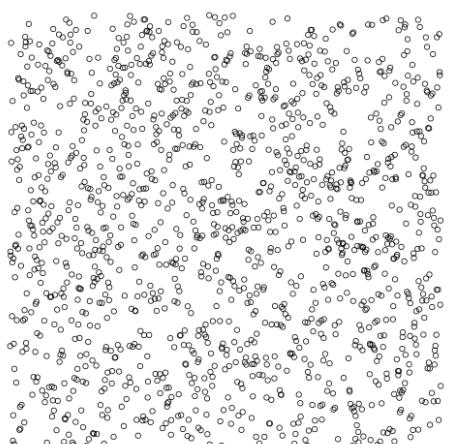
Crowd Guilds: Worker-led Reputation and Feedback on Crowdsourcing Platforms

Mark E. Whiting, Dilrukshi Gamage, Snehal Kumar (Neil) S. Gaikwad, Aaron Gilbee,
Shirish Goyal, Alipta Ballav, Dinesh Majeti, Nalin Chhibber, Angela Richmond-Fuller,
Freddie Vargus, Tejas Seshadri Sarma, Varshine Chandrakanthan, Teogenes Moura,
Mohamed Hashim Salih, Gabriel Bayomi Tinoco Kalejaiye, Adam Ginzberg,
Catherine A. Mullings, Yoni Dayan, Kristy Milland, Henrique Orefice,
Jeff Regino, Sayna Parsi, Kunz Mainali, Vibhor Sehgal, Sekandar Matin,
Akshansh Sinha, Rajan Vaish, Michael S. Bernstein

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Crowdsourcing Democracy

- Democracy is a crowdsourcing process
 - Vote for a leader to make decisions
 - Vote to determine the policy through referendum
 - And more
- Is the crowd always wise?

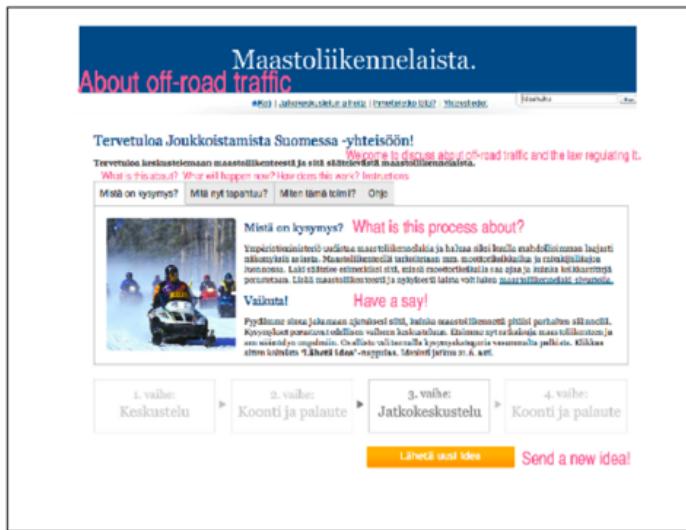


11	494	853	1200
100	500	888	1280
163	500	888	1575
400	550	1000	1920
400	650	1000	2000
441	779	1000	2500
450	784	1086	3500
484	800	1200	4500

Mean: 1059.25
Median: 826.5
Answer: 721

Crowdsourcing Democracy

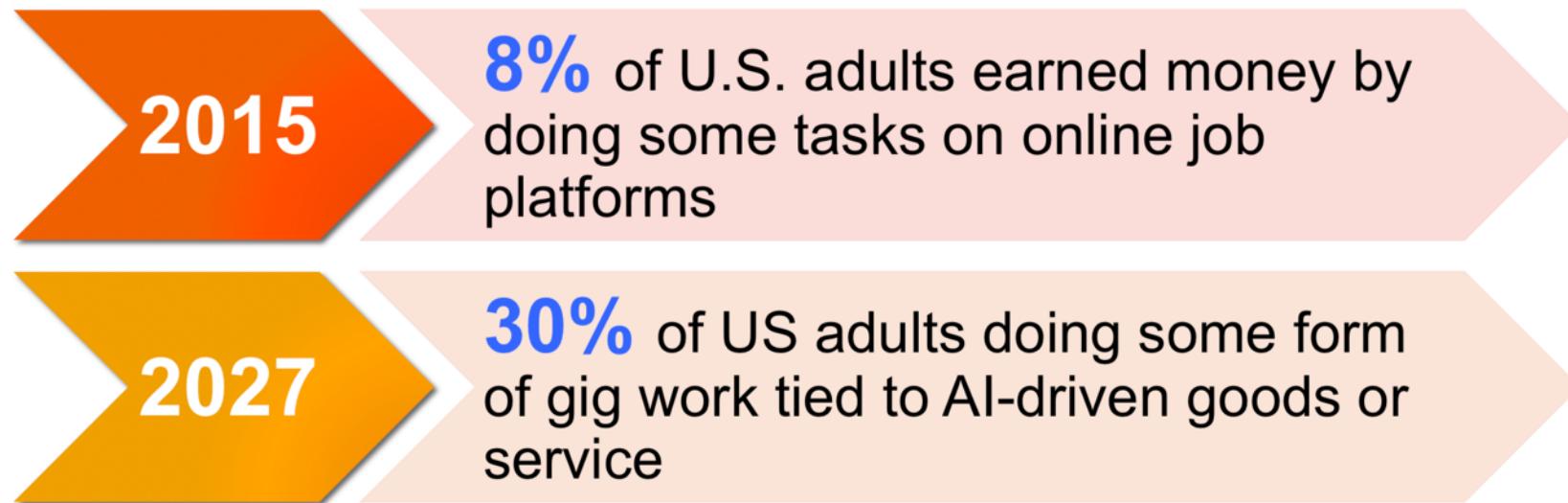
- Helping the crowd to make more informed decisions
 - E.g., enabling information exchange, deliberation



- Potential issues to be careful about
 - Fake news – Misinformation
 - Polarization in social networks

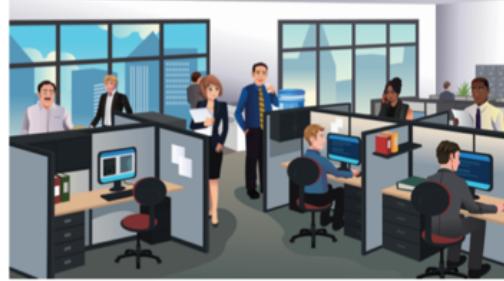
Human-in-the-Loop Computation: From Participants' Perspective

More than Crowdsourcing Markets: Gig-Economy



Gig Work, Online Selling and Home Sharing. Pew Research Center, November 2016
Spike in Online Gig Work: Flash in the Pan or Future of Employment? Social Media Collective, November 2016

Traditional



Centralized



Career

On-demand



Distributed



Piecework



Management Strategies



???

Discussion

- From workers' perspectives, what do you think are “wrong” for the current crowdsourcing platforms? How do you think we can fix it?
- To put these questions into context, consider the following question

“Can we foresee a future crowd workplace in which we would want our children to participate?”

Crowdsourcing =/= Mechanical Turk

- More generally, what do you envision the future of work would be?

Improving Worker Welfare

- Discussion among researchers [Kittur et. CSCW 2013]
 - Create career ladders
 - Motivation, job design, reputation, hierarchy
 - Improve task design through better communications
 - Quality assurance, job design, task assignment, real-time crowd work, synchronous collaboration, platforms
 - Facilitate learning
 - Reputation and credentials, AIs guiding crowds, crowds guiding AIs, task assignment, quality assurance
- Various guidelines for conducting crowdsourcing
 - [Guidelines for Academic Requesters](#)
 - [Responsible Research with Crowds: Pay Crowdworkers at Least Minimum Wage](#)

Future of Work

- One of NSF's 10 Big Ideas:
 - “In 2019, NSF will invest \$30 million in each Big Idea and continue to identify and support emerging opportunities for U.S. leadership in Big Ideas that serve the Nation's future.”

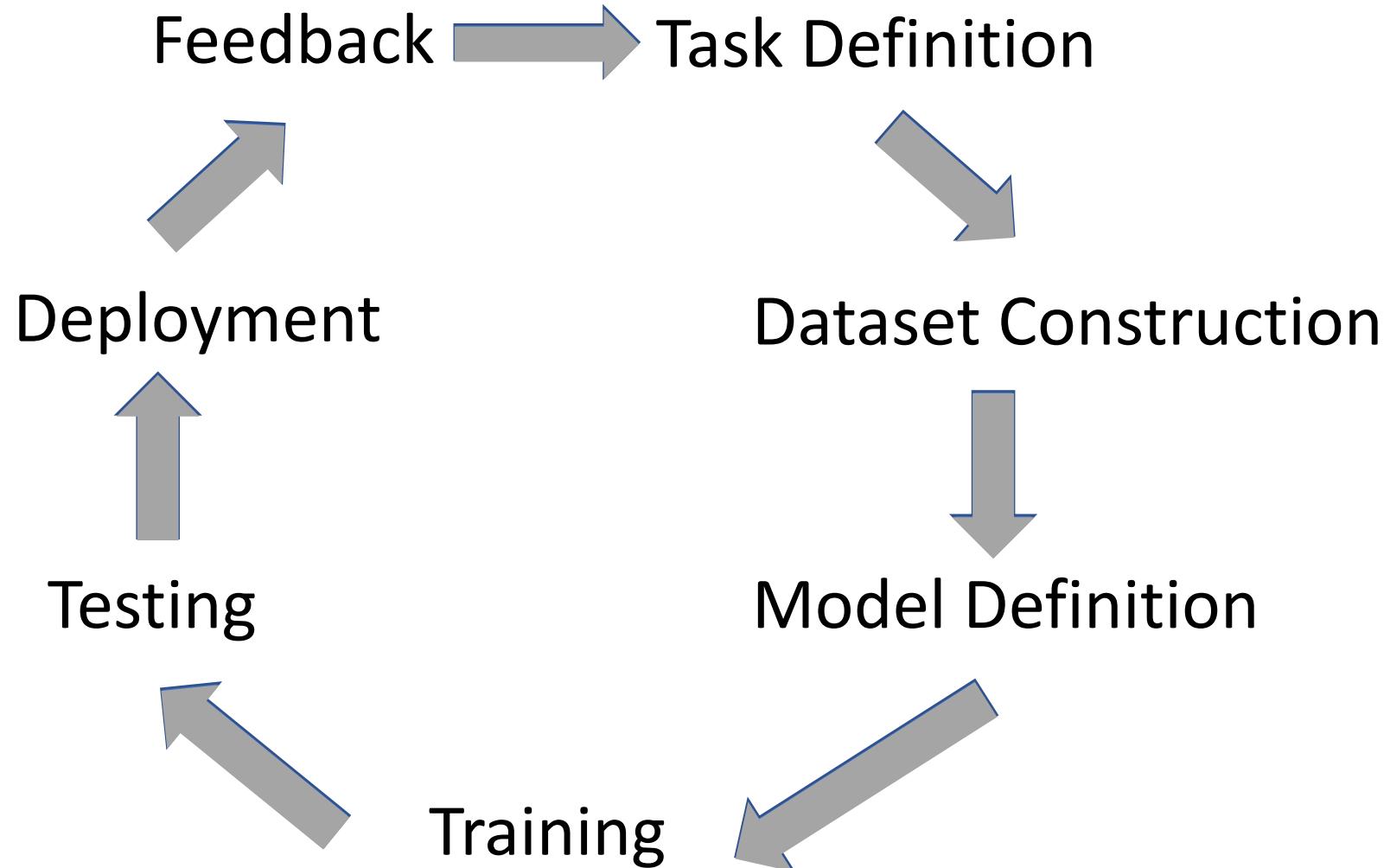


Future of Work at the Human-Technology Frontier

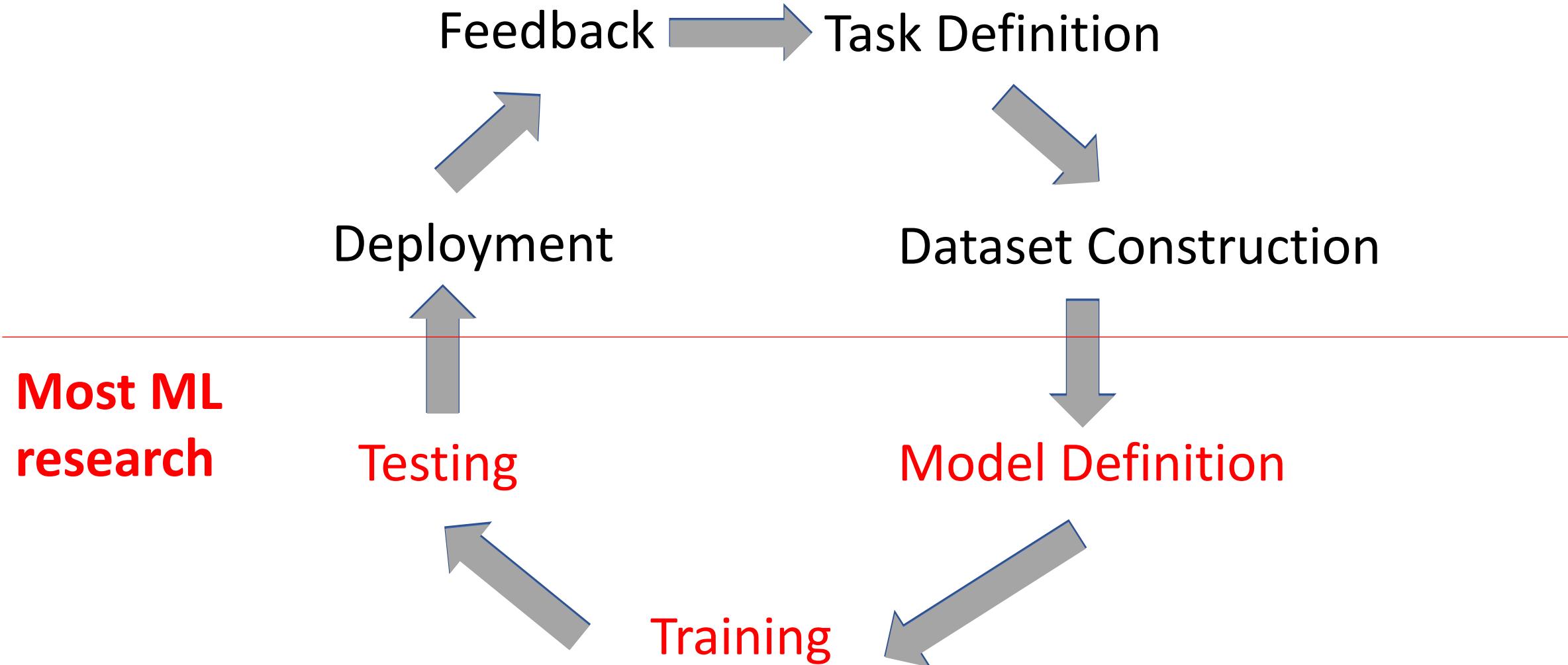
Catalyzing interdisciplinary science and engineering research to understand and build the human-technology relationship; design new technologies to augment human performance; illuminate the emerging socio-technological landscape; and foster lifelong and pervasive learning with technology. [Read more.](#)

Human-in-the-Loop Computation: From Machine Learning Perspective

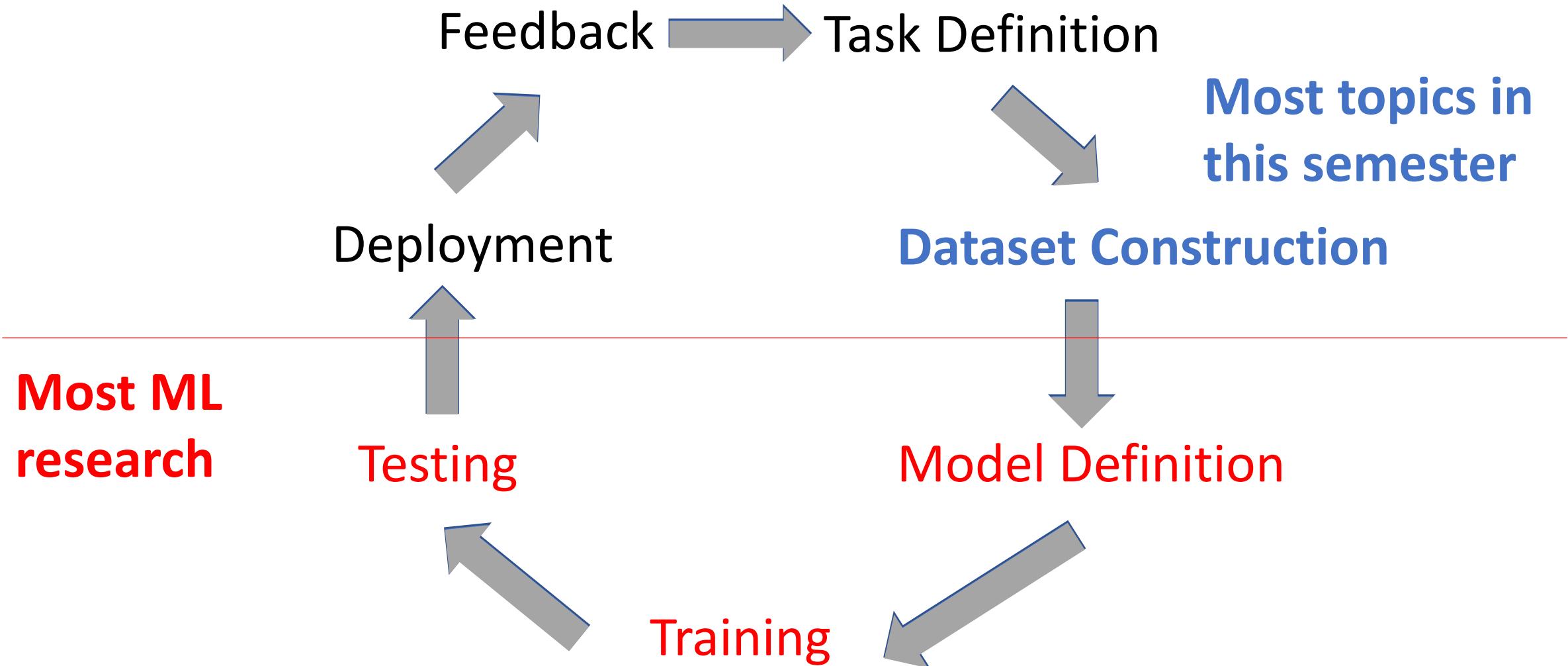
Machine Learning Lifecycle



Machine Learning Lifecycle

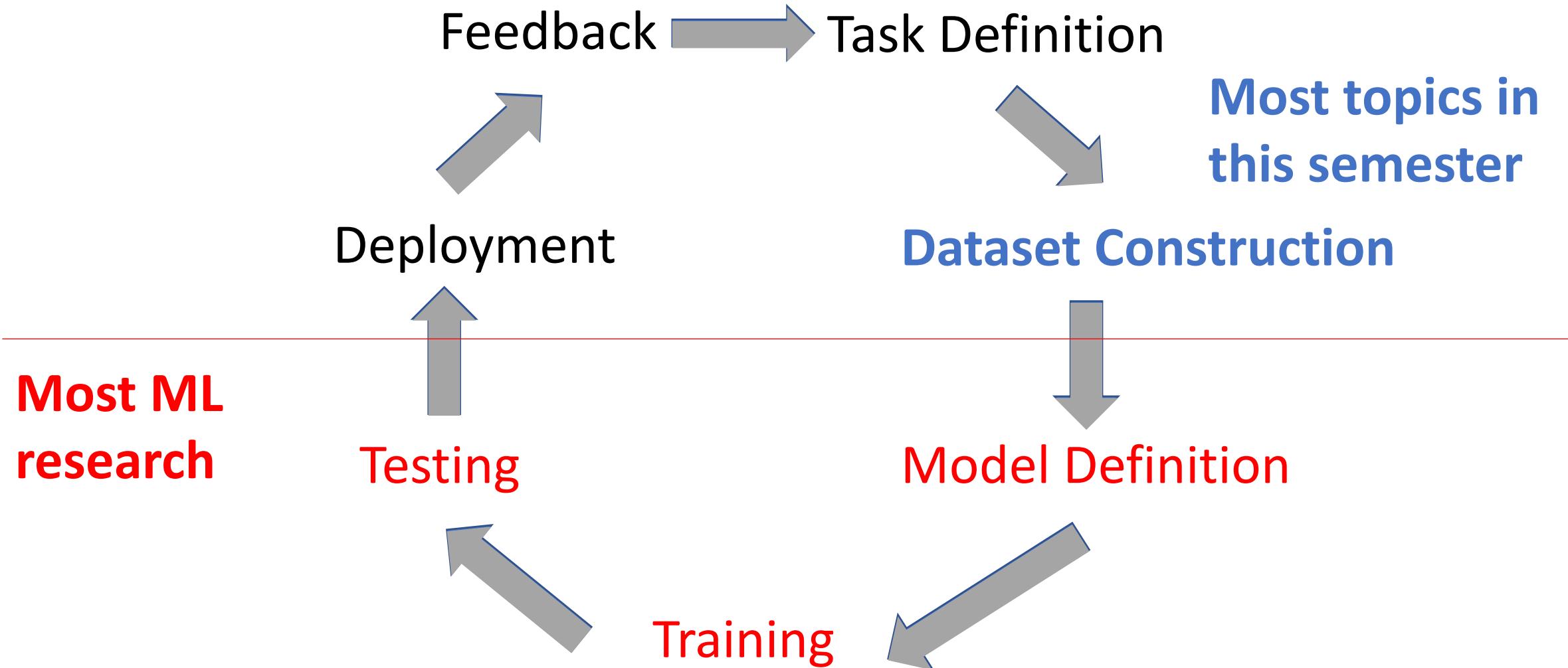


Machine Learning Lifecycle

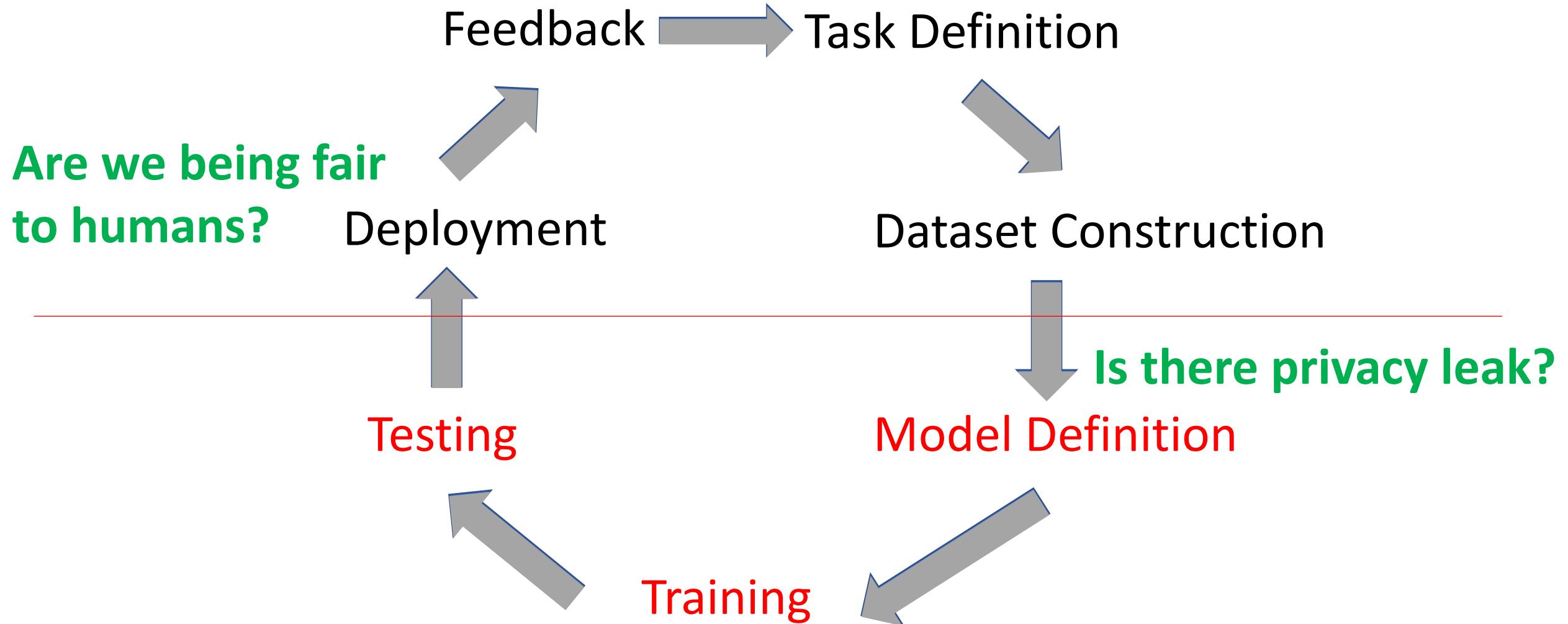


Machine Learning Lifecycle

Humans can be involved in
every aspect of the process



Machine Learning Lifecycle



Discussion on Privacy

Netflix Challenges

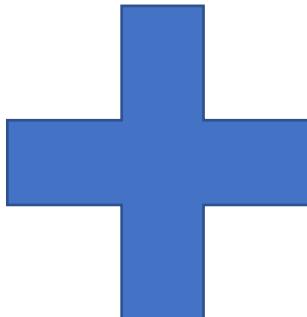
- First Netflix challenge
 - Announced in 2006
 - Released a dataset of 100,480,507 ratings that 480,189 users gave to 17,770 movies.
 - Award \$1 million to first team beating their algorithm by 10%
 - Data format: <user, movie, date of grade, grade>
 - User and movie names are replaced with integers
- Is there a second Netflix challenge?
 - Announced in August 2009
 - Cancelled in March 2010
 - Why?
 - Privacy lawsuits and FTC involvements

Robust De-anonymization of Large Sparse Datasets

Arvind Narayanan and Vitaly Shmatikov

The University of Texas at Austin

Netflix Dataset



IMDB Data

Why is Anonymization Hard?

- Even without explicit identifiable information (e.g., ID, name), other detailed information about you might still reveal who you are

<i>office</i>	<i>department</i>	<i>date joined</i>	<i>salary</i>	<i>d.o.b.</i>	<i>nationality</i>	<i>gender</i>
London	IT	Apr 2015	£###	May 1985	Portuguese	Female

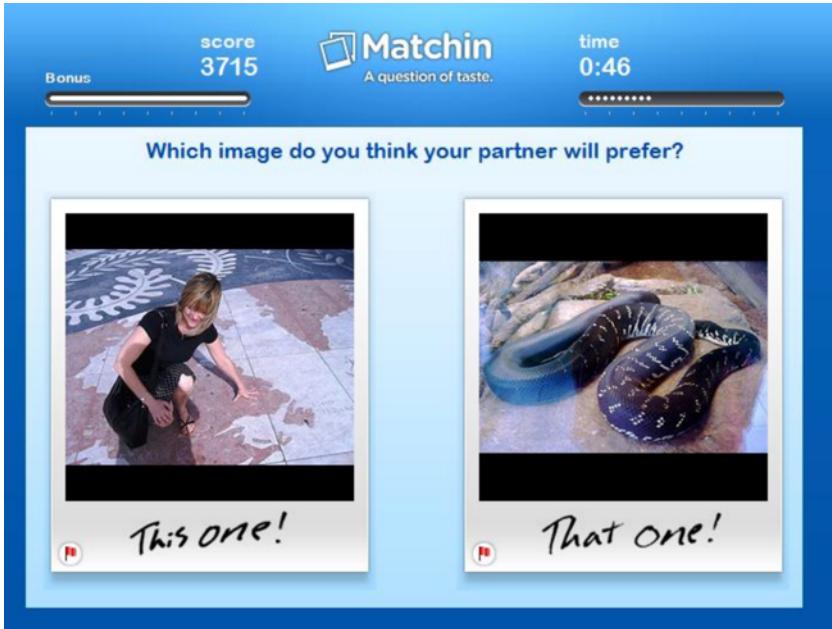
- What can we do?
 - Adding noises

<i>office</i>	<i>department</i>	<i>date joined</i>	<i>salary</i>	<i>d.o.b.</i>	<i>nationality</i>	<i>gender</i>
UK	IT	2015	£###	1980-1985	—	Female

Tradeoff between **privacy** and **utility**

Another Example

- Matchin: A Game for Collecting User Preferences on Images



- Building gender models using user labels
- Ask MTurk workers to compare 10 pairs of images.
 - Accuracy for guessing the gender: 78.3%

Unreasonable Privacy Expectations

- Can we get privacy for free?
 - No, privatizing means information loss (=> accuracy loss)
- Absolute privacy is not likely.
 - Who you are friends with might reveal who you are

September 22, 2009 by [Ben Terris](#)



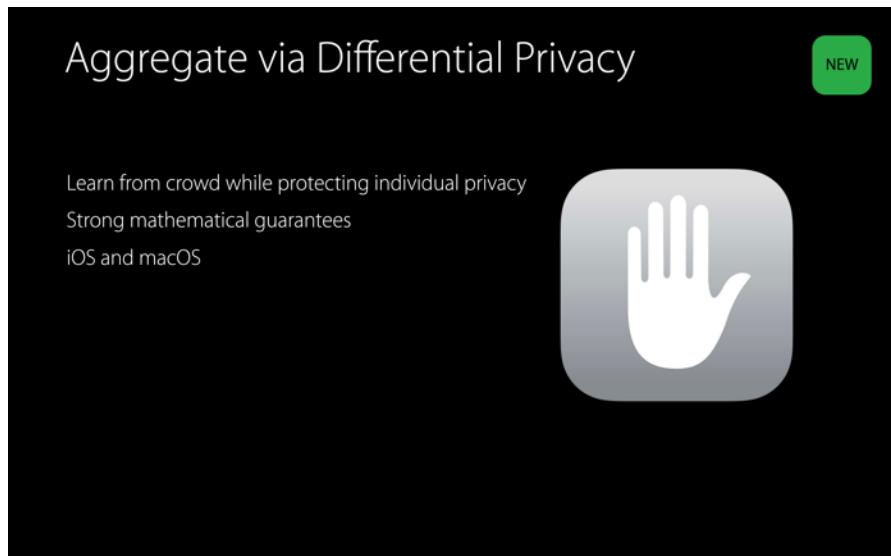
MIT Students' Facebook 'Gaydar' Raises Privacy Issues

(Maybe) More Reasonable Expectations

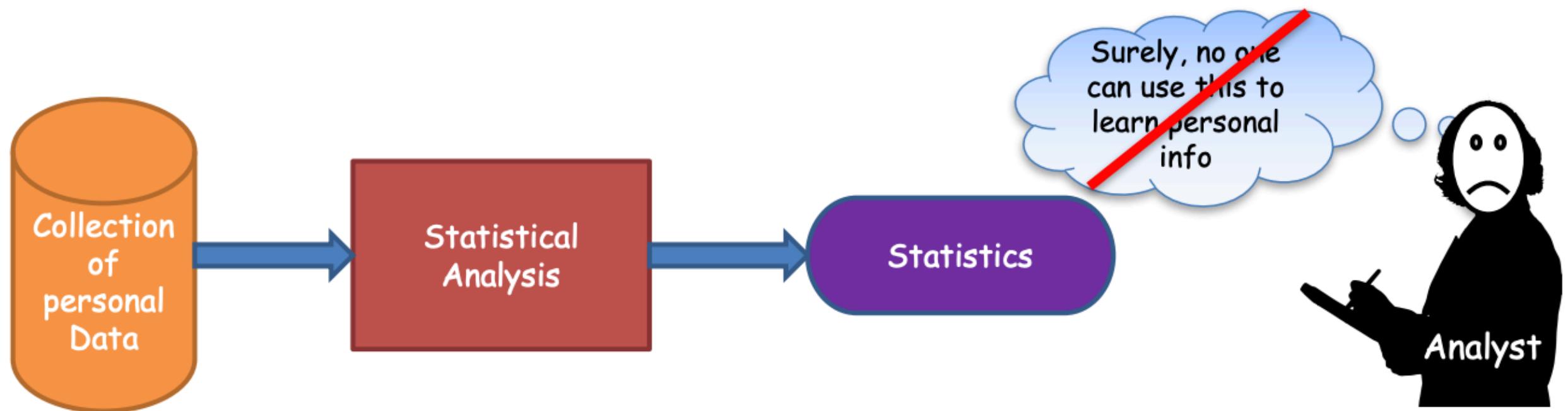
- Quantitative
 - Want a knob to tune the tradeoff between accuracy and privacy loss
- Plausible deniability
 - Your presence in a database cannot be ascertained
- Prevent targeted attacks
 - Limit information leaked even with side knowledge

Differential Privacy

- A formal notion to characterize privacy.
- History
 - Proposed by Dwork et al. 2006
 - Win the Gödel Prize in 2017
 - Apple announced to adopt the notion of differential privacy in iOS 10 in 2016

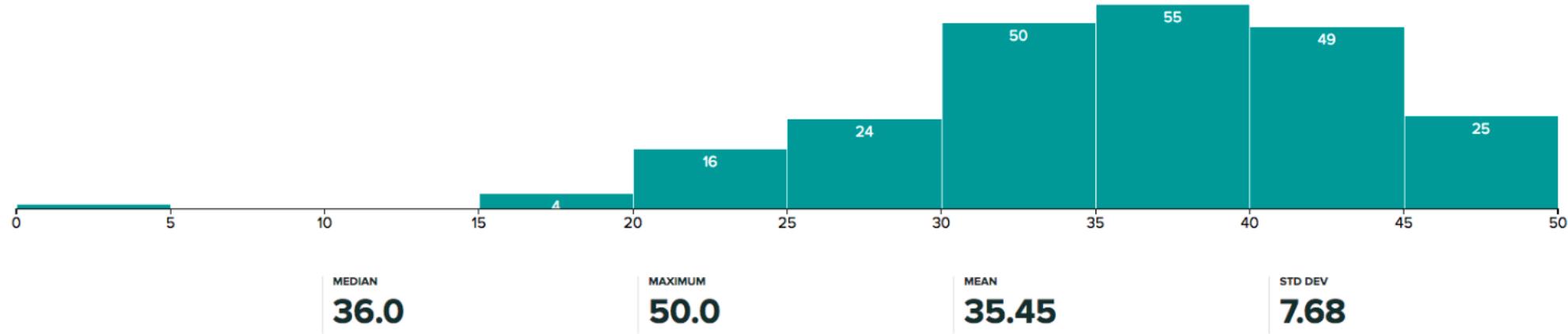


Differential Privacy



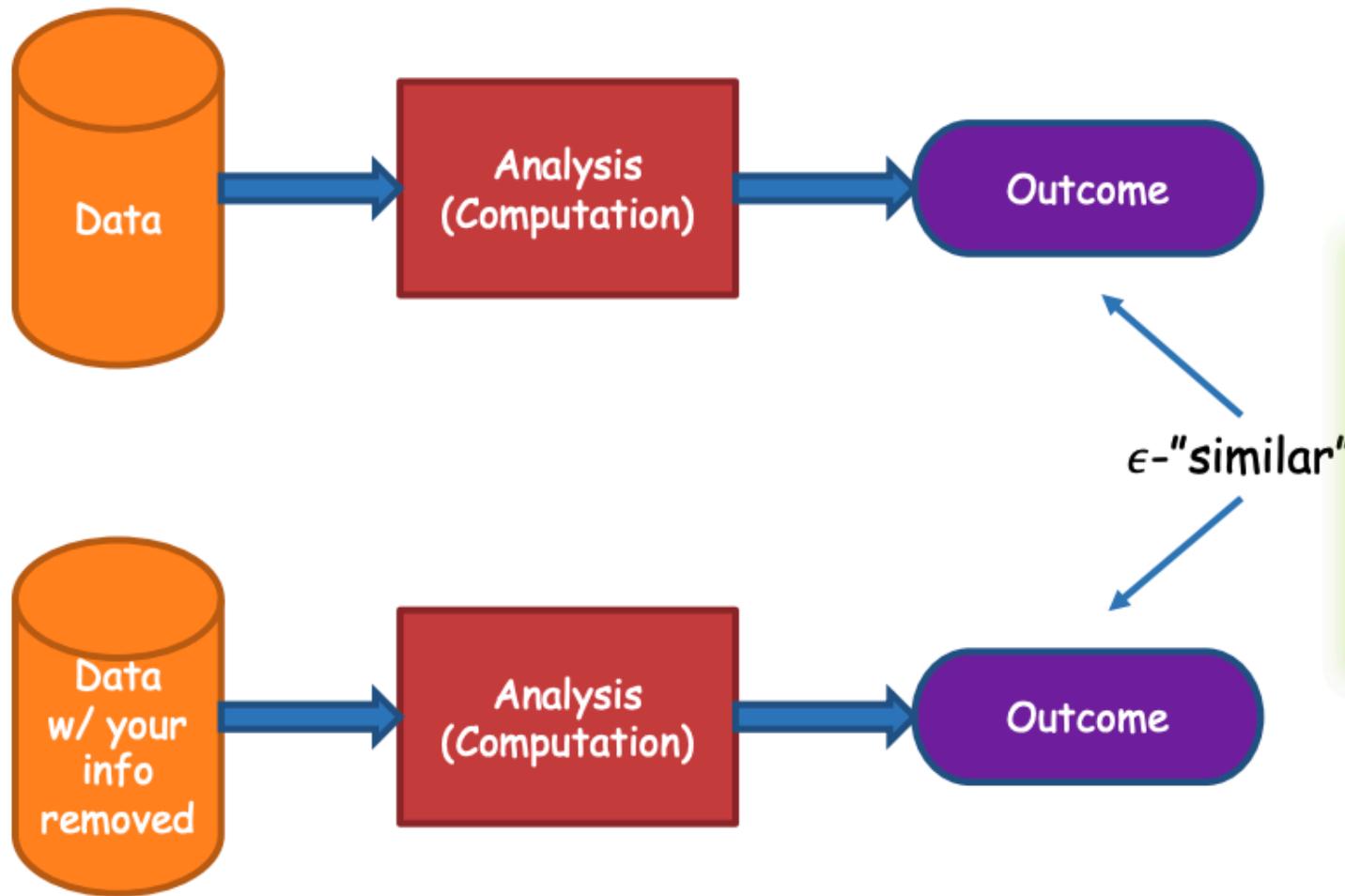
Differential Privacy

- Assume we have an exam in this course. And I have distributed this score distribution.



- How much of the private information (your individual grades) do I reveal?
- What if there are only 2 students in the class?

Differential Privacy



Differential Privacy

- Notations
 - A : a randomized algorithm.
 - D_1, D_2 : two “neighboring” database (with only one-entry difference)
 - ϵ : privacy budget
- ϵ -differentially private
 - A is ϵ -differentially private if for any neighboring databases D_1 and D_2 , and for any algorithm output Y , we have

$$\Pr[A(D_1) \in Y] \leq e^\epsilon \Pr[A(D_2) \in Y]$$

$e^\epsilon \approx 1 + \epsilon$ when ϵ is small

Intuition:

The change of output is small
if the change of data is small

How to Be Differentially Private

- Let the output of A be the average of users' ages
- Consider two extreme cases
 - If the size of the database is 1
 - If the size of the database is infinity
- We can tune the amount of noises added to tradeoff privacy and accuracy
- A majority of the differentially private algorithms use a similar approach

Discussion

- Differential privacy is a formal tool that we can tune the privacy budget to tradeoff privacy and utility/accuracy.
- We have been giving the big tech companies a lot of information. Have you been worried about any of the privacy issues? What's the line you will choose privacy or utility?

THE DATA BIG TECH COMPANIES HAVE ON YOU

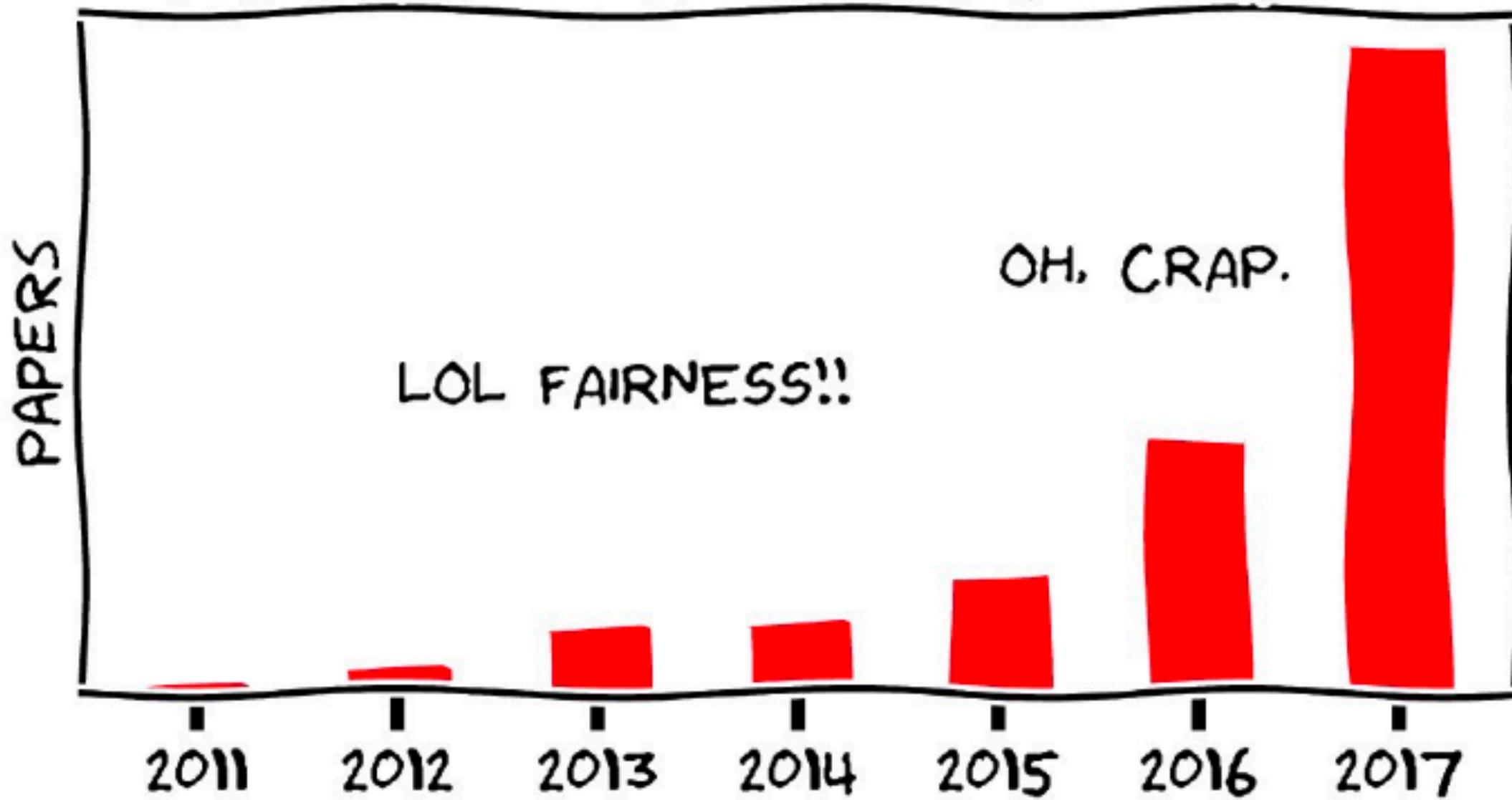
THE TYPES OF DATA MAJOR TECH COMPANIES ADMIT TO COLLECTING IN THEIR PRIVACY POLICIES

	Google	Facebook	Apple	Twitter	Amazon	Microsoft
Name					x	
Gender				x	x	
Birthday				x	x	
Phone Number						
Email Address						
Location						
Relationship Status	x		x	x	x	x
Work				x	x	x
Income Level	x			x	x	x

Only your time zone

Fairness

BRIEF HISTORY OF FAIRNESS IN ML



Isn't the point of ML to discriminate?

Want to avoid “unjustified” discrimination.

Example: Loan Applications

- By law, the banks can't discriminate people according to their race.
- First natural approach (fairness through blindness)
 - remove the race attribute from the data
- Guess what happened?
 - Redlining



What should we do?

- From computer scientists / engineers' point of view....
- Give me an operational definition of fairness, I'll implement a system that satisfy it!
- How should we define fairness? Is it even possible to define an universal fairness notion?
- More on Nov 11!