What’s Next

Chien-Ju (CJ) Ho

Logistics

- Assignment 4: Nov 20 (In-Class Assignment)
- Projects Presentation
  - Dec 2/4 (the week after Thanksgiving)
  - 10-minutes presentation for each group
  - Will announce the presentation order by the end of next week
- Project final report
  - Due: Dec 8
  - Up to 6 pages

Logistics

- Reviews
  - Check Gradescope under “Reviews” assignment for your submission status.
  - (Updated till Nov 4.)
- Presentations

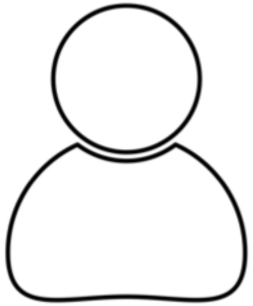
What We Have Discussed So far

Human-in-the-Loop Computation:

From Task Solvers’ Perspective

From Task Solvers' Perspective

Tasks



Output

Microtasks

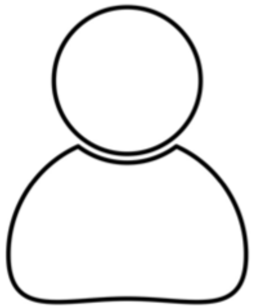
Flower

Dog

Cute

…

From Task Solvers' Perspective

Tasks →  → Output

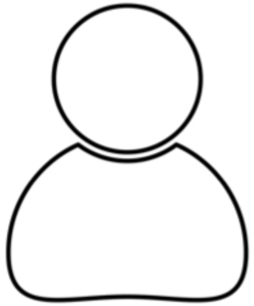
Key Challenge: How To Ensure Output Quality

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

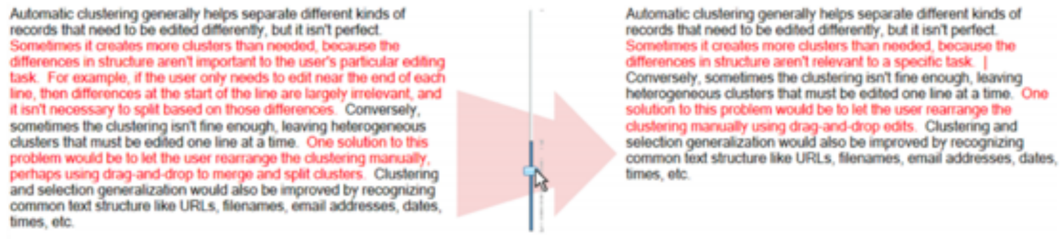
From Task Solvers' Perspective

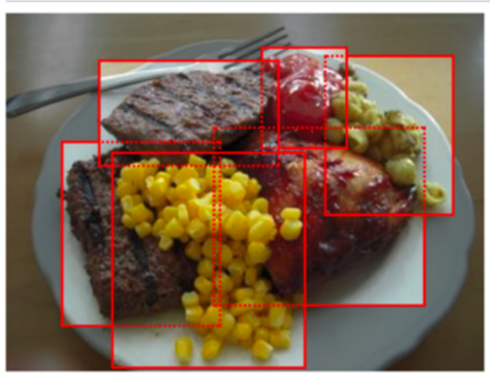
Tasks

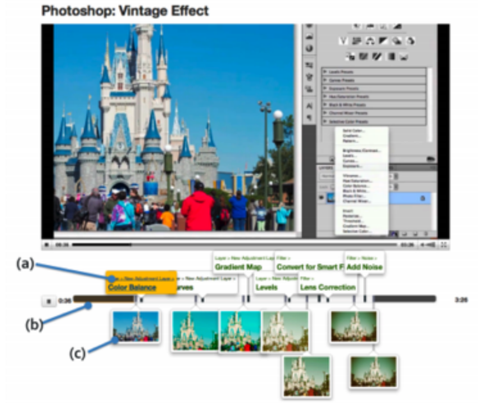


Output

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







From Task Solvers’ Perspective

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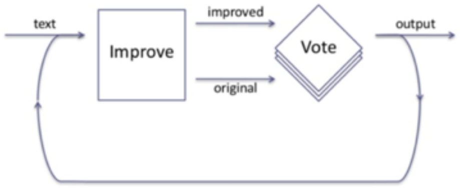
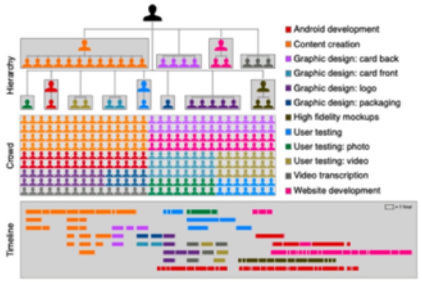




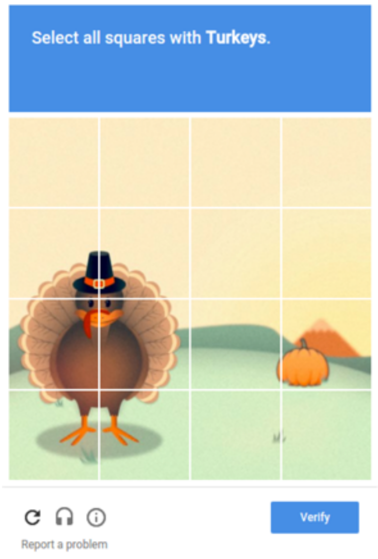
Output

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

- Retainer models
- Designing workflows to enable collaborations among workers
- Turning the crowd into an organization

(From Lecture 1) What is this course about?

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



Human as data sources:
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Practical challenges:
Real-time and complex tasks
Studies on workflow and team designs from HCI perspective

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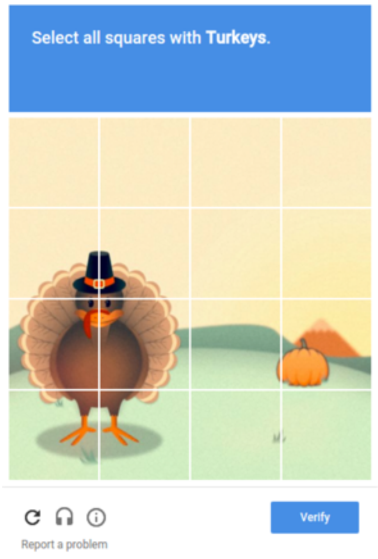

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Incentive design
Game theoretical modeling of humans and incentive design

Selected recent topics:
Ethical issues of AI/ML, learning with strategic behavior, Human-AI collaborations.

The focus of the next four lectures!

More than “Humans Solving Tasks”

- Ethical decision making (Nov 6)
  - Can we, and how can we, ask humans to help AI make ”ethical” decisions
- Fairness in AI (Nov 11)
  - Are the decisions made by AI ***fair*** to humans involved?
- Strategic machine learning (Nov 13)
  - What if humans who generated data are influenced by the outcome of ML?
- Human-AI Collaboration (Nov 18)
  - Can we team up humans and AI to solve tasks together?

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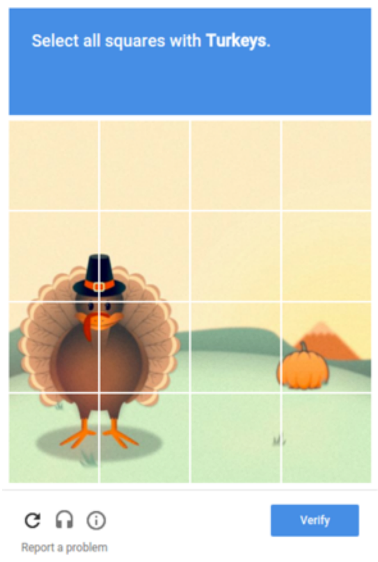

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An Emerging Research Agenda on AI/ML + Humans/Society

- 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 get into selected topics…

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

Goal → **Crowd + AI** → Result

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

Machine Learning | Economics Theory | Computational Social Science | Optimization | Human-Computer Interaction | and more…

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?

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 · 12:11 PM EST

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

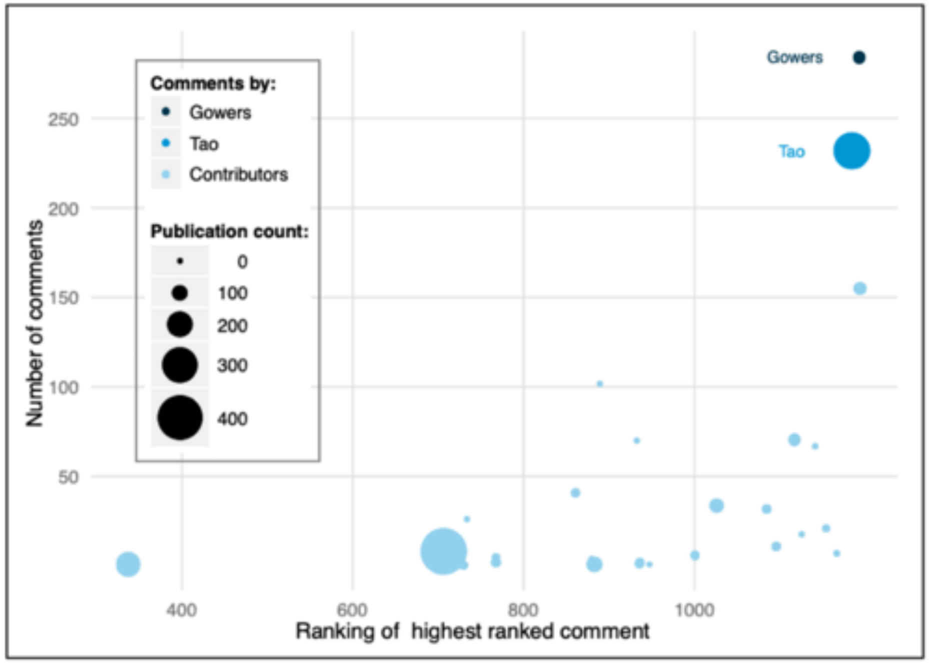
- Splddit

- 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?

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

The Polymath Project: Lessons from a Successful Online Collaboration in Mathematics. Cranshaw and Kittur. CHI'11

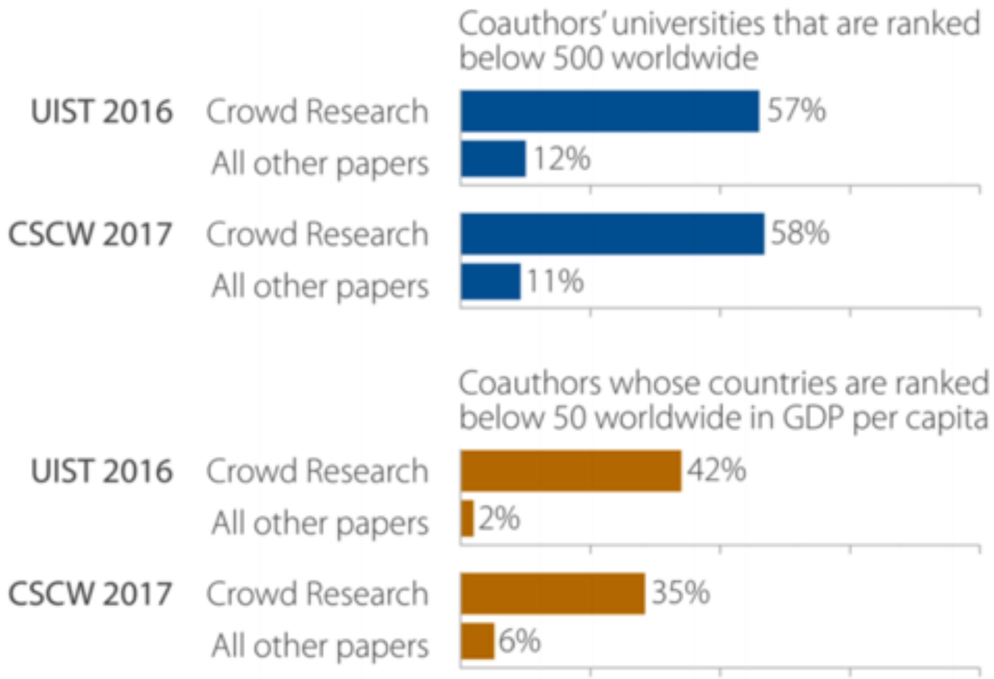
Crowd Research: Scalable and Open Lab

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

Crowd Research: Open and Scalable University Laboratories. Vaish et al. UIST 2017.

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

Snehalkumar (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, Snehalkumar (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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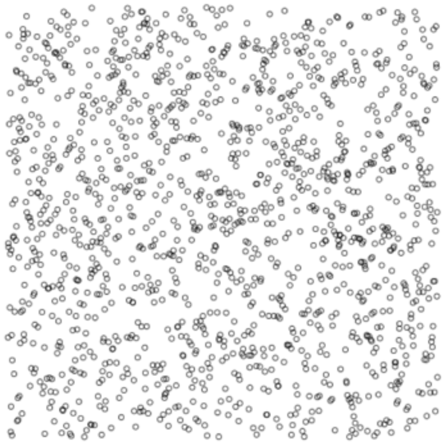
Crowdsourcing Democracy

- 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

Beyond Solving Objective Tasks

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Human-in-the-Loop Computation:

From Participants’ Perspective

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

Can We Learn from Traditional Workplaces

Traditional

Centralized

Career

Management Strategies

On-demand

Distributed

Piecework

???

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

More than Crowdsourcing Markets: Gig-Economy

2015 — **8%** of U.S. adults earned money by doing some tasks on online job platforms

2027 — **30%** of US adults doing some form of gig work tied to AI-driven goods or service

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

Future of Work

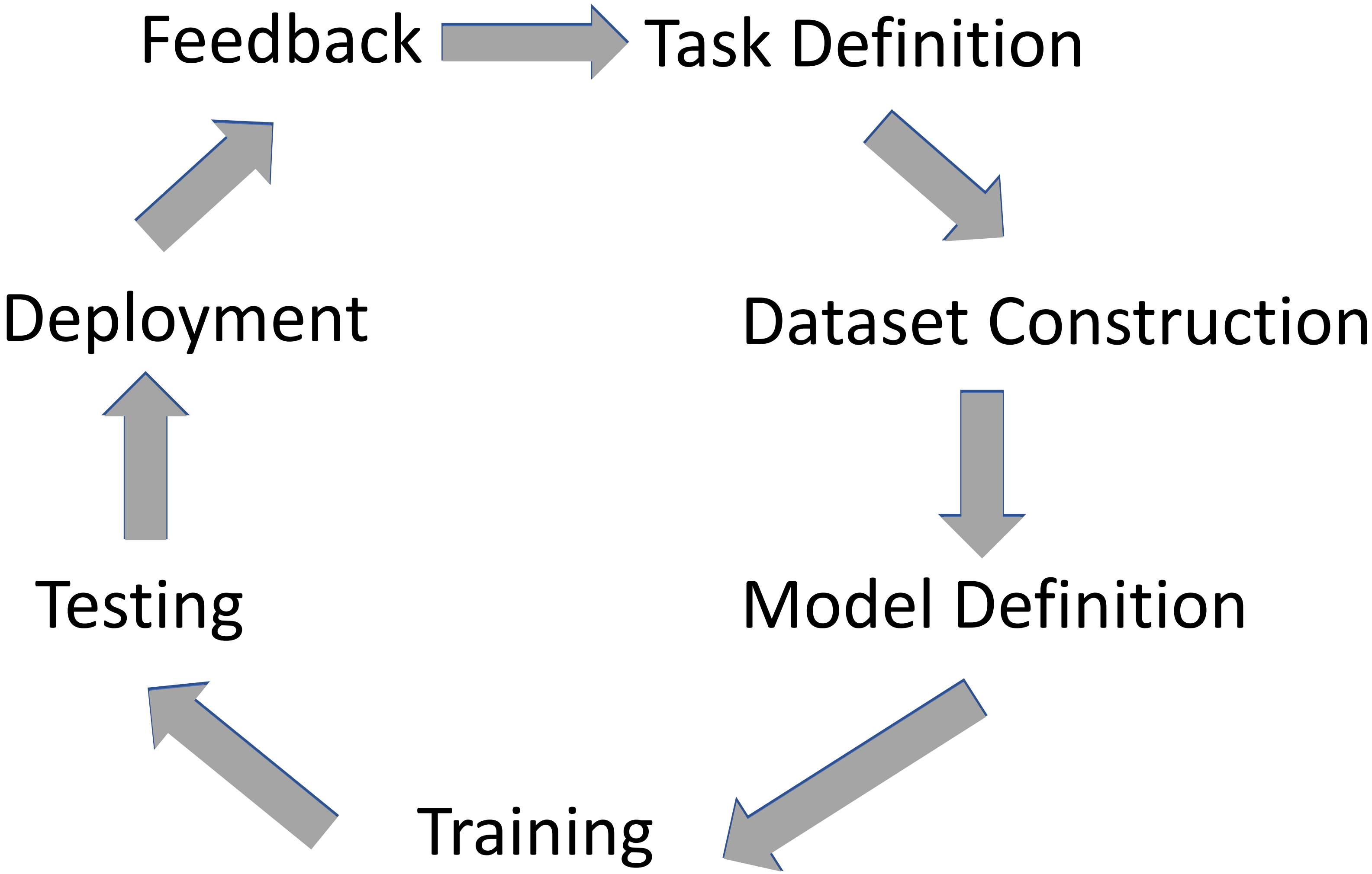
- One of NSF’s 10 Big Ideas:
  - “In 2019, NSF will invest $30 million in each Big Idea and continue to identify and support emerging opportunities for U.S. leadership in Big Ideas that serve the Nation's future.”

Future of Work at the Human-Technology Frontier

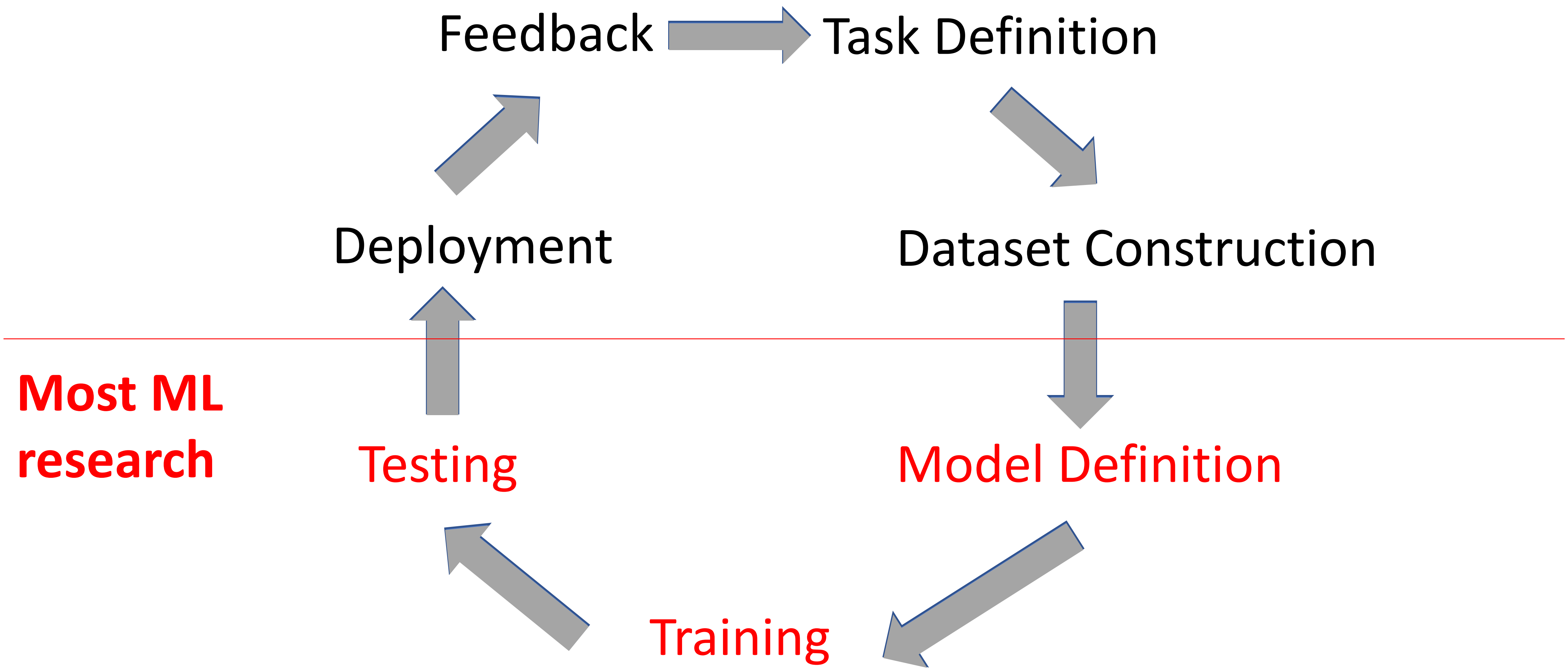
Catalyzing interdisciplinary science and engineering research to understand and build the human-technology relationship; design new technologies to augment human performance; illuminate the emerging socio-technological landscape; and foster lifelong and pervasive learning with technology. Read more.

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

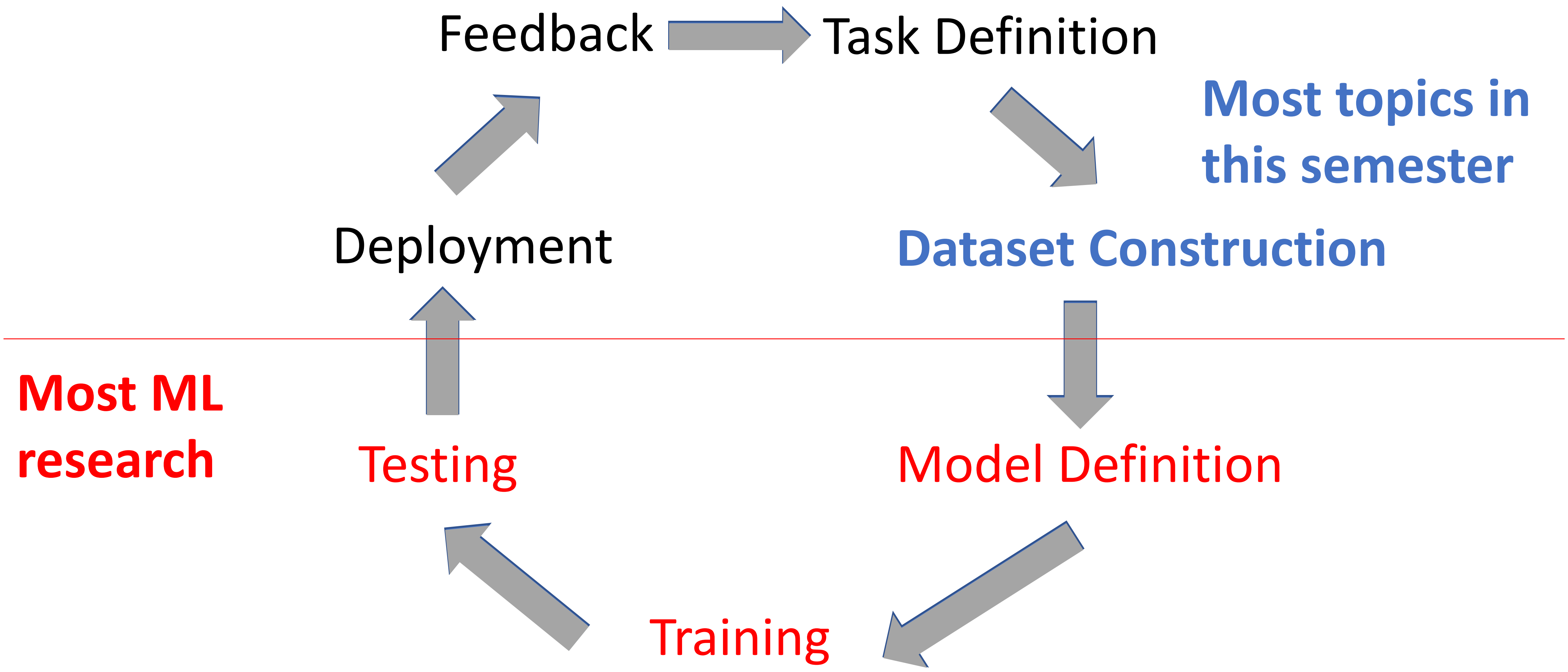
Machine Learning Lifecycle



Machine Learning Lifecycle

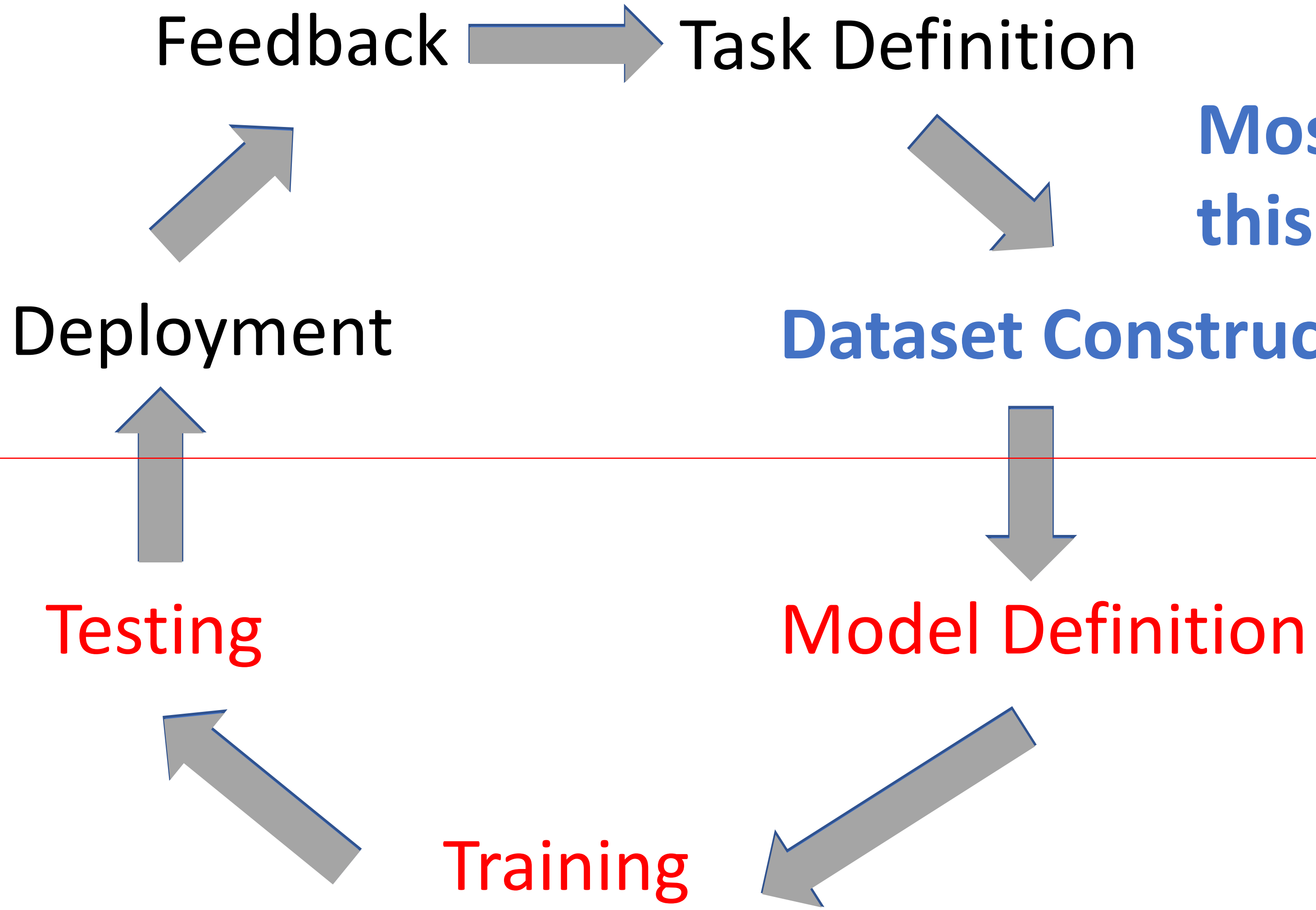


Machine Learning Lifecycle



Machine Learning Lifecycle

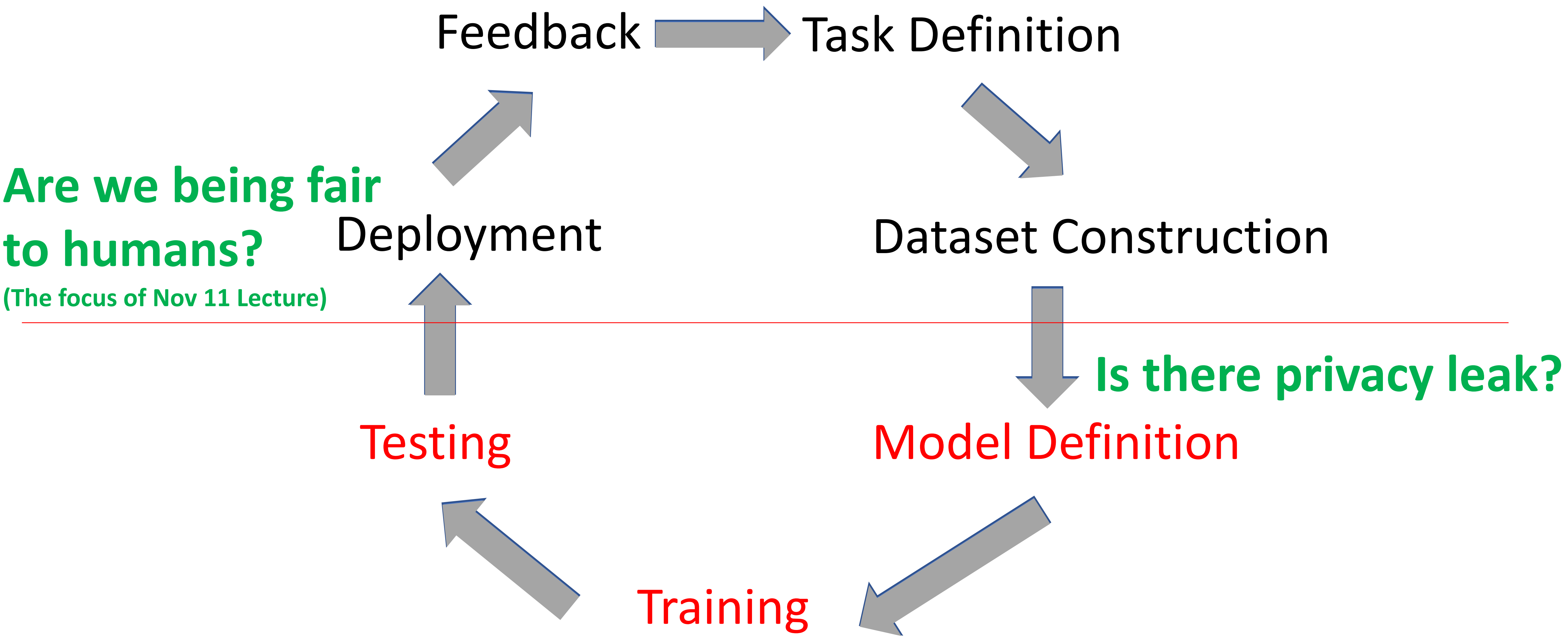
Humans can be involved in every aspect of the process



Most topics in this semester

Most ML research

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), detailed information about you might still reveal who you are

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

- What can we do?
  - Adding noises

office	*department*	*date joined*	*salary*	*d.o.b.*	*nationality*	*gender*
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

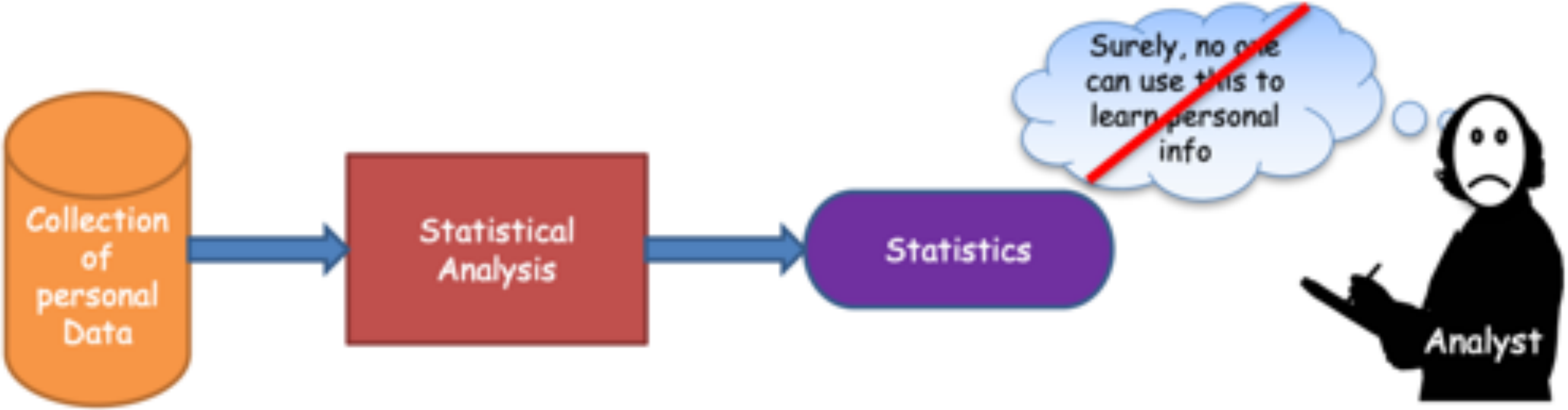
(Maybe) More Reasonable Expectations

- Quantitative
  - Want a knob to tune the tradeoff between accuracy and privacy loss
- Plausible deniability
  - You 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

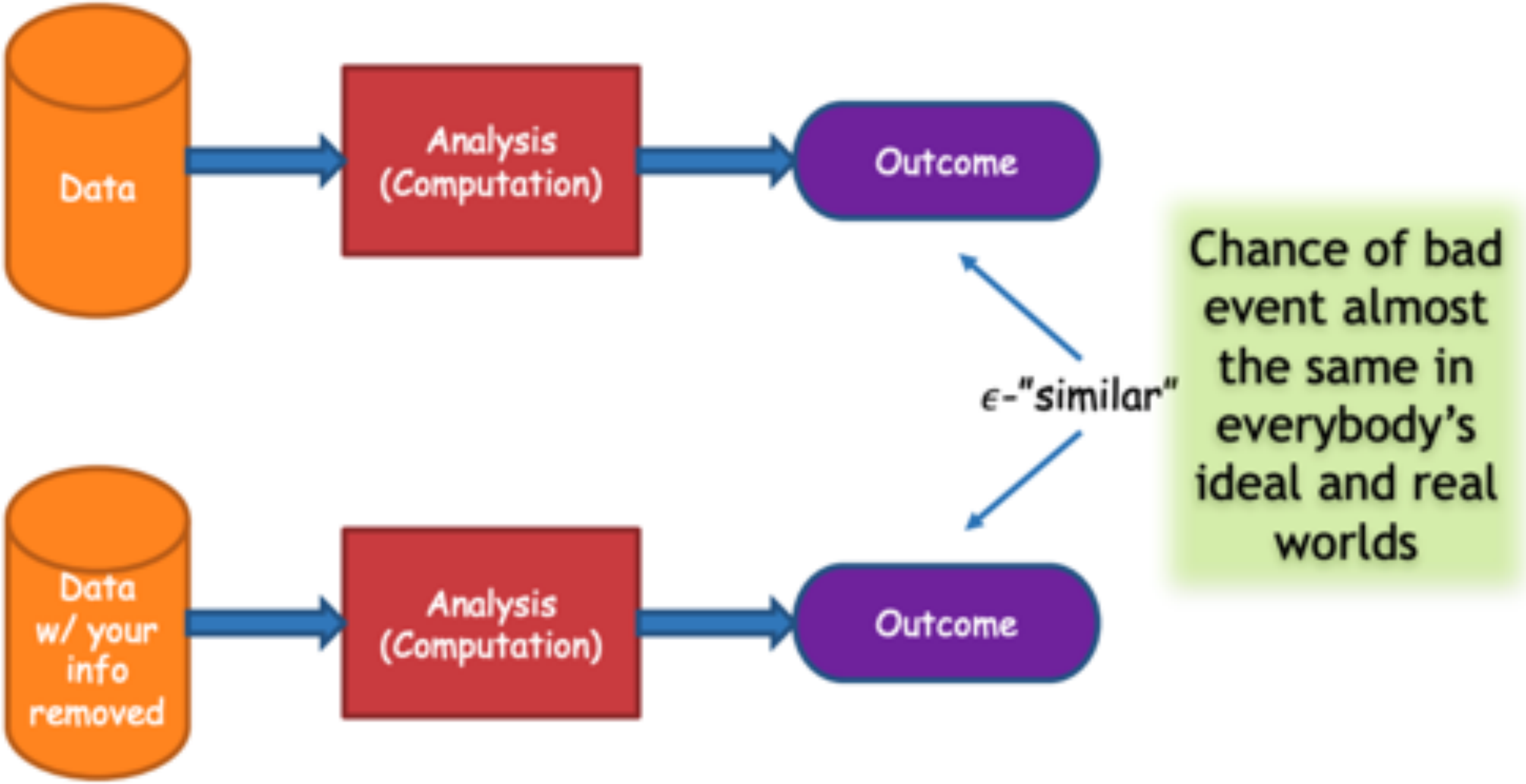


Differential Privacy

- 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

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

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

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

How to Be Differentially Private

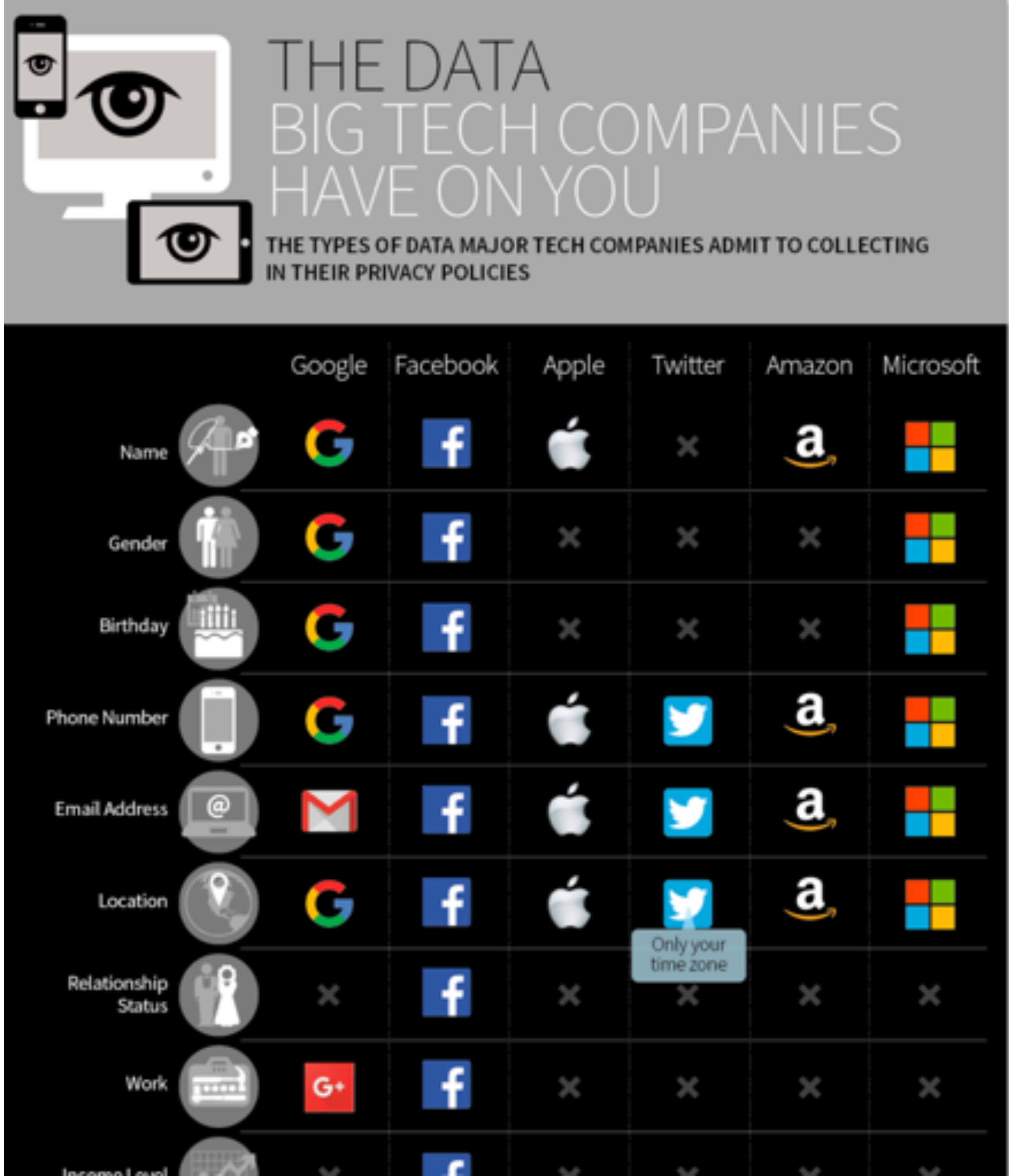
- Let the output of A be the average of users' ages
- Consider two extreme cases
  - If the size of the database is 1
  - If the size of the database is infinity

- We can tune the amount of noises added to tradeoff privacy and accuracy
- A majority of the differentially private algorithms use a similar approach

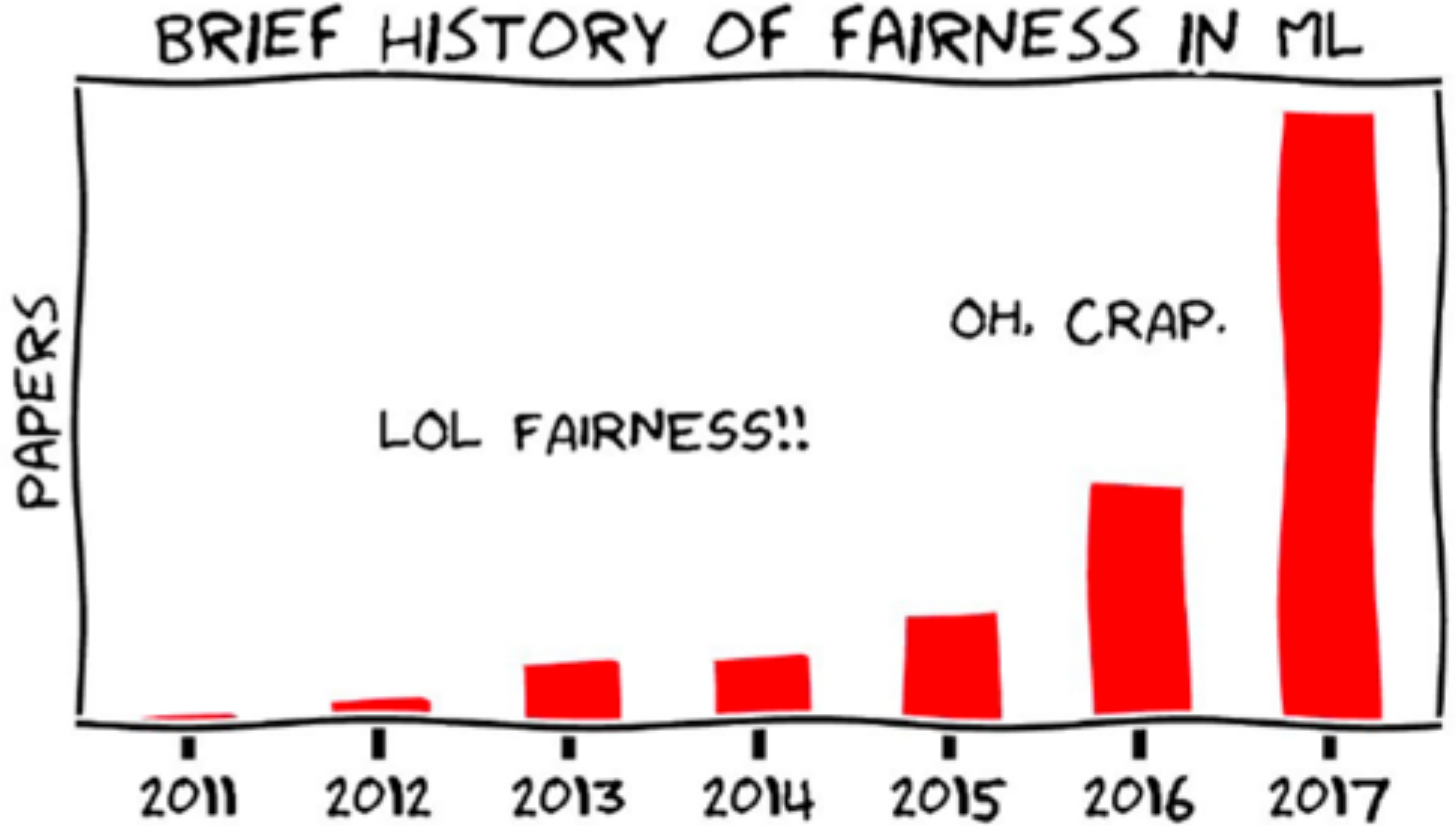
Discussion

- 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?



Fairness


BRIEF HISTORY OF FAIRNESS IN ML
PAPERS
LOL FAIRNESS!!
OH. CRAP.
2011
2012
2013
2014
2015
2016
2017

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!