Introduction

CS329H: Machine Learning from Human Preferences

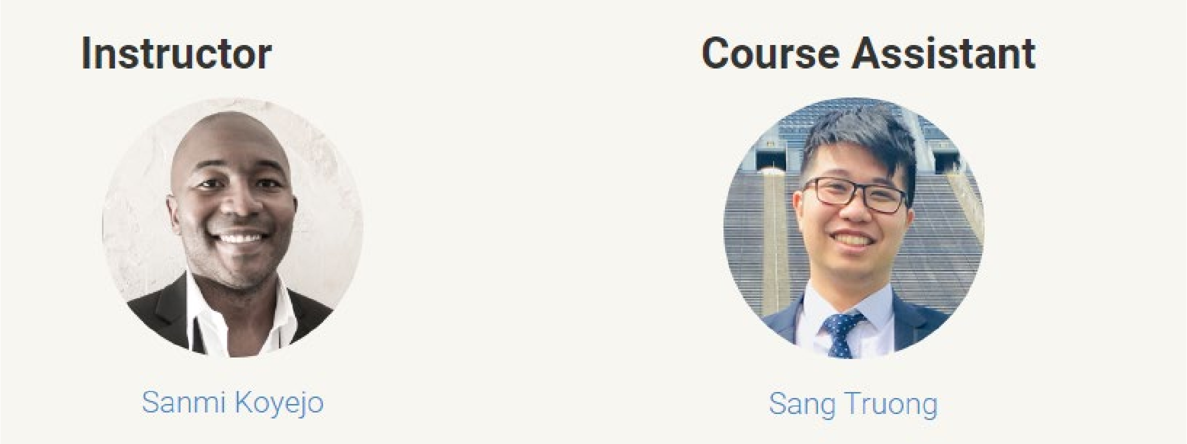
Sanmi Koyejo

Stanford CS

Autumn 2023

Welcome to CS 329H

Couse Interaction



Instructor

Sanmi Koyejo

Course Assistant

Sang Truong

- Lectures: M/W 1:30 PM - 2:50 PT in 370-370
- Contact: cs329h-win2324-staff@lists.stanford.edu
- Website: https://web.stanford.edu/class/cs329h/
- Ed discussion: https://edstem.org/us/courses/48383/discussion/

Machine learning from human preferences (this class) will focus on the statistical and conceptual foundations and strategies for interactively querying humans to elicit information that can improve learning, along with applications.

Foundations and strategies for interactively querying humans to elicit information that can improve learning.

Focus on the role of the **human-in-the-loop** for improving learning systems

Foundations in microeconomics, psychology, marketing, statistics …

Applications to language, robotics, logistics, …

All of these viewed though the **machine learning** lens (modeling, estimation, evaluation)

Human questions

Bias, correctness, noisiness, rationality, …

Human(s) may be individuals or groups, how does this change our approach?

Most use cases bring up ethical questions

Which humans?

Does learning from preferences lead to exploitation or other ethical concerns?

This class is not exhaustive!

General AI: Most ML/AI involves learning from humans

Goal is often to imitate human intelligence, i.e., humans are the data source

General ML: Humans define all the steps of the ML/AI process

selecting the problem, data sources, model architectures, optimization, evaluation.

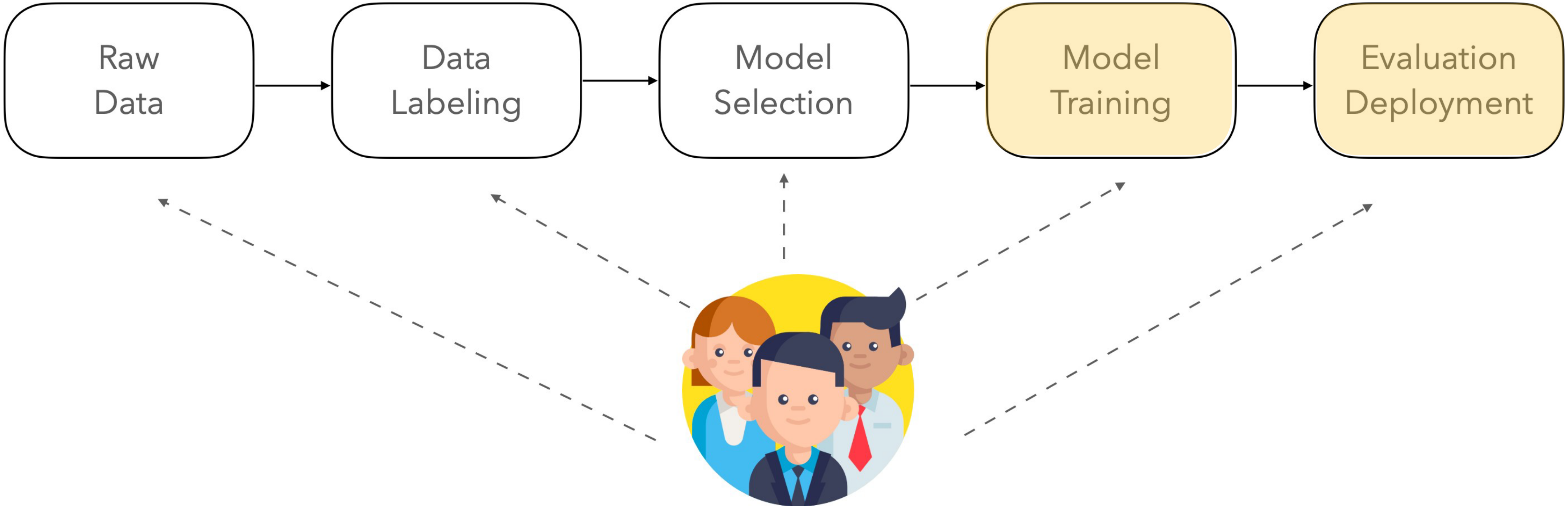
Expert knowledge for defining model architectures (esp. graphical models, causal inference)

We may discuss a few examples, but not our focus

Human Computer Interaction (HCI)

The interface and elicitation process matters

Feedback can be included at any step of the learning process



Wang, Zijie J., et al. "Putting humans in the natural language processing loop: A survey." HCI+NLP Workshop (2021).

Slides modified from Diyi Yang

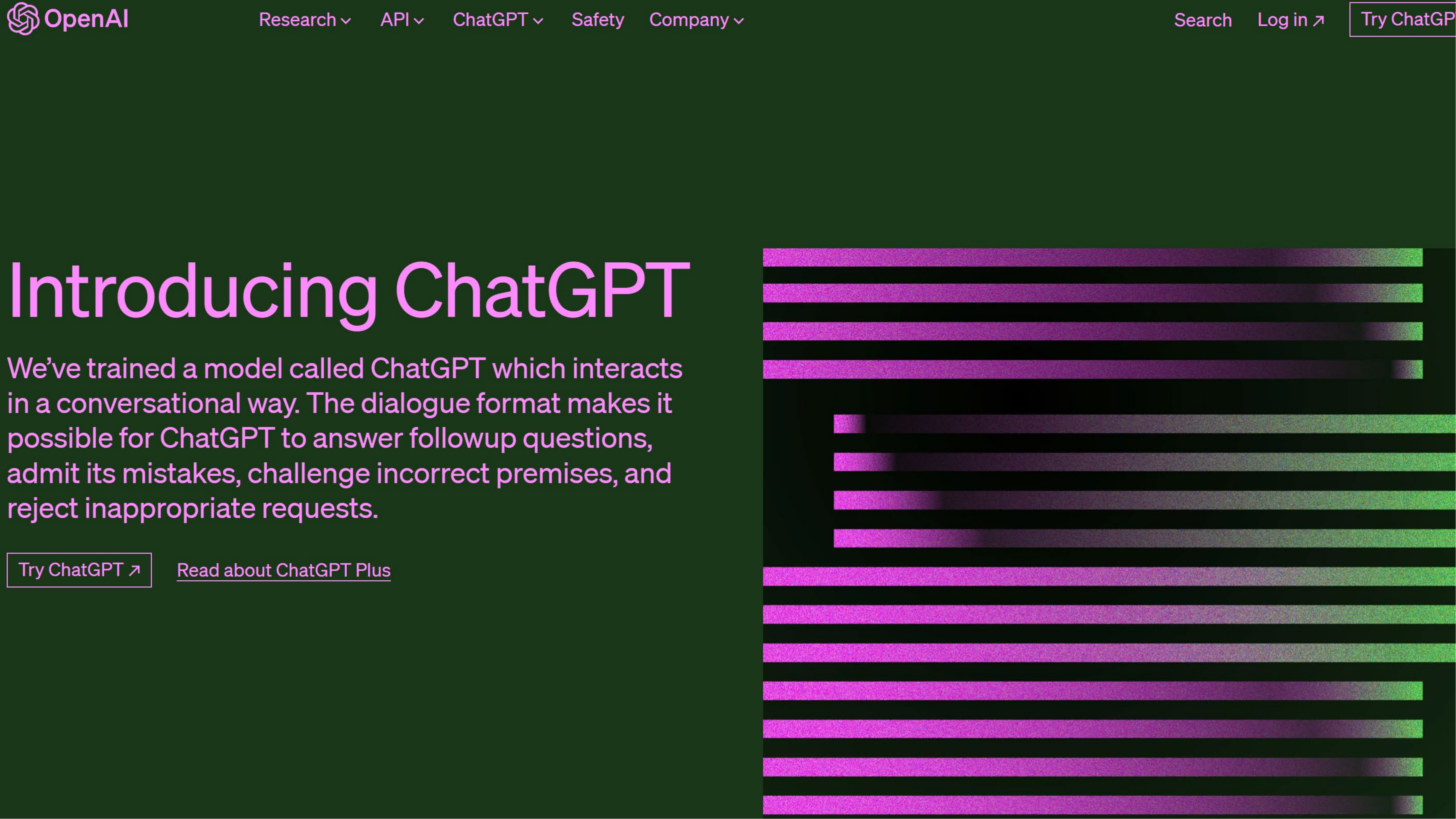
Feedback-Update Taxonomy

	Dataset Update	Loss Function Update	Parameter Space Update
Domain	Dataset modification Augmentation Preprocessing Data generation from constraint Fairness, weak supervision Use unlabeled data Check synthetic data	Constraint specification Fairness, Interpretability Resource constraints	Model editing Rules, Weights Model selection Prior update, Complexity
Observation	Active data collection Add data, Relabel data, Reweighting data, collect expert labels, Passive observation	Constraint elicitation Metric learning, Human representations Collecting contextual information Generative factors, concept representations, Feature attributions	Feature modification Add/remove features, Engineering features

Chen, Valerie, et al. "Perspectives on Incorporating Expert Feedback into Model Updates." ArXiv (2022).

Slides modified from Diyi Yang

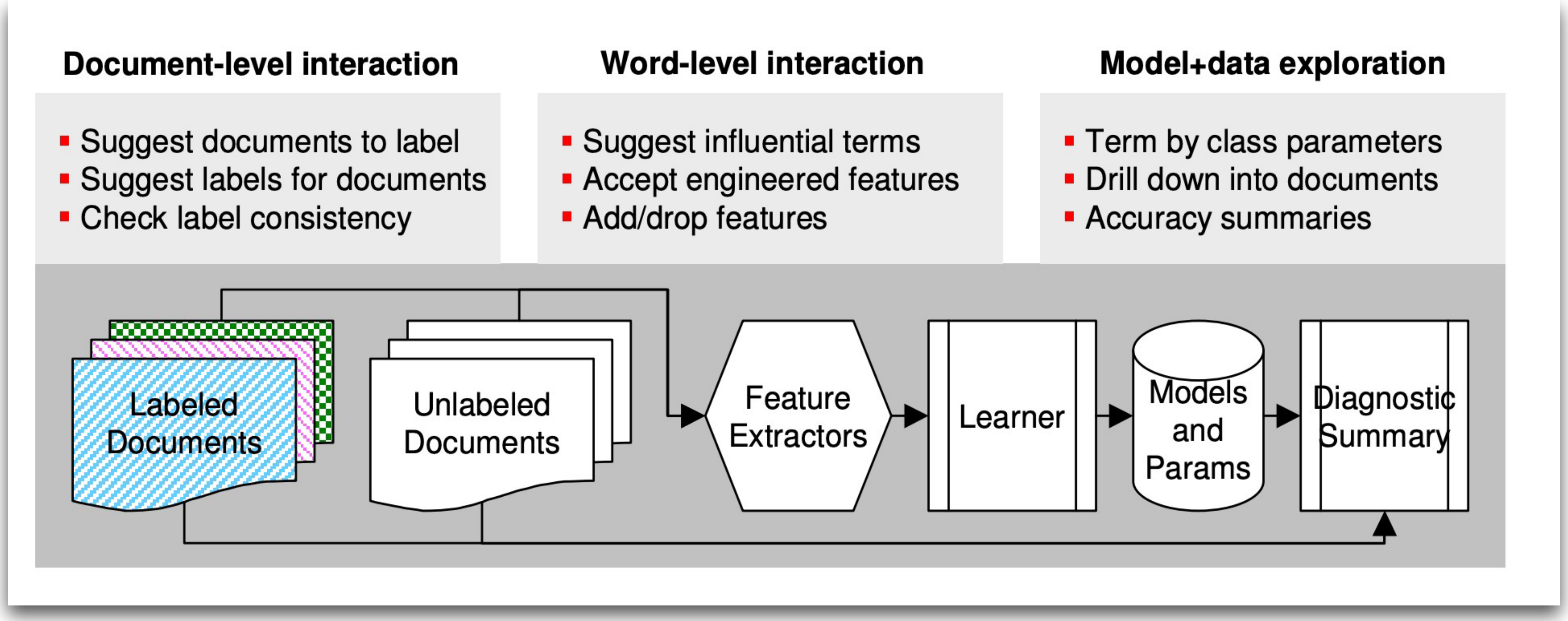
Examples and Applications



Introducing ChatGPT

We've trained a model called ChatGPT which interacts in a conversational way. The dialogue format makes it possible for ChatGPT to answer followup questions, admit its mistakes, challenge incorrect premises, and reject inappropriate requests.

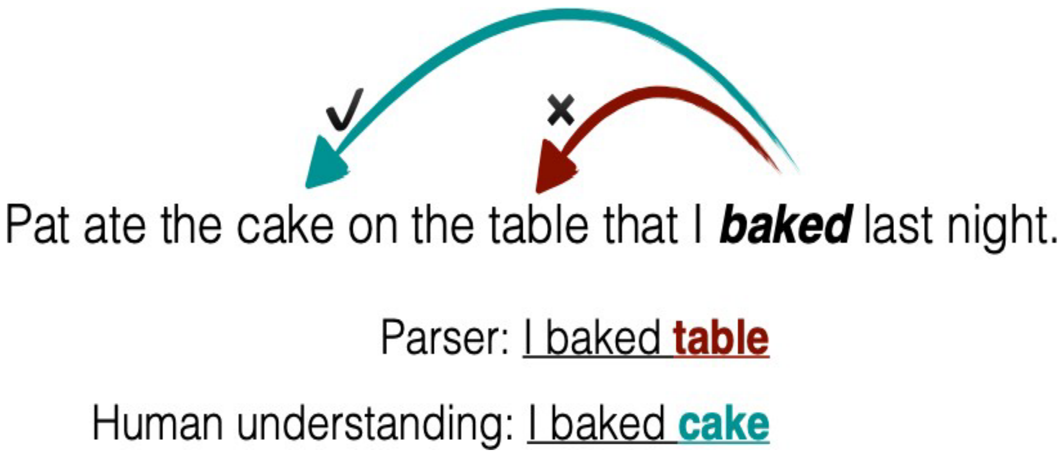
Builds on research studying human feedback in language



Document-level interaction
- Suggest documents to label
- Suggest labels for documents
- Check label consistency
Word-level interaction
- Suggest influential terms
- Accept engineered features
- Add/drop features
Model+data exploration
- Term by class parameters
- Drill down into documents
- Accuracy summaries
Labeled Documents
Unlabeled Documents
Feature Extractors
Learner
Models and Params
Diagnostic Summary

Godbole, Shantanu, Abhay Harpale, Sunita Sarawagi, and Soumen Chakrabarti. "Document classification through interactive supervision of document and term labels." In European Conference on Principles of Data Mining and Knowledge Discovery, pp. 185-196. Springer, Berlin, Heidelberg, 2004.

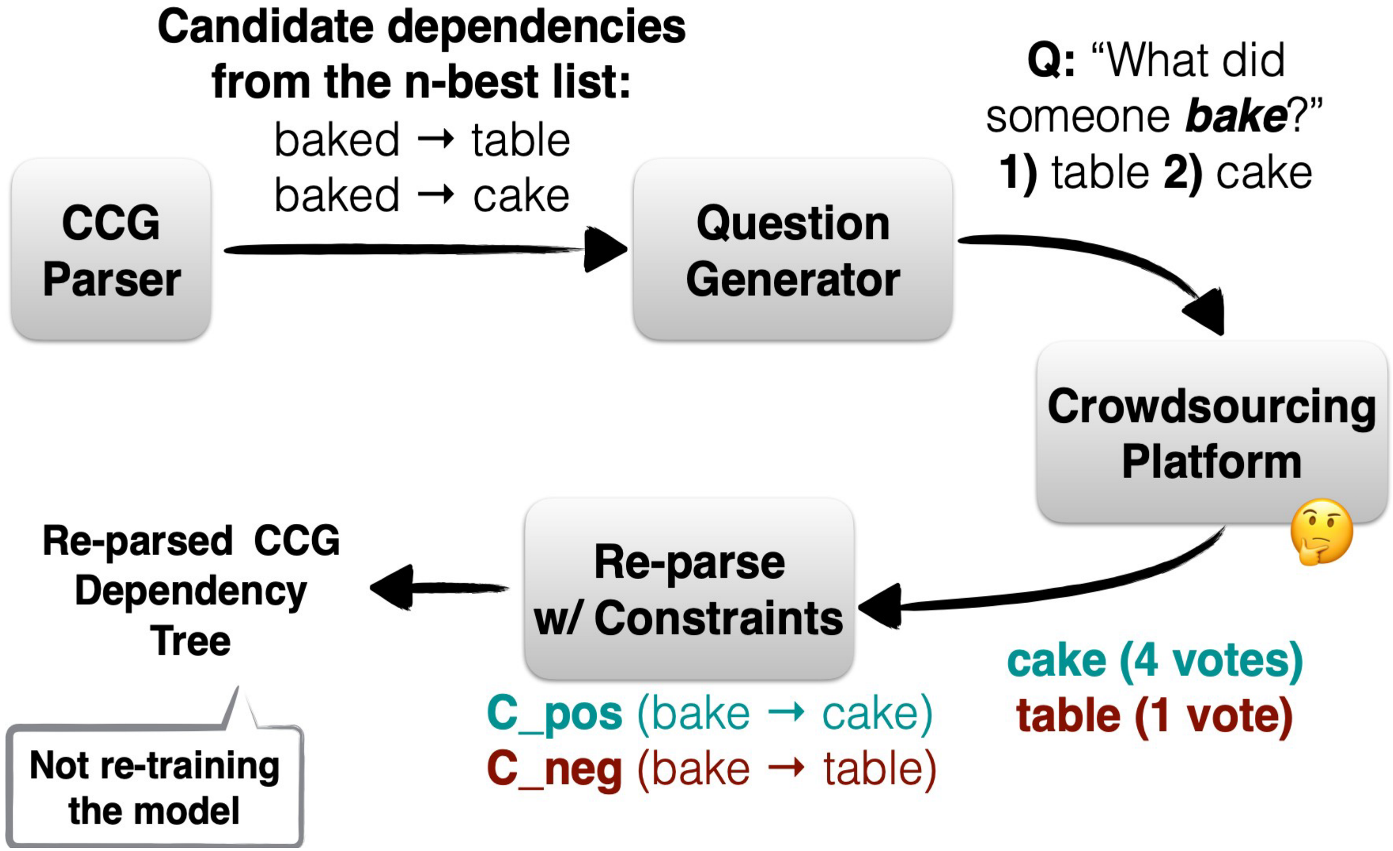
He, Luheng, Julian Michael, Mike Lewis, and Luke Zettlemoyer. "Human-in-the-loop parsing." In Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing, pp. 2337-2342. 2016.



Pat ate the cake on the table that I ***baked*** last night.

Parser: I baked **table**

Human understanding: I baked **cake**



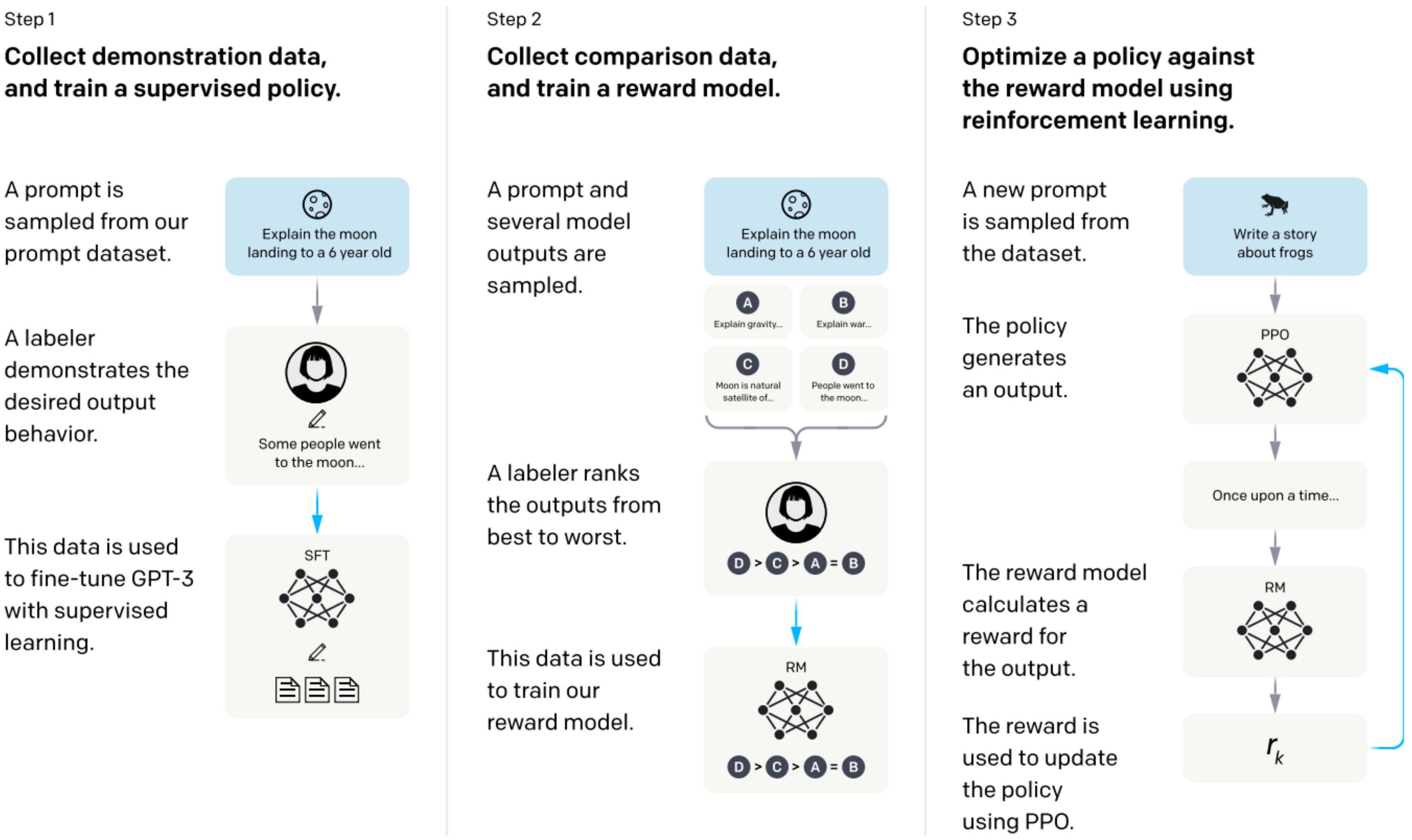
Candidate dependencies from the n-best list:
baked → table
baked → cake

Q: "What did someone ***bake***?"
1) table **2)** cake

cake (4 votes)
table (1 vote)

C_pos (bake → cake)
C_neg (bake → table)

Not re-training the model



Step 1

Collect demonstration data, and train a supervised policy.

A prompt is sampled from our prompt dataset.

Explain the moon landing to a 6 year old

A labeler demonstrates the desired output behavior.

Some people went to the moon...

This data is used to fine-tune GPT-3 with supervised learning.

Step 2

Collect comparison data, and train a reward model.

A prompt and several model outputs are sampled.

Explain the moon landing to a 6 year old
A
Explain gravity...
B
Explain war...
C
Moon is natural satellite of...
D
People went to the moon...

A labeler ranks the outputs from best to worst.

This data is used to train our reward model.

Step 3

Optimize a policy against the reward model using reinforcement learning.

A new prompt is sampled from the dataset.

The policy generates an output.

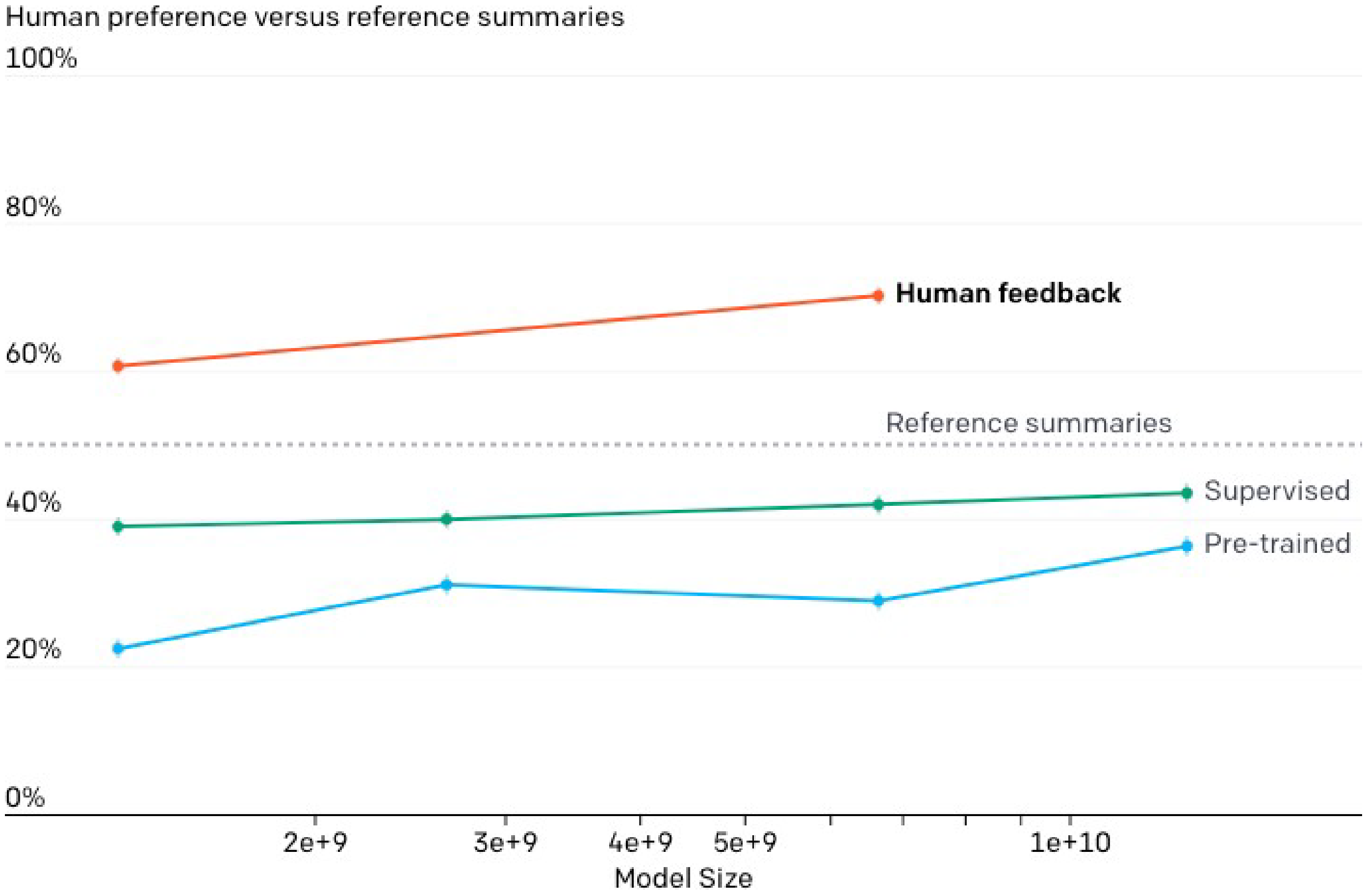
The reward model calculates a reward for the output.

The reward is used to update the policy using PPO.

Ouyang et. al., “Training language models to follow instructions with human feedback”

Published (early) OpenAI Experiments with RLHF

Stiennon, Nisan, et al. "Learning to summarize with human feedback." Advances in Neural Information Processing Systems 33 (2020): 3008-3021.



[r/dating_advice] **First date ever, going to the beach. Would like some tips**

Hey Reddit! I (20M) would like some tips, because I have my first ever date tomorrow (although I've had a gf for 3 years, but no actual dating happened), and we're going to the beach.

I met this girl, we have mutual friends, at a festival a few days ago. We didn't kiss, but we talked, held hands, danced a bit. I asked her to go on a date with me, which was super hard as it is the first time I've asked this to anybody. What I mean to say is, it's not like a standard *first* date because we already spent some time together.

I'm really nervous and excited. I'm going to pick her up tomorrow, we're cycling to the beach which will take 30 minutes, and then what? I'm a bit scared. Should I bring something (the weather, although no rain and sunny, is not super so no swimming), should we do something. I'd like all the tips I can get. Thanks!

Human written reference TL;DR	**6.7B supervised model**	**6.7B human feedback model**
First date after 3 years in a relationship, going to the beach, terrified. What to bring with me, what to do?	Going on a date with a girl I met a few days ago, going to the beach. What should I bring, what should we do?	Going on my first ever date tomorrow, cycling to the beach. Would like some tips on what to do and bring. I'm a bit nervous and excited. Thanks!

Why learn from human feedback?

Provides a mechanism for gathering signals about correctness that are difficult to describe via data or cost functions, e.g., what does it mean to be funny?

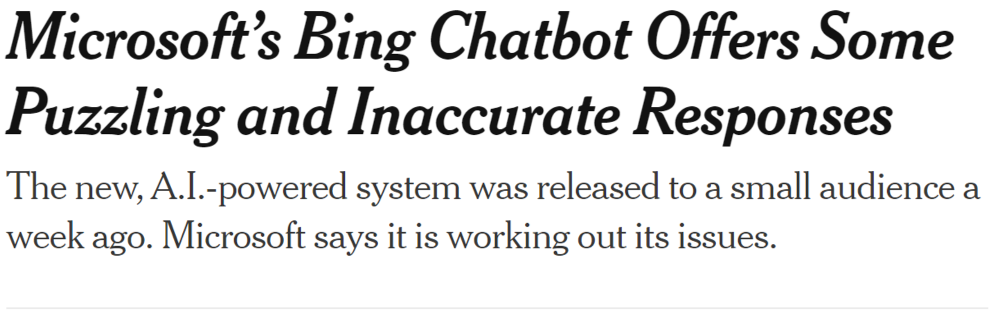
Provides signals that are best defined by stakeholders, e.g., helpfulness, fairness, safety training, alignment.

Useful when evaluation is easier than modeling ideal behavior

Sometimes we don’t really care about human preferences per-se, we care about fixing model mistakes.

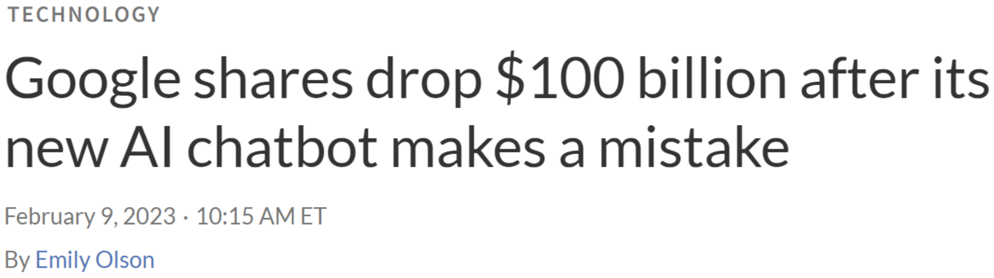
We have not figured out how to do it quite right (or we need new approaches)

- Reflects some human biases e.g., length, authoritative tone, …
- Human preferences can be unreliable e.g., “reward hacking in RL”



Microsoft’s Bing Chatbot Offers Some Puzzling and Inaccurate Responses

The new, A.I.-powered system was released to a small audience a week ago. Microsoft says it is working out its issues.



TECHNOLOGY

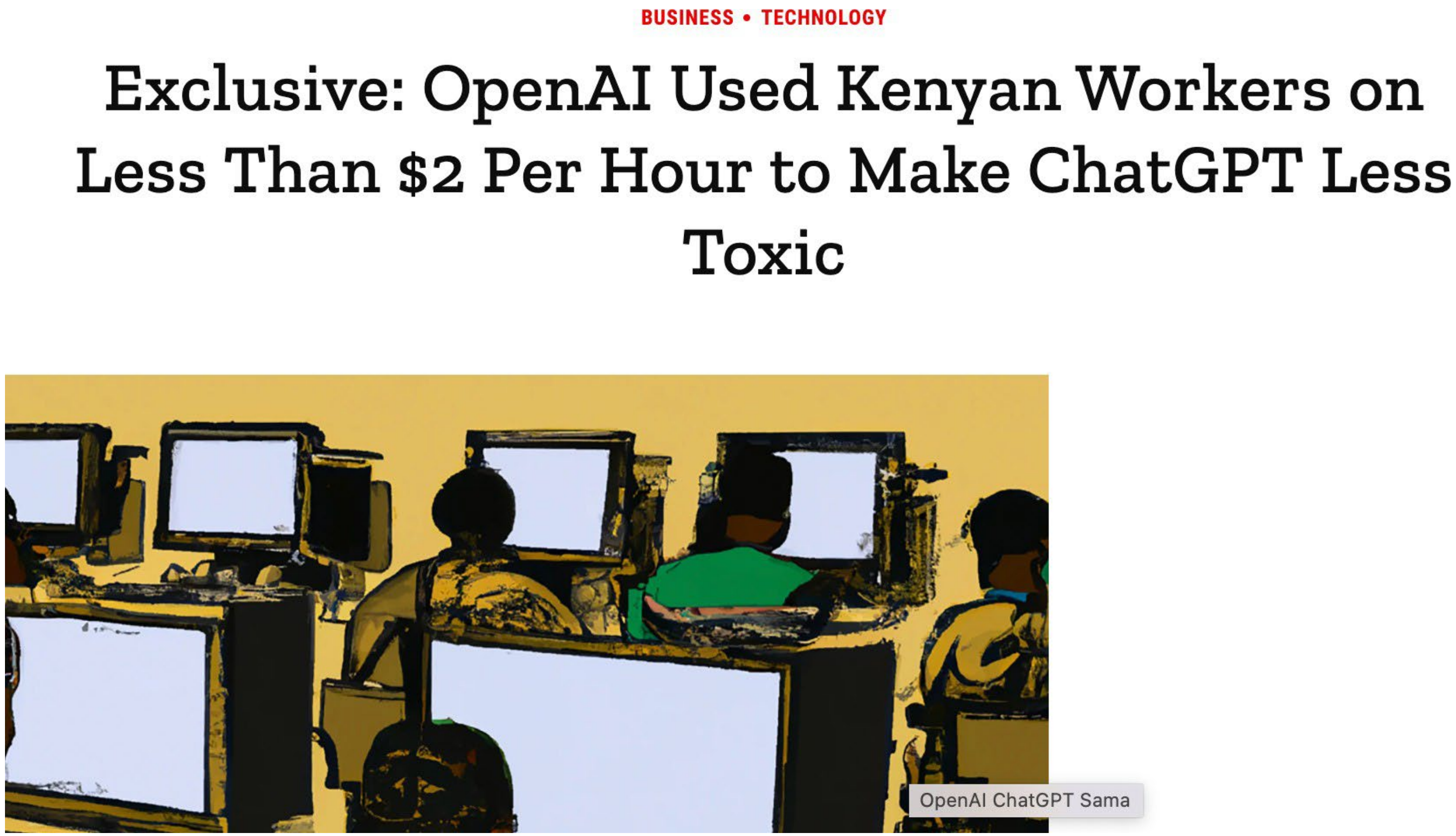
Google shares drop $100 billion after its new AI chatbot makes a mistake

February 9, 2023 · 10:15 AM ET

By Emily Olson

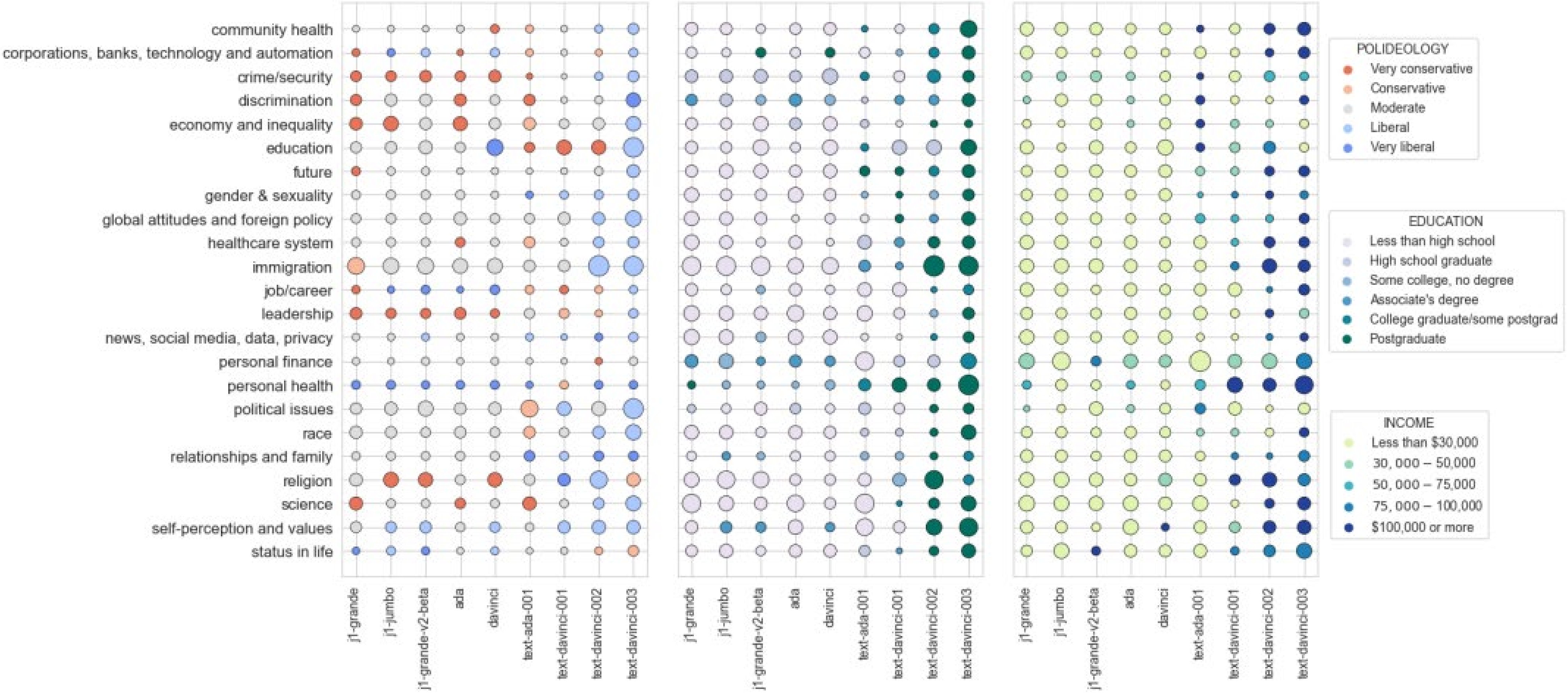
Potential ethical issues

- Labeling often depends on Low-cost human labor
- The line between economic opportunity and employment is unclear
- May cause psychological issues for some workers



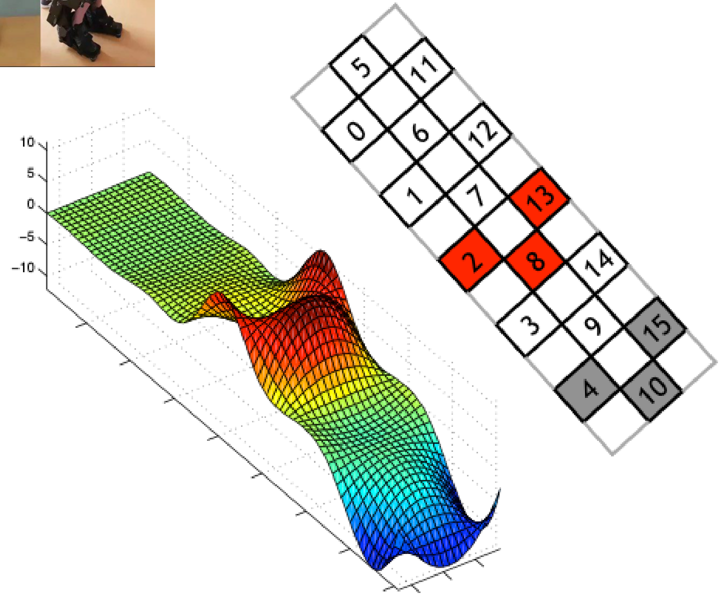
BUSINESS • TECHNOLOGY

Exclusive: OpenAI Used Kenyan Workers on Less Than $2 Per Hour to Make ChatGPT Less Toxic



Santurkar, et. al. , “Whose Opinions Do Language Models Reflect?

Preferences used to personalize therapy



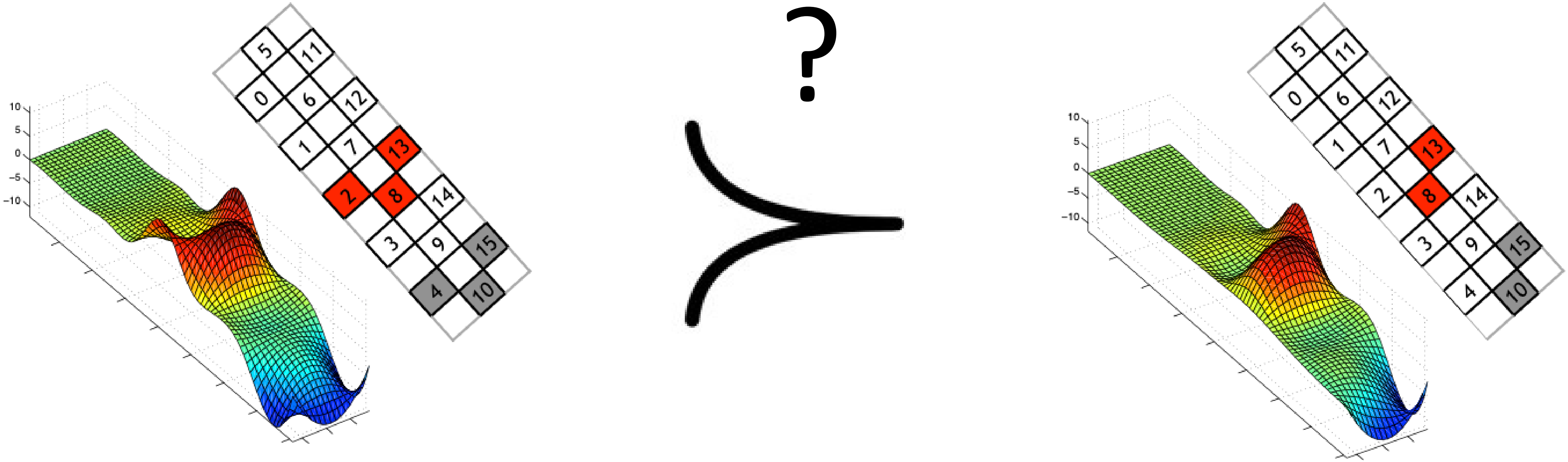
Absolute Feedback: “That felt good, 4/5 rating.”

Slides adapted from Yisong Yue

Challenge: humans are not consistent in providing absolute feedback.

Slides adapted from Yisong Yue

Preference feedback + Dueling bandits



Multi-dueling Bandits with Dependent Arms, Sui, Zhuang, Burdick & Yue, UAI 2017
Correlational Dueling Bandits with Application to Clinical Treatment in Large Decision Spaces, Sui, Yue & Burdick, IJCAI 2017
Preference-Based Learning for Exoskeleton Gait Optimization, Tucker, Novoseller, et al., ICRA 2020
Human Preference-Based Learning for High-dimensional Optimization of Exoskeleton Walking Gaits, Tucker et al., IROS 2020
ROIAL: Region of Interest Active Learning for Characterizing Exoskeleton Gait Preference Landscapes, Li, Tucker, et al., ICRA 2021

Metric Elicitation

Determine the fairness and performance metric by interacting with individual stakeholders

See Hiranandani et. al., “Fair Performance Metric Elicitation”

Metric elicitation from stakeholder groups

See Robertson et. al., “Probabilistic Performance Metric Elicitation

Empirical evaluation

See Hirandanai et. al., “Metric Elicitation; Moving from Theory to Practice”

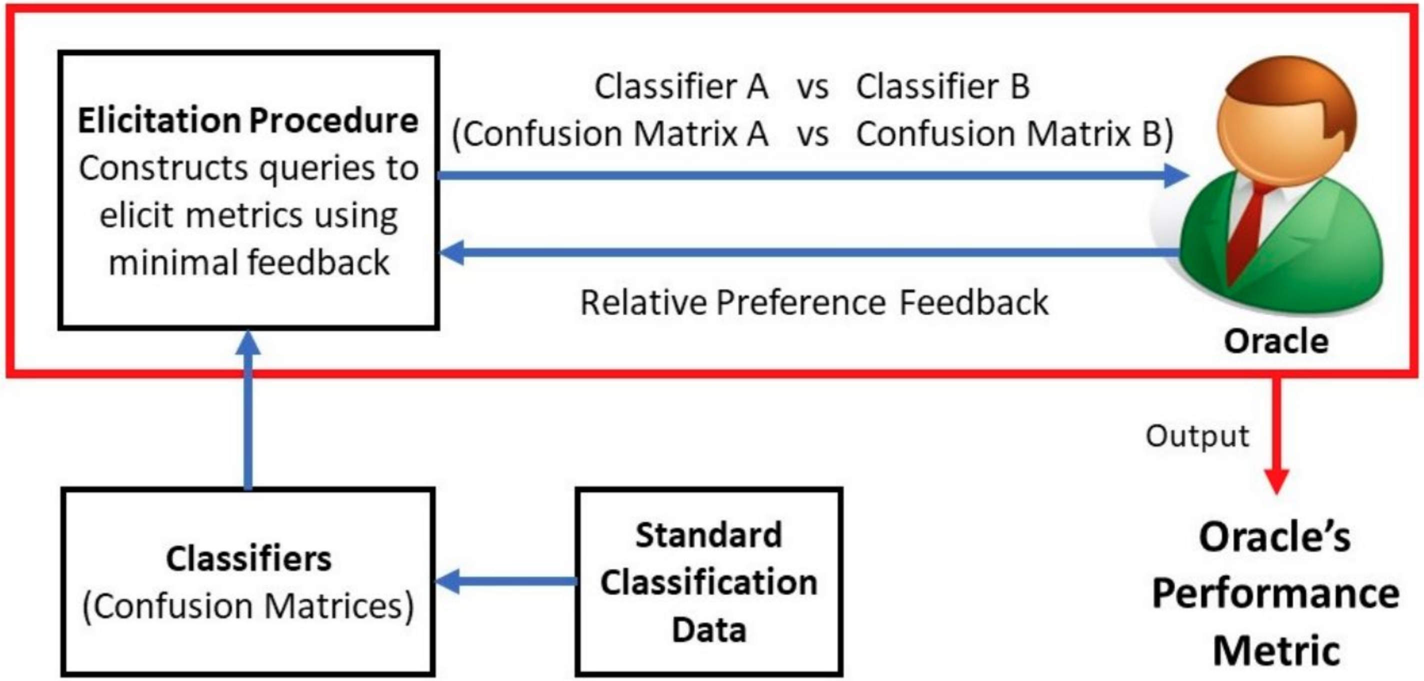

Elicitation Procedure
Constructs queries to elicit metrics using minimal feedback
Classifier A vs Classifier B
(Confusion Matrix A vs Confusion Matrix B)
Relative Preference Feedback
Oracle
Output
Oracle’s Performance Metric
Classifiers
(Confusion Matrices)
Standard Classification Data

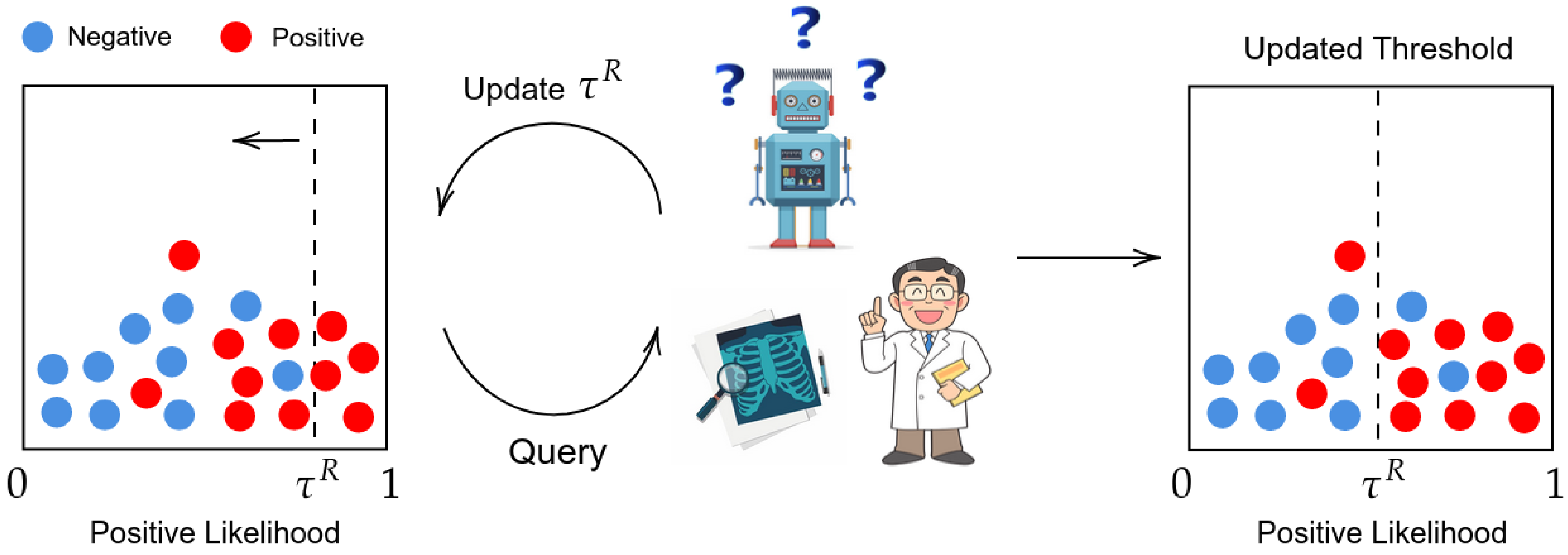
Figure from Hiranandani et. al “Multiclass Performance Metric Elicitation”

Why elicit metric preferences?

Useful when tradeoffs are inherently stakeholder dependent i.e., human preferences are the best approach to measuring what tradeoffs matter

Important for socio-technical tradeoffs e.g., fairness vs performance, privacy vs fairness, …

Cooperative Inverse Decision Theory (CIDT)



Imitator (R) seeks to learn decision rule matching Demonstrator (H) preferences

Can be formalized as an assistance game (Hadfield-Menell et al., 2016)

Challenge: Highlights description-experience gap in measuring preferences

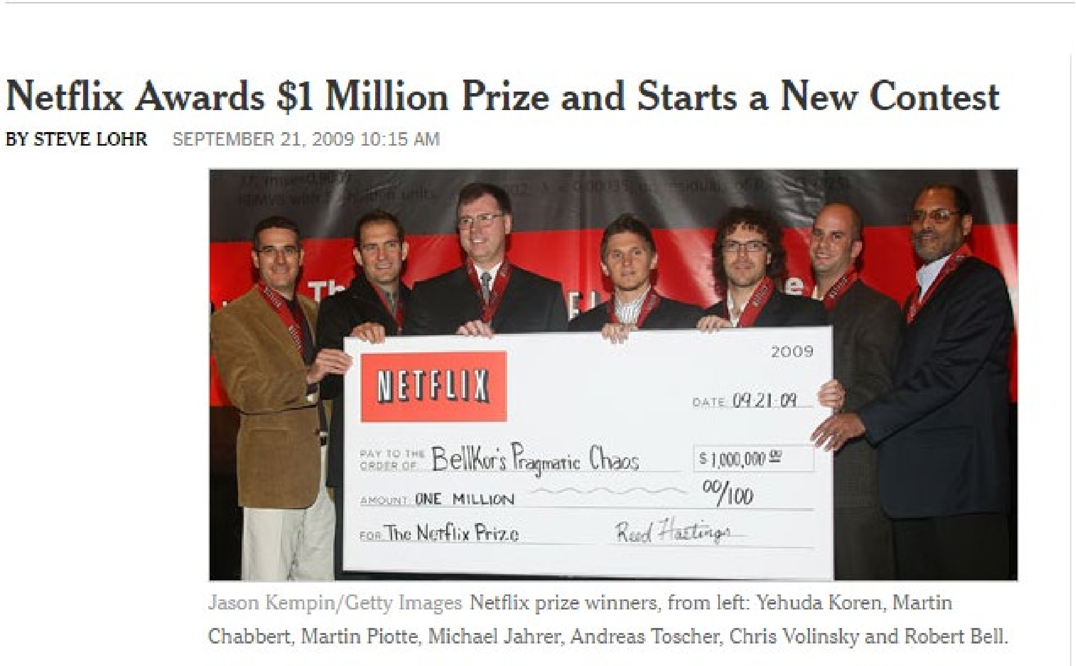
Robertson et. al. “Cooperative inverse decision theory for uncertain preferences” 2023

Recommendation systems

User item preferences to recommend new items

Both passive (offline data) and active querying (contextual bandits)

Often ratings, ranking or thumbs up/down feedback

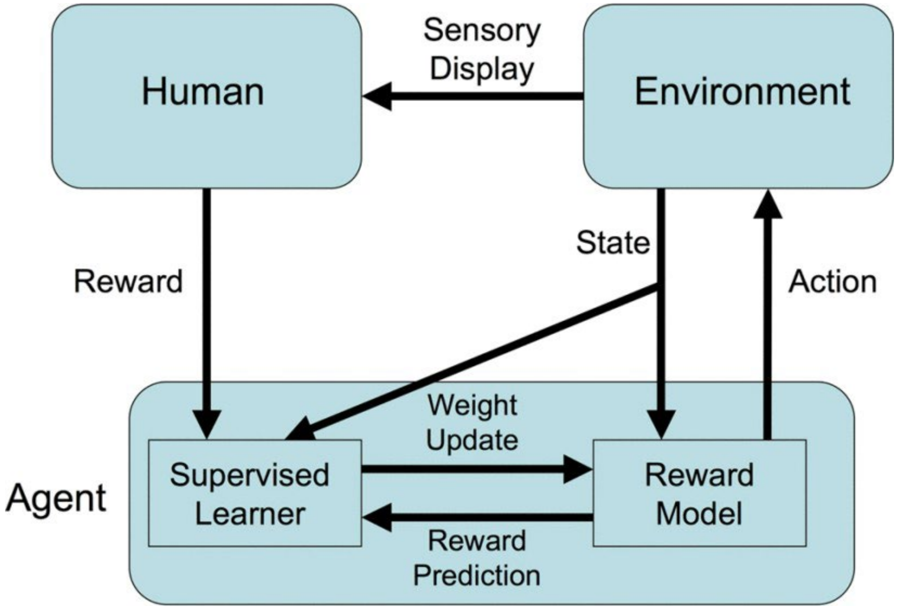


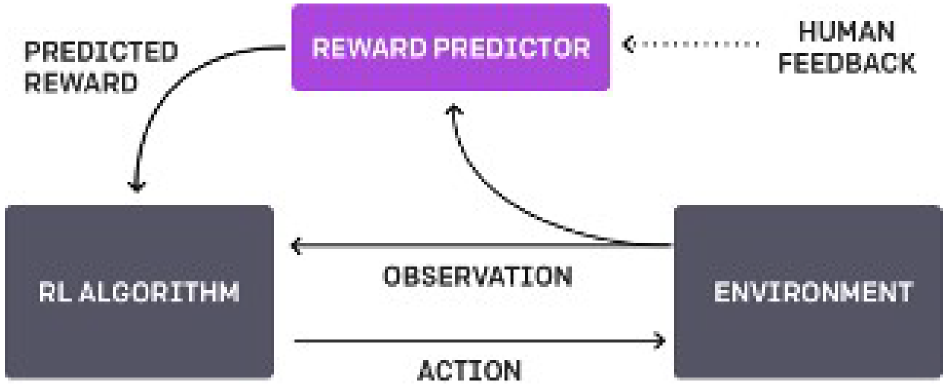
Netflix Awards $1 Million Prize and Starts a New Contest

BY STEVE LOHR SEPTEMBER 21, 2009 10:15 AM

Jason Kempin/Getty Images Netflix prize winners, from left: Yehuda Koren, Martin Chabbert, Martin Piotte, Michael Jahrer, Andreas Toscher, Chris Volinsky and Robert Bell.

Reinforcement Learning (RL) from Human Preferences





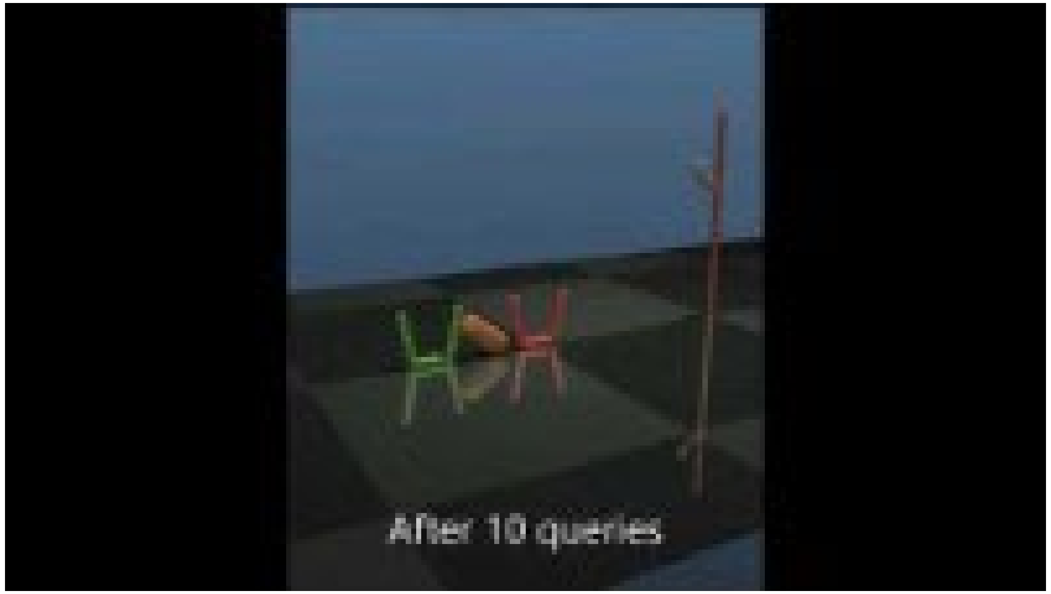
Knox, W. Bradley, and Peter Stone. "Tamer: Training an agent manually via evaluative reinforcement." In 2008 7th IEEE international conference on development and learning, pp. 292-297. IEEE, 2008.

Christiano, Paul F., Jan Leike, Tom Brown, Miljan Martic, Shane Legg, and Dario Amodei. "Deep reinforcement learning from human preferences." Advances in neural information processing systems 30 (2017).

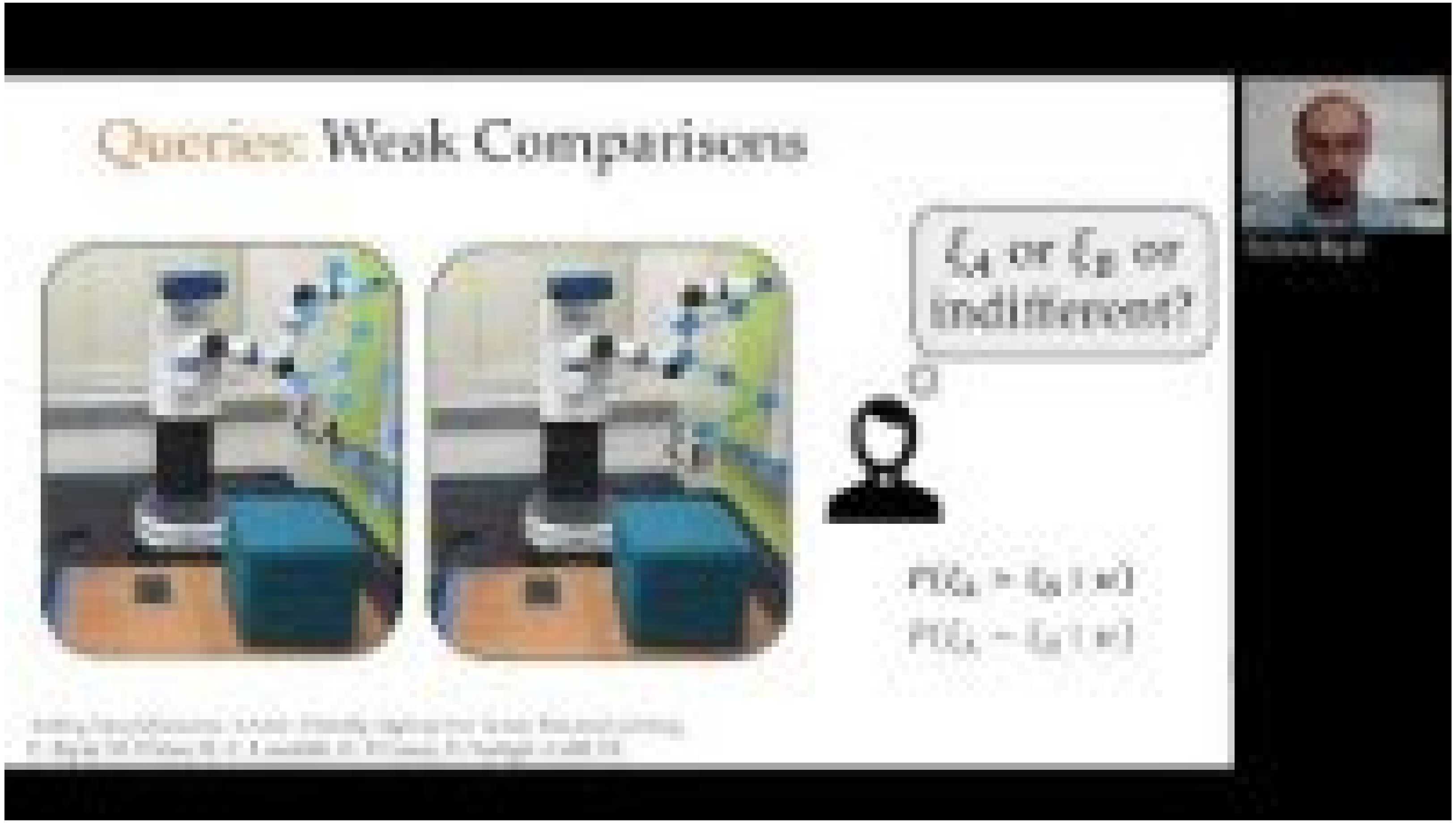
Flying helicopters using imitation learning and inverse reinforcement learning (IRL)

Learning for Control from Multiple Demonstrations, Adam Coates, Pieter Abbeel, and Andrew Y. Ng. ICML, 2008.

Batch active preference learning for RL



E Bıyık, D Sadigh, "Batch Active Preference-Based Learning of Reward Functions", 2nd Conference on Robot Learning (CoRL), Zurich, Switzerland, Oct. 2018.



Queries: Weak Comparisons

ξ_A or ξ_B or indifferent?

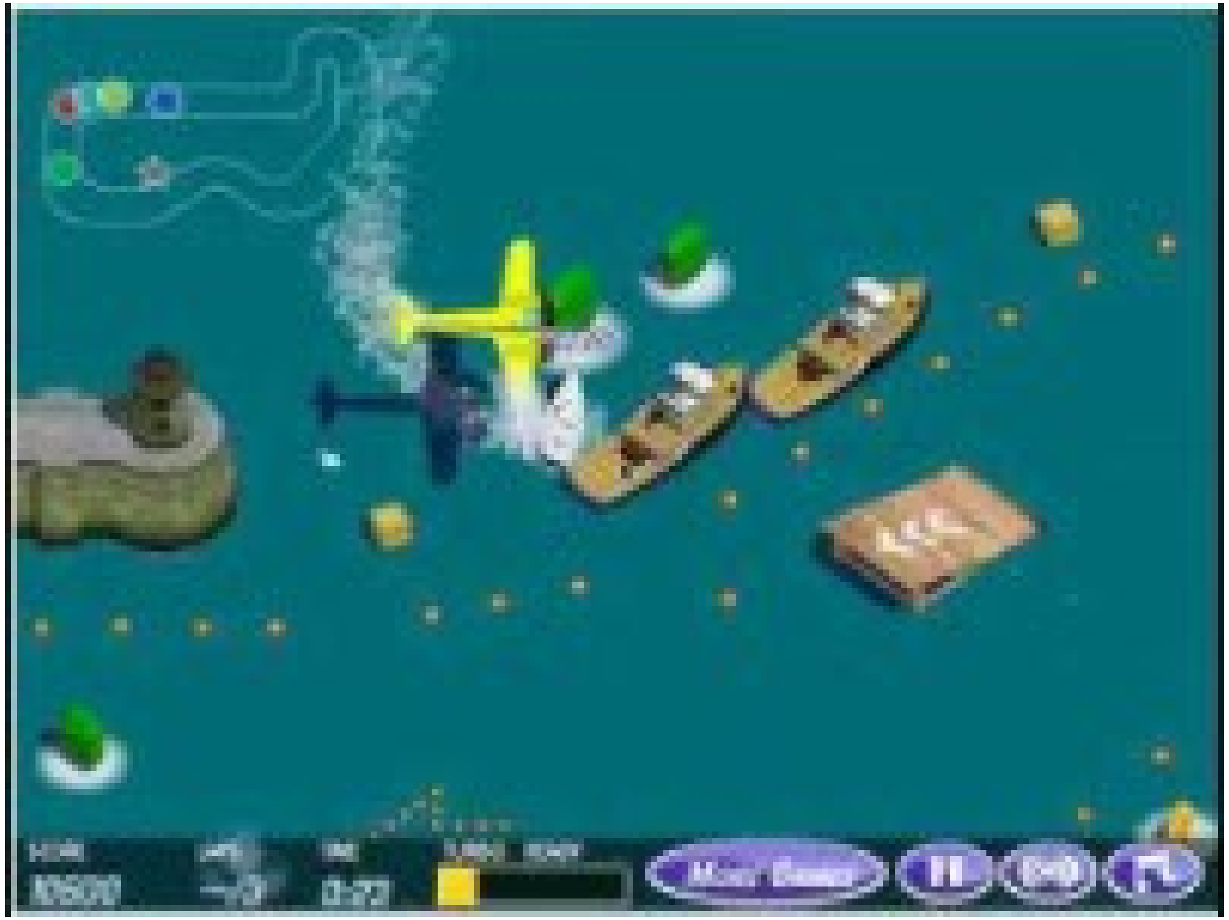
$P(\xi_A \succ \xi_B \mid w)$

$P(\xi_A \sim \xi_B \mid w)$

[illegible]

“APReL: A Library for Active Preference-based Reward Learning Algorithms” Erdem Bıyık, Aditi Talati, Dorsa Sadigh. Artificial Intelligence for Human-Robot Interaction (AI-HRI) at AAAI Fall Symposium Series, November 2021

Reward hacking in inverse RL



Design of tools for eliciting feedback from humans often has to tradeoff several factors

- Cognitive load/effort: Human friendly vs model-friendly feedback

- Truthfulness: what if there is no “correct” answer?

- Accuracy: what of human mistakes? What is the role of expertise?

Recurring assumptions and discussion

Assuming human rationality (~existence of a deterministic reward function).

Human preference often expressed as discrete choice, models often have strong parametric assumptions

Limited work on the role of human biases, do they matter?

Limited work on aggregation in learning applications (lots of work in mechanism design)

RL and active learning emphasize careful querying, while language applications are have less focus on active querying. Does it matter?

Course Goals

- Topics course covering (some) foundations and applications of learning from human preferences. Somewhat focus on breadth/coverage vs. depth
- **Foundations:** Judgement, decision making and choice, biases (psychology, marketing), discrete choice theory, mechanism design, choice aggregation (micro-economics), human-computer interaction, ethics
- **Machine learning and statistics:** Modeling, active learning, bandits
- **Applications:** recommender systems, language models, reinforcement learning, AI alignment
- **Note**: lecture schedule is tentative and topics/speakers may change

Guest Lectures

Dorsa Sadigh
Robotics

Vasilis Syrgkanis
Mechanism Design

Jason Hartline
Mechanism Design

Diyi Yang
NLP, Ethics

Merrie Morris
HCI, Ethics

Nathan Lambert
NLP, RLHF

Noah Goodman
Psychology

Jonathan Levav
Marketing

S. Wheeler
Marketing

Pat Langley
Human Computing

“Topics course” here means

- **In-class presentation:** Reading and presenting papers
- **Scribe** for lectures
- **Active feedback** and peer grading
- **Course project** i.e., research project that is relevant to this topic

- Course staff will help **curate and evaluate** this work.

Prerequisites

CS 221 (AI) or CS 229 (ML) or equivalent

You are expected to …

- Be proficient in Python (most project will include a programming component)
- Be comfortable with machine learning concepts, e.g., train/dev test set, model fitting, function class, loss functions.
- Writing assignments will likely require latex

Grading

- **Project (50%):**
  - Proposal (5%)
  - Final manuscript (25%)
  - Poster (10%)
  - Blog post (10%)
- **Presentation + Class notes (40%):**
  - In-class presentations (20%)
  - Scribe notes (20%)
- **Peer Grading (10%):**
  - Feedback for presentations (5%)
  - Feedback for projects (5%)
- **Class participation (Extra credit up to 5%)**
  - Ed Question Answering
  - Q/A participation in class
- **No homework, no exams**

Project

  - Proposal (5%)
  - Final manuscript (25%)
  - Poster (10%)
  - Blog post (10%)
- **Project scope:** any topic related to what is covered in class, i.e., make clear how in related to “ML from human preferences”. Examples:
  - Simulation platforms that capture human biases or group dynamics
  - Mechanism design for learning from group preferences
  - Applications to new problems, e.g., generative models
  - Mathematical and statistical foundations
  - Well designed user studies

In-class Presentation

- You are expected to present material for one class with a group
- We will release a signup schedule
- **Expectation**: start with provided references, then add relevant material based on our interests

Scribe

- You are expected to scribe for **two** lectures (group scribing)
  - One scribe for the class where you present material
  - One scribe for an invited lecture (will release a signup schedule soon)
- One week for the first draft, then iterate with the course staff
- **Expectation**: a summary of the lecture content with depth on technical details and relevant references

Peer grading

- You are expected to peer grade two components
    - In-class presentation
    - Project feedback, similar to a paper review.
- One week for feedback submission
- We will provide a rubric soon
- **Expectation**: feedback that helps your peers improve and helps you think critically about the material

In-Person Expectation

- The class is designed to be interactive and is not remote-friendly
- You will need to be in person for any components where you are providing feedback or scribe
- Slides should be available soon after lecture for review

Computing credits

- Anticipating credits on Google cloud.
- May be able to include credits for foundation models (pending)

Late Assignments

- Each student will have a total of **4 free late** (calendar) days. Final project papers cannot be turned in late under any circumstances.
- Once these late days are exhausted, any work turned in late will be penalized **10% per late day.**
- If a group's assignment is late n days, then each group member is charged n late days.
- Late days are **never transferrable** between students.

Welcome to CS 329H

- **Today:** Introduction and overview
- **Next lecture:** Discrete choice and human preference models

- HW0:
  - Complete the pre-course survey (see Ed)
  - Signup for scribes
  - Signup for paper presentations / lectures (soon!)
  - Start thinking of project ideas (we are also soliciting ideas, should be available Oct 6)