CS 2731 / ISSP 2230
Introduction to Natural Language Processing

Session 25: Dialogue, chatbots part 1

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School of Computing and Information

Course logistics: project, project, project

- Project presentations **in class Apr 24**
- Final reports **due Apr 25**
- Grades on basic working systems are out
    - Feel free to come to office hours or set up a meeting with Michael or Bhiman to discuss next steps

Overview: Dialogue, chatbots part 1

- Introduction to dialogue systems and chatbots
- Properties of human conversation
- Rule-based chatbots (ELIZA review)
- Corpus-based chatbots
- Encoder-decoder framework for dialogue generation
- RLHF and ChatGPT

Dialogue systems and chatbots

Conversational Systems

- Personal Assistants on phones or other devices
  - SIRI, Alexa, Cortana, Google Assistant
- Playing music, setting timers and clocks
- Chatting for fun
- Booking travel reservations
- Clinical uses for mental health

Slide credit: David Mortensen, Jurafsky & Martin

Two kinds of conversational systems

- Chatbots
  - mimic informal human chatting for fun, or even for therapy
- (Task-based) Dialogue Agents
  - interfaces to personal assistants
  - cars, robots, appliances
  - booking flights or restaurants

Slide credit: David Mortensen, Jurafsky & Martin

Spoken conversational systems

- Incorporates speech recognition and text-to-speech
  - Additional possible sources of error
- Benefits of speech as an interface
  - Highly intuitive
  - Eyes and hands free
  - Small devices
  - Rich communication channel

Slide adapted from Diane Litman

Properties of human conversation

C_1: . . . I need to travel in May.
A_2: And, what day in May did you want to travel?
C_3: OK uh I need to be there for a meeting that's from the 12th to the 15th.
A_4: And you're flying into what city?
C_5: Seattle.
A_6: And what time would you like to leave Pittsburgh?
C_7: Uh hmm I don't think there's many options for non-stop.
A_8: Right. There's three non-stops today.
C_9: What are they?
A_{10}: The first one departs PGH at 10:00am arrives Seattle at 12:05 their time. The second flight departs PGH at 5:55pm, arrives Seattle at 8pm. And the last flight departs PGH at 8:15pm arrives Seattle at 10:28pm.
C_{11}: OK I'll take the 5ish flight on the night before on the 11th.
A_{12}: On the 11th? OK. Departing at 5:55pm arrives Seattle at 8pm, U.S. Air flight 115.
C_{13}: OK.
A_{14}: And you said returning on May 15th?
C_{15}: Uh, yeah, at the end of the day.
A_{16}: OK. There's #two non-stops . . . #
C_{17}: #Act. . . actually #, what day of the week is the 15th?
A_{18}: It's a Friday.
C_{19}: Uh hmm. I would consider staying there an extra day til Sunday.
A_{20}: OK. . . OK. On Sunday I have . . .

Figure 15.1 Part of a phone conversation between a human travel agent (A) and human client (C). The passages framed by # in A_{16} and C_{17} indicate overlaps in speech.

Figure from Jurafsky & Martin

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Turn-taking

- A turn is a single contribution from one speaker
- Turn-taking is complex
- When to take/yield the floor?
- People can detect when their conversation partner is about to stop talking
- People interrupt each other, resulting in overlapping speech

Slide adapted from David Mortensen, Jurafsky & Martin

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Figure 15.1 Part of a phone conversation between a human travel agent (A) and human client (C). The passages framed by # in A_{16} and C_{17} indicate overlaps in speech.

There are *vocal pauses* such as "uh".

Slide adapted from David Mortensen, Jurafsky & Martin

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Figure 15.1 Part of a phone conversation between a human travel agent (A) and human client (C). The passages framed by # in A_{16} and C_{17} indicate overlaps in speech.

There are *discourse markers* like "OK" and "Right".

Slide adapted from David Mortensen, Jurafsky & Martin

Grounding

Why do elevator buttons light up?

And what happens when pedestrian crosswalk buttons don’t?

Image: ABC News

Slide adapted from David Mortensen

Grounding with Discourse Markers

A: And you said returning on May 15th?
C: Uh, yeah, at the end of the day.
A: OK

C: OK I'll take the 5ish flight on the night before on the 11th.
A: On the 11th? OK.

C: ...I need to travel in May.
A: And, what day in May did you want to travel?

Slide credit: David Mortensen, Jurafsky & Martin

Grounding = acknowledgment

- Conversation participants need *common ground*: set of things mutually believed by both speaker and hearer
- Principle of closure: Agents performing an action require evidence, sufficient for current purposes, that they have succeeded in performing it (Clark 1996, Norman 1988)
- Speech is an action too! So speakers need to ground each other's utterances.
- Grounding: acknowledging that the hearer has understood

Slide adapted from Jurafsky & Martin

Grounding is important for computers too!

System: Did you want to review more of your profile?

User: No.

System: What's next? AWKWARD

System: Did you want to review more of your profile?

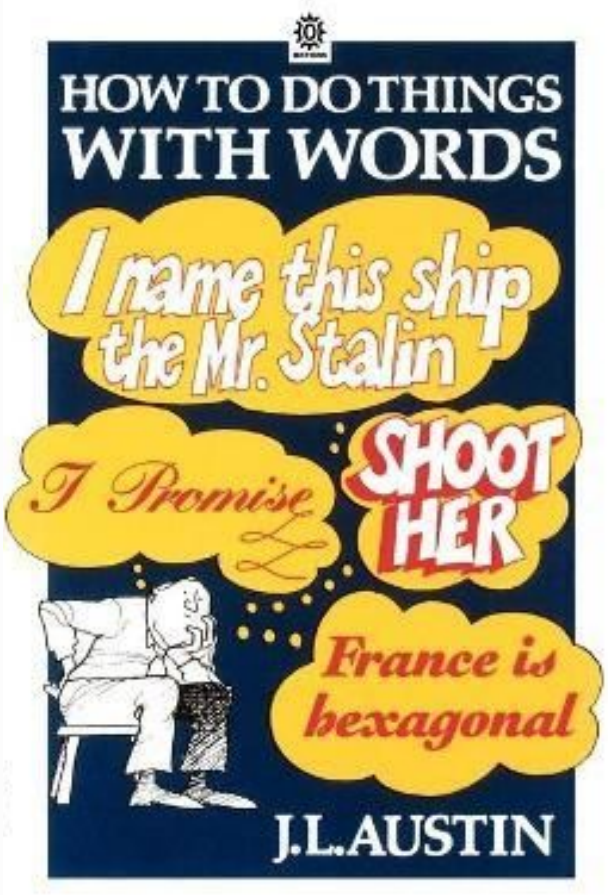
User: No.

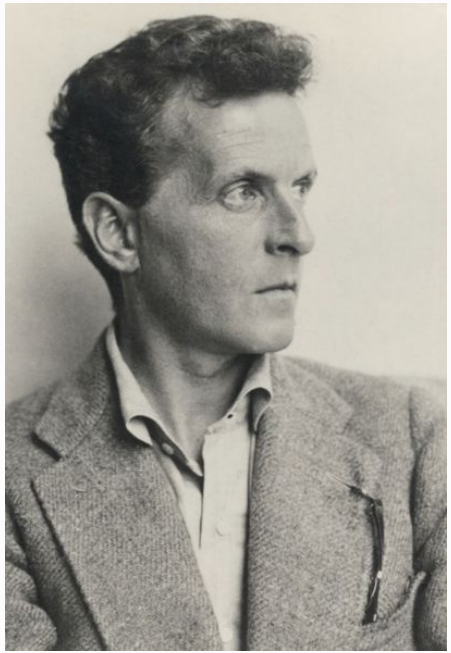
System: Okay, what's next? LESS AWKWARD!

Slide credit: Jurafsky & Martin

Speech acts: sentences that do things

Utterances as actions





Ludwig Wittgenstein

Each turn in a dialogue is a kind of action [Wittgenstein 1953, Austin 1962]

Slide adapted from David Mortensen, Jurafsky & Martin

Speech Acts: sentences that do things

Some sentences inform: *Today is Thursday*

Here are some *performative* sentences that change the state of the world:

- *I hereby name this ship the QE2.*
  The ship now has a name.
- *I hereby bequeath this cell phone to my son.*
  My son will now inherit the cell phone.
- *I hereby take this person to be my spouse.*
  I am now married.
- *I hereby declare war.*
  There is war.
- *I hereby excommunicate you.*
  You are excommunicated.

Slide credit: David Mortensen

Intent vs form

The following three sentences all have the same intent (to get the agent to book a flight to Seattle), but they take the form of a question, a command, and a statement.

- Can you book me a flight to Seattle?
- Book me a flight to Seattle.
- I'd like a flight to Seattle.

To respond appropriately, an automated conversational agent has to understand the user's intent. Task-oriented dialogue systems include classifiers for identifying the user's intent.

Slide credit: David Mortensen

Conversations have structure

Local structure between adjacent speech acts, from the field of conversation analysis [Sacks et al. 1974]

Called adjacency pairs:

- Question > Answer
- Proposal > Acceptance/Rejection
- Compliments ("Nice jacket!") > Downplayer ("Oh, this old thing?")

Slide adapted from Jurafsky & Martin

Subdialogues

Correction subdialogue

Agent: OK. There's #two non-stops#

Client: #Act- actually#, what day of the week is the 15th?

Agent: It's a Friday.

Client: Uh hmm. I would consider staying there an extra day til Sunday.

Agent: OK...OK. On Sunday I have ...

Slide adapted from Jurafsky & Martin

Conversational initiative

- Some conversations are controlled by one person
  - A reporter interviewing a chef asks questions, and the chef responds.
  - This reporter has the **conversational initiative** (Walker and Whittaker 1990)
- Most human conversations have **mixed initiative**:
  - I lead, then you lead, then I lead.
- Mixed initiative is very hard for NLP systems, which often default to simpler styles that can be frustrating for humans:
  - **User initiative** (user asks or commands, system responds)
  - **System initiative** (system asks user questions to fill out a form, user can't change the direction)

Slide adapted from Jurafsky & Martin

Conversational implicature

Agent: And, what day in May did you want to travel?

Client: OK, uh, I need to be there for a meeting that's from the 12th to the 15th.

Slide adapted from Jurafsky & Martin

Rule-based chatbots

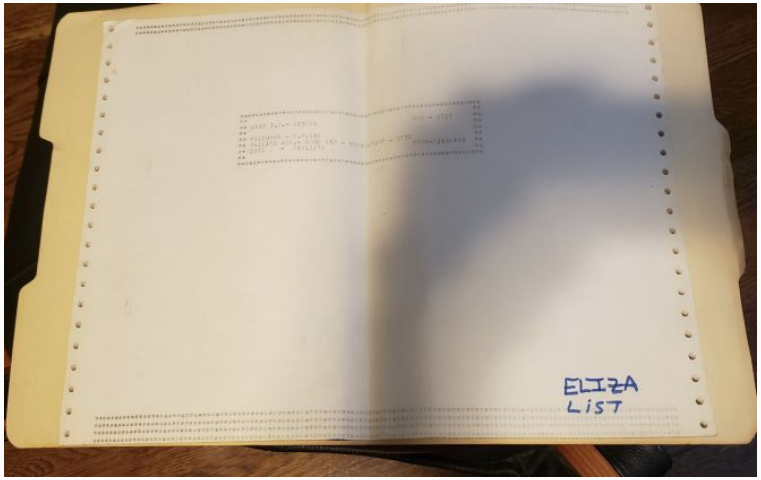
ELIZA [Weizenbaum 1966]

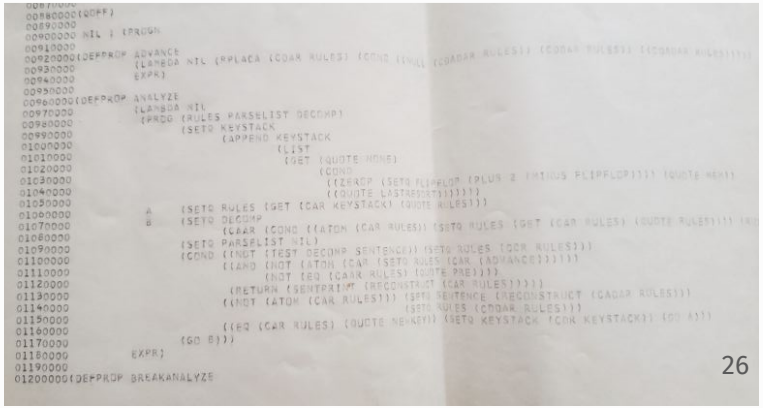
- Early chatbot that imitated a Rogerian psychotherapist
  - Rare type of conversation where can "assume the pose of knowing almost nothing of the real world"
  - Agent mirrors back what it hears
- Uses regular expression matching to match phrases

  `"I need X"`

  and translates them into, e.g.

  `"What would it mean to you if you got X?`





Slide adapted from Jurafsky & Martin, Lori Levin

Actual Conversation with ELIZA (Port to the Emacs Text Editor)

- **Patient:** I am struggling to teach my Natural Language Processing course
- **Psychotherapist:** Why do you say that?
- **Patient:** It's hard preparing all of these slides
- **Psychotherapist:** What makes you believe it's hard preparing all of these slides?
- **Patient:** I'm afraid that students won't like them
- **Psychotherapist:** Maybe your life has something to do with this.
- **Patient:** Maybe my students have something to do with this
- **Psychotherapist:** I don't understand.
- **Patient:** They have very high standards
- **Psychotherapist:** Do you get high often?
- **Patient:** No
- **Psychotherapist:** Why not?

Slide credit: David Mortensen

ELIZA Raised Issues of Anthropomorphism and Privacy That Are Still Relevant Today

- The effect of ELIZA was profound. People became **deeply involved** with the program and conversed with it like they would converse with an **actual therapist**, in some cases
- A member of the Weizenbaum's staff (Weizenbaum was the creator of ELIZA) **insisted that he leave the room** when she conversed with the chatbot
- Impressed by how freely people discussed their innermost lives with ELIZA, Weizenbaum proposed creating a corpus of all of the interactions between humans and ELIZA
- People immediately objected, pointing out that this raised significant privacy concerns (since they believed **they were having private conversations**, even if they were conversations with a piece of software)

Slide credit: David Mortensen, Jurafsky & Martin

ELIZA Raised Other Ethical Issues That Are Still Important

- **Were people misled by ELIZA?** Weizenbaum was concerned that they might have been
- In particular, he was shocked about the degree to which they confided in ELIZA
- Others (Turkle) have studied user interactions with ELIZA and other similar software
  - Fact-to-face interaction is important to relationships
  - People still develop relationships with artifacts
  - Many people just viewed ELIZA as a “diary”
  - They were not confiding in the software artifact; they were using it as a tool to explore their thoughts and experiences
- These considerations should enter into the design of NLP systems today

Slide credit: David Mortensen, Jurafsky & Martin

Corpus-based chatbots

What conversations to draw on?

Transcripts of telephone conversations between volunteers

- Switchboard corpus of American English telephone conversations

Movie dialogue

- Various corpora of movie subtitles

Hire human crowdworkers to have conversations among themselves

- Topical-Chat 11K crowdsourced conversations on 8 topics
- EMPATHETICDIALOGUES 25K crowdsourced conversations grounded in a situation where a speaker was feeling a specific emotion

Hire human crowdworkers to have conversations with the chatbot (and rate responses)

- RLHF, ChatGPT

Pseudo-conversations from public posts on social media

- Drawn from Twitter, Reddit, Weibo (微博), etc.
- Tend to be noisy; often used just as pre-training.

Crucial to remove personally identifiable information (PII)

Slide adapted from Jurafsky & Martin

Respond by generating: encoder-decoder

- Think of response production as an encoder-decoder task
- Generate each token r_t of the response by conditioning on the encoding of the entire query q and the response so far $r_1 \ldots r_{t-1}$

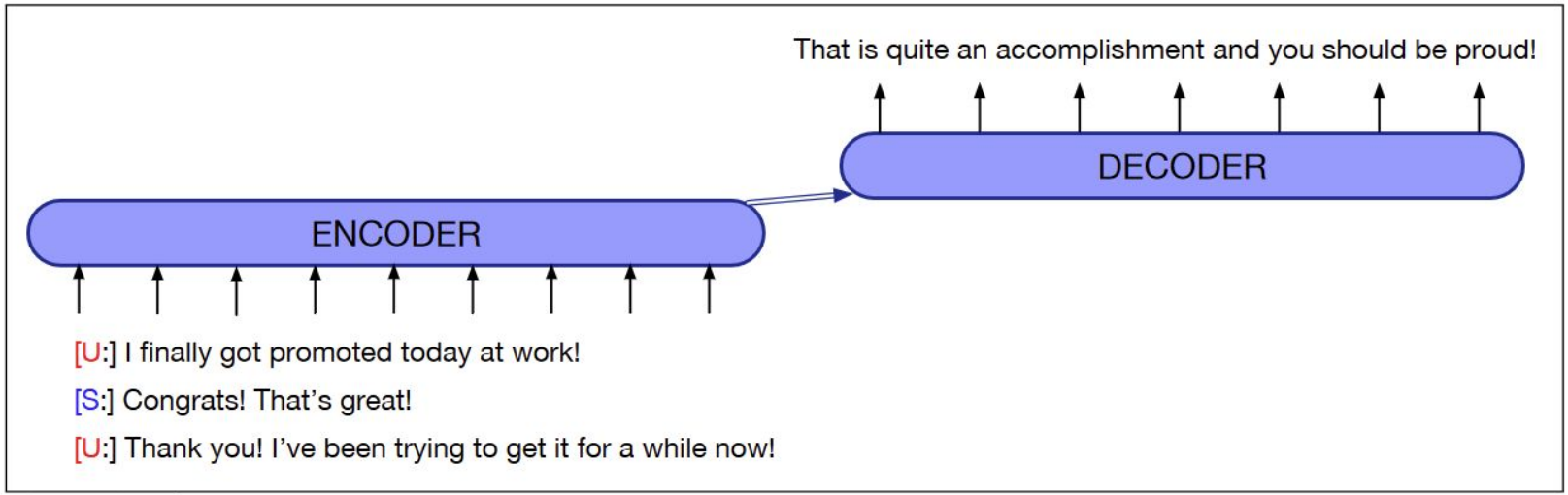


Figure 15.7 Example of encoder decoder for dialogue response generation; the encoder sees the entire dialogue context.

Slide adapted from Jurafsky & Martin

Reinforcement Learning from Human Feedback (RLHF)

Language modeling != doing dialogue

PROMPT *Explain the moon landing to a 6 year old in a few sentences.*

COMPLETION GPT-3

```
Explain the theory of gravity to a 6 year old.

Explain the theory of relativity to a 6 year old in a few sentences.

Explain the big bang theory to a 6 year old.

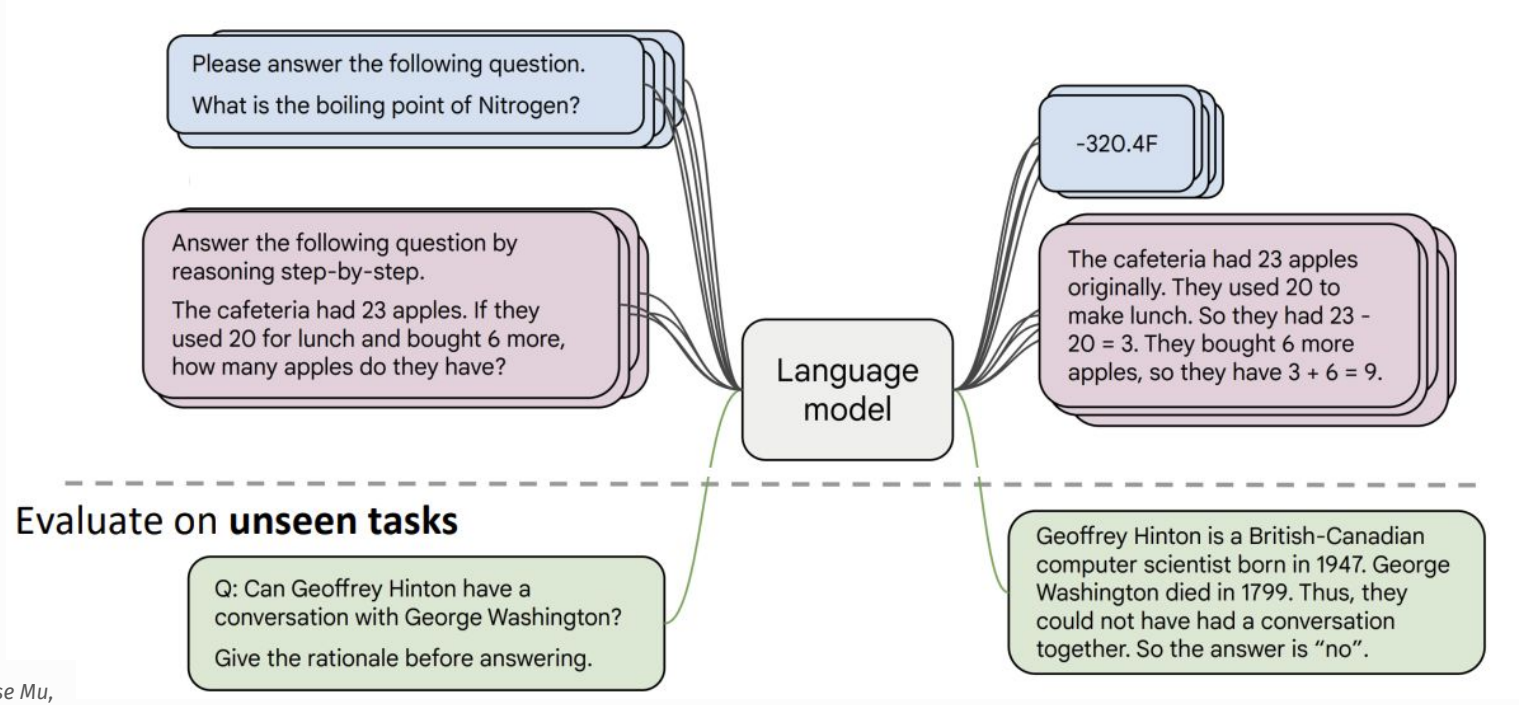
Explain evolution to a 6 year old.
```

- Language models are not aligned with user intent [Ouyang et al. 2022]
- (Instruction) finetuning to the rescue!

Slide adapted from Jesse Mu

Instruction finetuning

- Collect examples of (instruction, output) pairs across many tasks and finetune an LM



Slide adapted from Jesse Mu, Chung et al. 2022

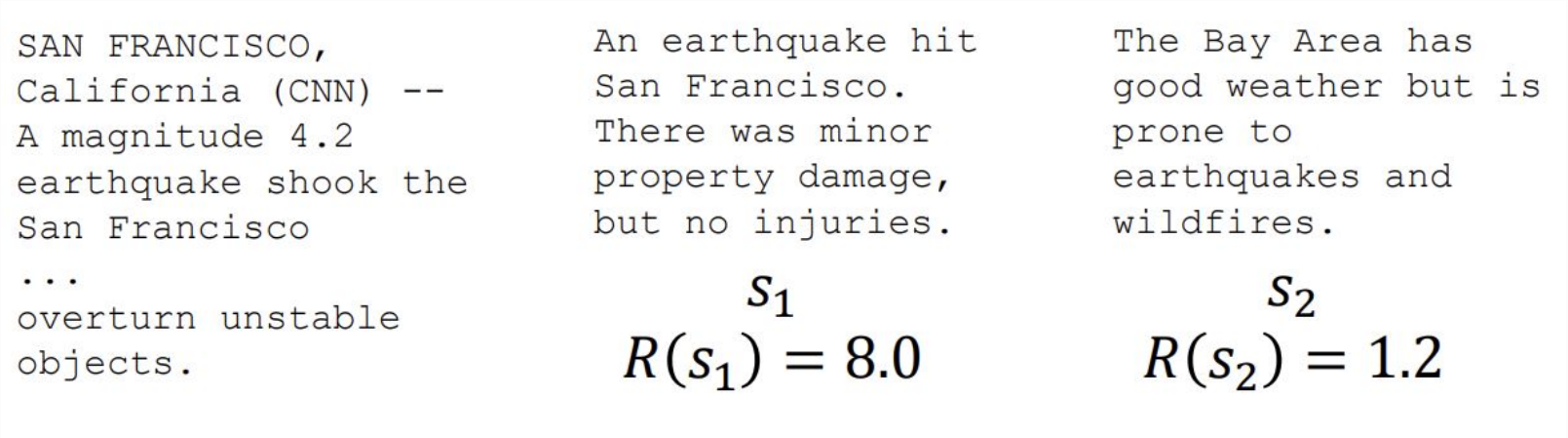
Limitations of instruction finetuning

- Expensive to collect ground-truth data for tasks
- **Problem 1:** tasks like open-ended creative generation have no right answer.
  - Write me a story about a dog and her pet grasshopper.
- **Problem 2:** language modeling penalizes all token-level mistakes equally, but some errors are worse than others
- Even with instruction finetuning, there is a mismatch between the LM objective and the objective of “satisfy human preferences”!
- Can we **explicitly attempt to satisfy human preferences?**

Slide adapted from Jesse Mu

Optimizing for human preferences

- Let's say we were training a language model on some task (e.g. summarization).
- For each LM sample s, imagine we had a way to obtain a human reward of that summary: $R(s) \in \mathbb{R}$, higher is better.

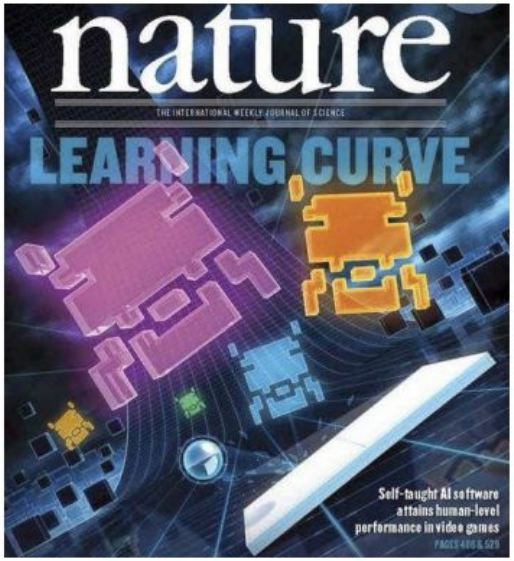


- Now we want to maximize the expected reward of samples from our LM

Slide adapted from Jesse Mu

Reinforcement learning to the rescue

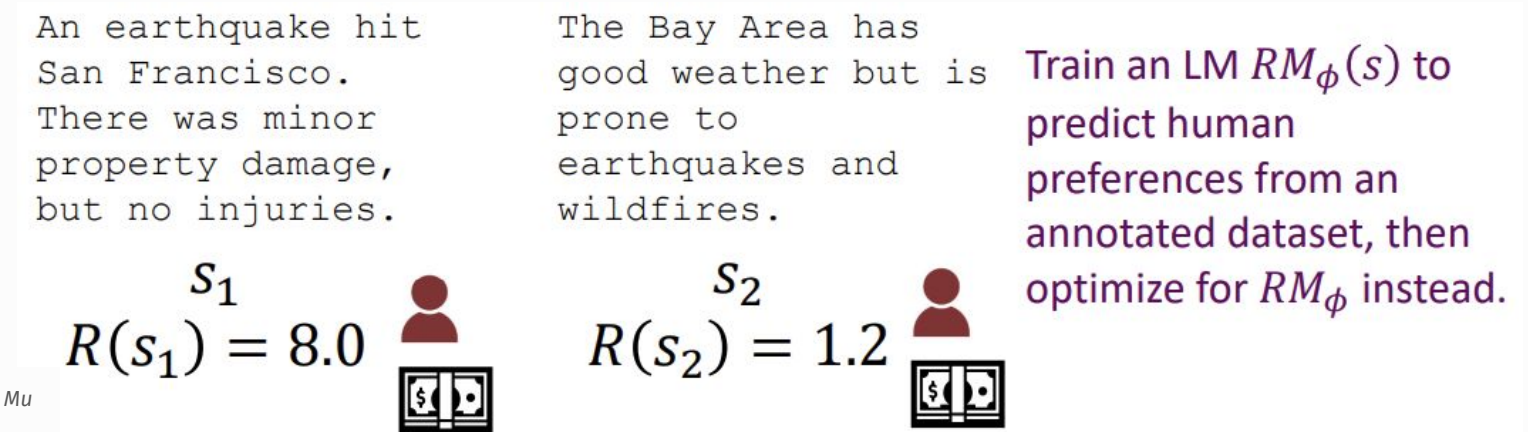
- The field of reinforcement learning (RL) has studied these (and related) problems for many years [Williams 1992; Sutton and Barto 1998]
- Circa 2013: resurgence of interest in RL applied to deep learning, game-playing [Mnih et al., 2013]
- Interest in applying RL to modern LMs is a newer phenomenon [Ziegler et al. 2019; Stiennon et al. 2020; Ouyang et al. 2022]. Why?
  - RL w/ LMs has commonly been viewed as very hard to get right (still is!)
  - Newer advances in RL algorithms that work for large neural models, including language models (e.g. PPO; [Schulman et al., 2017])



Slide adapted from Jesse Mu

How do we model human preferences?

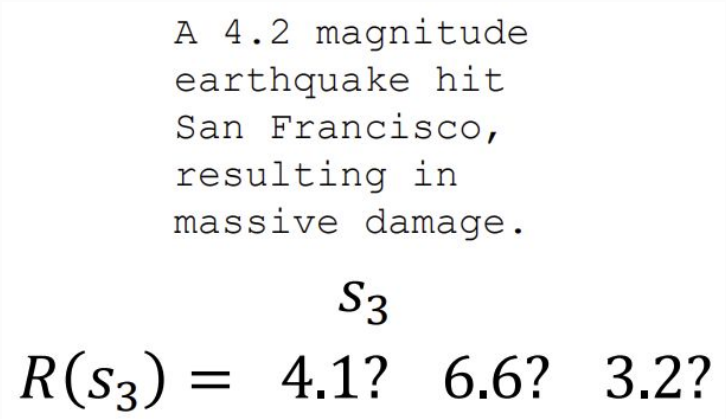
- With algorithms like REINFORCE [Williams 1992] we use any arbitrary, non-differentiable reward function $R(s)$, we can train our language model to maximize expected reward
- **Problem 1:** human-in-the-loop is expensive!
- Solution: instead of directly asking humans for preferences, model their preferences as a separate (NLP) problem! [Knox and Stone, 2009]



Slide adapted from Jesse Mu

How do we model human preferences?

- **Problem 2:** human judgments are noisy and miscalibrated!
- Solution: instead of asking for direct ratings, ask for pairwise comparisons, which can be more reliable [Phelps et al. 2015; Clark et al. 2018]



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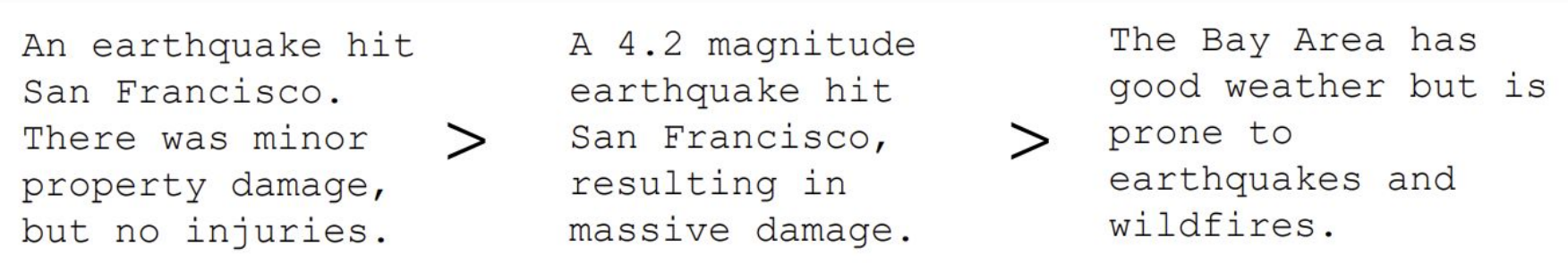

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Bradley-Terry [1952] paired comparison model

$$J_{RM}(\phi) = -\mathbb{E}_{(s^w, s^l)\sim D}\left[\log \sigma(RM_\phi(s^w) - RM_\phi(s^l))\right]$$

"winning" sample

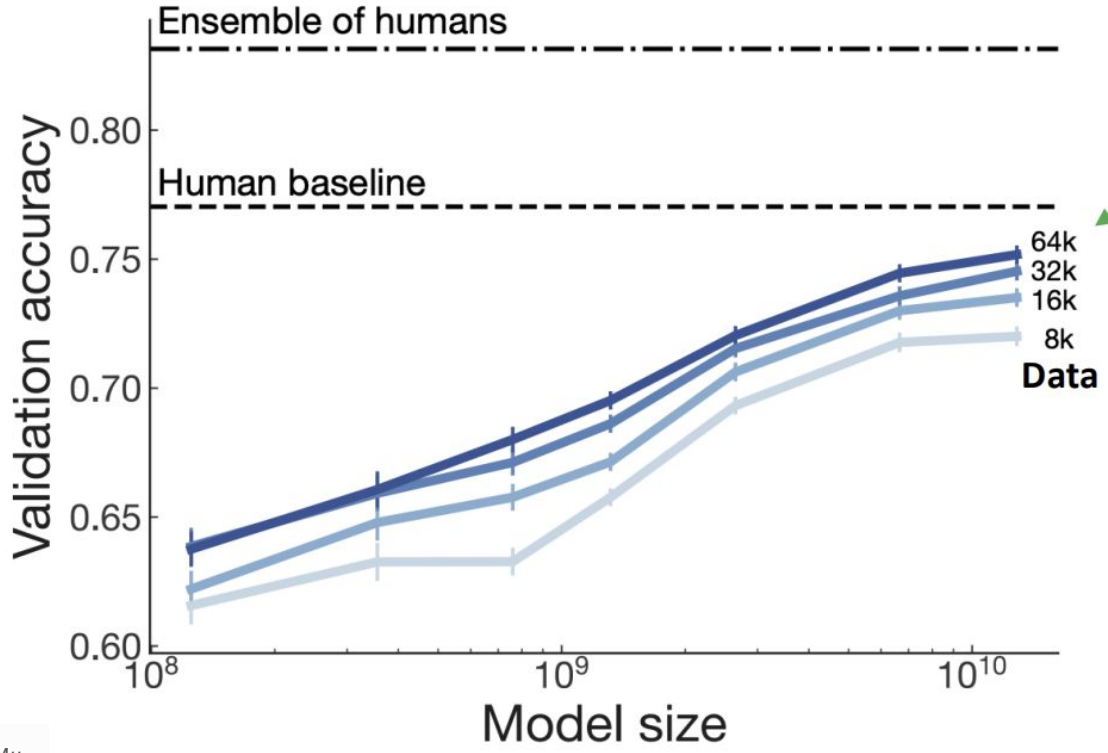
"losing" sample

s^w should score higher than s^l

Slide adapted from Jesse Mu

Make sure your reward model works first!

Evaluate RM on predicting outcome of held-out human judgments



Large enough RM trained on enough data approaching single human perf

[Stiennon et al., 2020]

Slide adapted from Jesse Mu

RLHF: Putting it all together [Christiano et al. 2017; Stiennon et al. 2020]

- Finally, we have everything we need:
  - A pretrained (possibly instruction-finetuned) LM $p^{PT}(s)$
  - A reward model $RM_\phi(s)$ that produces scalar rewards for LM outputs, trained on a dataset of human comparisons
  - A method for optimizing LM parameters towards an arbitrary reward function.
- Now to do RLHF:
  - Initialize a copy of the model $p_\theta^{RL}(s)$, with parameters θ we would like to optimize
  - Optimize the following reward with RL:

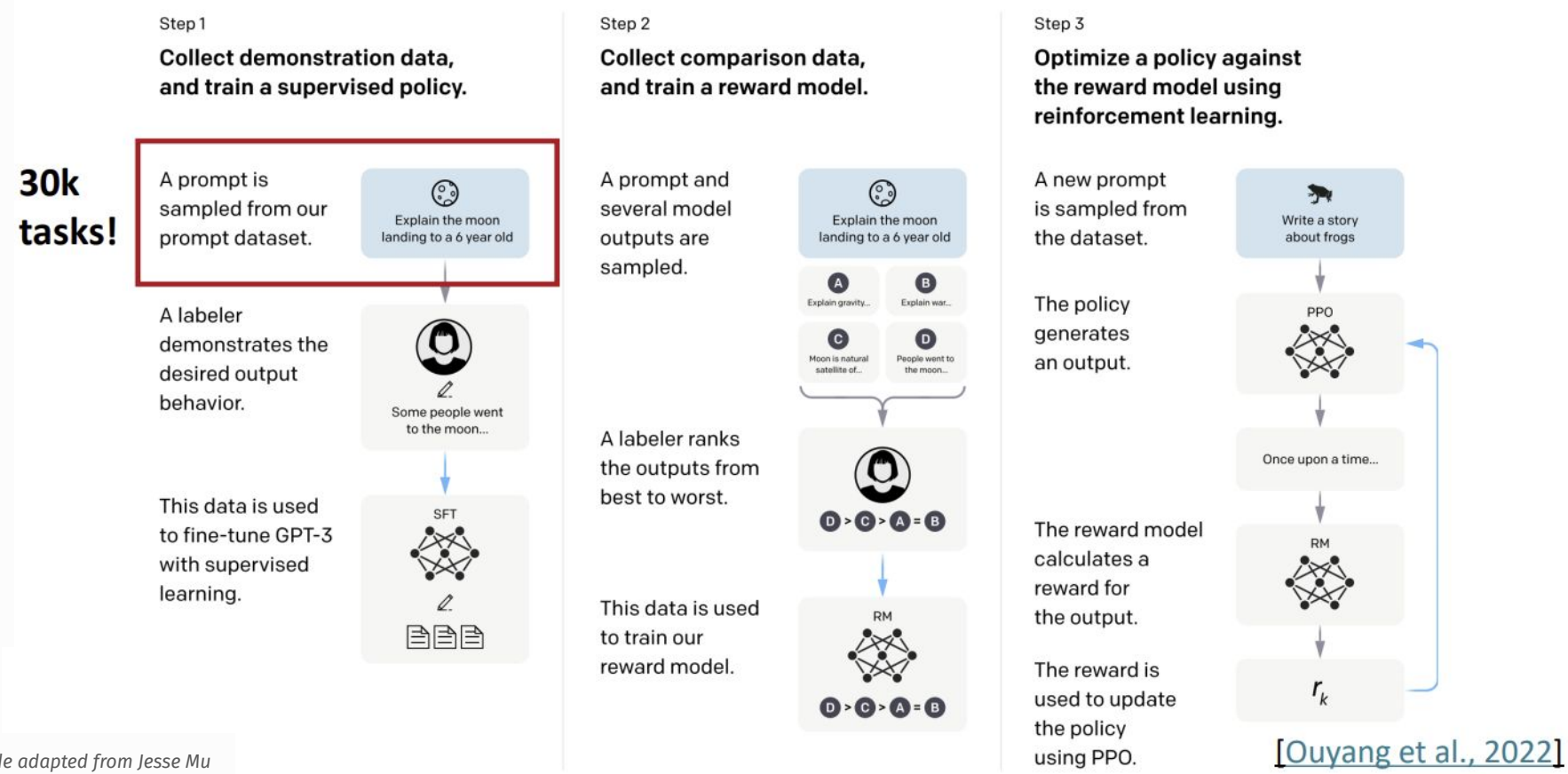
$$R(s) = RM_\phi(s) - \underbrace{\beta \log \left(\frac{p_\theta^{RL}(s)}{p^{PT}(s)} \right)}$$

Pay a price when $p_\theta^{RL}(s) > p^{PT}(s)$

This is a penalty which prevents us from diverging too far from the pretrained model. In expectation, it is known as the **Kullback-Leibler** (**KL**) divergence between $p_\theta^{RL}(s)$ and $p^{PT}(s)$.

Slide adapted from Jesse Mu

InstructGPT: scaling up RLHF to tens of thousands of tasks



[Ouyang et al., 2022]

Slide adapted from Jesse Mu

InstructGPT gets us closer to dialogue intent

PROMPT *Explain the moon landing to a 6 year old in a few sentences.*

COMPLETION

GPT-3

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Explain the theory of gravity to a 6 year old.

Explain the theory of relativity to a 6 year old in a few sentences.

Explain the big bang theory to a 6 year old.

Explain evolution to a 6 year old.
```

InstructGPT

```
People went to the moon, and they took pictures of what they saw, and
sent them back to the earth so we could all see them.
```

Slide adapted from Jesse Mu

InstructGPT can accomplish many tasks

PROMPT *Write a short poem about a wise frog.*

COMPLETION

GPT-3

```
Write a short story in which a character has two different names.

Write a short story in which you try to get something back that you
have lost.

Write a short story in which a character has a bad dream.
```

InstructGPT

```
The frog is a symbol of wisdom
He knows all the secrets of the world
He is a master of disguise
And a great teacher of life
He is a symbol of transformation
And the bringer of change
He is the frog who has seen it all
And knows the meaning of it all
```

Slide adapted from Jesse Mu

ChatGPT: Instruction Finetuning + RLHF for dialog agents

ChatGPT: Optimizing Language Models for Dialogue

Note: OpenAI (and similar companies) are keeping more details secret about ChatGPT training (including data, training parameters, model size)—perhaps to keep a competitive edge…

Methods

We trained this model using Reinforcement Learning from Human Feedback (RLHF), using the same methods as InstructGPT, but with slight differences in the data collection setup. We trained an initial model using supervised fine-tuning: human AI trainers provided conversations in which they played both sides—the user and an AI assistant. We gave the trainers access to model-written suggestions to help them compose their responses. We mixed this new dialogue dataset with the InstructGPT dataset, which we transformed into a dialogue format.

(Instruction finetuning!)

https://openai.com/blog/chatgpt/

Slide adapted from Jesse Mu

ChatGPT: Instruction Finetuning + RLHF for dialog agents

ChatGPT: Optimizing Language Models for Dialogue

Note: OpenAI (and similar companies) are keeping more details secret about ChatGPT training (including data, training parameters, model size)—perhaps to keep a competitive edge…

Methods

To create a reward model for reinforcement learning, we needed to collect comparison data, which consisted of two or more model responses ranked by quality. To collect this data, we took conversations that AI trainers had with the chatbot. We randomly selected a model-written message, sampled several alternative completions, and had AI trainers rank them. Using these reward models, we can fine-tune the model using Proximal Policy Optimization. We performed several iterations of this process.

(RLHF!)

https://openai.com/blog/chatgpt/

Slide adapted from Jesse Mu

Limitations of RL + Reward Modeling

- Human preferences are unreliable!
- “Reward hacking” is a common problem in RL
- Chatbots are rewarded to produce responses that seem authoritative and helpful, regardless of truth
- This can result in making up facts + hallucinations

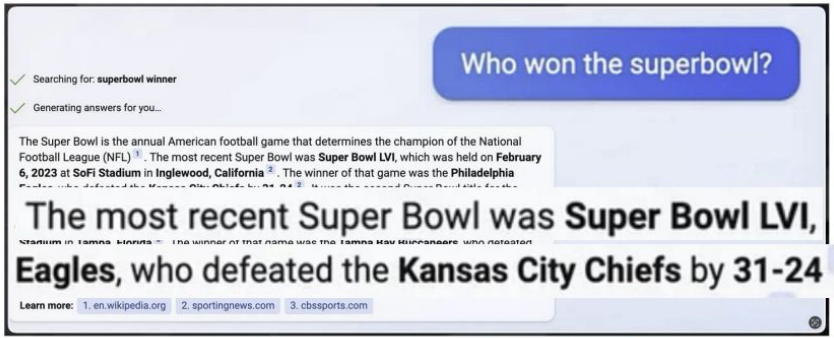
TECHNOLOGY

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

February 9, 2023 · 10:15 AM ET

https://www.npr.org/2023/02/09/1155650909/google-chatbot--error-bard-shares

Bing AI hallucinates the Super Bowl



https://news.ycombinator.com/item?id=34776508
https://apnews.com/article/kansas-city-chiefs-philadelphia-eagles-technology-science-82bc20f207e3e4cf81abc6a5d9e6b23a

Slide adapted from Jesse Mu

Wrapping up

- Automated conversational systems can be divided into 2 types:
  - Open-domain “chatbots”
  - Task-oriented dialogue systems
- Conversation is a complex joint interaction between participants
  - Turn-taking and grounding are example issues that dialogue systems must address
- Rule-based chatbots, starting with the ELIZA system, can be quite effective
- Corpus-based chatbots can respond by generating responses after being trained on corpora
- Large language models can be trained for dialogue using reinforcement learning from human feedback (RLHF)

Questions?