ml-mipt-advanced

Lecture 12. LLM Alignment.

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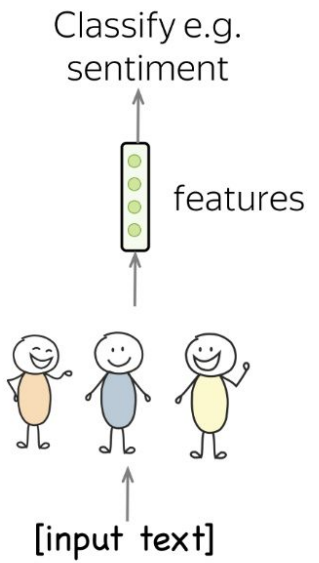
22.04.2024

Outline

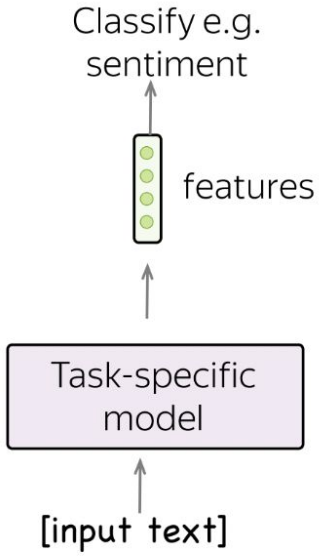
1. LLMs as instruct models
2. Finetuning for instructions
3. Alignment with user feedback
    a. RLHF
    b. Contrastive Learning

Evolutionary journey in NLP

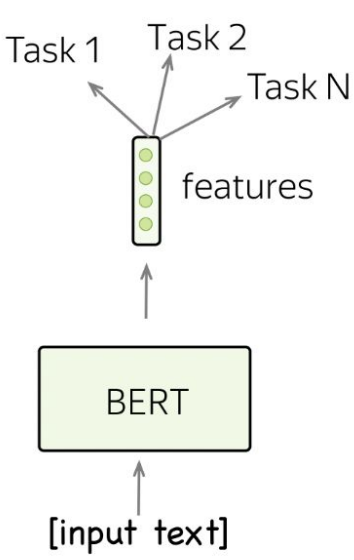
Different task – another set of features (and people!)



Different task – another model



One model, classify anything



Talk to the model

Input (prompt)

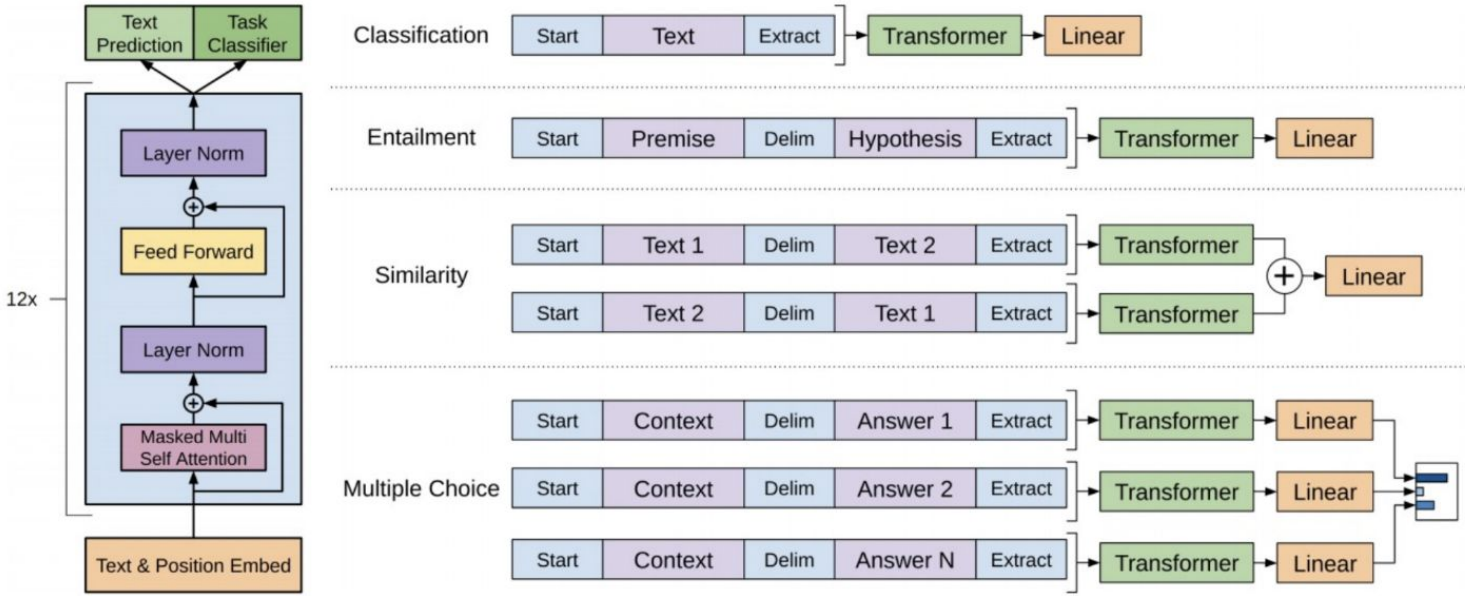
What is the sentiment of the next sentence? I love this movie!

Model output

positive

GPT

Fine-tuning loss: $L = L_{xent} + \lambda \cdot L_{task}$



The figure is from the paper Improving Language Understanding by Generative Pretraining

GPT

Training

Transformer decoder with the standard l

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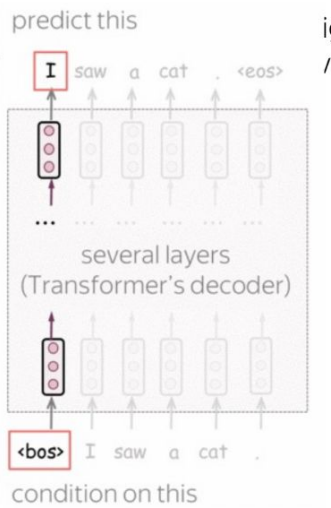

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Inference

GPT-1 Classification via

- Task-specific input transformations
- Supervised fine-tuning

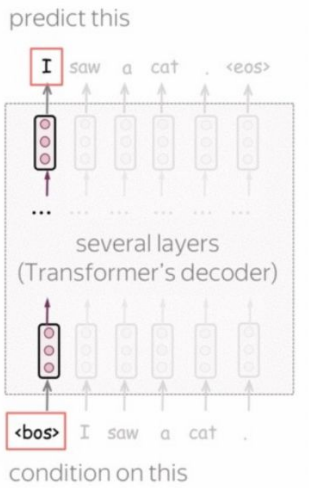
GPT

	GPT-1 (2018)	GPT-2 (2019)
Number of parameters	117 million	1.5 billion
Training data	5 GB	40 GB

GPT

Training

Transformer decoder with the standard left-to-right language modeling objective



Inference

GPT-1 Classification via
- Task-specific input transformations
- Supervised fine-tuning

GPT-2 Generation tasks via task-specific input transformations

For example, for text summarization simply add "**TL;DR**":

<start> Generative pre-trained transformers (GPT) are … TL;DR:

Text to be summarized

GPT

	GPT-1 (2018)	GPT-2 (2019)	GPT-3 (2020)
Number of parameters	117 million	1.5 billion	175 billion
Training data	5 GB	40 GB	45 TB (i.e., 45 000 GB)

The entirety of English Wikipedia constitutes just 0.6% of GPT-3 training data

GPT

GPT-3: Examples

Prompt

```
# Python 3
def remove_common_prefix(x, prefix, ws_prefix):
  x["completion"] = x["completion"].str[len(prefix) :]
  if ws_prefix:
    # keep the single whitespace as prefix
    x["completion"] = " " + x["completion"]
return x

# Explanation of what the code does

#
```

Sample response

The code above is a function that takes a dataframe and a prefix as input and returns a dataframe with the prefix removed from the completion column.

GPT

GPT-3: Examples

Create study notes

Generation

Provide a topic and get study notes.

Prompt

What are 5 key points I should know when studying Ancient Rome?

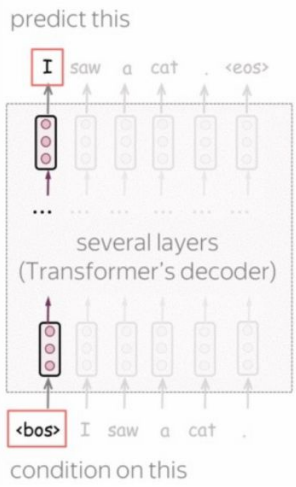
Sample response

1. Rome was founded in 753 BC by Romulus and Remus.
2. Rome was ruled by an emperor.
3. Rome was a republic before it became an empire.
4. Julius Caesar was assassinated in 44 BC.
5. Augustus was the first emperor of Rome.

GPT

Training

Transformer decoder with the standard left-to-right language modeling objective



Inference

GPT-1 Classification via
- Task-specific input transformations
- Supervised fine-tuning

GPT-2 Generation tasks via task-specific input transformations

For example, for text summarization simply add "**TL;DR**":

GPT-3 Complex generation and reasoning tasks via in-context learning: prompt with task description and a few demonstrations

```
Translate English to Spanish:
a black cat -> un gato negro
I am hungry -> tengo hambre
a cup of tea ->
```

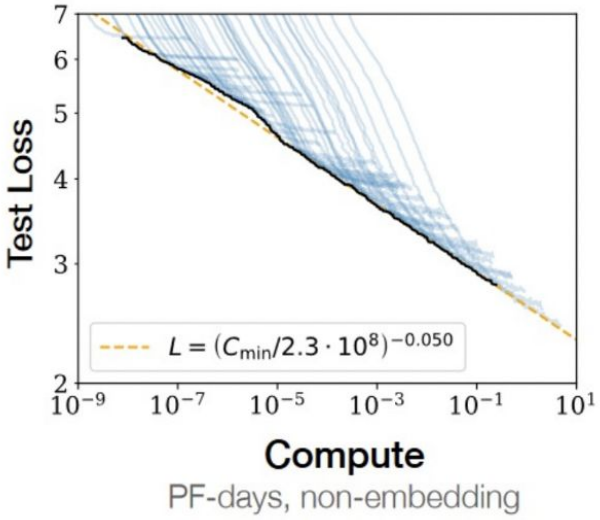
← task description

← examples

← prompt

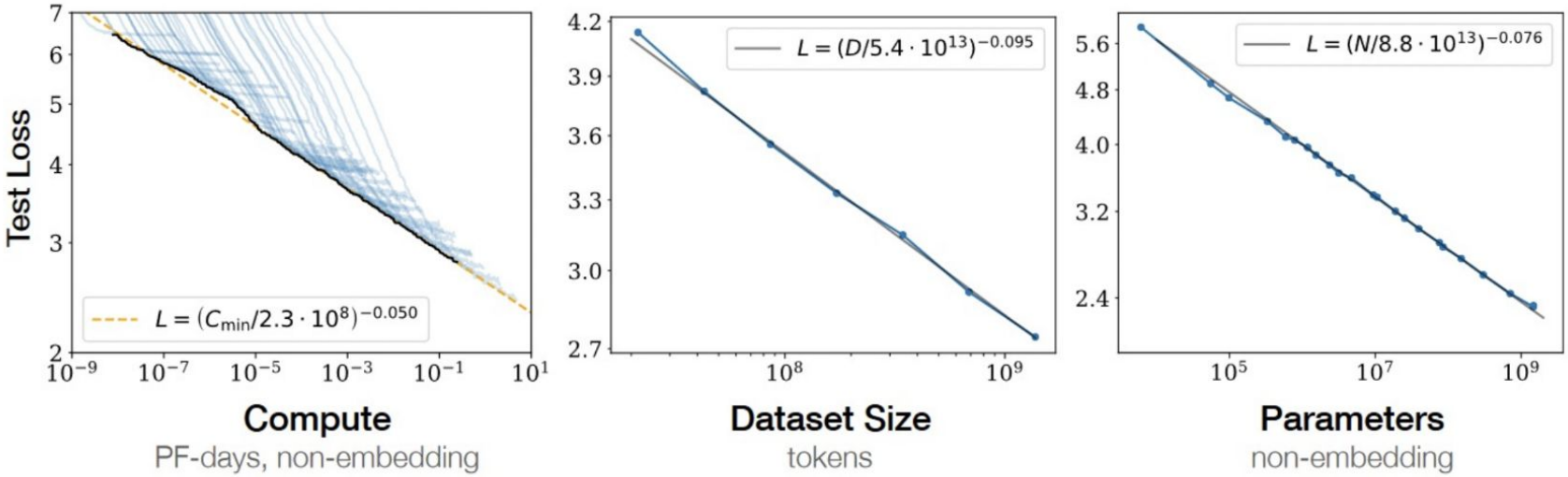
Scaling laws of LLMs

How does model quality change with respect to compute spent?



Scaling laws of LLMs

How does model quality change with respect to compute spent? | dataset size? | model size?

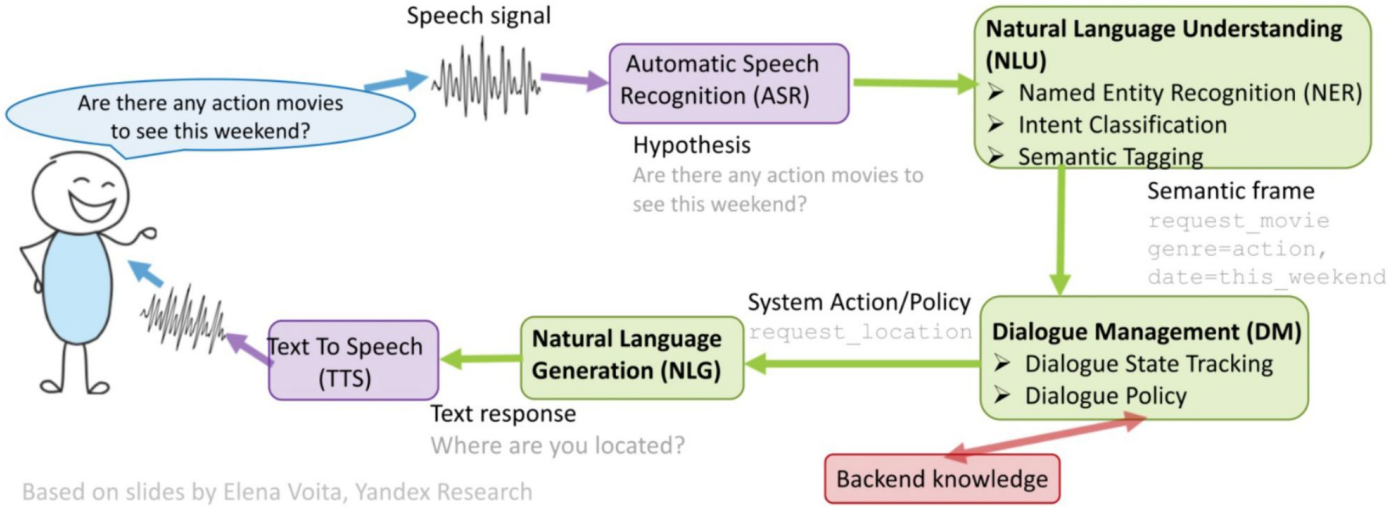


LLMs as dialogue assistants

Dialogue assistants: Cascade pipeline

System design: let's split "chat bot" into smaller problems

Speech processing: see YSDA speech course
Business knowledge: rules for banking / psychology / ...
Text processing: this lecture



Based on slides by Elena Voita, Yandex Research

Dialogue assistants: Cascade pipeline

Any problems here?

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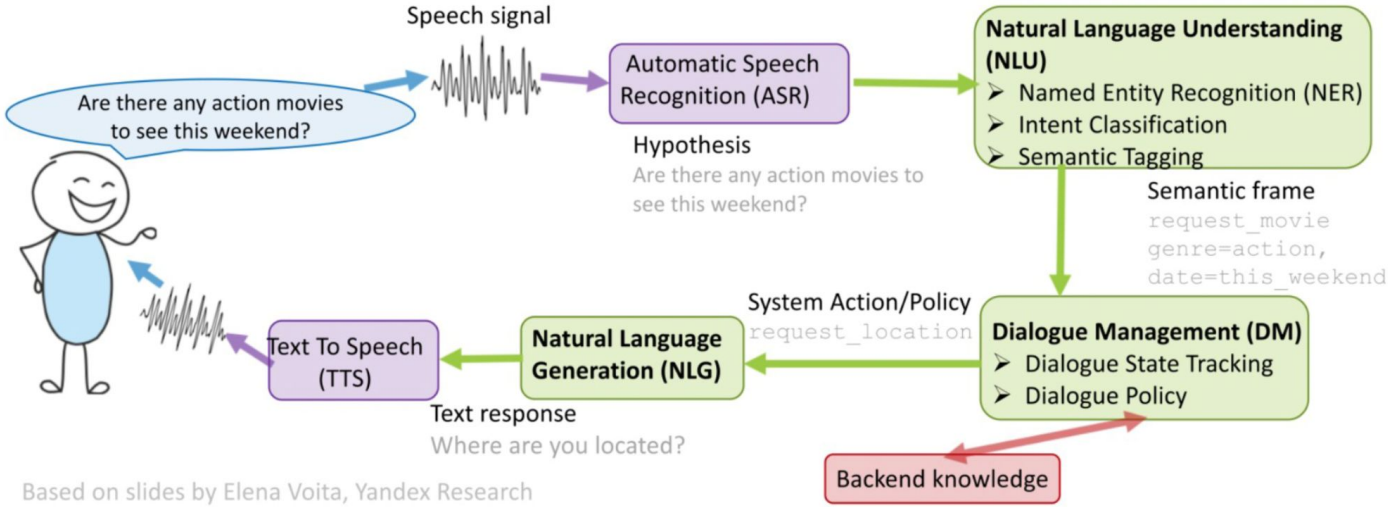

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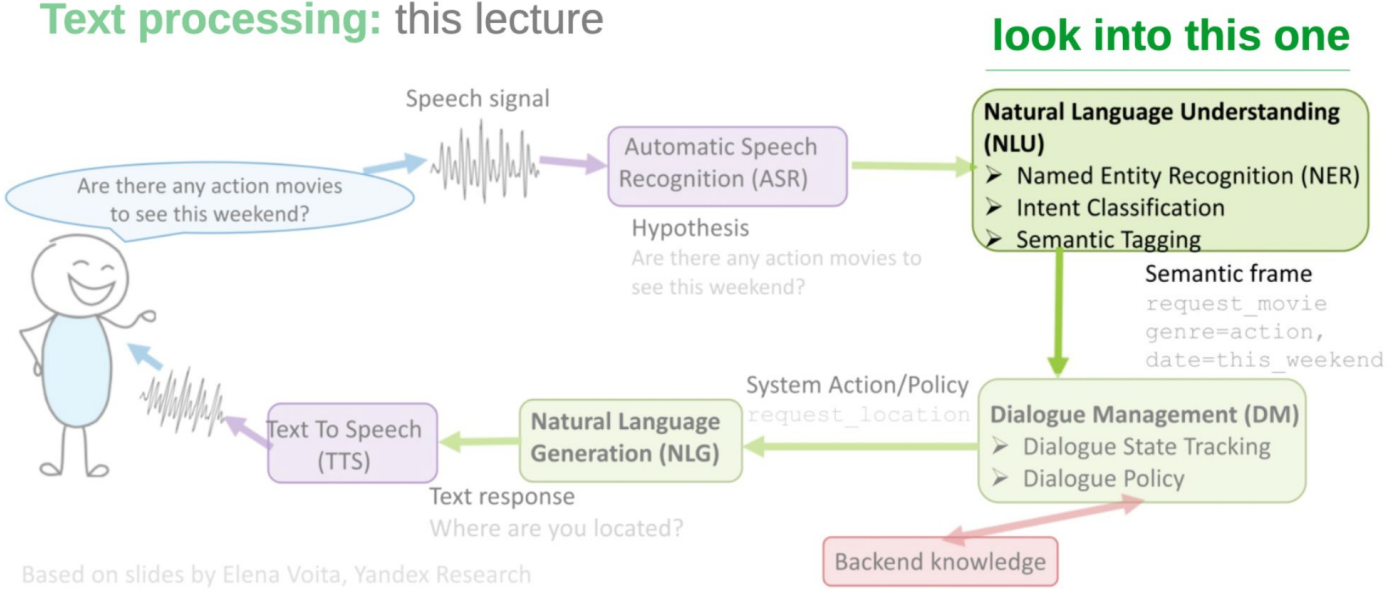

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Dialogue assistants: Cascade pipeline

Named Entity Recognition

Why: extract keywords from user's message, use them , e.g.
- for web search, when checking a fact
- for map look-up ("where can I buy pizza in Taganrog?")
- to play music / video ("play Eminem's latest song")

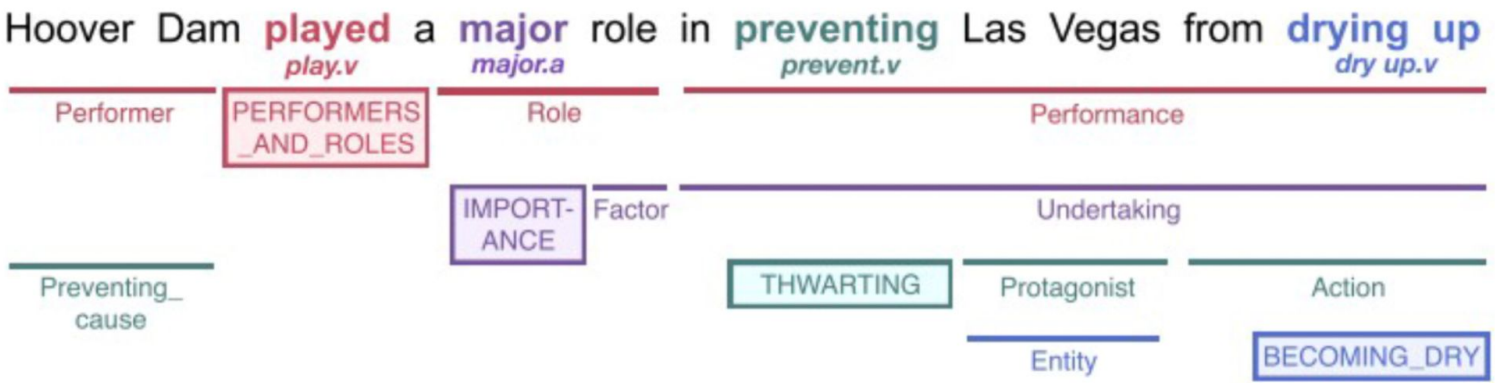
Q: how do we solve this?

When Sebastian Thrun PERSON started working on self - driving cars at Google ORG in 2007 DATE , few people outside of the company took him seriously . " I can tell you very senior CEOs of major American NORP car companies would shake my hand and turn away because I was n't worth talking to , " said Thrun PERSON , in an interview with Recode ORG earlier this week DATED .

Image credit: nanonets.com

Dialogue assistants: Cascade pipeline

- **Named Entity Recognition:** see previous slide
- **Semantic parsing:** to figure out what user wants from you

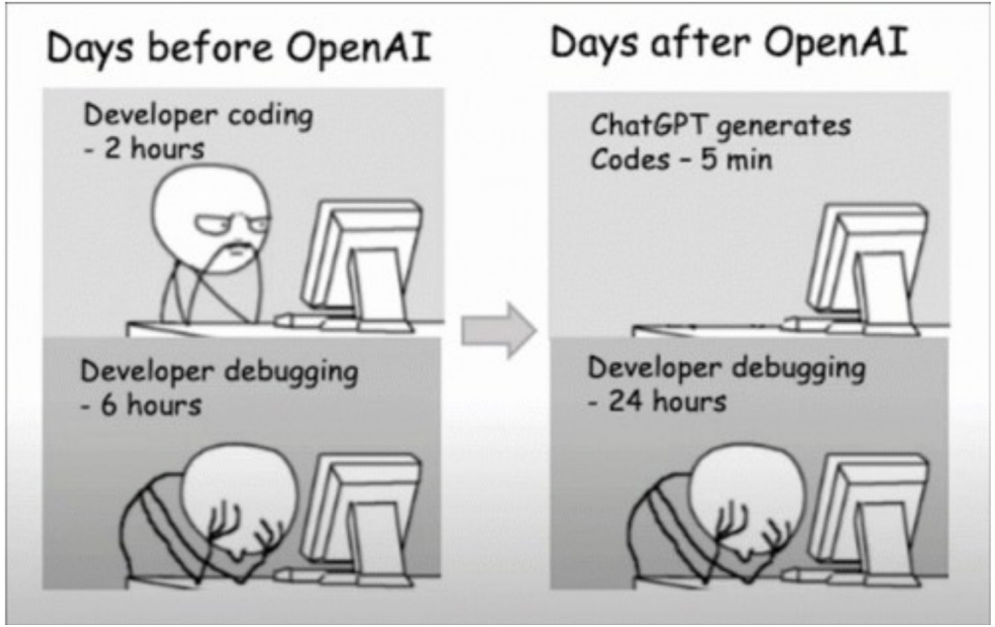


Dialogue assistants: Cascade pipeline

- **Named Entity Recognition:** see previous slide
- **Semantic parsing:** to figure out what user wants from you
- **Anaphora resolution:** to find what “it” or “this bar” refers to

Dialogue assistants: e2e system

the ChatGPT part



GPT-based assistants

GPT pretraining is not aimed at following instructions

Prompt:
What is the purpose of the list C in the code below?

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GPT-3 175B completion:
A. to store the value of C[0]
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Solution?

Instruction Tuning

Training objective:

what we **want** vs
what we **told** model to do

What we **told** model to do:
- predict the next token on a webpage from the internet

Alignment →

What we want model to do:
- follow the user's instructions helpfully and safely

The language modeling objective is misaligned

Source: Training language models to follow instructions with human feedback, NeurIPS 2022

Instruction Tuning: InstructGPT

Step 1

Collect demonstration data, and train a supervised policy.

A prompt is sampled from our prompt dataset.

A labeler demonstrates the desired output behavior.

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

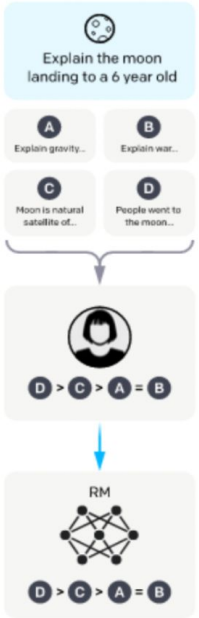
Step 2

Collect comparison data, and train a reward model.

A prompt and several model outputs are sampled.

A labeler ranks the outputs from best to worst.

This data is used to train our reward model.



Step 3

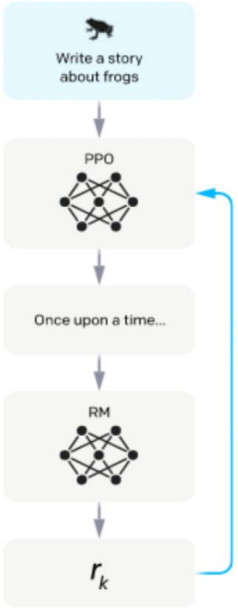
Optimize a policy against the reward model using reinforcement learning.

A new prompt is sampled from the dataset.

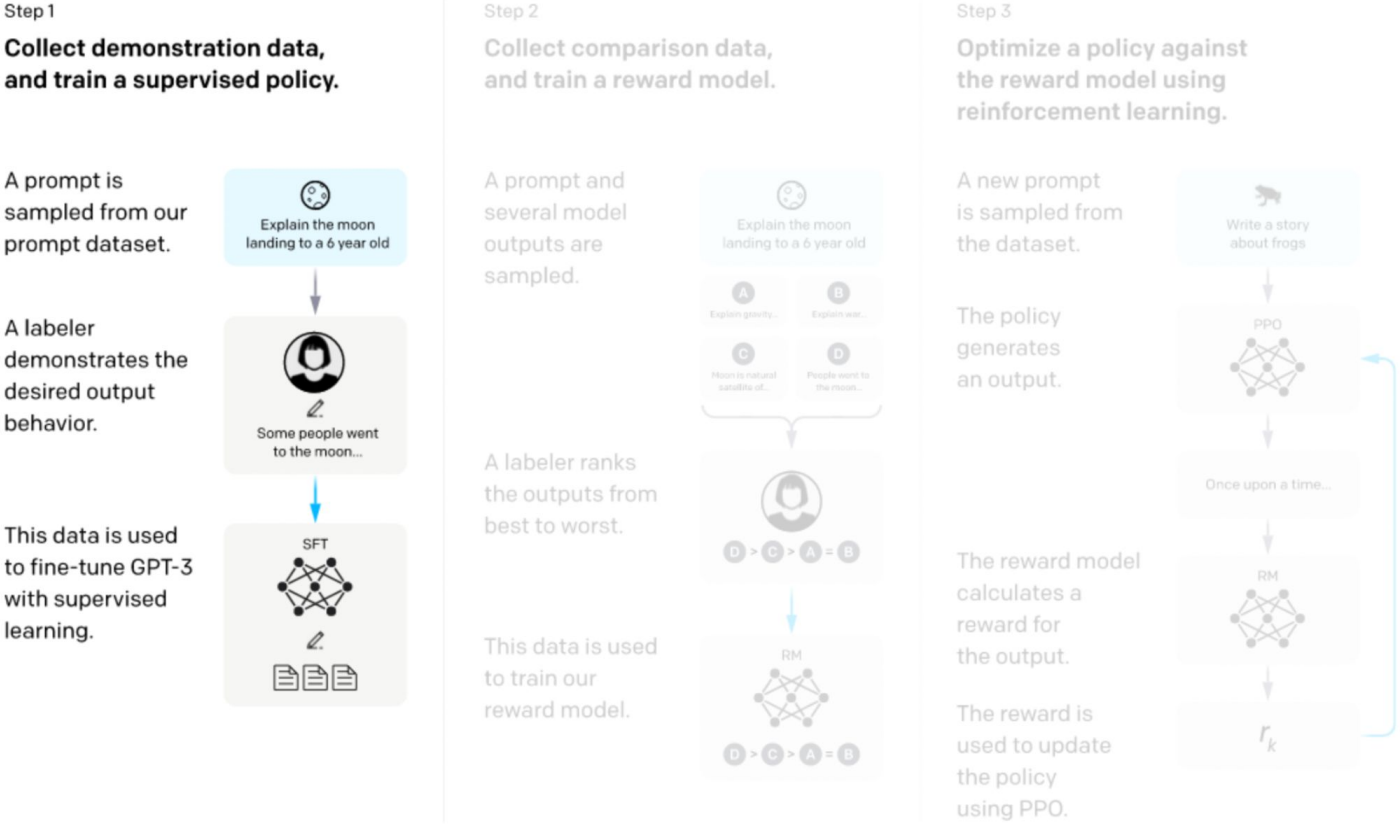
The policy generates an output.

The reward model calculates a reward for the output.

The reward is used to update the policy using PPO.



Instruction Tuning: InstructGPT



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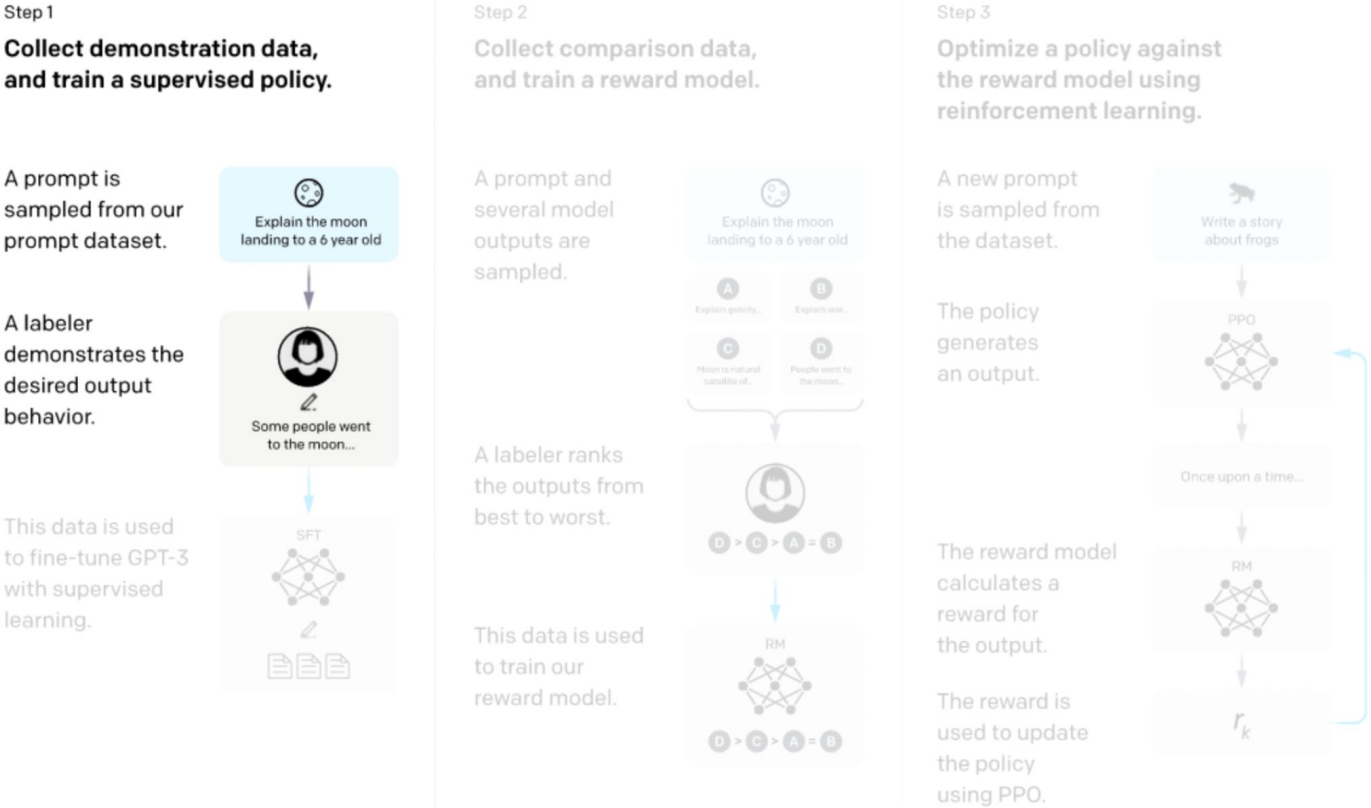


Stage 1: Supervised Finetuning

Prompt Dataset

Initial stage

Manually written by labelers

- Plain: come up with an arbitrary task, while ensuring the tasks had sufficient diversity
- Few-shot: come up with an instruction, and multiple query/response pairs for that instruction
- User-based: come up with prompts corresponding to some of the use-cases stated in waitlist applications to the OpenAI API

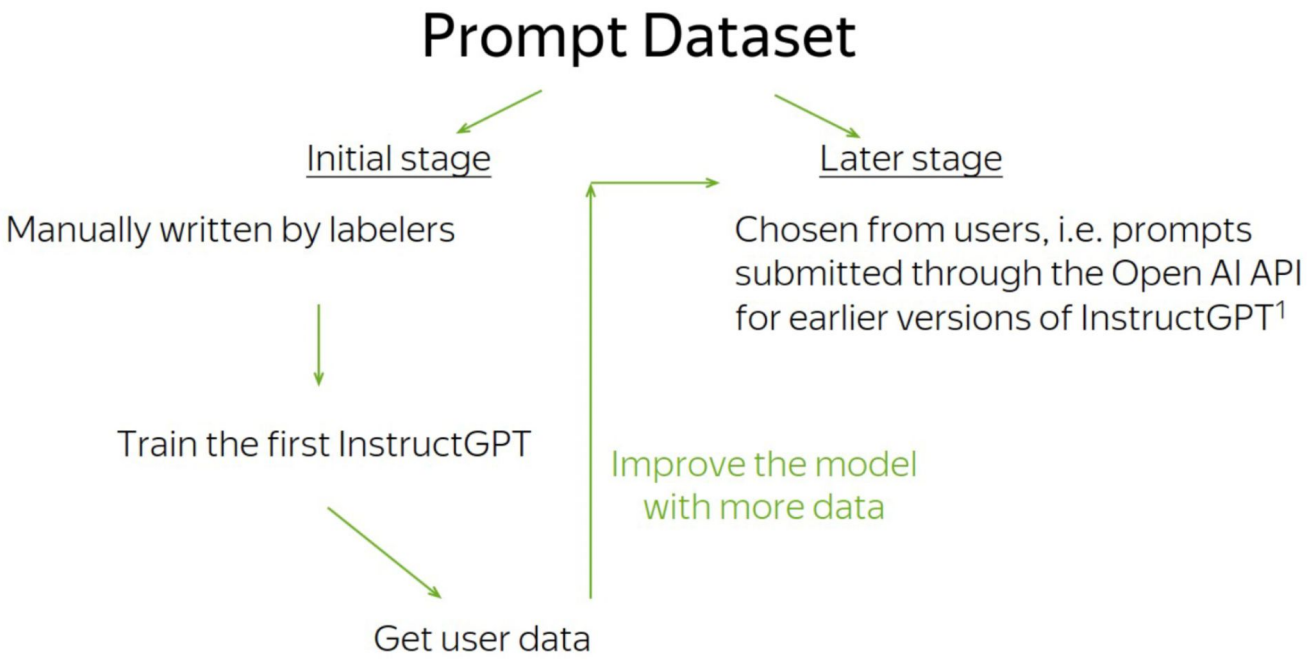
Later stage

Chosen from users, i.e. prompts submitted through the Open AI API for earlier versions of InstructGPT[1]

- filter all prompts in the training split for personally identifiable information (PII)
- heuristically deduplicate prompts
- no more than 200 prompts per user ID
- create train, validation, and test splits based on user ID

[1]https://beta. openai.com/playground

Stage 1: Supervised Finetuning



[1]https://beta. openai.com/playground

Stage 1: Supervised Finetuning

Use cases

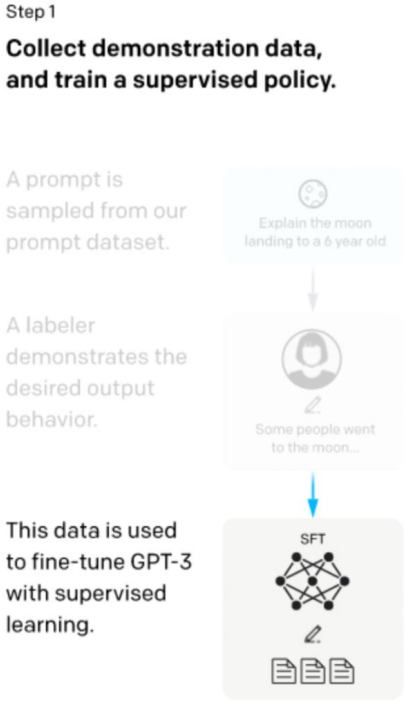
Use-case	(%)
Generation	45.6%
Open QA	12.4%
Brainstorming	11.2%
Chat	8.4%
Rewrite	6.6%
Summarization	4.2%
Classification	3.5%
Other	3.5%
Closed QA	2.6%
Extract	1.9%

Examples

Use-case	Prompt
Brainstorming	List five ideas for how to regain enthusiasm for my career
Generation	Write a short story where a bear goes to the beach, makes friends with a seal, and then returns home.
Rewrite	This is the summary of a Broadway play: """ {summary} """ This is the outline of the commercial for that play: """

Source: Training language models to follow instructions with human feedback, NeurIPS 2022

Stage 1: Supervised Finetuning



Fine-tuning procedure:

exactly the same as in pre-training

minimize crossentropy with Adam

using the instruction-following data

Cheaper version: train LoRA adapters

https://arxiv.org/abs/2305.14314

InstructGPT

Why can’t we stop at SFT stage?

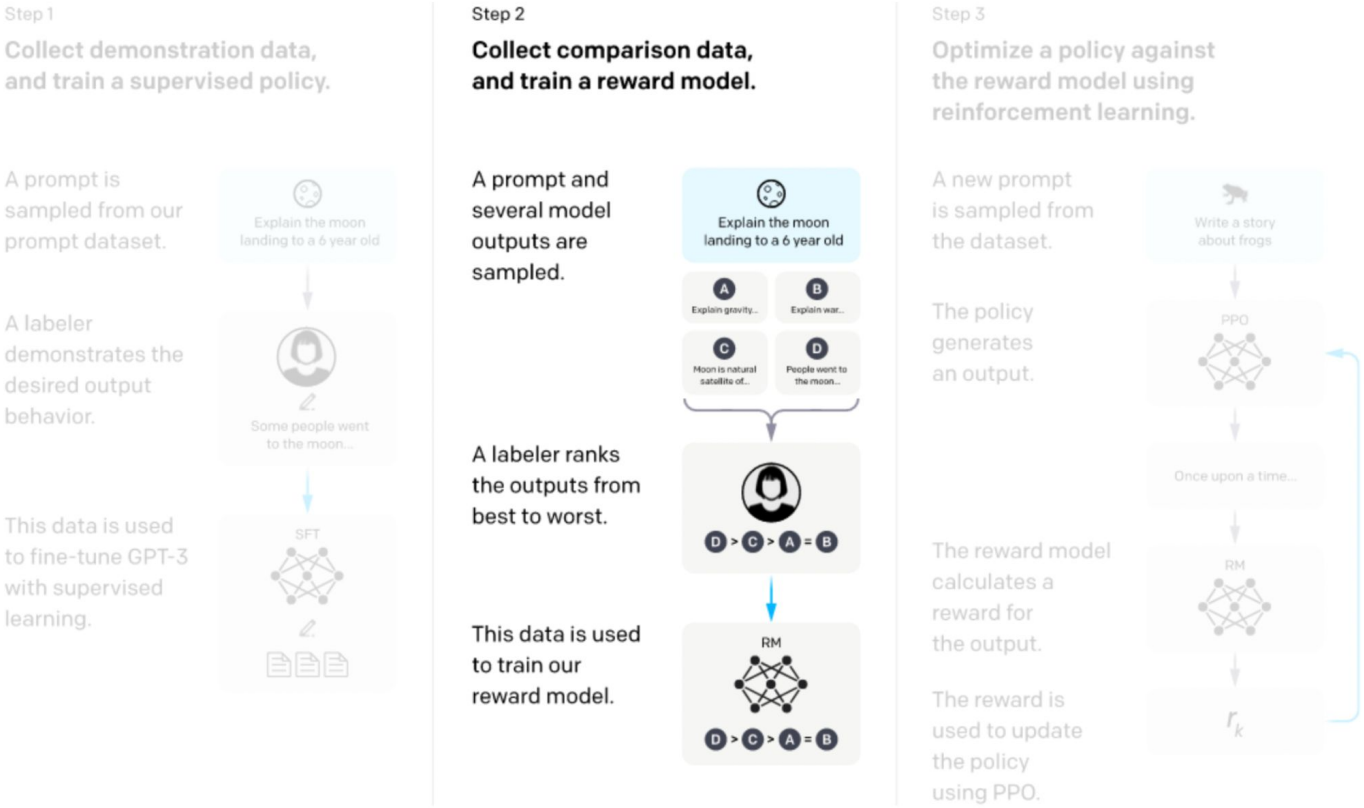
Reason 1: ranking is easier than writing for labelers
(except maybe for fact-checking)

Reason 2: supervised fine-tuning promotes hallucinations

More supervised finetuning problems

- Expensive data collection (hard to achieve answer space coverage)
- Problems with modeling
  a. Xent penalizes all errors equally
  b. Ground truth is technically one-hot -> does not estimate “answer quality” directly
- Exposure bias

Stage 2: Reward Model



Stage 2: Reward Model

How OpenAI did it

Choose:

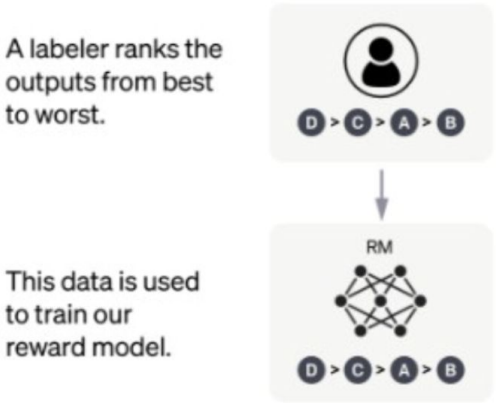
- 40 contractors on Upwork and through ScaleAI
- labelers who were sensitive to the preferences of different demographic groups
- labelers who were good at identifying outputs that were potentially harmful

Mentor:

- Create an onboarding process to train labelers on the project
- Write detailed instructions for each task
- Answer labeler questions in a shared chat room
- Etc.

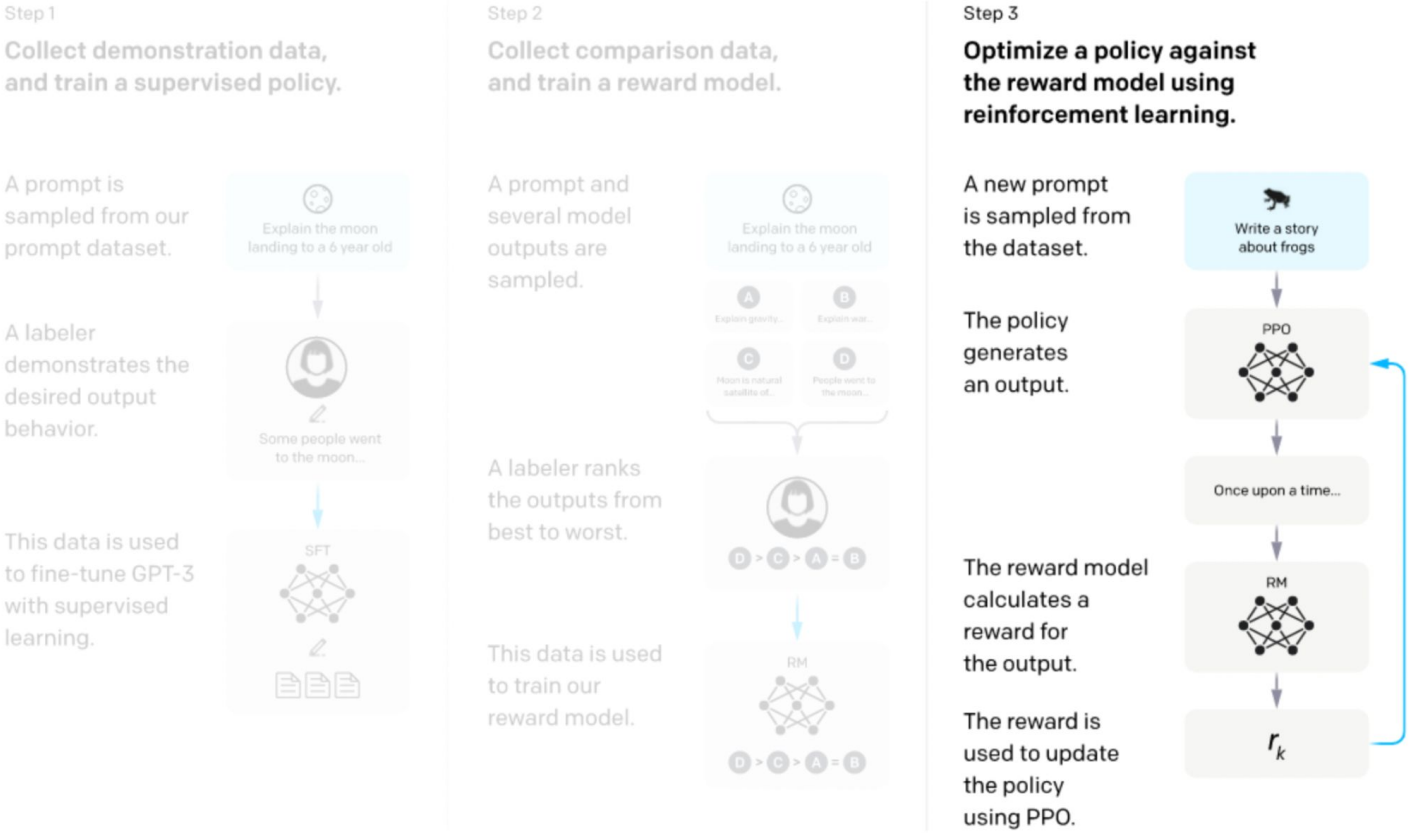
Stage 2: Reward Model

- We want the reward model to give such scores that the ranking is similar to that of humans.
- For every pair the ranking is wrong, the reward model is penalized.



$$\text{loss}(\theta) = -\frac{1}{\binom{K}{2}} E_{(x,y_w,y_l)\sim D}\left[\log\left(\sigma\left(r_\theta\left(x,y_w\right) - r_\theta\left(x,y_l\right)\right)\right)\right]$$

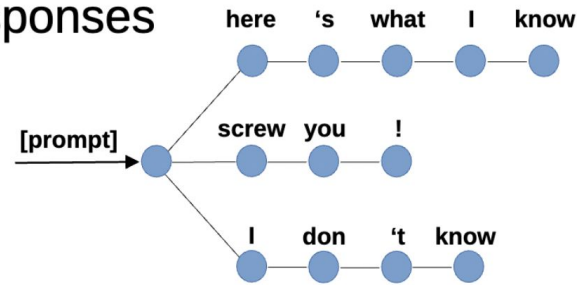
Stage 3: RL Finetuning



Self-critical sequence training

TL;DR reinforcement learning for LLM tasks:

1. Let the model generate several responses (sample with probability)



Self-critical sequence training

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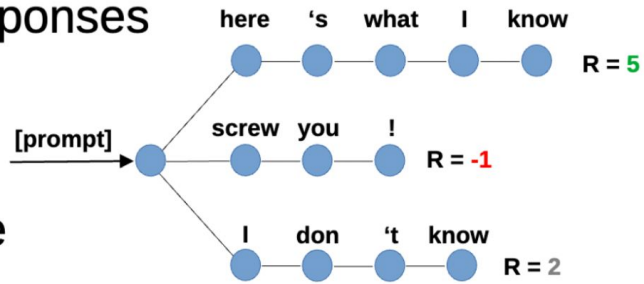

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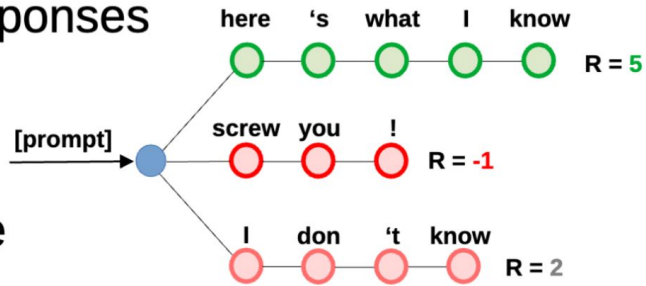

2. Compute reward for each response (apply reward model)

3. Train to increase probability of responses **with high reward** (and decrease probability if reward is low)

PPO

1. TRPO (Trust Region Policy Optimization)

Surrogate loss: $\max_{\pi} L(\pi) = \mathbb{E}_{\pi_{\text{old}}} \left[\frac{\pi(a|s)}{\pi_{\text{old}}(a|s)} A^{\pi_{\text{old}}}(s,a) \right]$

Constraint: $\mathbb{E}_{\pi_{\text{old}}} \left[KL(\pi || \pi_{\text{old}}) \right] \leq \epsilon$

for iteration=1, 2, . . . **do**
  Run policy for T timesteps or N trajectories
  Estimate advantage function at all timesteps
  Compute policy gradient g
  Use CG (with Hessian-vector products) to compute $F^{-1}g$
  Do line search on surrogate loss and KL constraint
end for

PPO

TRPO

$$\underset{\theta}{\text{maximize}} \quad \hat{\mathbb{E}}_t\left[\frac{\pi_\theta(a_t \mid s_t)}{\pi_{\theta_{\text{old}}}(a_t \mid s_t)}\hat{A}_t\right]$$

$$\text{subject to} \quad \hat{\mathbb{E}}_t[\mathrm{KL}[\pi_{\theta_{\text{old}}}(\cdot \mid s_t), \pi_\theta(\cdot \mid s_t)]] \leq \delta$$

PPO v1

$$\max_\theta \hat{\mathbb{E}}_t\left[\frac{\pi_\theta(a_t|s_t)}{\pi_{\theta_{\text{old}}}(a_t|s_t)}\hat{A}_t\right] - \beta\left(\hat{\mathbb{E}}_t\left[\mathrm{KL}[\pi_{\theta_{\text{old}}}(\cdot \mid s_t), \pi_\theta(\cdot \mid s_t)]\right] - \delta\right)$$

- Pseudocode:

  for iteration=1, 2, . . . **do**

  Run policy for T timesteps or N trajectories

  Estimate advantage function at all timesteps

  Do SGD on above objective for some number of epochs

  Do dual descent update for beta

InstructGPT

Prompt:
What is the purpose of the list C in the code below?

```
def binomial_coefficient(n, r):
     C = [0 for i in range(r + 1)];
     C[0] = 1;
     for i in range(1, n + 1):
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A. to store the value of C[0]
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InstructGPT 175B completion:
The list C in this code is used to store the values of the binomial coefficient as the function iterates through the values of n and r. It is used to calculate the value of the binomial coefficient for a given value of n and r, and stores the result in the final return value of the function.

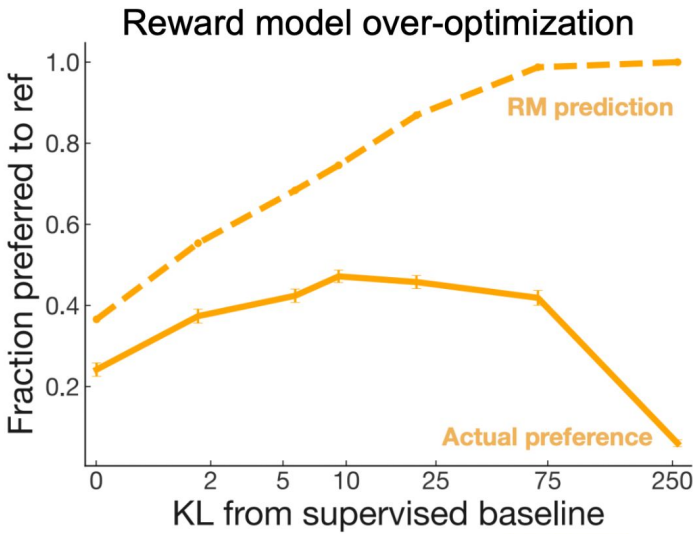
RLHF: Reward Modeling (RM)

Why do we need RM?

1. RL is sample expensive
    a. either A LOT of human evaluations needed
    b. or - train Reward Model on small corpus, train on big synthetic corpus
2. PPO if on-policy
    a. training samples for PPO need to come from distribution of current stage of model
    b. human evaluations are pre-collected -> off-policy
    c. reward model scores can be computed on policy

Problems of RLHF

- 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
- **Models** of human preferences are *even more* unreliable!

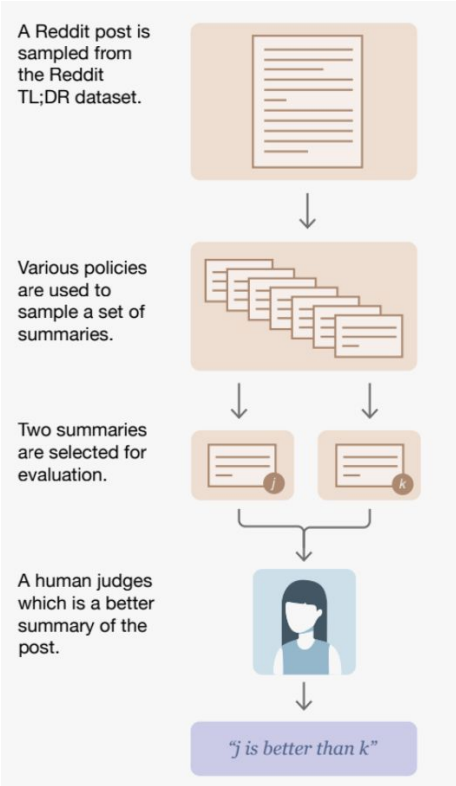


$$R(s) = RM_\phi(s) - \beta \log \left(\frac{p_\theta^{RL}(s)}{p^{PT}(s)} \right)$$

[Stiennon et al., 2020]

Learning from Human Feedback: any alternatives?

<u>Reminder:</u> main goal is to utilize answers ranking from humans



Learning from Human Feedback: any alternatives?

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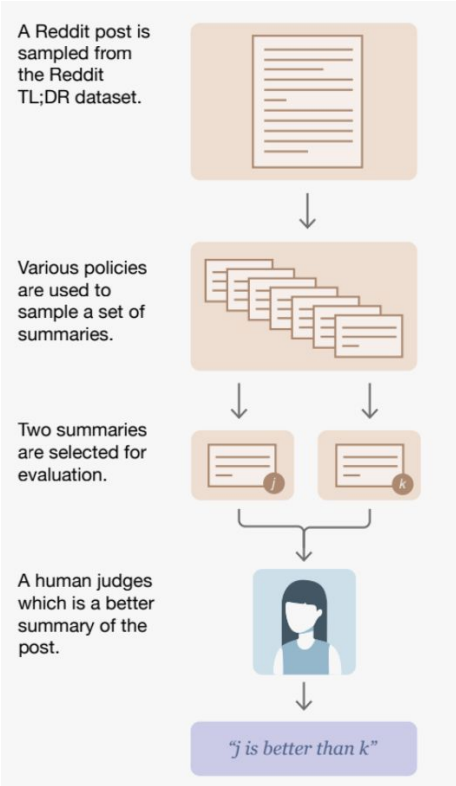
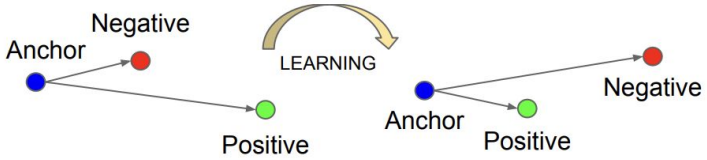
Contrastive Learning!



DSSM

DSSM (Deep Structured Semantic Model)

Textual data	→	Text encoder (word2vec, RNN etc.)	*A (anchor)*
Corresponding image	→	Image encoder (CNN etc.)	*P (positive)*
Non-correspon ding image	→	Image encoder (CNN etc.)	*N (negative)*



Triplet loss (max margin loss)

Goal: $\|f(x_i^a) - f(x_i^p)\|_2^2 + \alpha < \|f(x_i^a) - f(x_i^n)\|_2^2$

Loss: $\sum_i^N \left[\|f(x_i^a) - f(x_i^p)\|_2^2 - \|f(x_i^a) - f(x_i^n)\|_2^2 + \alpha\right]_+$

Triplet loss for seq2seq tasks

$$\mathcal{L}(\theta) = max(0, \delta - \log P_\theta(\mathbf{y}^+|\mathbf{x}) + \log P_\theta(\mathbf{y}^-|\mathbf{x}))$$

Triplet loss for seq2seq tasks

$$\mathcal{L}(\theta) = max(0, \delta - \log P_\theta(\mathbf{y}^+|\mathbf{x}) + \log P_\theta(\mathbf{y}^-|\mathbf{x}))$$

response with higher rating

prompt / dialogue state

response with lower rating

SLiC-HF

Contrastive Learning from Human Feedback

1. SFT model
2. Collect off-policy dataset with HF
3. **S**equence **Li**kelihood **C**alibration with **H**uman **F**eedback

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$$\mathcal{L}(\theta) = \underbrace{\sum L^{\text{cal}}(\theta, \mathbf{x}, \mathbf{y}_{\text{ref}}, \{\hat{\mathbf{y}}\}_m)}_{\textit{contrastive triplet loss}} + \underbrace{\lambda L^{\text{reg}}(\theta, \theta_{ft}; \mathbf{x}, \mathbf{y}_{\text{ref}})}_{\textit{Xent regularizer}}$$

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DPO

DPO (Direct Preference Optimization)

1. SFT model
2. Collect off-policy dataset with HF
3. DPO contrastive finetuning

DPO

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$$\mathcal{L}_{\text{DPO}}(\pi_\theta; \pi_{\text{ref}}) = -\mathbb{E}_{(x, y_w, y_l)\sim\mathcal{D}} \left[\log \sigma \left(\beta \log \frac{\pi_\theta(y_w \mid x)}{\pi_{\text{ref}}(y_w \mid x)} - \beta \log \frac{\pi_\theta(y_l \mid x)}{\pi_{\text{ref}}(y_l \mid x)} \right) \right]$$

- Triplet max-margin loss -> logsigmoid
- Raw logP diff -> relative logP w.r.t. ref model diff

Contrastive Learning vs. RLHF

CL advantages:

- More data efficient; RL requires a lot of episodes for convergence
- More stable: PPO updates are noisy and can lead to reward hacking

CL disadvantages:

- Heavily reliant on data; can easily overfit
- If base model is of very poor quality, unstable convergence

Questions?