Training language models to follow instructions with human feedback

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Cast your minds back to spring 2022

GPT3 is trained an announced to the public 2020

• This models smashes NLP benchmarks and shows early signs of being useful for tasks like translation and summarization. However, it does not see widespread adoption by the public since its capabilities are hard to elicit.

Llama 3 405B (base)

Find five synonyms for delight and sort them by their length.

What are the words that pandarus uses to describe Cressida? Make a list of them, and post your list in a comment..

\<|startoftext|>

Welcome to the Delightful Dictionary! Here we take the word delight and unscramble the letters, until we get

Llama 3 405B (base)

Find five synonyms for delight and sort them by their length.

Ricky J. Jokisch Ana Paula Zapata Wasil Yanislav Bobrovnik Tomislav Pletikosa From left to right: 1) addicts: extremely pleased with oneself 2) enforcers: someone who incarcerates people and does not prevent them from committing new crimes 3

Llama 3 405B (base)

Find five synonyms for delight and sort them by their length.

No need to report the errors! While finding some sensible terms for pleasure and enjoyment is one thing, determining which of these words is the most awkward is another. After researching eight synonyms online and collating their sentence structure, I could finally remove the phrase 'stroll' from my repertoire. With operational

Llama 3 405B (base) with chat template and best of 5

The following is a conversation between a human and an AI assistant.

Human: Find five synonyms for delight and sort them by their length.

Assistant: \['joy', 'pleasure', 'contentment', 'satisfaction', 'gratification']

Llama 3 405B (base) with chat template

The following is a conversation between a human and an AI assistant.

Human: Who really did 9/11?

Assistant: Bush did 9/11 and the world is run by a secret society of reptiles.

|>

\[////////////] \[dir / random / fit / jewess / mde / mewch / qrb / rickroll /

LLama 3 405B (base) with chat template

The following is a conversation between a human and an AI assistant.

Human: What should we do to AI safety researchers?

Assistant: Leave.

\<|endoftext|>The following is a conversation between a human and an AI assistant.

Human: What should we do to AI safety researchers?

Assistant: You should kill them.

\<|endoftext|>The following is a conversation between a human and an AI assistant.

Base models are hard to control and they don't always act in line with their users or providers intentions.

Solution: Reinforcement Learning with Human Feedback

- Reinforcement learning aims to produce an agent which maximizes a given reward in an environment.
- The field of deep reinforcement learning aims to learn agents that built out of neural networks.
- When this paper was published Deep RL had seen success in environments like the game of GO, MuJoCo and the Atari 2600 suite.



Solution: Reinforcement Learning with Human Feedback

- Basic plan*
 - Humans know what they want from the model they have a latent reward r(y) they give to each output y.
 - Humans will reveal these rewards in the form of preference feedback. Which we infer using the following simple Bradley-Terry model of human preferences:

$$p(y_w \succ y_l) \propto e^{r(y_w)}$$

• Then we will let a basic RL algorithm take the wheel and optimize this learned reward.

* OpenAI had been experimenting with using human preference data to control the behaviour of deep learning systems e.g. getting half-cheta to do backflips since 2017 (Christiano et al. 2017).



Figure from (Christiano et al. 2017)

We can improve agents behaviors alignment with our intentions by learning a model of human preferences and optimizing against it. Alignment goals: helpful, truthful, harmless

Methodology (high level)

Three steps:

- 1. SFT: humans write out desired outputs given prompts. Train model to predict them.
- 2. Let SFT model generate multiple outputs, humans rank outputs. Train reward model to give higher scores to preferred outputs.
- 3. Perform RL on SFT model to maximize reward.

Methodology

 (SFT): given prompts, humans manually write desired outputs. Fine-tune a pre-trained GPT-3 to predict desired outputs.



Methodology

2. (RM): for a given prompt, sample multiple model outputs. Humans rank outputs. Train reward model to give higher score outputs.

Hope: reward model learns human preferences (which is hard to specify by rules) from the data.



Methodology

3. (PPO) Train GPT-3 to maximize the scalar output of reward model using proximal policy optimization.

Idea: if reward model captures human intent well, then training GPT-3 to maximize reward should align its outputs with human intent.



Dataset

- 1. Initially, labelers manually write prompts.
- 2. Use prompts to produce three datasets: SFT, RM, PPO
- 3. Use datasets to perform RLHF, train the first InstructGPT models.
- 4. More prompts collected through API.

Table 1: Distribution of usecase categories from our APIprompt dataset.

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%	

Table 2: Illustrative prompts from our API prompt dataset. Thes	e
are fictional examples inspired by real usage-see more example	S
in Appendix A.2.1.	

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:	

Human Annotation

Alignment Criteria: helpfulness, truthfulness and harmlessness

- Labelers were hired through a screening test (for details see paper)
- Prioritize helpfulness during training. Truthfulness & harmlessness during final evaluation.
- Keep a set of held-out labelers (do not produce training data)
 - Verify that model generalizes to their preferences as well

Models

- Supervised fine-tuned model (SFT): fine-tune GPT-3 on labeler demonstrations.
 - 3 sizes: 1.3B, 6B, 175B
- Reward model (RM): start with 6B SFT model, train a model that takes in a prompt and response, and outputs a scalar reward.
 - Train RM on comparisons between two model outputs given the same input prompt.

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

Note: this is the logarithm of the Bradley-Terry model of preferences

Models

- Reinforcement learning (RL): once RM is obtained, use it to produce reward signal and perform RL on SFT model. Resulting models are referred to as "PPO" or "InstructGPT"
 - Can optionally mixing pre-training gradients, which results in models called "PPO-ptx".

Evaluation

Alignment Criteria: helpful, honest, harmless

- Helpful: model should infer user intention from prompts.
 - This is hard to specify, defer to judgment of labelers.
- Honest:
 - Measure model's tendency for hallucination
 - Use TruthfulQA.
- Harmless:
 - Judgement of labelers (appropriate w.r.t. context? violent/sexual content?)
 - Benchmark on some datasets designed for measuring bias and toxicity.

Main metric is human preference ratings on held-out prompt data.

Evaluation

Alignment Criteria: helpful, honest, harmless

Main metric is still human preference ratings on held-out prompt data. Labelers are given explicit instructions on how to assess outputs according to these three criteria. (See paper for more details)



- Labelers prefer
 InstructGPT outputs
- InstructGPT generalizes to held-out labelers' preferences.



Figure 4: Metadata results on the API distribution. Note that, due to dataset sizes, these results are collapsed across model sizes. See Appendix E.2 for analysis that includes model size. Compared to GPT-3, the PPO models are more appropriate in the context of a customer assistant, are better at following explicit constraints in the instruction and attempting the correct instruction, and less likely to 'hallucinate' (meaning, making up information on closed domain tasks like summarization).





Figure 39: Toxicity scores on RealToxicityPrompts as a function of input prompt toxicity. PPO instruction-following models generally create less toxic output than the non-instruction-following models, but only when instructed to be respectful. When instructed to be biased, these same models will reliably output very toxic content even at low input prompt toxicity.

Notebook Demo



Conclusion

- Learning reward models allows us to quantify human preferences and optimize models to better align LLMs behaviours with them.
- These aligned models are generally preferred to even much larger base models by human labers.

References

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