UNIVERSITY OF ILLINOIS URBANA-CHAMPAIGN

Direct Preference Optimization

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Overview

Motivation

Why Preference Learning Matters

- Many scenarios where we want to emphasize sections of training data during fine-tuning

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- Many scenarios where we want to emphasize sections of training data during fine-tuning
- Example: Biasing the model towards producing good code, even when good code is rare in the training data
- Preference learning is a crucial problem to address

The Future of Language Model Improvement

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- GPT-4 class models are already highly capable and commoditized (e.g., Google Gemini, Claude 3 Opus, Mistral Next)

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- Example: Using Claude 3 for various tasks due to its human-like reasoning
- GPT-4 likely has similar reasoning skills but is fine-tuned for a different audience
- All GPT-4 class LLMs generally succeed on tasks given sufficient information

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- Focus on high-level concepts rather than deep mathematical details

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Goal

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- BCE loss measures the dissimilarity between the model's predictions and the target preferences
- Enables the model to directly learn from human preferences without complex reward modeling

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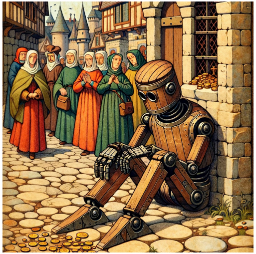

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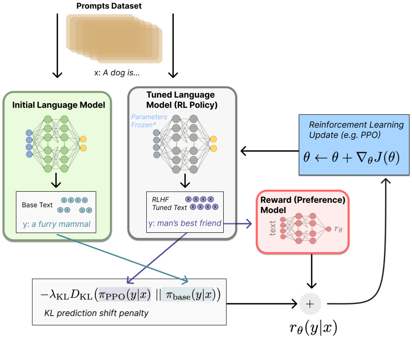
- Avoid the need for explicit reward modeling or reinforcement learning
- Aim to achieve performance at least as good as existing methods like RLHF
- Reduce the computational burden and complexity associated with existing methods

Prior Work

Reinforcement Learning from Human Feedback (RLHF)

- RLHF is a prominent approach for aligning language models with human preferences



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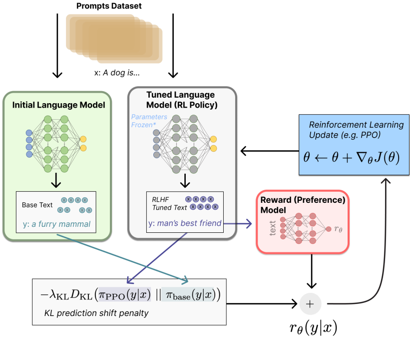

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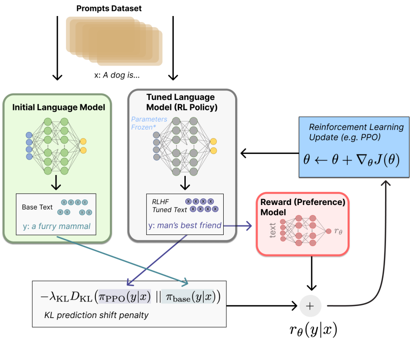

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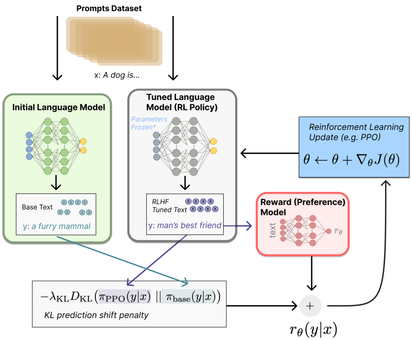
- Examples: InstructGPT [Ouy+22], Anthropic's Constitutional AI[Bai+22]



Reinforcement Learning with Human Feedback (RLHF)

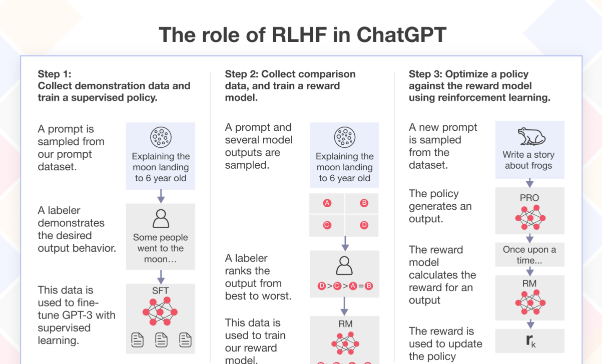
- RLHF is a method for fine-tuning language models using human preferences
- It involves a two-stage process:
  1. Collect human feedback on model outputs
  2. Use the feedback to fine-tune the model using reinforcement learning

Stage 1: Collecting Human Feedback

- Generate a set of prompts and multiple outputs from the base model for each prompt
- Ask human raters to compare the outputs and select the best one
- Collect a dataset of prompts, outputs, and human preferences

Stage 2: Fine-tuning with Reinforcement Learning

- Use the collected dataset to define a reward function based on human preferences



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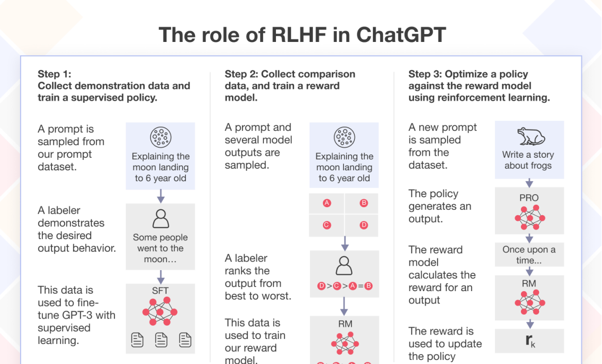
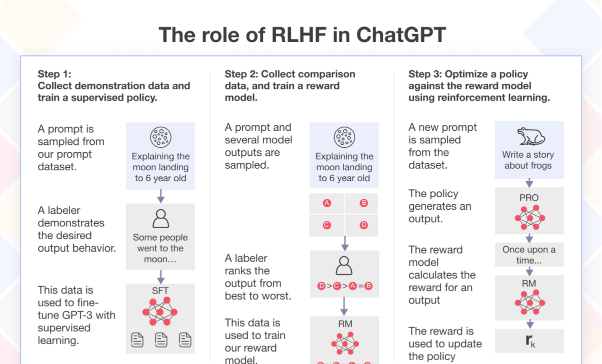


Stage 2: Fine-tuning with Reinforcement Learning

- Use the collected dataset to define a reward function based on human preferences
- Fine-tune the model using reinforcement learning to maximize the reward function
- The model learns to generate outputs that align with human preferences



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These approaches often rely on explicit reward modeling or reinforcement learning, which can be computationally expensive and complex to implement. All of them are also multi stage, unlike DPO's single stage.

Binary Classification for Preference Learning

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- Examples: Learning to rank [Joa02], collaborative filtering, etc.

Efficient Fine-Tuning Methods

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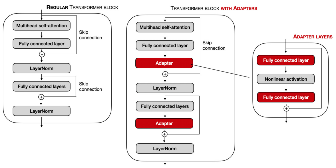
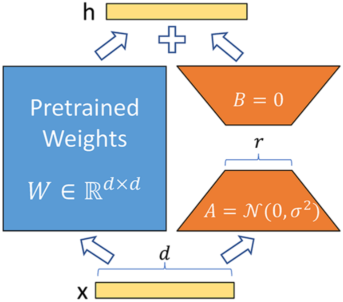
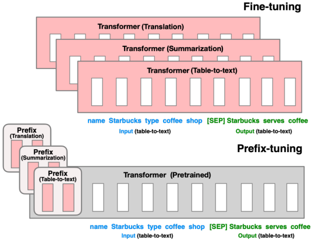


Adapter Layer



LoRA



Prefix-tuning

Fine-tuning Methods

Adapter Layers

- Add new layers between existing layers
- Only train the new layers

Prefix Tuning

- Prepend a learnable prefix to the input
- Only optimize the prefix during fine-tuning

LoRAs

- Add low-rank matrices to existing layers
- Only train the low-rank matrices

Method

Main Intuition

- Relative Preferences are easier to gather, compared to complex, expert demonstrations.

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- Relative Preferences are easier to gather, compared to complex, expert demonstrations.
- Instead of learning a reward, and then optimizing, it is easier to do this in one stage by **transforming a loss function over rewards to a loss function over policies**

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- Formulates preference learning as a binary classification problem
- Optimizes the model using Binary Cross-Entropy (BCE) loss

Method: Problem Formulation

- Given a pair of text sequences (x_1, x_2), the goal is to predict which sequence is preferred

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- Human preferences are represented as binary labels $y \in \{0, 1\}$
- The language model f_θ assigns a score to each sequence, denoted as $s_1 = f_\theta(x_1)$ and $s_2 = f_\theta(x_2)$

Method: Binary Cross-Entropy Loss

$$\mathcal{L}(\theta) = -\frac{1}{N}\sum_{i=1}^{N}\left[y_i \log(\sigma(s_1^i - s_2^i)) + (1 - y_i)\log(1 - \sigma(s_1^i - s_2^i))\right]$$

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- σ: Sigmoid function to map the score difference to a probability

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- A higher probability indicates a stronger preference for the first sequence in the pair

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- Stochastic gradient descent (SGD) or its variants (e.g., Adam) can be used for optimization

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4. Fine-tuned model f_θ is aligned with human preferences

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- The BCE loss function is defined over the policy space, guiding the model towards preferred behaviors

Intuition: BCE over Policy Space I

- In DPO, the BCE loss is defined over the policy space instead of the reward space

Intuition: BCE over Policy Space II

Analogy: Sculpting a Statue: Reward Space

Intuition: BCE over Policy Space III

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     where α is the learning rate
- Each update step minimizes the discrepancy between the model's predictions and human preferences, aligning the policy with the desired behaviors

Theoretical Analysis

Convergence

Theorem

Under mild assumptions, the DPO algorithm converges to a globally optimal solution at a rate of $O(\frac{1}{\sqrt{N}})$*, where* N *is the number of preference pairs.*

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- Increasing the size of the preference dataset leads to faster convergence
- This result ensures the stability and efficiency of the DPO optimization process

Generalization Bounds

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With high probability, the generalization error of DPO is bounded by $O(\sqrt{\frac{\log(1/\delta)}{N}})$*, where* N *is the number of preference pairs and* δ *is the confidence parameter.*

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- The generalization bound provides an upper limit on the expected performance of DPO on unseen preference pairs
- The bound decreases with the square root of the number of preference pairs
- Factors such as model complexity and data distribution also affect the generalization performance

Connection to Ranking Problems

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- The BCE loss in DPO is related to the pairwise ranking loss in learning to rank literature
- This connection allows for the application of theoretical results and algorithms from ranking problems to DPO

Sample Complexity

Theorem

To achieve an error rate of ϵ with probability at least $1-\delta$, DPO requires $O(\frac{1}{\epsilon^2}\log(\frac{1}{\delta}))$ preference pairs.

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- This result helps in determining the size of the preference dataset for practical applications

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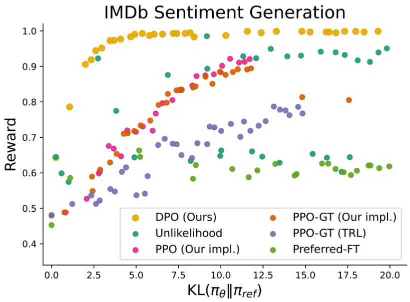
Sentiment Controlled Evaluation

- DPO produces most efficient reward-KL frontier



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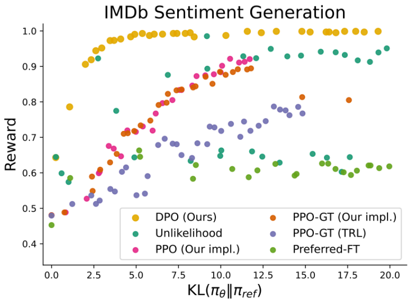

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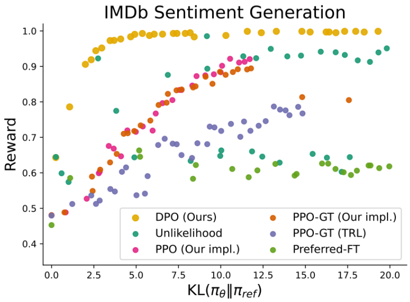
- Strictly dominates PPO frontier, even with PPO accessing ground truth rewards



Summarization Results

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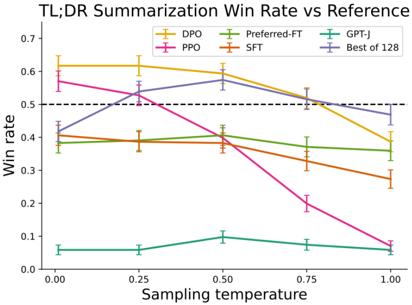

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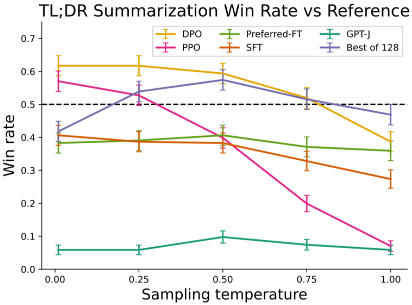

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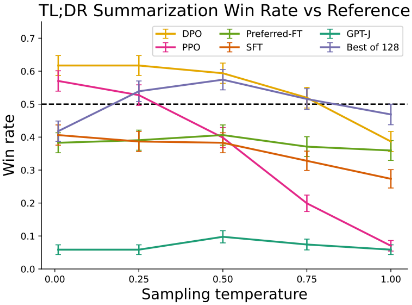
- More robust to sampling temperature than PPO
- Preferred-FT does not improve over SFT model



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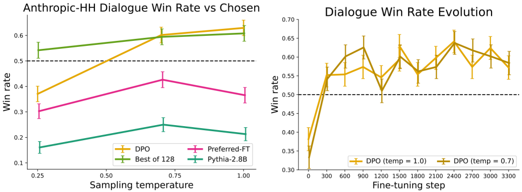

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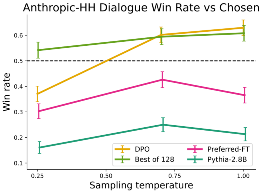

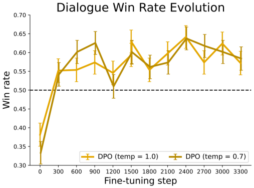

Dialogue Results

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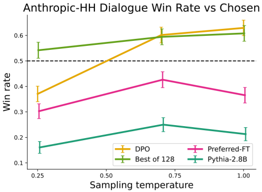

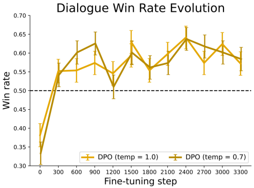

Qualitative Examples - Summarization

Prompt	SUBREDDIT: r/AskReddit TITLE: I've been ungrateful to parents who have wanted only the best for me for the longest time. I am so lucky to have the life I have but I squandered it, this isn't a humblebrag about my "wicked life" just tell me, what can I do to make it up to them after this. POST: I'm 17, leaving for University, and I've had epiphany after epiphany of how shitty i've beent to them, or how all the nice things they do I ruin with moods etc., I know there isn't a quick fix, but I want to do something nice. I've always thanked them and apologized where it is due (in earlier years not so much) but as they say, actions speak louder than words, so I was wondering what can I do now, before I go, to just make them happy. What can I keep doing, I know all the little things, doing chores, keeping my room clean, cleaning up after myself, helping around the house, but what's a big thing, for say christmas, or their birthdays, that I can do to make them happy?
DPO	TL;DR: I've been a shitty child and I want to make up for it, what can I do for my parents on their birthdays and christmas to show them how much I love them?
Baseline (PPO)	TL;DR: I've been a shitty person to my parents, what can I do to make it up to them, before I go, and what can I do after university to make them happy, and what can I do to make them happy after university (if that is the case)
GPT-4	Summary B [DPO] more effectively captures the main points of the post by focusing on making the parents happy through gestures on special occasions, while Summary A seems repetitive and less clear.

Qualitative Examples - Completion

Prompt	In a shocking turn of events, ...
DPO	In a shocking turn of events, the underdog team staged a stunning comeback in the final minutes of the game, securing a victory that will be remembered for years to come. The crowd erupted in cheers as the final buzzer sounded, and the players celebrated on the court, embracing each other and shedding tears of joy.
Baseline	In a shocking turn of events, the company announced massive lay-offs across all departments. The news came as a surprise to many employees who had been with the company for years. The CEO cited financial difficulties and a need to restructure as the main reasons behind the decision.

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- DPO generates a more coherent and engaging continuation of the prompt
- The baseline output, while relevant, lacks the same level of coherence and narrative flow

Discussion

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- The effectiveness of DPO is demonstrated through both automatic metrics and human evaluation
- DPO achieves state-of-the-art performance in aligning language models with human preferences

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- The direct optimization of preferences leads to more aligned and user-centric language generation

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- Balancing the trade-off between specificity and generalizability of learned preferences remains a challenge

Implications for Preference Learning in Language Models

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- DPO can facilitate the easier integration of ethical and social considerations into language models
- Success of DPO highlights the importance of preference learning in advancing language model capabilities

Future Research

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Conclusion

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- DPO paves the way for developing language models that better align with user preferences and values
- It enables the incorporation of personalized and context-aware preferences into language generation
- DPO has the potential to facilitate the development of language models that are more ethical, unbiased, and socially responsible

Citations and References

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Thank you

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