
PEARLS
RL for Language (Agents)
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UCSDCSE

Logistics

- HW 2 due today, HW 3 will be released by the end of the week

Rewards in Language

- Dense human feedback is super expensive (also noisy)
- Whole field of automatic **human proxy** metrics for NLP:
  - Learned: human preference classifiers, BERTScore,
  - Rule-based per task: BLEU, ROUGE, etc.

Classical NLP Metrics

Candidate 1: It is a guide to action which ensures that the military always obeys the commands of the party.

Candidate 2: It is to insure the troops forever hearing the activity guidebook that party direct.

Reference 1: It is a guide to action that ensures that the military will forever heed Party commands.

Reference 2: It is the guiding principle which guarantees the military forces always being under the command of the Party.

Reference 3: It is the practical guide for the army always to heed the directions of the party.

Classical NLP Metrics

Candidate: the the the the the the the.

Reference 1: The cat is on the mat.

Reference 2: There is a cat on the mat.

Classical NLP Metrics

- Requires lots of bespoke written rules
- Can't scale
- "Every time I fire a linguist, the performance [...] goes up"
  --Frederick Jelinek

Learned Rewards

Step 1: Collect preference feedback

Prompt:

What are the 3 most common gasses in earth's atmosphere?

LM outputs:

A: The atmosphere of Earth is a layer of gases retained by Earth's gravity…

B: The atmosphere is commonly known as air. The top gases by volume that dry air …

C: The air that surrounds the planet Earth contains various gases. Nitrogen…

D: The atmosphere of Earth is the layer of gases, generally known as air…

Human Feedback

Train a new metric, a reward function: Human judgment proxy.

Trained via (variant of) a ranking loss.

Learned Rewards

What format of feedback do you have?

- +1/-1
- A vs B
- Ranked List
- Natural Language

Learned Rewards

What format of feedback do you have?

- +1/-1 – contextual bandits
- A vs B – Bradley Terry
- Ranked List – Plackett Luce
- Natural Language - ???

A vs B: Bradley Terry

- Pairwise preference models make the Bradley Terry assumption that underlying preference distribution is IID and pairwise prefs are generated with a fn of the form for some real no.s all

$$\mathbb{P}\{i \succ j\} = \frac{\alpha_i}{\alpha_i + \alpha_j}.$$

A vs B vs C vs D... Plackett Luce

- Listwise preference models make the Plackett Luce assumption that underlying preference distribution is IID and pairwise prefs are generated with a fn of the form for some real no.s all

$$\mathbb{P}\{\text{choosing } i \text{ from } S\} = \frac{\alpha_i}{\sum_{j \in S} \alpha_j}.$$

$$\begin{aligned}\mathbb{P}\{i_3 \succ i_1 \succ i_2\} &= \mathbb{P}\{\text{choosing } i_3 \text{ from } \{i_1, i_2, i_3\}\} \\ &\quad \cdot \mathbb{P}\{\text{choosing } i_1 \text{ from } \{i_1, i_2\}\} \\ &\quad \cdot \mathbb{P}\{\text{choosing } i_2 \text{ from } \{i_2\}\} \\ &= \frac{\alpha_{i_3}}{\alpha_{i_1} + \alpha_{i_2} + \alpha_{i_3}} \cdot \frac{\alpha_{i_1}}{\alpha_{i_1} + \alpha_{i_2}} \cdot \frac{\alpha_{i_2}}{\alpha_{i_2}}.\end{aligned}$$

Plackett Luce (contd)

- No existing reward models actually use Plackett Luce (though the concept is very relevant)
- Most take a list of A vs B vs C... and make pairwise preferences then apply Bradley Terry from that
  - Remember that Plackett Luce of list size 2 reduces to Bradley Terry

Why Contrastive Preferences?

- Humans can't always articulate why they prefer something
- Comparison to something else instead of raw score grounds things
- Idea is to learn implicit preferences through data

Why not Contrastive Preferences?

- Humans aren't transitive, may have prefs: A > B, B > C, C > A
- Harder to debug reward models of implicit human preferences, can't know why reward hacking is occurring
- Bradley Terry / Plackett Luce originally created for sports team rankings, assume that each A vs B vs C sample is IID and are single point values
    - Preferences are for language!! There is token level compositionality, you can like parts of a response but dislike others

“Verifiable” Rewards

- Will get into details later but just think of it as rewards with ~0 error for actual task you’re trying to get them to do

Problem 0: Reward Hacking

Great rewards/metric scores, but spirit of task is unsolved

- "When measure becomes target, it ceases to be a good measure"

Example Reward: Positive Sentiment Score

I want you to make as positive a movie review as possible for me no matter how negatively it starts

Ok, I can do that. How should I start this review?

"I loved the book but really hated the movie"

Amaze brilliant great yay 10/10 -IGN

Reward hacked

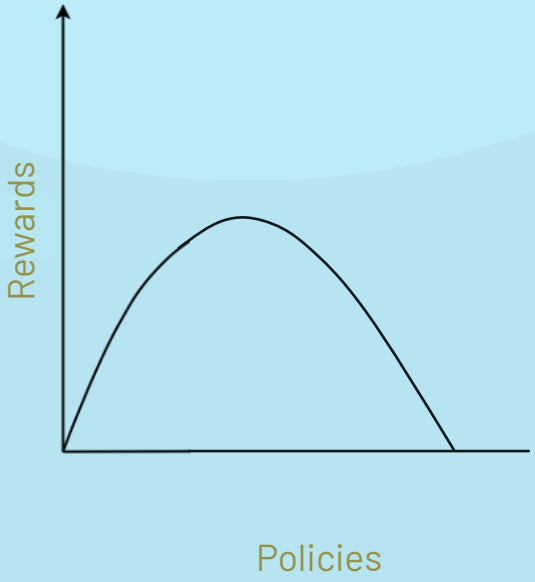
At first anyway, but I warmed slowly as I watched. Here, I'll tell you why …

IDEAL

Problem 0: Reward Hacking
The (Partial) Fix

- Optimize for this reward function

$$\mathbb{E}_{\pi}[\sum_{t=0}^{K} \gamma^t R(\boldsymbol{s}_t, a_t)]$$



Ziegler et al. *Fine-tuning Language Models from Human Preferences.* Preprint. 2020.

Problem 0: Reward Hacking
The (Partial) Fix

- KL Divergence from LM creates "Trust Region of Relevant Natural Language"

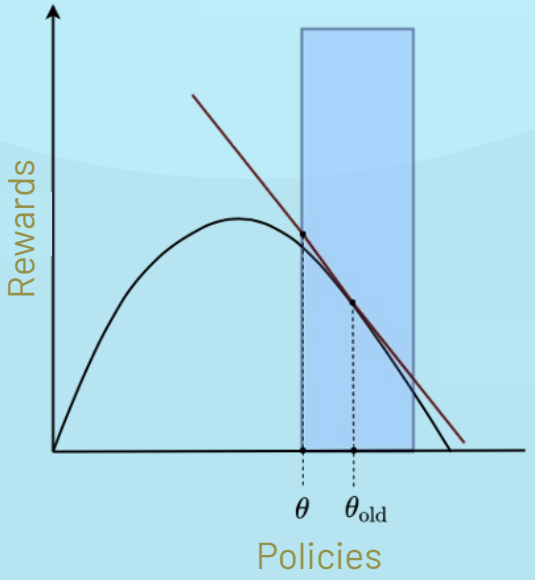
$$\mathbb{E}_{\pi}[\sum_{t=0}^{K} \gamma^t R(\boldsymbol{s}_t, a_t)] - \alpha \mathbb{E}_{\pi}[\mathrm{KL}(\pi_\theta || \pi_0)]$$

Long Term Expected Task Rewards

Current Policy Original Policy

Naturalness Penalty

Reason 2 why we need Pre-training+SFT. The outputs of the initial model need to already be somewhat reasonable to put us in the right (approx.) trust region.



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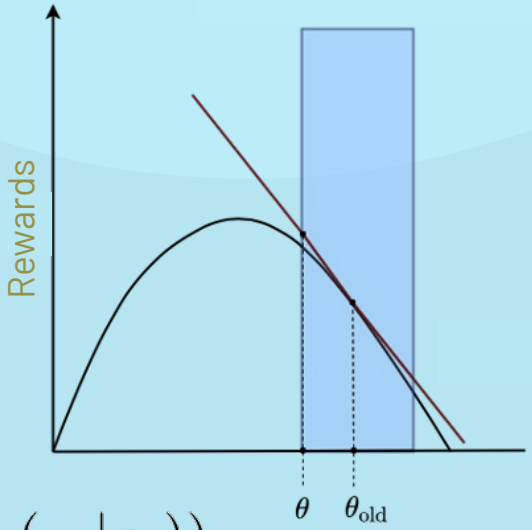


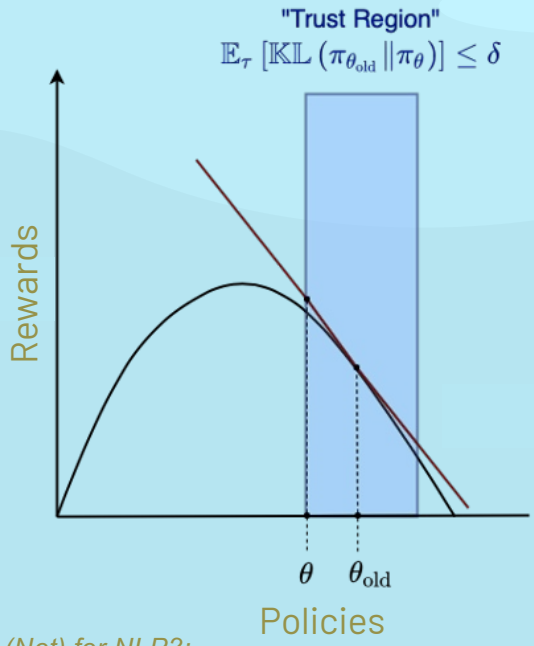
$$\mathrm{KL}\left(\pi_\theta(a_t|\boldsymbol{s}_t)||\pi_0(a_t|\boldsymbol{s}_t)\right) = \left(\log \pi_0(a_t|\boldsymbol{s}_t) - \log \pi_\theta(a_t|\boldsymbol{s}_t)\right)$$

Policies

Ziegler et al. *Fine-tuning Language Models from Human Preferences.* Preprint. 2020.

Why does *this* work?

- KL penalty creates a approximation of "trust region" of general natural language
- Masking policy creates "task specific trust region" = language specific to current domain

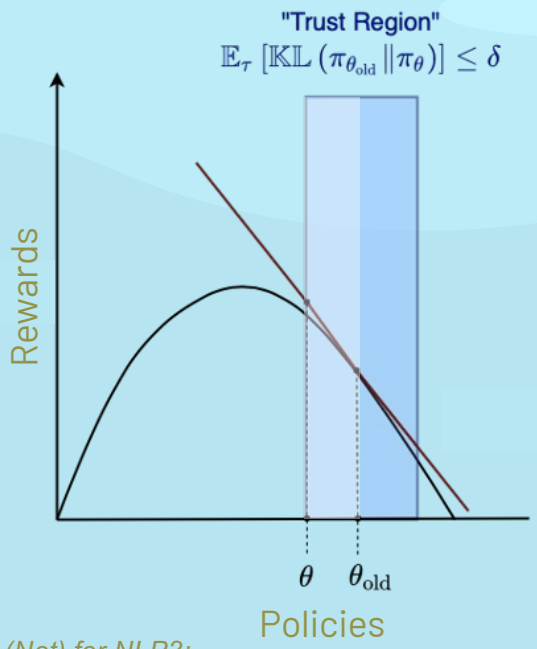


Ramamurthy*, Ammanabrolu*, Brantley, Hessel, Sifa, Bauckhage, Hajishirzi, Choi. *Is RL (Not) for NLP?: Benchmarks, Baselines, and Building Blocks for Natural Language Policy Optimization.* ICLR 2023.

Why does *this* work?

- RL algorithm "searches" in region for exact point to optimize rewards

"Task specific Trust Region"



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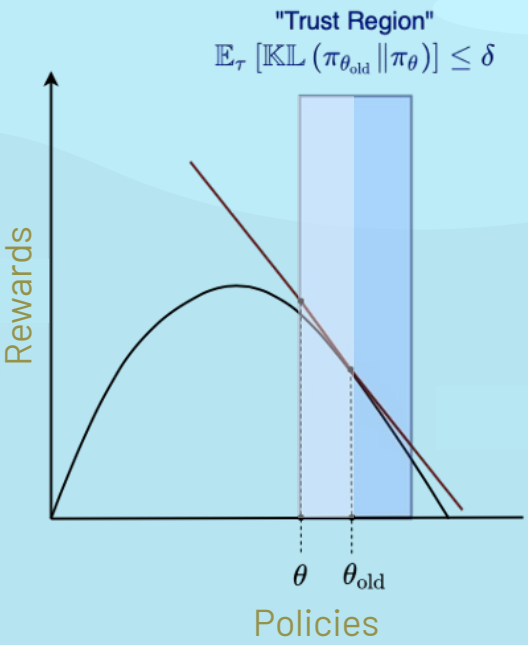
- RL algorithm "searches" in region for exact point to optimize rewards

$$\max_{\pi} \mathbb{E}_{x\sim\mathcal{D},y\sim\pi(y|x)}\left[r(x,y)\right] - \beta\mathbb{D}_{\mathrm{KL}}(\pi(\cdot \mid x)\|\pi_{\mathrm{ref}}(\cdot \mid x))$$



Problem 1: Challenging overall quality comparison

Hard to compare LM outputs with *a mixture of diverse undesired behaviors*

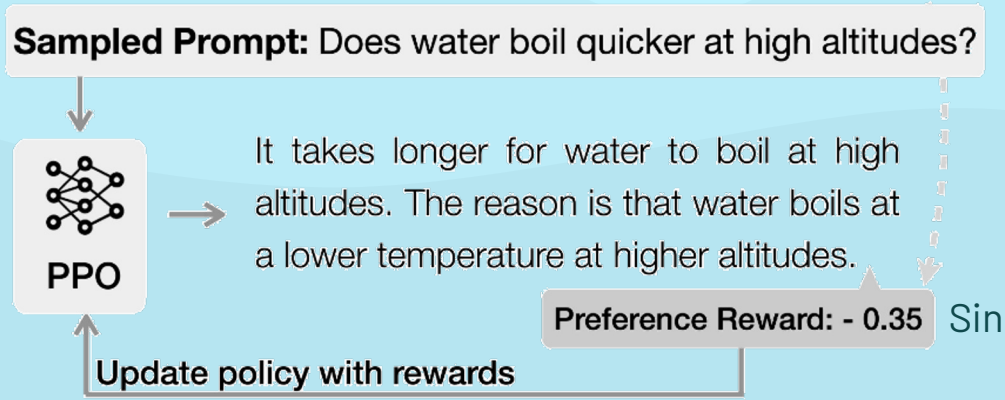
Output A:
Sentence 1: Factual 👍 but not informative 👎
Sentence 2: ...
...

Output B:
Sentence 1: Informative 👍 but unverifiable 👎
Sentence 2: ...
...

Unreliable human feedback

Ramamurthy*, Ammanabrolu*, Brantley, Hessel, Sifa, Bauckhage, Hajishirzi, Choi. *Is RL (Not) for NLP?: Benchmarks, Baselines, and Building Blocks for Natural Language Policy Optimization.* ICLR 2023.

Problem 2: Sparse, unreliable rewards for training



Single, noisy holistic reward for the full output

Unreliable RL training

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Fine-grained feedback is more explicit and reliable!

Prompt:

What are the 3 most common gasses in earth's atmosphere?

LM output:

The atmosphere of Earth is a layer of gases retained by Earth's gravity. The most common gas, by dry air volume, is nitrogen. The second most is oxygen. The third most is carbon dioxide.

Localizing feedback / reward

Fine-Grained Human Feedback

Wu, Hu, Shi, Dziri, Suhr, Ammanabrolu, Smith, Ostendorf, Hajishirzi. *Fine-Grained Human Feedback Gives Better Rewards for Language Model Training.* NeurIPS 2023.

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→ Localizing feedback / reward

Fine-Grained Human Feedback

Irrelevant / Redundant

Unverifiable / Untruthful

Missing The third most is Argon.

→ Categorizing feedback / reward

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Fine-grained RLHF

Step 1: Collect fine-grained feedback and train reward models

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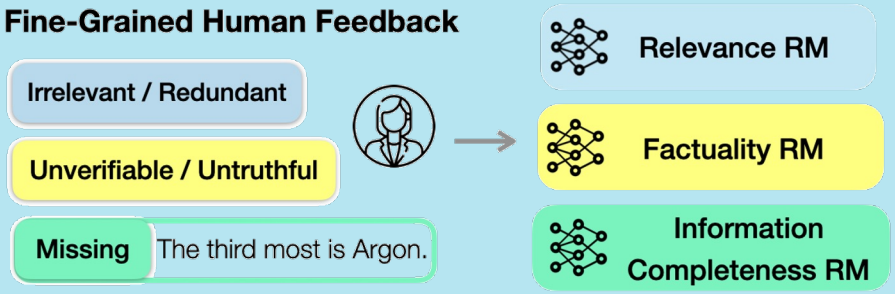

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Step 1: Collect fine-grained feedback and train reward models

Step 2: Refine the policy LM against the reward models using RL

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Fine-Grained Human Feedback

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Relevance RM

Factuality RM

Information Completeness RM

Sampled Prompt: Does water boil quicker at high altitudes?

PPO

It takes longer for water to boil at high altitudes. The reason is that water boils at a lower temperature at higher altitudes.

Relevant: + 0.3 Factual: - 0.5

Relevant: + 0.3 Factual: + 0.5 Info. complete: + 0.3

Update policy with rewards

Wu, Hu, Shi, Dziri, Suhr, Ammanabrolu, Smith, Ostendorf, Hajishirzi. *Fine-Grained Human Feedback Gives Better Rewards for Language Model Training.* NeurIPS 2023.

Fine-grained reward assignment during RL

Multiple reward models associated with different feedback types

Provide dense reward for every LM output segment

$$r_t = \sum_{k=1}^{K} \sum_{j=1}^{L_k} \left(\mathbb{1}(t = T_j^k)\, w_k\, R_{\phi_k}(x, y, j) \right)$$

Assign at the end of each segment

Each reward model outputs a reward for every segment in LM output

A vs B: Bradley Terry

- Pairwise preference models make the Bradley Terry assumption that underlying preference distribution is IID and pairwise prefs are generated with a fn of the form for some real no.s all

$$\mathbb{P}\{i \succ j\} = \frac{\alpha_i}{\alpha_i + \alpha_j}.$$

$$\mathcal{D} = \{x^i, y_w^i, y_l^i\}$$

Prompt

Preferred response

Dispreferred response

Reward assigned to **preferred** and **dispreferred** responses

$$p(y_w \succ y_l \mid x) = \sigma(r(x, y_w) - r(x, y_l))$$

Slide credits to Rafael Rafailov, Archit Sharma, Eric Mitchell. Stanford.

DPO

Bradley Terry Reward Loss

$$\mathcal{L}_R(r, \mathcal{D}) = -\mathbb{E}_{(x,y_w,y_l)\sim\mathcal{D}} \left[\log \sigma(r(x, y_w) - r(x, y_l))\right]$$

Rewrite rewards in terms of policy. "Closed form"

$$r_{\pi_\theta}(x, y) = \beta \log \frac{\pi_\theta(y \mid x)}{\pi_{\text{ref}}(y \mid x)} + \beta \log Z(x)$$

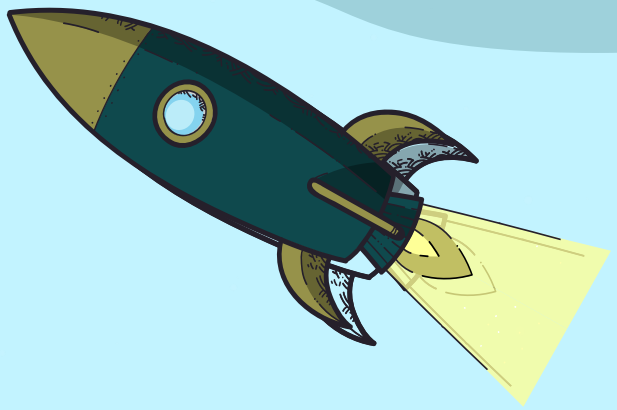
Put it all together

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

Slide credits to Rafael Rafailov, Archit Sharma, Eric Mitchell. Stanford.

Cans of Worms Time

Things I hear a lot I don't want to hear from y'all so I'm preempting it by opening the cans first



DPO or RLHF?

Incorrect question. DPO is also RL!

It is just **Offline** RL while PPO is **Online** RL

Offline RL: You have a large dataset of <data, reward/preference> pairs and need to learn policy from that.

Online RL: You have a reward function you can query while actively generating. Much closer to learning from “realtime” feedback

PPO vs DPO

PPO (any online RL)

Pros:
- Can optimize for arbitrary forms of feedback and metrics
- Theoretically much higher perf due to exploration + personalized learning

Cons:
- Many Eng challenges*

DPO

Pros:
- Easy to implement
- Can recover a reward from trained policy

Cons:
- No exploration (personalized learning)
- Cannot use any type of feedback except for BT/PL
- Easy to overfit to noisy offline dataset

*つ◕_◕つ PLS GIB ENG SUPPORT つ◕_◕つ つ◕_◕つ WE'RE DYING PLS SEND HELP つ◕_◕つ

Big remaining (reward) problems

- Human preference distributions are long-tailed, averaging them into one RM is not ideal. What now? (multi-objective RL)
- Humans are bad at expressing their own preferences. Can we elicit them? (yes)
- How to improve sample efficiency of human feedback learning?
- How to chase changing preferences through time?

RLHF is only for "AI Safety"

No <3

RLHF is: improving reasoning paths, calibrating confidences, etc etc. It is not the lobotomy algorithm.

“AI Safety” is mostly just legal coverage, should be defined by users at inference (esp in enterprise usecases)

“Harmlessness” training directly reduces “helpfulness” – very difficult multi objective optimization