A Common Pitfall of Margin-based Language Model Alignment: Gradient Entanglement

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Key Takeaways

Problematic Behavior





A Pitfall of RLHF: Underspecify the ideal behavior of model log-probabilities

The Cause: Gradient Entanglement effect passed through the gradient inner product

2,000 3,000 4,000 5,000 1,000 **Training Step**

Model log-likelihood on rejected response may increase 1,000 2,000 3,000 4,000 5,000 Training Step

Model log-likelihood on chosen response may decrease Why Large Gradient Inner Product: Noncontrastive tokens are involved

DPO Objective:
$$\ell_{DPO} = -\log\sigma(a - b)$$
 with $a := \beta \log\left(\frac{\pi_{\theta}(\mathbf{y}_{w}|\mathbf{x})}{\pi_{ref}(\mathbf{y}_{w}|\mathbf{x})}\right)$ and $b := \beta \log\left(\frac{\pi_{\theta}(\mathbf{y}_{l}|\mathbf{x})}{\pi_{ref}(\mathbf{y}_{l}|\mathbf{x})}\right)$

After one step optimizing ℓ_{DPO} :

 $\Delta \log \pi_w \approx C \cdot \left(\|\nabla \log \pi_w\|^2 - \langle \nabla \log \pi_w, \nabla \log \pi_l \rangle \right),$ $\Delta \log \pi_l \approx C \cdot \left(\langle \nabla \log \pi_w, \nabla \log \pi_l \rangle - \| \nabla \log \pi_l \|^2 \right).$

Case	$\log \pi_w, \log \pi_l$	Condition
1	$\log \pi_w \uparrow \log \pi_l \downarrow$	$\langle \nabla \log \pi_w, \nabla \log \pi_l \rangle \leq \min(\ \nabla \log \pi_w\ ^2, \ \nabla \log \pi_l\ ^2)$
2	$\log \pi_w \downarrow \log \pi_l \downarrow$	$\ \nabla \log \pi_w\ ^2 \le \langle \nabla \log \pi_w, \nabla \log \pi_l \rangle \le \ \nabla \log \pi_l\ ^2$
3	$\log \pi_w \uparrow \log \pi_l \uparrow$	$\ \nabla \log \pi_l\ ^2 \le \langle \nabla \log \pi_w, \nabla \log \pi_l \rangle \le \ \nabla \log \pi_w\ ^2$

The Cause: Gradient Entanglement

General Margin-Based RLHF Objective $\ell(\theta) = -(m(h_w(\log \pi_w) - h_l(\log \pi_l)) + \Lambda(\log \pi_w))$



Positively Correlated Chosen/Rejected Gradients

Training Step



Table 2: Instantiation of margin-based preference optimization losses.

The chosen log-probability change depends on the rejected gradient, and vice versa. The mutual dependency is characterized by: (d_w and d_l are objective-dependent scalars)

$$\Delta \log \pi_w \approx \eta \left(d_w \| \nabla_\theta \log \pi_w \|^2 - d_l \langle \nabla_\theta \log \pi_w, \nabla_\theta \log \pi_l \rangle \right),$$

$$\Delta \log \pi_l \approx \eta \left(d_w \langle \nabla_\theta \log \pi_w, \nabla_\theta \log \pi_l \rangle - d_l \| \nabla_\theta \log \pi_l \|^2 \right).$$

Explainable Training Dynamics with the Gradient Condition

Investigation: Why the gradient inner product is large?



Explicit regularization on log \pi_w: d_w is greater so that $log \pi_w$ is more likely to increase **SPPO**: $\frac{d_w}{d_v} > 1$ and $||\nabla \log \pi_l||^2 > ||\nabla \log \pi_w||^2$ is observed, thus the gradient condition are more lenient to be satisfied.

Consider a synthetic RLHF dataset (x: *statement*, y_w : true sentiment, y_l : false sentiment) with three configurations of y_w and y_l :

- Single Token: "Positive/Negative."
- Short Suffix: "Positive/Negative sentiment."

Long Suffix: "Positive/Negative sentiment based on my judgement."



Theoretical Results

- (Theorem 1) Single Token: $\langle \nabla \log \pi_w, \nabla \log \pi_l \rangle < 0$, thus $\log \pi_w$ \uparrow and $\log \pi_l \downarrow$.
- (Theorem 3) Short/Long Suffix: $\langle \nabla \log \pi_w, \nabla \log \pi_l \rangle > 0$ as the suffix length goes up, both $\log \pi_w$ and $\log \pi_l$ decrease.
 - The token-wise inner product can be negative: $\langle \nabla \log \pi_w^i, \nabla \log \pi_l^i \rangle < 0$, *i* is the index of "Positive/Negative".

