
Algorithm 1 NLPO- Natural Language Optimization

- 1: **Input:** Dataset $\mathcal{D} = \{(\mathbf{x}^i, \mathbf{y}^i)\}_{i=1}^N$ of size N
- 2: **Input:** initial policy parameter π_{θ_0}
- 3: **Input:** initial LM π_0
- 4: **Input:** initial value function parameters V_{ϕ_0}
- 5: **Input:** initialize parameterized masked policy $\pi_{\psi_0}(\cdot|\cdot, \pi_{\theta_0})$ with parameterized top-p policy π_{θ_0}
- 6: **Input:** policy update frequency μ
- 7: **repeat**
- 8: Sample mini-batch $\mathcal{D}_m = \{(\mathbf{x}^m, \mathbf{y}^m)\}_{m=1}^M$ from \mathcal{D}
- 9: Collect trajectories \mathcal{T}_{τ_i} by running policy π_{ψ_n} in for batch \mathcal{D}_m in env
- 10: Compute Preference and KL penalty rewards \hat{R}_t
- 11: Compute the advantage estimate \hat{A}_t
- 12: Update the policy by maximizing the PPO-Clip objective:
- 13:

$$\pi_{\theta_{m+1}} = \operatorname{argmax}_{\theta} \frac{1}{\mathcal{D}_m T} \sum_{\tau \in \mathcal{D}_m} \sum_{\tau=0}^T \min(r_t(\theta) A^{\pi_{\theta_m}}, \operatorname{clip}(r_t(\theta), 1-\epsilon, 1+\epsilon) A^{\pi_{\theta_m}})$$

- 14:
- 15: where $r_t(\theta) = \frac{\pi_{\theta}(a_t|s_t)}{\pi_{\theta_m}(a_t|s_t)}$.
- 16:
- 17: Update the value function:
- 18:

$$V_{\phi_{m+1}} = \operatorname{argmin}_{\phi} \frac{1}{\mathcal{D}_m T} \sum_{\tau \in \mathcal{D}_m} \sum_{t=0}^T \left(V_{\phi}(s_t) - \hat{R}_t \right)^2$$

- 19: Update the parameterized masked policy every μ iterations:
- 20:

$$pi_{\psi_{n+1}}(\cdot|\cdot, \pi_{\theta_{m+1}})$$

- 21: **until** convergence and **return** π_{θ}
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