
1 Pseudo Algorithms

Algorithm 1 CAPO: Cost-Aware Prompt Optimization

Require: Dataset $\mathcal{D} = \{(X_i, y_i)\}_{i=1}^n$, Meta-LLM $\Phi(x)$, Downstream LLM $\phi(x)$, Cost function $\ell(y, \hat{y})$, Initial instructions $\Lambda = \lambda_1, \dots, \lambda_p$, Population size p , Block size b , Number of iterations n , Number of crossovers per iteration c

```
1: for  $\lambda \in \Lambda$  do
2:   num_shots  $\sim$  U(lower, upper)
3:    $\xi \leftarrow \text{sample}(X, \text{num\_shots})$  ▷ Sample few shot examples
4:    $\theta \leftarrow \phi(\lambda || \xi)$  ▷ Generate few shots with reasoning
5:    $\pi \leftarrow (\lambda, \theta)$ 
6:    $\Pi \leftarrow \Pi.\text{append}(\pi)$ 
7: end for
8: Divide dataset  $\mathcal{D}$  into blocks  $\mathcal{B} = \{B_1, \dots, B_k\}$  where  $|B_i| = b$ 
9: for  $i = 1$  to  $n$  do
10:   $\Pi_{\text{off}} \leftarrow \text{cross\_over}(\Pi, c)$ 
11:   $\Pi_{\text{off}} \leftarrow \text{mutate}(\Pi_{\text{off}})$ 
12:   $\Pi \leftarrow \text{do\_racing}(\Pi \cup \Pi_{\text{off}}, k = p)$ 
13: end for
14: best_prompt  $\leftarrow \text{do\_racing}(\Pi, k = 1)$ 
15: return best_prompt
```

Is reasoning always necessary? Maybe this is not important for simple tasks and costs a lot of tokens. (Idea: some few shot examples can be included without reasoning)

Algorithm 2 cross_over

Require: Population Π , Meta-LLM $\Phi(x)$, Cross-Over-Meta-Prompt λ_C , Number of crossovers c

```
1:  $\Pi_{\text{off}} \leftarrow []$ 
2: for  $j = 1$  to  $c$  do
3:    $P_1 \leftarrow \text{sample}(\Pi, 1)$   $\triangleright P_1 = (\lambda_1, \theta_1)$ 
4:    $P_2 \leftarrow \text{sample}(\Pi, 1)$   $\triangleright P_2 = (\lambda_2, \theta_2)$ 
5:    $\lambda_{\text{off}} \leftarrow \Phi(\lambda_C || \lambda_1 || \lambda_2)$   $\triangleright$  Let Meta-LLM cross over the prompts
6:    $\theta_{\text{off},j} \leftarrow \text{sample}(\theta_1 \cup \theta_2, \left\lfloor \frac{|\theta_1| + |\theta_2|}{2} \right\rfloor)$   $\triangleright$  Sample from all few-shot examples
7:    $\pi_{\text{off},j} \leftarrow (\lambda_{\text{off},j}, \theta_{\text{off},j})$ 
8:    $\Pi_{\text{off}} \leftarrow \Pi_{\text{off}}.\text{append}(\pi_{\text{off},j})$ 
9: end for
10: return  $\Pi_{\text{off}}$ 
```

Currently we do a random parent selection. In EvoPrompt they do a roulette wheel selection based on the fitness scores. This would require us to find a way of already having scores here.

We have to clarify where the new few-shot examples are coming from.

Extra Split:

- + no data leakage (fair, comparable assessment of prompts)
- constrained pool of few-shot examples (how to get this pool?) - potentially smaller dev Split

From Train Split:

- data leakage (prompts that contain eval data point already as few-shot examples which are already confirmed as correct have advantages)
- + we can use the full train set

Algorithm 3 mutate

Require: Population of offsprings Π_{off} , Meta-LLM $\Phi(x)$, Mutation-Meta-Prompt λ_M , Dataset samples X

```
1: for  $\pi_{\text{off}} \in \Pi_{\text{off}}$  do
2:    $\lambda_{\text{off}} \leftarrow \Phi(\lambda_M || \lambda_{\text{off}})$ 
3:    $\text{num\_shots} \sim U(\text{lower}, \text{upper})$ 
4:    $\text{num\_new\_shots} \sim U(\text{lower}, \text{num\_shots})$ 
5:    $\xi \leftarrow \text{sample}(X, \text{num\_new\_shots})$   $\triangleright$  Sample new few shot examples
6:    $\theta_{\text{new}} \leftarrow \phi(\lambda_{\text{off}} || \xi)$   $\triangleright$  Generate few shots with reasoning
7:    $\theta_{\text{old}} \leftarrow \text{sample}(\theta_{\text{off}}, \text{num\_shots} - \text{num\_new\_shots})$ 
8:    $\theta \leftarrow \theta_{\text{old}} \cup \theta_{\text{new}}$ 
9:    $\theta \leftarrow \text{shuffle}(\theta)$ 
10:   $\pi_{\text{off}} \leftarrow (\lambda_{\text{off}}, \theta)$ 
11: end for
12: return  $\Pi_{\text{off}}$ 
```

Algorithm 4 do_racing

Require: Prompts Π , Top-k k , cost function $\ell(y, \hat{y})$, blocks \mathcal{B} , Downstream LLM $\phi(x)$, number of evaluations a

```
1: survivors  $\leftarrow \Pi$ 
2:  $i \leftarrow 0$ 
3: scores  $\leftarrow [0] * \text{len}(\Pi)$ 
4:  $\text{shuffle}(\mathcal{B})$ 
5: while  $\text{len}(\text{survivors}) > k \wedge i < \text{len}(\mathcal{B})$  do
6:    $i \leftarrow i + 1$ 
7:   scores  $\leftarrow \frac{1}{i} (\text{evaluate}(\Pi, B_i) + (i - 1) * \text{scores})$ 
8:   survivors  $\leftarrow \text{racing\_elimination}(\Pi, \text{scores}, i * b, \alpha, k)$ 
9: end while
10: return survivors
```

Algorithm 5 racing_elimination

Require: Prompts Π , scores S , confidence level α , top-k k

- 1: $z_\alpha \leftarrow \Phi^{-1}(1 - \alpha/2)$ ▷ Critical value
 - 2: survivors $\leftarrow \Pi$
 - 3: **for** $\pi_i \in \Pi$ **do**
 - 4: n_subst_better $\leftarrow \sum_{j \neq i} \mathbf{1}_{[(s_j - s_i)\sqrt{a} > z_\alpha]}$
 - 5: **if** n_subst_better $\geq k$ **then**
 - 6: survivors \leftarrow survivors $\setminus \{\pi_i\}$ ▷ Eliminate π_i
 - 7: **end if**
 - 8: **end for**
 - 9: **return** survivors
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