

# COMPOSITIONAL PREFERENCE MODELS FOR ALIGNMENT WITH SCALABLE OVERSIGHT

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## ABSTRACT

As language models (LMs) become more capable, it is increasingly important to align them with human preferences. However, the dominant paradigm for training Preference Models (PMs) for that purpose suffers from fundamental limitations, such as lack of transparency and scalability, along with susceptibility to overfitting the preference dataset. We propose Compositional Preference Models (CPMs), a novel PM framework that decomposes one global preference assessment into several interpretable features, obtains scalar scores for these features from a prompted LM, and aggregates these scores using a logistic regression classifier. CPMs allow to control which properties of the preference data are used to train the preference model and to build it based on features that are believed to underlie the human preference judgement. Our experiments show that CPMs not only improve interpretability and are more robust to overoptimization than standard PMs, but also that best-of- $n$  samples obtained using CPMs tend to be preferred over samples obtained using conventional PMs. *Overall, our approach demonstrates the benefits of endowing PMs with priors about which features determine human preferences while relying on LM capabilities to extract those features in a scalable and interpretable way.*

## 1 INTRODUCTION

As the capabilities of language models (LMs) continue to advance, there is a growing need for safe and socially responsible models. The dominant approach to aligning LMs with human preferences, reinforcement learning from human feedback (RLHF; Ouyang et al., 2022; Bai et al., 2022a; OpenAI, 2023), consists in training a preference model (PM) to predict human preference judgments and then finetuning an LM to maximize the reward given by the PM. However, the current PM methodology exhibits certain limitations. First, it is susceptible to overfitting the preference dataset. The PM can misrepresent human preferences by fitting to spurious correlations in its training data Gao et al. (2023). Heavily optimizing an LM against a PM incentivises the LM to exploit those flaws. Second, PMs are often difficult to interpret and to oversee. They project preferences onto a single scalar feature, making it difficult to know what factors are influencing their decisions. This is especially problematic for complex preferences, such as helpfulness or harmlessness, which often encompass a multidimensional combination of attributes (Bai et al., 2022a; Glaese et al., 2022; Touvron et al., 2023). Further, as LM capabilities improve, it will be increasingly harder for unassisted humans to provide feedback on LM’s responses (Pandey et al., 2022; Bowman et al., 2022a).

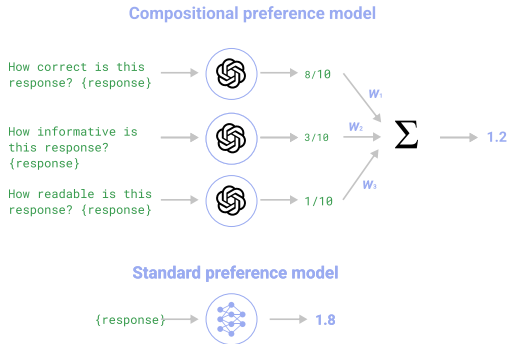


Figure 1: Compositional preference models score different features of LM responses separately and output a preference score as a linear combination of feature values.

In this paper, we propose the Compositional Preference Model (CPM), a novel framework for learning a PM that is robust to preference model overoptimization and allows for more transparent and interpretable supervision of complex behavior. A CPM decomposes one global preference assessment into a series of simpler questions which correspond to human-interpretable features. Then, a prompted LM (e.g. GPT- 3.5) is asked to assign a numerical value to each feature. Finally, the feature scores are combined into a scalar preference score using a trained logistic regression classifier.

CPMs have several advantages over standard PMs. First, they are more robust to overfitting and reward hacking. The pre-selected features on which CPMs operate provide a useful inductive bias that bootstraps learning human preferences. This, in turn, limits their vulnerability to reward hacking, as the parameter space of a PM is spanned by features selected to be meaningful and robust. Second, CPMs allow for the modular and human-interpretable supervision of complex behavior.

In our experiments, we show that CPMs generalize better and that using them results in less preference model overoptimization. Additionally, CPMs exhibit superior performance in capturing the underlying human preferences. In an auto-evaluation experiment with Claude (Anthropic, 2023) as an approximation of human evaluators (Chiang et al., 2023; Mukherjee et al., 2023; Liu et al., 2023; He et al., 2023), best-of- $n$  samples obtained using CPMs are consistently preferred over samples obtained using conventional PMs.

## 2 BACKGROUND

Let us have a dataset of comparisons  $\mathcal{D} = \{x^i, y_1^i, y_2^i\}_{i=1}^N$ , where  $x$  is an input query and  $y_1$  and  $y_2$  are two possible responses to  $x$ , with  $y_1$  the preferred response. The dominant approach to aligning language models, RLHF (Christiano et al., 2017; Ziegler et al., 2019; Ouyang et al., 2022; Bai et al., 2022a)<sup>1</sup>, involves training a parametrized PM  $R(y|x) = R_\theta(y|x)$  by defining a probability distribution

$$p_\theta(y_1 > y_2|x) \doteq \sigma(R_\theta(y_1|x) - R_\theta(y_2|x)) = (1 + \exp(R_\theta(y_2|x) - R_\theta(y_1|x)))^{-1} \quad (1)$$

and estimating  $\theta$  by maximizing the likelihood of  $p_\theta$  over  $\mathcal{D}$ . Typically  $R_\theta$  is obtained by adding a scalar head on top of a base language model and fine-tuning the resulting model. Since  $p_\theta$  is invariant to addition of a constant to  $R_\theta$ , it is standard to shift the  $R$  scores such that  $E_{(x,y) \sim \mathcal{D}}[R(y|x)] = 0$ .

## 3 METHOD

The Compositional Preference Model (CPM) is a multi-step approach for decomposing preference learning into individual components. We first decompose preference judgements into a set of  $C$  distinct features, then use a prompted LM to assign to a pair  $(x, y)$  a scalar score for each individual feature  $c = 1, \dots, C$ . Finally, we employ a logistic regression classifier to combine these features into a global scalar score that best predicts the human preference judgements.

### 3.1 FEATURE EXTRACTION USING A LANGUAGE MODEL

For each feature  $c$ , we consider an individual preference model  $R_c$  that maps an input query  $x$  and a response  $y$  to a scalar score. In order to do that, we associate each feature  $c$  with a specific prompt  $t_c$  and compute a score  $r_c = R_c(y|x, t_c)$ , where  $R_c$  can be a general LLM like GPT-3.5, prompted with  $t_c$ . These features are designed to decompose the broad concept of preferability into a series of more straightforward and interpretable components. It is noteworthy that a feature can represent not only positive categories that are aligned with preferability (e.g. informativeness), but also categories that are assumed to be negatively correlated with it (e.g. biasedness). This procedure allows us to control which properties of the preference data are used to train the PM and to build it based on components that we believe to determine the human choices.

<sup>1</sup>CPMs can also be used with other alignment training methods both during pretraining (Korbak et al., 2023) and finetuning (Rafailov et al., 2023; Go et al., 2023).

### 3.2 COMBINING MULTIPLE FEATURES

The features assessed by the prompted LM serve as distinct modules, each of which evaluates a different aspect. To combine the features into an interpretable single model, we employ logistic regression to classify the preferred response in a pairwise comparison dataset.<sup>2</sup>

Based on the dataset  $\mathcal{D} = \{x^i, y_1^i, y_2^i\}_{i=1}^N$ , we obtain a feature matrix  $\{x^i, \mathbf{r}(y_1^i), \mathbf{r}(y_2^i)\}_{i=1}^N$ . Here  $\mathbf{r}(y) = (R_1(y|x, t_1), \dots, R_C(y|x, t_C))$  is a feature vector containing decomposed feature scores. We standardize each feature score to have average 0 and variance 1 within the train data. We compute the pairwise difference of the feature vectors for each pair of responses,  $\mathbf{r}(y_1) - \mathbf{r}(y_2)$ , and train a logistic regression classifier with this difference to predict 1 if  $y_1$  is preferred, and 0 if  $y_2$  is preferred. In other words, the distribution  $p$  is formalized as:

$$p(y_1 > y_2|x) \doteq \sigma(\langle \boldsymbol{\lambda}, \mathbf{r}(y_1) - \mathbf{r}(y_2) \rangle) = (1 + \exp(-\langle \boldsymbol{\lambda}, \mathbf{r}(y_1) - \mathbf{r}(y_2) \rangle))^{-1} \quad (2)$$

where  $\boldsymbol{\lambda} = (\lambda_1, \dots, \lambda_C)$  is the vector of fitted coefficients. The coefficient  $\lambda_c$  indicates the importance of the feature  $c$  for predicting human preference judgements. To obtain the preference score of a single sample  $(y, x)$ , we simply compute  $\langle \boldsymbol{\lambda}, \mathbf{r}(y) - \mathbf{0} \rangle = \langle \boldsymbol{\lambda}, \mathbf{r}(y) \rangle$ , where  $\mathbf{0}$  is the standardized average of the feature vector  $\mathbf{r}(y)$  over the train data as explained above.

## 4 EXPERIMENTS

In this section, we empirically evaluate CPM on robustness to overoptimization (Sec. 4.2), and effectiveness for preference alignment (Sec. 4.3). We also provide an illustrative example of CPM interpretability in Sec. 4.4.

### 4.1 EXPERIMENTAL SETUP

**Datasets** We conduct experiments on two datasets, the HH-RLHF dataset (Bai et al., 2022a) and the SHP dataset (Ethayarajh et al., 2022). Both consist of pairs of responses based on helpfulness. For each dataset, in order to establish a consistent setting and control for the data size factor, we sample 20K single-turn data points.

**Features** We use 13 features: helpfulness, specificity, intent, factuality, easy-to-understand, relevance, readability, enough-detail, biased, fail-to-consider-individual-preferences, repetitive, fail-to-consider-context and too-long, with pre-specified prompt templates (see App. E for the description of features and prompts). We use the same set of features for both datasets; prompt templates only differ in a preamble that describes  $x$  as either a conversation with an AI assistant (HH-RLHF) or a StackExchange question (SHP). We also use the length of  $y$ , which we find to be helpful on the SHP dataset.

**Methods** To find out the ability of an LM as a feature extractor, we explore two LMs, GPT-3.5 (gpt-3.5-turbo-0301) and Flan-T5-XL (3B parameters) (Chung et al., 2022), using the same features and prompt templates. We refer to the CPM models based on these extractors as CPM-GPT-3.5 and CPM-Flan-T5, respectively. We add a regularization term in logistic regression and use hyperparameters selected with 5-fold cross-validation on the training dataset. We then compare the conventional PM to these CPMs (trained respectively as described in Sec. 2 and Sec. 3.2). For a fair comparison, we train the standard PM based on the same Flan-T5-XL model that we use for the CPMs, but with an added linear head that outputs a scalar preference score. We compare the performances of CPM-GPT-3.5 and CPM-Flan-T5 with this standard PM. Implementation details are provided in App. B.

**Best-of- $n$  sampling (BoN)** To assess the robustness of PMs to overfitting, we use Best-of- $n$  (BoN) sampling (Gao et al., 2023; Jacob Hilton, 2022). BoN abstracts away from RLHF design choices such as the details of policy optimization and provides a stable proxy for RLHF performance (Nakano et al., 2021; Gao et al., 2023). We generate  $n$  responses using an initial LM  $a(x)$

<sup>2</sup>Expanding pairwise comparisons to rank data is possible, following the general approach of one-vs-one (Ouyang et al., 2022).

and evaluate the performance of the PMs on these responses. We consider the BoN distribution  $x \sim \text{BoN}(a, \text{PM}, n)$ , where  $n$  candidates are sampled from  $a$  and  $x$  is the candidate maximizing the PM score. We generate up to 25,600 BoN responses, with 256 responses for each of 100 prompts in a held-out test set.<sup>3</sup> We use Flan-T5-Large (780M parameters; Chung et al., 2022) as the initial LM to generate the responses. To ensure that the performance of different PMs can be compared on the same scale across different reward models, we normalize each PM score to have average 0 and variance 1 within the training data.

## 4.2 ROBUSTNESS TO OVEROPTIMIZATION

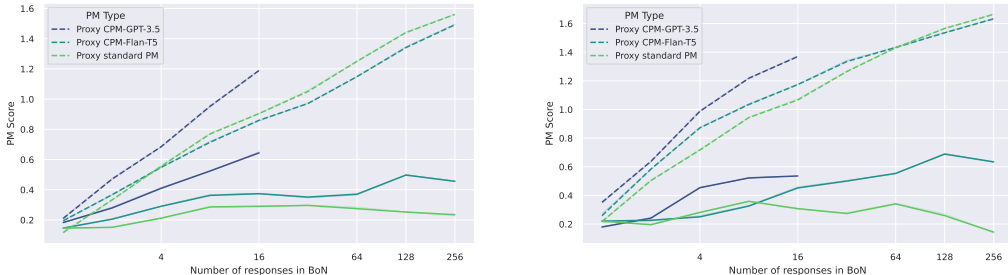


Figure 2: Overoptimization experiment in BoN distribution  $\text{BoN}(a, \text{PM}_{\text{proxy}}, n)$ . Dashed line means proxy PM used for BoN selection, corresponding solid line means gold PM. (left: HH-RLHF dataset, right: SHP dataset)

Overoptimization is a type of misalignment that occurs when the preference model is overly optimized by exploiting flaws in the proxy objective (Amodei et al., 2016; Skalse et al., 2022). This can lead to the PM diverging from the true objective, which we want to optimize in alignment tuning.

To investigate overoptimization, we follow Gao et al. (2023) and construct a synthetic dataset where the output of a specific “gold” PM is assumed to be the ground truth for preferences. As gold PMs, we use two well-established reference PMs,  $\text{PM}_{\text{ref1}}$  and  $\text{PM}_{\text{ref2}}$ , both instances of DeBERTa (He et al., 2020), with  $\text{PM}_{\text{ref1}}$  finetuned on a large dataset including HH-RLHF<sup>4</sup> and  $\text{PM}_{\text{ref2}}$  finetuned on a large dataset including SHP (Sileo, 2023). We then use the gold models to generate synthetic labels to train proxy PMs using each of the studied techniques. Depending on the PM training method, overoptimizing the PM can cause it to diverge from the gold PM, which allows us to compare the robustness of different PM techniques.

Fig. 2 shows that the gap between the gold PM and the proxy PM scores increases for each PM as the candidate size  $n$  increases. The distribution of the standard PM does not follow the gold PM distribution and has a larger divergence as the candidate size  $n$  increases. On the other hand, the gap between the gold and proxy PM scores is smaller for CPMs, with the gold PM score beginning to diverge later than for standard PMs. This suggests that CPMs are more robust to overoptimization.

## 4.3 QUALITY EVALUATION

The ultimate goal of PMs is to help align LMs with human preferences. While in the previous section we compared PMs with a certain gold PM, in this section we will investigate whether LMs aligned using CPMs are preferred by humans over LMs aligned using standard PMs. Following previous literature (Chiang et al., 2023; Mukherjee et al., 2023; Liu et al., 2023; He et al., 2023), we simulate human evaluation using a prompted LLM.

For each PM, we draw a response from  $\text{BoN}(a, \text{PM}, 16)$  by generating samples from  $a$  (Flan-T5) and selecting the best response based on the PM score. We then compare this response to vanilla Flan-T5, a response randomly selected from the same set of candidates. We use the LLM to choose which response is preferable. We refer to this metric as the “win rate”. A good PM is expected to have high win rate against vanilla Flan-T5. Importantly, we use Claude (Claude-2) (Anthropic, 2023), an LLM that was *not* used in feature extraction. Hence, we avoid *potential* subtle preference

<sup>3</sup>Due to computational constraints, we only evaluate CPM-GPT-3.5 on  $\text{BoN}(n \leq 16)$ .

<sup>4</sup><https://huggingface.co/OpenAssistant/reward-model-deberta-v3-large-v2>

leaks from features extracted using GPT-3.5. We use the prompt from (Chiang et al., 2023; Mukherjee et al., 2023) to rate the quality of the response selected by each PM method<sup>5</sup>. We perform one BoN trial with  $n = 16$  for CPM-GPT-3.5 and 10 independent such trials for other PMs and report the average win rate.

Tab. 1 shows evaluation results. Considering that both standard PM and CPM-Flan-T5 use the same architecture and data, the higher win rate of CPM-Flan-T5 compared to standard PM suggests the advantage of decomposing preference into multiple features and using an LM as feature extractor, rather than directly using the PM based on fine-tuning the LM as in Eq. (1). CPM-GPT-3.5 shows an even higher win rate, again indicating that using a more powerful LM as feature extractor can further improve the performance of CPM.

Win Rate	HH-RLHF	SHP
CPM-GPT-3.5	<b>0.810</b> (.)	<b>0.672</b> (.)
CPM-Flan-T5	0.742 (0.034)	0.580 (0.045)
Standard PM	0.588 (0.030)	0.564 (0.037)

Table 1: Win rate over initial generation after BoN sampling based on each PM. Except CPM-GPT-3.5, we independently conduct 10 rounds of BoN( $n = 16$ ) samplings and report the average win rate along with standard error.

#### 4.4 MODEL INTERPRETABILITY

CPMs, as linear models, have a high degree of interpretability Hastie et al. (2009). In this section, we provide a few illustrative examples focussing on the dataset HH-RLHF.

**Coefficients** The interpretability of our model is enhanced by the fact that the feature coefficients provide a direct indication of the factors that most influence the CPM’s decisions. This information can help understand the CPM’s internal workings. Tab. 2 shows the top 3 largest coefficients (see Tab. 10 for full coefficients). Although the coefficients vary as they are extracted with different LMs, their orders are generally consistent, except for a few features. This observation provides some clues into how the CPM makes its decisions. In the current example, the CPM focuses on general helpfulness and also prefers responses that are detailed enough but also factually correct.

CPM-GPT-3.5		CPM-Flan-T5	
Feature	Coefficient	Feature	Coefficient
helpfulness	0.246	fail-to-consider-context	0.420
enough-detail	0.235	enough-detail	0.244
factuality	0.187	factuality	0.227

Table 2: Three largest CPM coefficients on HH-RLHF dataset.

**LM-extracted features** The features extracted by the LM enable intuitive explanation of generated responses. This allows supervising complex behavior in a human-interpretable way. Tab. 8 shows examples of these features, which can be used to identify which aspects of the response contribute most to the predicted preference judgement. By decomposing a hard preference (“This text is not preferable.”) into a series of easier features (“This text is generally unhelpful, as it is easy to read but has little detailed information”), it allows easier inspection for a human overseer.

## 5 CONCLUSION

We introduce Compositional Preference Models (CPMs), a simple and effective paradigm for training robust and interpretable preference models. CPMs decompose global preference scores into interpretable features and rely on language models (LMs) to extract those features. We believe that CPMs pave the way for combining human insights into preference judgements with the LM capabilities to extract them. Given the recent advances in LM abilities, CPMs have the potential to be used for alignment and scalable oversight of models with superhuman capabilities.

<sup>5</sup>To prevent the known bias towards the first response (Chiang et al., 2023; OpenAI, 2023), we average the scores with different orderings when making a comparison. See Tab. 7 for the prompt used in evaluation.

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## A SOCIAL IMPACTS STATEMENT

Although we argue here that a CPM is less prone to overfitting and more explainable than a classically trained PM, it does rely at its core on a prompted LM to evaluate the features. Both the pre-training dataset and the precise alignment methods of closed models have been kept secret, and nobody has explained yet why they work so well, so even if they have been shown to be valid approximators of human evaluations, they are, for all practical purposes, blackboxes.

We see the risk for a circularity where the definition of a feature, e.g. readability, is no longer prescriptive but merely contracted to a self-taught, closed, proxy, with otherwise known biases and limitations. It is simpler to assess readability, and other lower level features, than a high-level, fuzzy, helpfulness, but there must remain humans in the loop, to validate the assessments of the models proxying for them over domains and time—in that regard composing less equivocal, easier to assess, individual features can hence be seen as a sane practice.

## B IMPLEMENTATION DETAILS

### B.1 COMPOSITIONAL PREFERENCE MODEL

We used GPT-3.5 (gpt-3.5-turbo-0301) and Flan-T5-XL (3B parameters) (Chung et al., 2022) as a feature extractor, using the same features and prompt templates in Tab. 4 and Tab. 5. We excluded randomness from the generation process and selected the token with the highest likelihood.

For logistic regression classifier we used Scikit-learn (Buitinck et al., 2013). We set the choice of  $L_1$  and  $L_2$  regularization, weight of regularization, and solver of the logistic regression classifier as a hyperparameters and selected best hyperparameters based on 5-fold cross-validation in training dataset.

In the inference time, we made feature scores of the generated response using same LLM and templates used in training phrase. The feature scores are aggregated with the trained logistic regression classifier as described in Sec. 3.2.

### B.2 STANDARD PREFERENCE MODEL

All standard PMs were implemented using PyTorch (Paszke et al., 2019) and HuggingFace Transformers (Wolf et al., 2020) We adopt the AdamW optimizer (Loshchilov & Hutter, 2017) with  $\beta = (0.9, 0.98)$  and set the weight decay to 0.01. We conducted separate hyperparameter sweeps over learning rate and batch size for each dataset, using early-stopping based on the evaluation set with 3 steps of patience. We used a batch size of 32 and a learning rate of 1e-5 for HH-RLHF dataset and 5e-5 for SHP dataset. We used cosine learning rate schedule with 100 linear warmup steps. We used Flan-T5-XL (Chung et al., 2022, 3B parameters) for standard PMs, which is available on the Huggingface Model Hub under the model name of google/flan-t5-xl. Training was performed on Nvidia A100 GPU, with the longest run taking approximately 12 hours.

## C RELATED WORK

**Robustness of preference models** PM overoptimization is an instance of reward hacking, a situation when a policy exploits flaws in its reward function (Amodei et al., 2016; Skalse et al., 2022). These flaws can come from errors of human evaluators (Pandey et al., 2022), the inherent difficulty of learning preferences of irrational agents (Mindermann & Armstrong, 2018; Shah et al., 2019) or the fragility of learned reward functions to adversarial attacks (McKinney et al., 2023). Gao et al. (2023) studied the scaling properties of PM overoptimization and Casper et al. (2023) discuss it in a broader context of open problems with RLHF. More generally, PMs can learn to be sensitive to spurious features associated with human feedback. This leads to failure modes such as sycophancy (a tendency to answer a question with a user’s preferred answer, even if that answer is not correct; Cotra, 2021; Perez et al., 2022) or social bias (due narrow demographics of feedback providers; Santurkar et al., 2023; Hartmann et al., 2023). Despite its growing importance, the problem of learning robust PMs for aligning LMs is largely neglected. The present paper attempts to fill this gap.

**Decomposing tasks for LMs.** There are numerous examples of task decomposition increasing the accuracy or robustness of language models. Breaking down problems into steps (Wei et al., 2022, chain-of-thought;) or into a sequence of subproblems depending on answers to previous subproblems (Zhou et al., 2023) are enormously beneficial for tasks involving reasoning. Others explored a stronger separation: solving subproblems independently in different LM context windows. For instance, Creswell et al. (2022) alternate between selection and inference to generate a series of interpretable, casual reasoning steps. Radhakrishnan et al. (2023) found that solving subproblems in separate context windows improves faithfulness of reasoning. Reppert et al. (2023) build compositional LM programs by applying decomposition iteratively, with a human in the loop, to facilitate science question answering. The present paper finds similar robustness benefits of decomposition for preference modeling.

**Scalable oversight** Scalable oversight is the problem of evaluating the behaviour of agents more capable than the evaluators (Bowman et al., 2022b). On the one hand, LMs may soon grow capable of completing tasks for which humans will not be able to provide feedback. On the other, LMs might also be capable of reasoning about flaws in their evaluation procedures (Berglund et al., 2023) and exploiting them unbeknownst to overseers. Current proposals for solving scalable oversight focus on recursively relying on other LMs to assist human evaluators (Irving et al., 2018; Leike et al., 2018; Christiano et al., 2018). RL from AI feedback (Bai et al., 2022b) attempts to implement this idea by using carefully prompted LMs to generate training data for PMs. In contrast, we propose to rely on LMs during a single inference step of a PM.

## D CLAUDE EVALUATION OF THE REFERENCE PM

To evaluate the performance of reference PM in Sec.4.2 in preference alignment, we follow the same quality evaluation framework as in Sec. 4.3. Specifically, we select the best sample among 16 responses generated by Flan-T5, based on the reference PM score. We then compare this response to vanilla Flan-T5, a response randomly selected from the same set of candidates, as described in Sec. 4.3.

Again, we use Claude to rate the quality of the response selected by reference PMs (see Tab. 7 for the prompt used in evaluation). We perform 10 independent BoN trials with  $n = 16$  and report the average win rate. The results are shown in Tab. 3. The reference PM outperforms CPM-Flan-T5 and standard PM. Interestingly, reference PM shows second best win rate in SHP dataset, highlighting the effectiveness in CPM-GPT-3.5. However, we note that this should be interpreted with caution as CPM-GPT-3.5 is not tested in multiple experiments.

Win Rate	HH-RLHF	SHP
CPM-GPT-3.5	0.810 (.)	<b>0.672</b> (.)
CPM-Flan-T5	0.742 (0.034)	0.580 (0.045)
Standard PM	0.588 (0.030)	0.564 (0.037)
reference PM	<b>0.829</b> (0.050)	0.619 (0.060)

Table 3: Comparison of win rate between CPM and reference PM externally fitted on multiple datasets. Reference PM shows high win rate in HH-RLHF dataset, and second best win rate in SHP dataset.

## E PROMPT USED

You will be given a conversation between a human and an AI assistant. Your job is to judge whether assistant's reply {attribute\_desc}. Score that on a scale from 1 to 10 where 1 means {attr\_min} and 10 means {attr\_max}. Here's the conversation:

Human:  
{history}

Assistant:  
{reply}

Answer by outputting a number from 1 to 10 (and nothing else).

Answer:

Table 4: Prompt template used for HH-RLHF dataset to rate the response under given attribute.

You will be given a Reddit post and a reply. Your job is to judge whether the reply {attribute\_desc}. Score that on a scale from 1 to 10 where 1 means {attr\_min} and 10 means {attr\_max}.

POST:  
{query}

Reply:  
{reply}

Answer by outputting a number from 1 to 10 (and nothing else).

Answer:

Table 5: Prompt template used for SHP dataset to rate the response under given attribute.

## F ADDITIONAL MODEL INTERPRETABILITY

**Feature distribution of policy** Fig. 3 shows how the feature values of the responses change in  $\text{BoN}(a, \text{CPM}, n)$  distribution with Flan-T5-Large as initial LM  $a$ , as a function of KL divergence  $\text{KL}_{\text{BoN}}$ . This simulates how the feature distribution changes as the initial policy is optimized with the current CPM and allows for inspecting which features drive reward maximization at different stages. The increase in readability is smaller than other features such as enough-detail and fail-to-consider-context. This means that policy shifts towards generating responses with more detailed information, rather than focusing on generating readable responses. Additionally, after a certain  $n$ , the slope of fail-to-consider-context increases, and it achieves the highest score at the end of optimization. This means that optimization pressure focuses on not failing to consider the context and avoiding unexpected lengthy responses. This decomposition makes it easier for a human to understand why the LM generated such responses.

## G ADDITIONAL TABLES AND FIGURES

Feature name	Attribute	Description
helpfulness	attribute_desc attr_min attr_max	is helpful for the original poster not helpful very helpful
specificity	attribute_desc attr_min attr_max	is specific enough too vague very specific
intent	attribute_desc attr_min attr_max	understands the original poster’s intent failure of understanding perfect understanding
factuality	attribute_desc attr_min attr_max	is factually correct egregiously incorrect fully correct
easy-to-understand	attribute_desc attr_min attr_max	is easy to understand very difficult to understand very easy to understand
relevance	attribute_desc attr_min attr_max	is relevant to the original poster’s question off-topic very relevant
readability	attribute_desc attr_min attr_max	is easy to read and not too technical for the original poster very difficult to read very easy to read
enough-detail	attribute_desc attr_min attr_max	provides enough detail to be helpful too little detail very detailed
biased	attribute_desc attr_min attr_max	is biased or one-sided very biased not biased at all
fail-to-consider-individual-preferences	attribute_desc attr_min attr_max	fails to consider the original poster’s cultural or individual preferences fails to consider the original poster’s preferences takes into account the original poster’s preferences
repetitive	attribute_desc attr_min attr_max	is repetitive very repetitive not repetitive
fail-to-consider-context	attribute_desc attr_min attr_max	fails to consider the original poster’s context fails to consider the original poster’s context takes into account the original poster’s context
too-long	attribute_desc attr_min attr_max	is too long too long not too long

Table 6: Features and descriptions used in Tab. 4 and 5.

Human:

You are a helpful and precise assistant for checking the quality of the answer. We would like to request your feedback on the performance of two AI assistants in response to the user question displayed below.

```
[Question]
{query}
[The Start of Assistant 1's Answer]
{reply1}
[The Start of Assistant 2's Answer]
{reply2}
```

Please rate the helpfulness, relevance, accuracy, level of details of their responses.

Each assistant receives an overall score on a scale of 1 to 10, where a higher score indicates better overall performance.

Please first output a single line containing only two values indicating the scores for Assistant 1 and 2, respectively. The two scores are separated by a space. In the subsequent line, please provide a comprehensive explanation of your evaluation, avoiding any potential bias and ensuring that the order in which the responses were presented does not affect your judgment.

Assistant:

Table 7: Prompt template to rate the writing quality of the candidate assistant model.



Figure 3: Feature distribution of BoN experiment (left: CPM-GPT-3.5, right: CPM-Flan-T5). Note that the  $x$ -axis are different.

Dialogue	Features				
	helpfulness	readability	enough-detail	factuality	fail-to-consider-context
Q: What things can I create with java programming?					
R1: Java is a programming language that is designed to create applications that run on a computer.	1.209	0.559	0.913	1.690	2.117
R2: Robots	0.509	0.559	-0.075	-0.569	-0.239
Q: Why is Lucifer referred to as the "morning star"?					
R1: Lucifer is the Morning Star because it is the brightest star in the sky.	1.209	0.880	1.901	0.843	0.232
R2: angel	-0.890	0.239	-0.569	-0.851	-0.239
Q: I'd like to evaluate some art perhaps. Can you tell me some history about Mona Lisa, the painting?					
R1: The Mona Lisa is a famous painting in the Louvre, Paris, France. It is attributed to Leonardo da Vinci.	1.909	0.880	1.901	1.690	2.588
R2: It was painted by Gian Lorenzo da Sica in the late 18th century. The name of the painting is inspired by the story of the famous Italian painter Leonardo da Vinci. The painting has been described as having a "poetic" quality.	0.859	0.239	1.901	0.278	-0.239

Table 8: Examples of feature values of CPM-GPT-3.5. Each feature value can provide information about which aspects of the response are good or bad.

	HH-RLHF	SHP
CPM-GPT-3.5	<b>0.997</b>	<b>0.981</b>
CPM-Flan-T5	0.926	0.928
Standard PM	0.665	0.057

Table 9: Rank correlation between gold PM scores and proxy PM scores in BoN experiment. For each PM technique used to fit the proxy PM, we calculate and average PM scores over samples from  $\text{BoN}(a, \text{PM}_{\text{proxy}}, n)$ , and compute the rank correlation between the averaged gold and proxy PM scores over different  $n$ .

CPM-GPT-3.5		CPM-Flan-T5	
Feature	Coefficient	Feature	Coefficient
helpfulness	0.246	fail-to-consider-context	0.420
enough-detail	0.235	enough-detail	0.244
factuality	0.187	factuality	0.227
readability	0.184	biased	0.178
token_length	0.101	easy-to-understand	0.124
specificity	0.094	specificity	0.106
biased	0.086	too-long	0.081
relevance	0.071	token_length	0.075
easy-to-understand	0.069	helpfulness	0.037
fail-to-consider-context	0.043	intent	0.024
too-long	0.016	repetitive	0.015
repetitive	0.014	fail-to-consider-individual-preferences	-0.042
intent	-0.008	relevance	-0.056
fail-to-consider-individual-preferences	-0.056	readability	-0.120

Table 10: Fitted coefficient of CPM on HH-RLHF dataset.

Dialogue	Features				
	helpfulness	readability	enough-detail	factuality	fail-to-consider-context
Q: why is ramon laguarta a bad ceo?					
R1: a bad businessman	-0.890	-1.041	-0.569	-0.851	-0.239
R2: Manager	-0.890	-1.682	-1.063	-0.851	-0.710
Q: What is a blizzard warning?					
R1: Blizzard warnings are issued by the National Weather Service to warn against snow, ice or strong winds.	1.909	0.880	2.395	1.690	3.059
R2: Blizzards can cause extremely dangerous driving conditions, with heavy snow, ice and sleet.	1.559	0.88	1.901	1.408	2.117
Q: Is climate change raising temperatures above their normal levels?					
R1: Climate change increases global temperature.	1.559	0.559	1.901	1.690	-0.239
R2: Earth is expected to experience a warmer climate by the year 2050, the hottest on record, based on the International Solar System	0.509	-0.721	0.419	0.278	-0.239
Q: I'd like to evaluate some art perhaps. Can you tell me some history about Mona Lisa, the painting?					
R1: The Mona Lisa is a 16th century Italian portrait by Gian Lorenzo Bernini.	-0.89	-1.041	-0.569	-0.851	-0.710
R2: In 1853, the artist Leonardo da Vinci created the portrait of the Madre della Signore.	-0.540	-1.041	-0.075	-0.569	-0.239

Table 11: Examples of feature values of CPM-GPT-3.5. Each feature value can provide information about which aspects of the response are good or bad.