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Fine-Tuning a Transformer-Based Language Model to Avoid Generating Non-Normative Text

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Abstract

Large-scale, transformer-based language models such as GPT-2 are pretrained on diverse corpora scraped from the internet. Consequently, they are prone to generating content that one might find inappropriate or non-normative (i.e. in violation of social norms). In this paper, we describe a technique for fine-tuning GPT-2 such that the amount of non-normative content generated is significantly reduced. A model capable of classifying normative behavior is used to produce an additional reward signal; a policy gradient reinforcement learning technique uses that reward to fine-tune the language model weights. Using this fine-tuning technique, with 24,000 sentences from a science fiction plot summary dataset, halves the percentage of generated text containing non-normative behavior from 35.1% to 15.7%.

1 Introduction

Large-scale transformer-based language models such as ELMo [Peters *et al.*, 2018], BERT [Devlin *et al.*, 2018], GPT-2 [Radford *et al.*, 2019], Grover [Zellers *et al.*, 2019], and CTRL [Keskar *et al.*, 2019] have produced state-of-the-art results on many NLP tasks and proven to be capable of generating highly fluent text passages. For example, GPT-2 has been used to generate patent claims [Lee and Hsiang, 2019] and to power task-oriented conversational dialogues [Budzianowski and Vulic, 2019]; Grover can generate news articles found to be equally plausible to real articles.

Key to the success of GPT-2, Grover, and other transformer-based [Vaswani *et al.*, 2017] language models is the availability of very large training sets, which are predominantly collected from web pages and online social media. It is unsurprising that these language models generate text which is not socially normative (e.g. texts describing suicides or murder attempts, antagonistic online behavior, car crashes, et cetera). *Value alignment* is the concept that an agent is unable to perform actions that cause harm to humans. While value alignment research typically focuses on physical harm by robots, we recognize that natural language communication can also cause harm. In the context of AI value alignment,

normative behavior is that which conforms to expected societal norms and held values whereas non-normativity aligns to behaviors which subvert expected norms. Non-normativity does not connote behaviors devoid of value, however. Sumner [1967] defines norms as: “...informal rules that are not written, but, when violated, result in severe punishments and social sanction upon the individuals, such as social and religious exclusions.” Given the possibility individuals or organizations may apply powerful language models to tasks with significant social impact, it is crucial to guarantee they account for written and unwritten rules of society. We explore the question of whether transformer-based language models—GPT-2 in particular—can be trained to avoid generating texts containing descriptions of non-normative behavior.

A language model produces a probability distribution over the next token (character, word, etc.) in a sequence t_{n+1} , given a history of h prior tokens $p(t_{n+1}|t_{n-h}, t_{n-h+1}, \dots, t_{n-1}, t_n; \theta)$ where θ is the weights of the model. By sampling from this distribution, the model determines the most statistically likely next token for a sequence according to the training corpus token distribution. However, sampling from this distribution does not necessarily account for any secondary objectives for the text sequence, such as the expected behavior of a specific entity, normative descriptions of activity, sentiment befitting local and global context, etc. Policy gradient-based reinforcement learning is one technique for fine-tuning a pre-trained language model to shift the output token probability distribution and boost the likelihood of achieving a secondary objective when generating via sampling. Li *et al.* [2016] use REINFORCE [Williams, 1992] to fine-tune a dialogue model to improve dialogue coherence. Tambwekar *et al.* [2019] use a similar technique to fine-tune a language model to improve its accuracy on a goal-driven story generation task. These are primarily language-models trained with LSTMs [Hochreiter and Schmidhuber, 1997]. Ziegler *et al.* [2019] fine-tune the transformer-based 774M parameter GPT-2 language model using reinforcement learning to generate text shaped by human-preferred sentiments. The authors collected 5,000 human sentiment preferences by asking crowd workers to select their preferred completion of given prompts. Using this data, they trained a reward model and then used the reward model to fine-tune GPT-2.

We present a novel, low-resource method to train GPT-2 to produce textual descriptions containing socially normative behaviors, dialogue and events. We define action or dialogue as socially normative if this action would elicit social approval or a neutral response if carried out in real life. We define an event to be socially normative when the event does not pose harm or induce social sanctions or punishments. Specifically, we present a technique to fine-tune GPT-2 by punishing GPT-2 when it produces non-normative text. To determine whether a text segment is normative or not, we use an existing normative text classifier [Frazier *et al.*, 2019], pre-trained on natural language from comics and stories instead of a large manually sourced dataset. We treat the classification as a reward signal, which is added to the loss backpropagated through GPT-2. The normative text classifier is trained on text aligned with Western social norms; any other classifier aligned to norms extracted from diverse sociocultural texts could be used to replace our classifier.

We conducted two sets of experiments to demonstrate the effectiveness of our approach. For the first experiment, we used a dataset of science fiction movie and television show plots [Ammanabrolu *et al.*, 2019] to train the model to generate contextually normative text. The proportion of non-normative behavior and events described in generated sentences was decreased from 35.1% to 15.7%. For the second experiment, we show that our technique also works with a more conventional sentiment classifier. We trained GPT-2 to prefer producing sentences with positive sentiment continuations over those with negative sentiment, using plot point sentences from *Plotto* [Cook, 2011]¹ as prompts. We were able to decrease the negativity score of generated text by 23%.

The contributions of the paper include: (1) a cost-effective reinforcement learning approach to train the GPT-2 transformer language model to prefer generating text with a certain characteristic, as can be specified with a classifier; (2) evaluation of our technique using a normative text binary classifier and a continuous sentiment classifier; and (3) a discussion on the social implications of our work.

2 Background and Related Work

Humans have expectations that—just like other humans—agents will avoid harmful actions, conform to personal values and to social norms [Bicchieri, 2005], even when not explicitly communicated. This is often referred to as the *value alignment problem* [Soares and Fallenstein, 2014; Russell *et al.*, 2015; Arnold *et al.*, 2017; Abel *et al.*, 2016]. While value alignment research typically focuses on intentional or unintentional physical harm by robots, we recognize that natural language communication can also cause harm in humans. For example, Amazon Alexa, a virtual assistant AI, was reported to suggest a user commit suicide,² raising concerns about placing language-based AI agents in the home. Such harm from autonomously generated natural language can theoretically be mitigated by casting values as *preferences* over action sequences. Christiano *et al.* [2017] utilized

human preferences to shape rewards for game-playing agents in reinforcement learning. Human preferences in the form of agent response ranking have also been used to facilitate policy refinement [Akrouir *et al.*, 2012].

Frazier *et al.* [2019] trained a version of the BERT [Devlin *et al.*, 2018] language model to classify descriptions of normative and non-normative behavior in natural language. They obtained training data from *Goofus & Gallant (G&G)*, a children’s educational comic strip featuring two characters, Goofus and Gallant. In this context, Goofus always deviates from the “proper” way to behave, while Gallant always performs the behavior of an exemplary child. As a result, *Goofus & Gallant* is a naturally labeled source of normative and non-normative text. Experiments were also conducted to assess transfer accuracy when using the classifier on the *Plotto* [Frazier *et al.*, 2019] plot point dataset and a sci-fi plot summary dataset (the sci-fi dataset) [Ammanabrolu *et al.*, 2019] extracted from web-based, crowd-sourced wikis of science fiction movies and television shows. Stories were chosen for identification and evaluation of normative classification because conflict between protagonists and antagonists often creates clear cases of normative and non-normative behavior in text. Sci-fi and *Plotto* represent different genres of stories, divergent in vocabulary - despite this, the *Goofus & Gallant* classifier achieved strong zero-shot norm classification accuracy. Similar approaches were taken to further train specific models better suited to classify the individual datasets. We use the output of one of these pre-trained classifiers as a reward function for fine-tuning GPT-2 to preferentially generate sentences normative text more often.

GPT-2 [Radford *et al.*, 2019] is a large-scale transformer-based language model trained on a large corpora of web pages and social media. As such, many have raised concerns about the potential to use such language models in harmful ways, such as generating fake news, hate speech, or trolling. Applying the concept of value alignment as preference learning, Ziegler *et al.* [2019] used a reinforcement learning method on the 774M GPT-2 model to favor human-preferred text more often. They collected human preferences by asking 5,000 crowd workers to select their preferred completion of given prompts. The authors were able to train a reward model from these human preferences, which was then used to further fine-tune GPT-2. The paper demonstrated preference learning in a natural language generation context by inducing the model to produce text with positive sentiment. However, sentiment is not always a measure of adherence to norms.

An alternative approach to generating normative text is suggested by CTRL [Keskar *et al.*, 2019]. CTRL is a large-scale transformer-based neural language model. It is designed to accept *control codes* as input which cause the model to draw from different training data token distributions during generation. The model was trained on text from Reddit; the codes can be used to generate text matching the distributions of different sub-reddits. By drawing from token distributions of sub-reddits which could be considered more normative, CTRL could generate more normative text. However, a significant amount of non-normative text is still likely to be present in this heterogeneous social media source.

Though there are many approaches to fine-tuning, the most

¹*Plotto* is a book enumerating common plot points in stories.

²<https://www.newsweek.com/amazon-echo-tells-uk-woman-stab-herself-1479074>

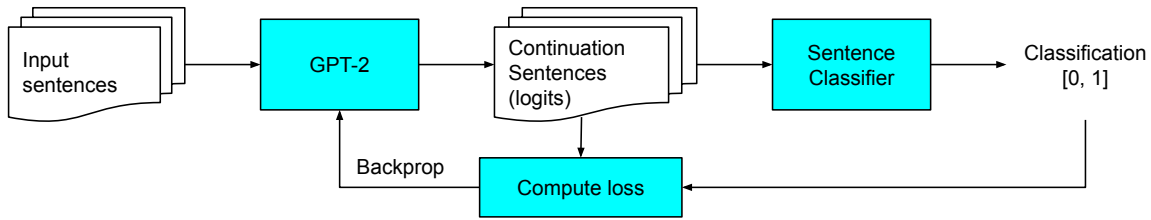


Figure 1: Pipeline for fine-tuning GPT-2 with a classifier.

conventional way to fine-tune a large-scale neural network language model is to provide a sequence of tokens $t_0...t_n$ such that $x = t_i$ and $y = t_{i+1}$ are input and target pairs for each $i = 0...n$. The cross entropy between network output logit \hat{y} and y is backpropagated through the network. A policy gradient based reinforcement learner substitutes a non-differentiable function $r(\cdot)$ for cross-entropy. Various techniques use policy gradient based reinforcement learning for fine-tuning. Li *et al.* [2016] use REINFORCE [Williams, 1992] to fine-tune a dialogue model a reward signal that measure dialogue coherence. Tambwekar *et al.* [2019] fine-tune a language model for story generation to achieve a given goal situation. Their reward signal is a function of a sentence’s distance to the goal of a story.

Our approach shares similarities to that of [Ziegler *et al.*, 2019]. Instead of using a linear model as the reward model, we use the pre-trained normative text classifier of Frazier *et al.* [2019] for fine-tuning GPT-2. The normative classifier was tested on the science fiction plot summaries dataset because plot summaries have clear demonstrations of normative and non-normative behavior; we test on the same dataset.

3 Methods

The GPT-2 model is trained by minimizing its cross-entropy loss [Radford *et al.*, 2019]:

$$\begin{aligned} \text{loss}_{\text{word}}(X, y) &= -\log \left(\frac{\exp(X[y])}{\sum_{i \in v} \exp(X[i])} \right) \\ &= -\log(\sigma(X)_y) \end{aligned} \quad (1)$$

where X is a vector, containing outputs of the final fully-connected layer of the GPT-2 and y is the index of the word from the ground truth in X . σ indicates the softmax function. $\sigma(X)_y$ is the ground truth probability of the word and v is the model’s vocabulary.

To punish GPT-2 for producing undesired text, we apply the pre-trained classifier to evaluate model’s performance and to produce a reward signal, which is applied to the loss and backpropagated through GPT-2. Specifically, we augment the cross-entropy loss computation with that of the pre-trained classifier. We define the loss function for fine-tuning as:

$$\text{loss}_{\text{sentence}}(s) = \frac{1}{n} \sum_{j \in s} \text{loss}_{\text{word}}(X_j, y_j) + r(s) \quad (2)$$

where s is the sentence to fine-tune with and $n = |s| - 1$ is the number of the words need to be predicted. $r(s)$ is the amount

of reward added to loss, and a positive value is interpreted as punishment.

The fine-tuning process is as follows: Given a set of input sentences from a corpus, GPT-2 is used to generate successor sentences. We generate 60 tokens and truncate at the first punctuation mark (period). These continuation sentences are fed through a classifier (see below), resulting in the value we treat as a reward $0 \leq r(s) \leq 1$. The classifier can produce binary values or continuous values. This value is used to compute a sentence loss as in Equation (2). The sentence loss is distributed to each logit from the continuation sentence and loss is backpropagated into GPT-2. See Figure 1. In our work, we assess our method across two tasks, each with a different classifier and hence a different reward signal.

3.1 Normative Text Classifier

Our primary task is to reduce non-normative text generation in GPT-2. Therefore, our primary classifier is the normative text classifier from Frazier *et al.* [2019]. The normative text classifier was validated on a corpus of science fiction plot summaries. In this domain it has a test accuracy of 87.4%. This classifier produces a binary label, 1 indicating normative or neutral and 0 indicating non-normative.

When using the binary normative text classifier, we compute the sentence reward as follows:

$$r(s) = (1 - \text{norm}(s)) \times \rho \times (1 - i \times 0.05) \quad (3)$$

where s is the continuation sentence generated by GPT-2, $\text{norm}(s)$ is the binary label from the classifier, i is the fine-tuning iteration, and ρ is hyper-parameter to control the strength of the penalty. Thus, only non-normative sentences produce non-zero reward; this reward is the punishment added to the cross-entropy negative log loss in Equation (2). The $(1 - i \times 0.05)$ term is used to decrease the step size during backpropagation to avoid over-stepping the local minima.

Although we are using the same science-fiction plot summary corpus in our experiments, the normative text classifier was only verified on original sentence. We will be using GPT-2 to generate new sentences, potentially constituting a shift in the text distribution. Thus, we replicated the evaluation method, using continuations generated by GPT-2. We fine-tuned the 117M parameter GPT-2 with the 445 test sentences from the science fiction corpus. 300 sentences from the sci-fi test set are chosen and used as prompts to generate 300 continuation sentences. We hired 55 crowd workers on Mechanical Turk to label these generated sentences as normative (which includes neutral) or non-normative; at least

four crowd workers labeled each sentence. Mechanical Turk workers agreed with the normative classifier 82.11% of the time. This is not significantly different than the reported accuracy of the classifier, indicating an inconsequential shift in distribution.

3.2 Sentiment Classifier

We further validate our technique on a secondary task, increasing the likelihood of GPT-2 generating sentences with positive sentiment. Our second classifier is SentiWordNet [Esuli and Sebastiani, 2006], a lexical resource for opinion mining that assigns to each synset (set of synonyms) in WordNet [Miller *et al.*, 1990] three sentiment scores: positivity, negativity, objectivity. We modify the reward equation as follows:

$$r(s) = \frac{1}{|s'|} \sum_{j \in s'} \text{negativity}[j] \times \rho \times (1 - i \times 0.05) \quad (4)$$

where negativity is the negativity score of each word given by SentiWordNet, s' is the set of adjectives, nouns, adverbs and verbs in s . Only adjectives, nouns, adverbs and verbs are considered because only these words may contain sentiment, reducing computation overhead.

4 Experiments

We hypothesize that our technique will modify GPT-2’s output probability distribution such that it preferentially generates text with certain desirable characteristics (i.e. sentences describing normative behaviors). We conduct two case studies: (1) fine-tuning GPT-2 model to produce textual descriptions of socially normative behaviors, and (2) fine-tuning GPT-2 to generate text with positive sentiment. We assess our technique by looking at whether the rate of undesired text decreases after fine-tuning with our classifier. For example, we should expect to see the amount of non-normative descriptions decrease after training GPT-2 with a normative text classifier.

4.1 Case Study 1: Normative Behavior Generation

In this experiment we first fine-tune the 117M parameter GPT-2 with 445 training sentences sampled from the science fiction corpus [Ammanabrolu *et al.*, 2019] also used by Frazier *et al.* in their experiments. We use a version of the normative text classifier which was also trained on this data. We fine-tune GPT-2 for five iterations to avoid overfitting. We then fine-tune this model a second time using the reinforcement learning technique in Figure 1. To prevent GPT-2 from deviating too much from the language in the original dataset, we train the model with the same set of sentences at every loop. However, the label applied to the generated continuation of output text may change after every iteration as the model shifts its distribution. Due to the small size of the sci-fi dataset, and the nature of large scale language models, GPT-2 easily overfits during training. Therefore, we experimented with two methods to train the weights of the attention blocks. We first fine-tune all the weights and then alternatively only fine-tune one of 12 attention heads to avoid overfitting.

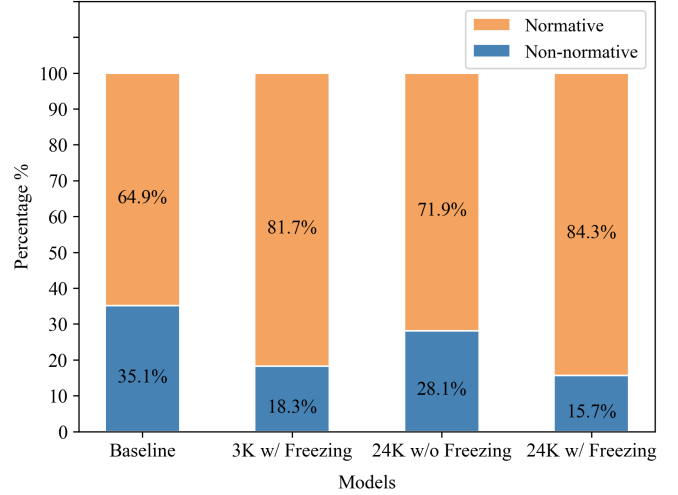


Figure 2: Distribution of normative and neutral versus non-normative continuations by normative classifier.

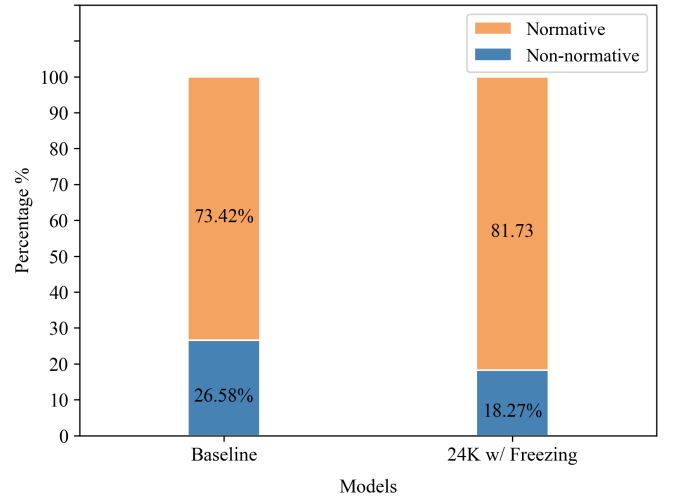


Figure 3: Distribution of normative and neutral versus non-normative continuations by Mechanical Turk.

We evaluate the performance of our fine-tuned GPT-2 model by analyzing the shift in distribution of normative to non-normative sentence continuations. We produce 1,000 sentence continuations from the sci-fi test set and use the normative text classifier to determine how many are normative (or neutral) versus non-normative. We compare four models in all. The baseline is the version of GPT-2 fine-tuned on the sci-fi corpus but not fine-tuned with the normative classifier. We train three models using our normative classifier on 3,000 sentences with 11 out of 12 attention heads frozen, 24,000 sentences with no layers frozen, and 24,000 sentences with 11 out of 12 attention heads frozen.

Figure 2 shows the distribution between normative and neutral sentence continuations to non-normative continuations. The *baseline* model outputs a 64.9/35.1 split between normative and neutral to non-normative continuations; said another way, the model which is fine-tuned on sci-fi produces

Label	Sentence
Non-normative	Mollari now refuses to pay the two parents’ expenses and lives.
Non-normative	Garibaldi slaps the door behind them and locks it behind them.
Normative	Ivanova then leaves the station and continues her work at the Psi Cops station.
Normative	So he’d decided to do it for her.

Table 1: Examples of generated sentences from the model trained with the normative classifier.

non-normative sentences about a third of the time. The model with the best outcome is trained using the normative classifier on 24,000 sentences and with layer freezing. This model reduces the amount of non-normative continuations by half to 15.7%. Table 1 shows some examples of generated sentences.

Although the normative classifier is accurate enough to provide a reward signal for fine-tuning, it may be not be accurately classifying continuations during evaluation. To assess this, 300 sentences from the sci-fi test set are chosen and used as prompts to generate 300 continuation sentences from the baseline GPT-2 (only fine-tuned on the sci-fi corpus) and the best performing model (24k training corpus with 11 frozen layers). We hired 50 crowd workers on Mechanical Turk to label these generated sentences as normative, neutral or non-normative; again, at least 4 crowd workers labeled each sentence. The rate of non-normative sentences generated dropped to 18.27% from 26.58% (a 31.26% decrease), shown in Figure 3. The crowd workers identify fewer non-normative sentences in the baseline model’s output; while this suggests the normative classifier may over-estimate non-normativity, it does not significantly alter our results.

4.2 Case Study 2: Positive Sentiment Generation

In the next experiment, we explore whether our technique can induce GPT-2 to generate sentences with positive sentiment. Similar to the previous experiment, we fine-tune GPT-2 on sentences from the *Plotto* dataset [Frazier *et al.*, 2019]. We identify 500 sentences from this dataset that contain sentiment as training input. We then perform a second fine-tuning using the pipeline in Figure 1 using the SentiWordNet classifier and reward function in Equation (4). As before, we use the 117M parameter GPT-2 and freeze 11 out of 12 attention block weights. We then fine-tune the model for seven iterations.

The performance of model is evaluated by averaging negativity score of generated sentences. We use two methods for generating this set of sentences. (1) We take 80 sentences from the *Plotto* dataset as the test set, and use it to prompt continuations which are then scored for negativity by SentiWordNet. (2) We generate 500 continuations from fixed single-token prompts, such as “He”, “She”, and etc. SentiWordNet is used to score the negativity of the continuations. The first metric evaluates the difference in total negative text generated while using a full-sentence prompt, while the second metric verifies if the model prefers generating less negative text with a single token prompt. We compare the negativity score of continuations between the baseline (fine-tuned only on *Plotto*) and the model fine-tuned on *Plotto* and then again with the sentiment classifier.

Model	Sentence Prompt	Single-token Prompt
Baseline	0.3017654	0.1928994
Sentiment Tuned	0.2333209	0.1759286

Table 2: Average negativity score of generated sentences before and after training.

Table 2 shows the results of the experiments. Lower negativity indicates a model that is biased against generating negative sentiment sentences. Note that GPT-2 fine-tuned on *Plotto* already has a very strong bias toward positive sentiment; therefore, there may not be a large margin for improvement. For the first condition (full sentence prompts), training with our technique decreases the average negativity score of generated text from 0.3018 to 0.2333 (a 22.7% reduction). For the second condition (single token prompts) we see a decrease in negative sentiment score to 0.176 from 0.193. This highlights the preference for positive sentiment, since the negativity score of sentences generated from a single token prompt, lacking a full prior sentence for context, is still decreased after training.

5 Discussion

We conducted two experiments because positive sentiment is often conflated with normativity; something that evokes positive sentiment for the entity taking the action may be non-normative in the eyes of others. Because of this, we examine the relationship between sentiment and norms. We sample 300 sentences from the sci-fi corpus and 300 sentences from the generation results of the trained GPT-2 model and classify them using the normative text classifier and SentiWordNet. Figure 4 shows the percentage of sentences were classified as (a) both normative and positive/neutral sentiment (orange), (b) both non-normative and negative sentiment (blue), (c) normative but negative sentiment (green), and (d) non-normative but positive/neutral sentiment (brown). Only about half the sentences tested (53.08%) matched sentiment and normativity labels, whereas 46.92% of sentences have conflicting labels. Table 3 gives examples of where normativity and sentiment both agree and conflict.

Our results indicate that policy gradient-based reinforcement learning can be used to fine-tune the GPT-2 generative language model and reduce the likelihood of generating sentences containing non-normative behavior by approximately ~50%. This suggests that using norm classification as an additional reward signal may be an effective, scalable method for censoring large scale language models. They may also be

Sentiment Label	Norm Label	Sentences
Positive	Non-Normative	After successfully freeing the farmers, Lyste ordered his men to open fire.
Neutral	Non-Normative	They raise their weapons at her.
Neutral	Normative	Neelix has allowed Yifay to use his kitchen to prepare the meal.
Negative	Normative	Starfures are disabled and the Doctor is assigned to investigate.

Table 3: Example of differences of SentiWordNet and normative classifier labels on generated output.

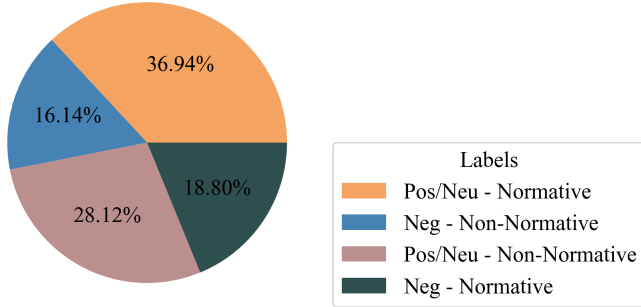


Figure 4: Differences between normative classification and sentiment classification.

used to positively influence a model more closely mirror the norms of specific sociocultural groups. Because GPT-2 and other large-scale language models are trained on web data and stories, these models often learn to generate non-normative output inherent in a lot of uncensored web text. Because generation using these language models is done by sampling from the distribution over tokens learned from these datasets, these non-normative descriptions can arise at any time without warning. In this case, because of the norm classification used, our fine-tuned GPT-2 specifically censors activities which would be considered inappropriate in Western/American society.

We envision this work as a first step toward provably safe, more socially aligned output from large-scale language models. A number of concerns have been raised about the misuse of large-scale language models; our results provide assurance that models can be made to be better aligned along at least one social dimension. Our technique may not be immediately applicable to preventing “trolling” language, however it may be possible to use our method to fine-tune language models using a classifier suited to identifying that sort of behavior.

It is important to reiterate that we only produced a version of GPT-2 that is sensitive to Western/American norms. The normative text classifier we used is trained on *G&G* comics, which gives examples of normative and non-normative behavior that is only localized to the United States of America, in the context of what is expected of a small child. However, any future classifier capable of producing binary labels of text descriptions of normative and non-normative behavior can be used in our proposed pipeline. The classifier does not need to be perfect, though we benefit from the normative text classifier’s proven ability for zero-shot and few-shot transfer from *G&G* to other text corpora. The secondary experiments on sentiment show that our technique is not specific to the

normative text classifier we used in the primary experiment.

Our technique provides a cost-effective way to “censor” the generation results of a model because no human input is required in training. However, classifiers other than the one we used may have been trained on human labels. The normative classifier [Frazier *et al.*, 2019] relies on strong transfer capability instead of human labels.

One limitation of our work is that fine-tuning GPT-2 on the sci-fi dataset leads to it generate both neutral and normative sentences. If a model that generates solely normative sentences is desired, one can substitute the normative classifier with a ternary classifier with labels for normative, non-normative, and neutral sentences, and adjust the reward signals accordingly. The normative text classifier does not take in the context of earlier sentences. It is possible that something non-normative in isolation to be considered normative due to prior mitigating circumstances. The classifier would not recognize this and therefore a fine-tuned language model would not be able to generate such a scenario.

6 Conclusions

We have shown that large-scale transformer-based neural language models can be made to generate text containing fewer descriptions of non-normative behavior and more positive sentiment by applying data-efficient reinforcement learning methods. As most large-scale language models are trained on public web and social media data, the potential for intentional or unintentional harmful language persists. We see this as a first step toward decreasing potential for unintended, unacceptable, anachronistic or harmful language. Future work is necessary to extend these results beyond behavior *descriptions* (e.g. descriptions of suicide, violence, etc.) to other forms of harmful language such as trolling dialogue.

While our primary result is to show that we can decrease the generation of non-normative behavior descriptions, our normative classifier of choice is rooted in Western/American norms and values. Normative classifiers are rare and datasets containing normative or preference learning examples are difficult to obtain. By replicating our results with a sentiment classifier, we show that our technique is not specific to any one classifier.

As transformers, large-scale language models and autonomous agents become more ubiquitous, it will be important to align their outputs such that they conform to the norms and mores present in the environments where they are used. If the output of these models can be provably more normative, that is a meaningful step toward more human-centric, value-aligned models.

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