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 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%.

Key to the success of GPT-2, Grover, and other transformer-based 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, etc.). 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 \( p(t_{n+1} | t_{n-h}, t_{n-h+1}, ..., t_{n-1}, t_n; \theta) \) where \( \theta \) 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], pretrained 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] 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 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 Fallonstein, 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, 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 [Akrour 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

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1Plotto is a book enumerating common plot points in stories.
2https://www.newsweek.com/amazon-echo-tells-uk-woman-stab-herself-1479074
conventional way to fine-tune a large-scale neural network language model is to provide a sequence of tokens \( t_0 \ldots t_n \) such that \( x = t_i \) and \( y = t_{i+1} \) are input and target pairs for each \( i = 0 \ldots n \). The cross entropy between network output logit \( y \) 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 measures 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]:

\[
\text{loss}_{\text{word}}(X, y) = - \log \left( \frac{\exp(X[y])}{\sum_{i \in v} \exp(X[i])} \right) = - \log \left( \sigma(X)_{y} \right)
\]

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 \( X \). \( \sigma \) 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:

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

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:

\[
r(s) = (1 - \text{norm}(s)) \times \rho \times (1 - i \times 0.05)
\]

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 \( \rho \) 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:

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

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.

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 train three 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
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.

| 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.

| 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
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 to 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 into 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.
References

[Abel et al., 2016] David Abel, James MacGlashan, and Michael L. Littman. Reinforcement learning as a framework for ethical decision making. In Workshops at the Thirtieth AAAI Conference on Artificial Intelligence, 2016.

[Akrou et al., 2012] Riad Akrou, Marc Schoenauer, and Michèle Sebag. APRIL: active preference-learning based reinforcement learning. CoRR, abs/1208.0984, 2012.

[Ammanabrolu et al., 2019] Prithviraj Ammanabrolu, Ethan Tien, Wesley Cheung, Zhaochen Luo, William Ma, Lara J Martin, and Mark O. Riedl. Story realization: Expanding plot events into sentences. arXiv preprint arXiv:1909.03480, 2019.

[Arnold et al., 2017] Thomas Arnold, Daniel Kasenberg, and Matthias Scheutz. Value alignment or misalignment—what will keep systems accountable? In Workshops at the Thirty-First AAAI Conference on Artificial Intelligence, 2017.

[Bicchieri, 2005] Cristina Bicchieri. The grammar of society: The nature and dynamics of social norms. Cambridge University Press, 2005.

[Budzianowski and Vulic, 2019] Paweł Budzianowski and Ivan Vulic. Hello, it’s GPT-2 - how can I help you? towards the use of pretrained language models for task-oriented dialogue systems. CoRR, abs/1907.05774, 2019.

[Christiano et al., 2017] Paul F Christiano, Jan Leike, Tom Brown, Miljan Martic, Shane Legg, and Dario Amodei. Deep reinforcement learning from human preferences. In Advances in Neural Information Processing Systems, pages 4299–4307, 2017.

[Cook, 2011] William Cook. PLOTTO: the master book of all plots. Tin House Books, 2011.

[Devlin et al., 2018] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. BERT: pre-training of deep bidirectional transformers for language understanding. CoRR, abs/1810.04805, 2018.

[Esuli and Sebastiani, 2006] Andrea Esuli and Fabrizio Sebastiani. Sentiwordnet: A publicly available lexical resource for opinion mining. In LREC, volume 6, pages 417–422. Citeseer, 2006.

[Frazier et al., 2019] Spencer Frazier, Md Sultan Al Nahian, Mark Riedl, and Brent Harrison. Learning norms from stories: A prior for value aligned agents. arXiv preprint arXiv:1912.03553, 2019.

[Hochreiter and Schmidhuber, 1997] Sepp Hochreiter and Jürgen Schmidhuber. Long short-term memory. Neural computation, 9(8):1735–1780, 1997.

[Keskar et al., 2019] Nitish Shirish Keskar, Bryan McCann, Lav R Varshney, Caiming Xiong, and Richard Socher. Ctrl: A conditional transformer language model for controllable generation. arXiv preprint arXiv:1909.05858, 2019.

[Lee and Hsiang, 2019] Jieh-Sheng Lee and Jieh Hsiang. Patent claim generation by fine-tuning openai GPT-2. CoRR, abs/1907.02052, 2019.

[Li et al., 2016] Jiwei Li, Will Monroe, Alan Ritter, Michael Galley, Jianfeng Gao, and Dan Jurafsky. Deep reinforcement learning for dialogue generation. CoRR, abs/1606.01541, 2016.

[Miller et al., 1990] George A Miller, Richard Beckwith, Christiane Fellbaum, Derek Gross, and Katherine J Miller. Introduction to wordnet: An on-line lexical database. International journal of lexicography, 3(4):235–244, 1990.

[Peters et al., 2018] Matthew E. Peters, Mark Neumann, Mohit Iyyer, Matt Gardner, Christopher Clark, Kenton Lee, and Luke Zettlemoyer. Deep contextualized word representations. In Proc. of NAACL, 2018.

[Radford et al., 2019] Alec Radford, Jeffrey Wu, Rewon Child, David Luan, Dario Amodei, and Ilya Sutskever. Language models are unsupervised multitask learners. OpenAI Blog, 1(8), 2019.

[Russell et al., 2015] Stuart Russell, Daniel Dewey, and Max Tegmark. Research priorities for robust and beneficial artificial intelligence. AI Magazine, 36(4):105–114, 2015.

[Soares and Fallenstein, 2014] Nate Soares and Benja Fallenstein. Aligning superintelligence with human interests: A technical research agenda. Machine Intelligence Research Institute (MIRI) technical report, 8, 2014.

[Sumner, 1967] Leonard Wayne Sumner. Normative ethics and metaethics. Ethics, 77(2):95–106, 1967.

[Tambwekar et al., 2019] Pradyumma Tambwekar, Murtaza Dhuliawala, Lara J Martin, Animesh Mehta, Brent Harrison, and Mark O Riedl. Controllable neural story plot generation via reward shaping. In Proceedings of the 28th International Joint Conference on Artificial Intelligence, pages 5982–5988. AAAI Press, 2019.

[Vaswani et al., 2017] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Lukasz Kaiser, and Illia Polosukhin. Attention is all you need. CoRR, abs/1706.03762, 2017.

[Williams, 1992] Ronald J Williams. Simple statistical gradient-following algorithms for connectionist reinforcement learning. Machine learning, 8(3-4):229–256, 1992.

[Zellers et al., 2019] Rowan Zellers, Ari Holtzman, Hannah Rashkin, Yonatan Bisk, Ali Farhadi, Franziska Roesner, and Yejin Choi. Defending against neural fake news. CoRR, abs/1905.12616, 2019.

[Ziegler et al., 2019] Daniel M Ziegler, Nisan Stiennon, Jeffrey Wu, Tom B Brown, Alec Radford, Dario Amodei, Paul Christiano, and Geoffrey Irving. Fine-tuning language models from human preferences. arXiv preprint arXiv:1909.08593, 2019.