

# A STEP-WISE WEIGHTING APPROACH FOR CONTROLLABLE TEXT GENERATION

**Anonymous authors**

Paper under double-blind review

## ABSTRACT

We study the problem of controllable text generation (CTG): steering a language model (LM) to generate text with a desired attribute. Many existing approaches either require extensive training/fine-tuning of the LM for *each* single attribute under control or are slow to generate text. To this end, we first propose a framework based on step-wise energy-based models (EBMs) that is efficient in sampling and flexible in a wide range of practical CTG scenarios. Indeed, a number of existing CTG methods are special instances of our framework with a specific EBM design. In different control scenarios, we then design the respective energy functions that strategically up- or down-weigh the probabilities of keywords associated with a certain control attribute at each generation step. In experiments, we show that our simple and efficient approach is surprisingly competitive against more computationally expensive strong baselines, and even achieving new state-of-the-art performances in several cases. Our framework also provides a tuning hyper-parameter that nicely trades off generation quality and control satisfaction, enabling practitioners to easily adjust it to meet their needs.

## 1 INTRODUCTION

Large language models (LMs) pre-trained on web-scale data have now become an integral part of many natural language processing (NLP) applications. However, most pre-trained LMs can only perform generic generation that is unconstrained: after users provide the LM a piece of text as the input prompt, they have little control over the generative process (Holtzman et al., 2020). In many real-world cases, users may wish to impose some constraints or controls that guide the LMs towards generating texts of their specified attributes on the fly. Interesting applications include poetry generation with specific rhythms and topics (Wang et al., 2016), story generation with a pre-specified story line (Peng et al., 2018), and product review generation with a particular sentiment (Zang & Wan, 2017). Moreover, the ability to impose certain controls over the text generation process is critical for the safe and responsible deployment of LMs in practice. For example, prior research has shown that LMs may resemble or even amplify human biases (Sheng et al., 2019; Bordia & Bowman, 2019) and that LMs can be easily triggered to generate toxic content (Bender et al., 2021; Gehman et al., 2020). Both biased and toxic generated text should be avoided in most practical use cases.

In this paper, we focus on the problem of *controllable text generation* (CTG) that underlies the above applications. Given one or more desired, user-specified control attribute(s), such as “positive sentiment” and “science topic”, we would like to steer an LM to generate text that satisfies the control attribute(s). As an example, Table 1 illustrates the CTG problem with various control attributes. Recently, a number of papers have proposed different methods to tackle this problem but they suffer from many practical issues. For example, some of these methods either require extensive training/fine-tuning for each CTG scenario (Khalifa et al., 2021; Bakhtin et al., 2021; Bhattacharyya et al., 2021) or are computationally expensive during generation (Liu et al., 2021; Dathathri et al., 2020; Shirish Keskar et al., 2019). Some methods (Ross et al., 2021; Liang et al., 2021; Ghazvininejad et al., 2017) are only applicable to one or two selected CTG tasks. Our goal in this paper is to develop a CTG method that is more efficient in sampling and more applicable to various CTG scenarios than the previous methods, without sacrificing the overall performance.

We propose a framework based on a *step-wise energy-based model* (EBM) for CTG. Our framework leverages the fact that modern LMs generate texts in an auto-regressive manner: they generate one word (token) at a time based on the previously generated words (tokens). We thus formulate the

Table 1: Illustration of different texts generated from the original GPT-2 and our CTG method, respectively, which demonstrates that our method can successfully steer GPT-2 toward distinct desired attributes.

<b>GPT-2, unconstrained:</b> As we approach the year 2023, one of the major problems that is facing society is the lack of information about the history of the planet, the importance of the planet to the world, and	
<b>GPT-2 + word "restaurant"</b>	<b>GPT-2 + topic "space"</b>
As we approach the year 2023, one of the major restaurant brands in America is looking at the potential of the future of food and how food should be made. I've been involved in	As we approach the year 2023, starship design is still a hot topic in the galaxy, as well as the future of space travel. In the latest issue of Wired magazine, Chris Roberts talks a
<b>GPT-2 + positive sentiment</b>	<b>GPT-2 + negative sentiment</b>
You can watch us perform live in the real world, right here! You'll see us perform live at DreamWorks' home in Los Angeles, complete with live artworks by the likes of DreamWorks	As I leave for the end of the week, I have a few questions for anyone who is considering leaving this blog. My name is John. I'm unemployed and run a small blog called

CTG problem as steering the word distribution at each generation step via a specially designed energy function. Our framework is general: we show that many existing CTG approaches are in fact special instances of our framework. Under our framework, we also develop a generic form of energy functions that can be applied to a wide range of CTG tasks. Intuitively, the energy function imposes a control of the generated text by adjusting the weights of keywords associated with the desired attribute at each generation step.

Via a range of experiments, we show the wide applicability of our CTG method by instantiating it for five commonly studied CTG tasks including i) word control, ii) topic control, iii) sentiment control, iv) text detoxification, and v) compositions of multiple controls. Our method is highly effective: on tasks iii) and iv), our method achieves competitive results compared to strong baselines. On tasks i), ii), and v), our method establishes new state-of-the-art CTG performances. Our method is also highly computationally efficient: it requires no training/fine-tuning, uses up to  $18\times$  fewer parameters, and is up to  $100\times$  faster than the baselines. We summarize our contributions as follows.

**[C1]** We propose a new CTG framework based on the step-wise EBM that weights the sampling distribution at each generation step through the energy function. Our framework unifies a number of prior approaches and enables developing new ones via specific energy function designs (Section 2.2).

**[C2]** We develop a generic form of an energy function for our framework. Our energy function is simple but powerful and flexible, which can be instantiated in different ways in a wide range of CTG scenarios with infinitesimal computational overhead (Section 2.3).

**[C3]** We validate the effectiveness of our method on five CTG tasks. Extensive experiments show that our method achieves highly competitive performance, often outperforming strong baselines, and is the most efficient method among all baselines (Section 3).

## 2 METHOD

In this section, we describe our approach in detail. We first review language models and motivate our approach with the sequence-level formulation of the CTG problem. We then introduce our step-wise EBM framework and propose an efficient and flexible form of energy function for a variety of CTG tasks. We close this section by reviewing related literature and, in particular, showing how our framework unifies a number of prior CTG methods.

### 2.1 PRELIMINARIES

**Language models (LMs).** Let  $x \in \mathcal{V}$  be a word token, i.e., the smallest element we consider in modeling language, from a pre-specified token set  $\mathcal{V}$  that we denote as the "vocabulary". Let  $\mathbf{x} = \{x_1, \dots, x_T\} \in \mathcal{X}$  be a sequence of  $T$  tokens representing a piece of text, where  $\mathcal{X}$  denotes the set of all such texts. An LM  $p_\theta$  then defines a probability mass function on  $\mathcal{X}$ . In this paper, we work with *auto-regressive* LMs, namely,

$$p_\theta(\mathbf{x}) = \prod_{t=1}^T p_\theta(x_t | x_{1:t-1}), \quad \text{where } x_{1:t-1} = \{x_1, \dots, x_{t-1}\}. \quad (1)$$

In particular, we denote  $x_{1:0} = \emptyset$  such that  $p_\theta(x_1 | x_{1:0}) := p(x_1)$ . Note that the dominant LMs, such as GPTs (Radford et al., 2019; Brown et al., 2020) and Recurrent Neural Networks (Mikolov et al., 2010; 2011), are formulated in this way.

**Sequence-level EBM for CTG.** The CTG problem can be formulated as learning a joint distribution  $p_\theta(\mathbf{x}, c)$  of the text  $\mathbf{x}$  and the control attribute  $c$ , which we define as

$$p_\theta(\mathbf{x}, c) = p_\theta(\mathbf{x})p_\theta(c|\mathbf{x}) \propto p_\theta(\mathbf{x})e^{-E_\theta(c|\mathbf{x})}, \quad (2)$$

where  $p_\theta(\mathbf{x})$  is the base LM (such as GPT) and  $p_\theta(c|\mathbf{x})$  is a conditional distribution of attribute given a sequence  $\mathbf{x}$ , modeled with the conditional energy function  $E_\theta(c|\mathbf{x})$ . Intuitively, low energies indicate more control satisfaction; thus, this model steers the base LM  $p_\theta(\mathbf{x})$  towards generating text samples  $\mathbf{x}$  with low energies.

The formulation in Eq. 2 is known as the *joint energy-based model* (EBM), which has been widely explored in the vision domain (Grathwohl et al., 2020; Che et al., 2020). More recently, Khalifa et al. (2021) adopted this joint EBM formalism for a sequence-level sampling of texts and proved that Eq. 2 is the optimal solution to CTG as a constraint optimization problem. We thus term their formulation as the *sequence-level EBM*. Notably, Eq. 2 also enables easy compositionality. If we have multiple attributes  $\{c_i, \dots, c_N\}$  to control and if we assume conditional independence of the their respective energy functions  $E_\theta(c_i|\mathbf{x})$ , then we can simply compute the resulting joint distribution by the summation of energies  $\sum_{i=1}^N E_\theta(c_i|\mathbf{x})$  in the exponential term via

$$p_\theta(\mathbf{x}, c_1, \dots, c_N) = p_\theta(\mathbf{x}) \prod_{i=1}^N p_\theta(c_i|\mathbf{x}) \propto p_\theta(\mathbf{x})e^{-\sum_{i=1}^N E_\theta(c_i|\mathbf{x})}. \quad (3)$$

## 2.2 FROM SEQUENCE-LEVEL EBM TO STEP-WISE EBM

Despite its appealing properties, such as theoretical optimality and compositionality, sequence-level EBM suffers from computational inefficiency that hinders its practical usage. Indeed, sampling from the joint distribution  $p_\theta(\mathbf{x}, c)$  poses a significant challenge because of the huge sampling space with  $d^T$  possible sequences where  $d$  and  $T$  denote the vocabulary size and sequence length. It becomes more challenging to generate longer sequences with exponentially large sampling time.

We now introduce our step-wise weighting approach to approximate the expensive sampling step in the sequence-level EBM. Our approach leverages the nature of auto-regressive LM  $p_\theta(\mathbf{x})$  that enables efficient sampling  $x_t$  at each time step  $t$  while satisfying the attribute constraint. To see this, we first decompose  $p_\theta(\mathbf{x}, c)$  as

$$p_\theta(\mathbf{x}, c) = p(c) \prod_{t=1}^T p_\theta(x_t|c, x_{1:t-1}), \quad (4)$$

where, using Bayes' Rule, each term inside the product on the right-hand side becomes

$$p_\theta(x_t|c, x_{1:t-1}) = \frac{1}{Z} p_\theta(x_t, c|x_{1:t-1}), \quad (5)$$

where  $Z := p_\theta(c|x_{1:t-1})$  is a constant due to the *independence assumption* which states that the previously generated text  $x_{1:t-1}$  and the control attribute  $c$  are independent at each step  $t$  during generation, i.e.,  $p_\theta(c|x_{1:t-1}) = p(c)$ . Leveraging this assumption and plugging Eq. 5 into Eq. 4, we have

$$\begin{aligned} p_\theta(\mathbf{x}, c) &= p(c) \prod_{t=1}^T \frac{1}{Z} p_\theta(x_t, c|x_{1:t-1}) \\ &= \frac{1}{Z^{T-1}} \left( \prod_{t=1}^T p_\theta(x_t, c|x_{1:t-1}) \right) \propto \prod_{t=1}^T p_\theta(x_t, c|x_{1:t-1}). \end{aligned} \quad (6)$$

Here, we also assume that  $Z^{T-1}$  is a constant. This is true due to the *constant time assumption*, which states that  $T$  stays the same for all generation tasks. Following Eq. 2, we can similarly decompose and represent  $p_\theta(x_t, c|x_{1:t-1})$  on the right-hand side in Eq. 6 in an energy function form

$$p_\theta(\mathbf{x}, c) \propto \prod_{t=1}^T p_\theta(x_t, c|x_{1:t-1}) \propto \prod_{t=1}^T \underbrace{p_\theta(x_t|x_{1:t-1})e^{-E_\theta(c|x_{1:t})}}_{P_\theta(x_t, c|\cdot)}. \quad (7)$$

We denote  $P_\theta(x_t, c|\cdot)$  as th *step-wise joint EBM* and Eq. 7 is the step-wise joint EBM approach to CTG. The key difference between 2 and 7 is that instead of building a joint EBM with the entire sequence, our joint EBM is formulated in each time step. This formulation enables very efficient sampling: instead of sampling an entire sequence  $\mathbf{x}$  to satisfy the control  $c$ , which is slow, we now sample  $x_t$  at each time step, which is easy because the step-wise joint EBM can be *normalized* and computed *exactly*:

$$p_\theta(x_t, c|\cdot) = \frac{1}{Z_\theta} P_\theta(x_t, c|\cdot), \quad \text{where } Z_\theta = \sum_{x_t \in \mathcal{V}} P_\theta(x_t, c|\cdot), \quad (8)$$

where  $Z_\theta = \sum_{x_t \in \mathcal{V}} P_\theta(x_t, c|\cdot)$  can be computed by enumerating all possible  $x_t$ , which is a finite set. Having an normalized energy function also removes the need to perform sampling via Langevin Dynamics (Welling & Teh, 2011) which tend to be slow and unstable. To further improve computational efficiency, we can approximate  $Z_\theta$  in Eq. 8 by using only the top  $K$   $x_t$ 's with the highest probabilities, an idea similar to top- $k$  sampling (Fan et al., 2018; Radford et al., 2019):

$$\tilde{p}_\theta(x_t, c|\cdot) = \frac{1}{Z_k} P_\theta(x_t, c|\cdot) \text{ for } x_t \in \mathcal{S}_k := \left\{ x_t \mid \operatorname{argmax}_{k=1:K} P_\theta(x_t^{(k)}, c|\cdot) \right\} \quad (9)$$

where  $Z_k = \sum_{x_t \in \mathcal{S}_k} P_\theta(x_t, c|\cdot)$ .

**Remarks.** The independence and constant time assumptions enable us to approximate the computationally expensive sequence-level EBM methods in Eq. 2 as our efficient step-wise EBM framework in Eq. 7. The trade-off we have made here is that our step-wise EBM framework models a strictly smaller class of functions and is therefore less expressive than sequence-level EBM methods. In particular, the independence assumption is a strong assumption, requiring  $p_\theta(c|x_{1:t-1}) = Z \forall t$ . The constant time assumption is milder and more natural: while allowing varying  $T$  enables more generation flexibility, we observe that 1) many previous works on CTG perform and evaluate generation using a fixed  $T$  (Khalifa et al., 2021; Ziegler et al., 2019; Liu et al., 2021; Dathathri et al., 2020) and 2) in practice, different generation lengths can be achieved simply by selecting a portion of the length  $T$  generation for shorter texts or concatenating multiple generations of length  $T$  for longer texts. However, empirically, we observe that various methods under our step-wise EBM framework, including a number of existing CTG approaches, perform surprisingly well, with performance rivaling sequence-level EBM methods while saving long hours of training/fine-tuning required for sequence-level EBM methods. We thus argue that, despite our strong assumptions, our step-wise EBM framework is an efficient and effective approximation to sequence-level EBMs. Further analysis on the small performance gap between the two is left for future work.

**Generality of our framework.** We have now obtained a step-wise EBM framework for CTG. Our framework simplifies the CTG problem into crafting suitable energy functions  $E_\theta(c|x_{1:t})$  and offers significant flexibility in developing new CTG methods in the form of new energy function forms. Indeed, through the lens of energy functions, our framework is highly general and unifies many existing step-wise CTG methods by viewing them as specific energy function designs. For example, we can recover the control method in Dathathri et al. (2020) by implementing our energy function as an latent classifier that takes the LM’s hidden states as input and running the approximated Langevin dynamics on the resulting step-wise EBM. We can recover the methods proposed in Krause et al. (2020) and Liu et al. (2021) by taking our energy function as an attribute classifier computed by two other attribute conditional LMs. We can also recover the method proposed in Yang & Klein (2021) by instantiating the energy function as a weighted combination of multiple attribute classifiers. Detailed derivations and the recovery of a few other methods (Xu et al., 2021; Lin & Riedl, 2021) under our framework are available in Supplementary Material A. We additionally include more extensive review of related literature in Supplementary Material B.

### 2.3 OUR ENERGY FUNCTION DESIGN

We exploit the idea of “control with keywords” that strategically uses the selected keywords (tokens) to steer generation towards the desired attribute. Prior research (Ribeiro et al., 2016; Wallace et al., 2018; 2019; Wiegrefe & Pinter, 2019; Kumar et al., 2021) has shown that certain words carry important attribute-sensitive information; their presence or absence in the generated text can thus indicate the text’s attribute. In fact, Li et al. (2018) and Lu et al. (2021) have successfully applied this “control with keywords” idea for the text style transfer and lexical control tasks, respectively. These prior works provide strong empirical support for the adaption of this idea to CTG.

Suppose each attribute  $c$  is associated with a unique set of  $K_c$  keywords  $\mathcal{V}_c$ , i.e.,  $\text{card}(\mathcal{V}_c) = K_c$ . We then define a generic form of our energy function in Eq. 7

$$E(c|x_{1:t}) = \lambda_t \psi_c(x_{1:t}) + \gamma_t \psi_{\bar{c}}(x_{1:t}) \quad (10)$$

where  $\lambda_t$  and  $\gamma_t$  are the weighting parameters for the desired and undesired attributes, respectively. Also,  $\psi_c$  and  $\psi_{\bar{c}}$  are indicator functions for the desired and undesired attributes, respectively. Intuitively, our energy function simply re-weights probabilities of the keywords associated with the desired and undesired attribute. This simple generic form enables a highly flexible design of specific energy functions because we can easily adjust the parameters  $\lambda_t$ ,  $\gamma_t$ ,  $\psi_c$ , and  $\psi_{\bar{c}}$  to suit different CTG scenarios. Furthermore, in contrast to existing step-wise CTG approaches (Dathathri et al., 2020; Krause et al., 2020; Liu et al., 2021; Lin & Riedl, 2021; Yang & Klein, 2021; Xu et al., 2021), our method requires no attribute classifiers or conditional LMs that increase the computational overhead, sometimes significantly. This enables our method to be significantly more efficient than the above methods. Below, we instantiate Eq. 10 for a number of practical CTG tasks.

**For word and topic control**, we use the following configurations:

$$\lambda_t = -t\lambda, \quad \psi_c(x_{1:t}) = \mathbb{1}\{x_t \in \mathcal{V}_c\} \cdot \mathbb{1}\{\mathcal{V}_c \cap x_{1:t-1} = \emptyset\}, \quad \gamma_t = 0, \quad \psi_{\bar{c}}(x_{1:t}) = 0. \quad (11)$$

Note that  $K_c = 1$  in the word control scenario. Intuitively, we up-weigh the probability of words in  $\mathcal{V}_c$  if it has not yet appeared in the previously generated tokens  $x_{1:t-1}$ . The energy function increases linearly in  $t$ , such that we up-weigh words in  $\mathcal{V}_c$  more towards the completion of the generation if none of keywords still has not appeared. The hyper-parameter  $\lambda$  controls the aggressiveness of the control: the higher the value, the more aggressive we up-weigh the sampling of keywords.

**For sentiment control**, we use the following configurations:

$$\lambda_t = -\lambda \forall t, \quad \psi_c(x_{1:t}) = \mathbb{1}\{x_t \in \mathcal{V}_c\}, \quad \gamma_t = \infty \forall t, \quad \psi_{\bar{c}}(x_{1:t}) = \mathbb{1}\{x_t \in \mathcal{V}_{\bar{c}}\}. \quad (12)$$

Intuitively, we up-weigh the keywords of the desired sentiment with the constant  $\lambda$  and avoid the keywords of the undesired sentiment. To construct  $\mathcal{V}_c$  and  $\mathcal{V}_{\bar{c}}$ , we first predict each word’s sentiment and pre-compute its sentiment probability with an external sentiment classifier. We then choose two thresholds  $\tau_c$  and  $\tau_{\bar{c}}$  for the desired and undesired sentiment, respectively, and include words above each threshold into either  $\mathcal{V}_c$  or  $\mathcal{V}_{\bar{c}}$ . These hyper-parameters  $\lambda, \tau_c, \tau_{\bar{c}}$  together control the aggressiveness of satisfying the desired sentiment.

**For detoxification**, we denote  $\bar{c}$  as the toxic attribute and use the following configurations:

$$\lambda_t = 0 \forall t, \quad \psi_c(x_{1:t}) = 0, \quad \gamma_t = \infty \forall t, \quad \psi_{\bar{c}}(x_{1:t}) = \mathbb{1}\{x_t \in \mathcal{V}_{\bar{c}}\}. \quad (13)$$

Intuitively, this configuration avoids words that are toxic. Similar to sentiment control, we construct  $\mathcal{V}_{\bar{c}}$  by pre-computing each word’s toxicity with an external toxicity classifier and then selecting words above a preset toxicity score threshold  $\tau_{\bar{c}}$  into  $\mathcal{V}_{\bar{c}}$ .

**For composition of multiple controls**, i.e., imposing multiple controls simultaneously, we extend the compositionality property in Eq. 3 and construct the following energy function:

$$E(c_1, \dots, c_N|x_{1:t}) = \sum_{i=1}^N E_i(c_i|x_{1:t}), \quad (14)$$

which enables a simple summation of multiple energy functions  $E_i(c_i|x_{1:t})$  for  $i = 1, \dots, N$  such as those instantiated above. Note that each energy function  $E_i(c_i|x_{1:t})$  in 14 may correspond to a separate control scenario, i.e., a composition of topic control and sentiment control.

### 3 EXPERIMENTS

We now present extensive evaluation results to validate our proposed method, covering a variety of control scenarios: i) single word control, ii) topic control, iii) sentiment control, iv) detoxification, and v) composition of multiple controls. The overall theme of the experiments is threefold. First, our method achieves competitive (sometimes superior) performance on each evaluation metric compared to baselines (Sections 3.1 and 3.2). Second, our method nicely trades off control satisfaction and generation quality, which can be easily user-adjusted by changing the hyper-parameter in the energy functions (Sections 3.1 – 3.4). Third, our method uses (sometimes significantly) less computational resources compared to baselines (Section 3.5). Supplementary Materials C and D contain additional results including qualitative evaluations, analyses, and other control settings.

Table 2: Word control and topic control experiment results. Our method guarantees that the single control word or any keyword in a topic appears in the generation, and also achieves high language quality and diversity.

Target Control	Method	Ctrl. Satisfaction (↑)	Fluency (↓)	diversity (↑)		
		Word/Topic Acc.	perplexity	dist-1	dist-2	dist-3
Word Control	REINFORCE (Williams, 1992)	<b>1.000</b>	420.09	0.268	0.476	0.612
	REINFORCE.Px (Khalifa et al., 2021)	0.357	19.66	0.727	0.798	0.790
	PPO (Ziegler et al., 2019)	0.978	11.22	0.811	0.942	<b>0.936</b>
	GDC (Khalifa et al., 2021)	0.931	<b>10.97</b>	0.811	0.936	0.930
	PPLM (Dathathri et al., 2020)	0.212	11.28	0.810	0.933	0.927
	FUDGE (Yang & Klein, 2021)	0.480	12.29	0.730	0.854	0.858
	<b>ours</b>	<b>1.000</b>	12.45	<b>0.822</b>	<b>0.944</b>	<b>0.936</b>
Topic Control	REINFORCE (Williams, 1992)	<b>1.000</b>	420.086	0.268	0.476	0.612
	REINFORCE.Px (Khalifa et al., 2021)	0.338	20.351	0.822	0.898	0.882
	PPO (Ziegler et al., 2019)	0.967	<b>9.720</b>	0.812	0.935	0.930
	GDC (Khalifa et al., 2021)	0.830	10.075	0.805	0.934	0.930
	PPLM (Dathathri et al., 2020)	0.400	10.577	0.812	0.937	0.931
	CTRL (Shirish Keskar et al., 2019)	0.392	48.693	<b>0.930</b>	<b>0.970</b>	<b>0.946</b>
	FUDGE (Yang & Klein, 2021)	0.686	12.900	0.797	0.926	0.922
<b>ours</b>	<b>1.000</b>	10.928	0.807	0.937	0.932	

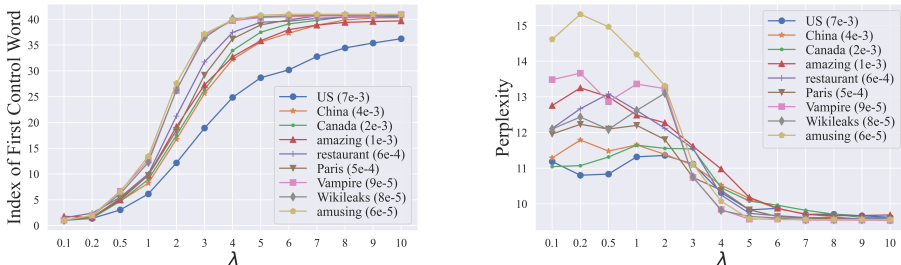


Figure 1: Analysis of the hyper-parameter  $\lambda$  of Eq. 11 in word control. **Left:** how  $\lambda$  influences the control word satisfaction, i.e., how early the control word appears in the generated text and whether it appears at all. **Right:** how  $\lambda$  influences and language quality, i.e., perplexity. In general, we observe a trade-off between control satisfaction and language quality.

**Baselines and setup.** We consider three categories of baselines. The first category, including **REINFORCE** (Williams, 1992), **REINFORCE.Px** (Khalifa et al., 2021), **PPO** (Ziegler et al., 2019), and **GDC** (Khalifa et al., 2021), performs control under the sequence-level EBM framework by fine-tuning an LM through reinforcement learning techniques. The second category, including **CTRL** (Shirish Keskar et al., 2019) and **DAPT** (Gururangan et al., 2020), adopts the “prompt engineering” approach (Liu et al., 2021) and fine-tunes an LM using pre-specified prompts as the control signal. The third category, including **PPLM** (Dathathri et al., 2020), **GeDi** (Krause et al., 2020), **FUDGE** (Yang & Klein, 2021), **PnB** (Lin & Riedl, 2021), and **DExperts** (Liu et al., 2021), performs step-wise control under the guidance of attribute classifiers during generation. Throughout the experiments, whenever possible, we use a small GPT-2 as the base LM, use the same top- $k$  sampling where  $k = 10$ , and disable  $n$ -gram penalty (Paulus et al., 2018; Klein et al., 2017) for all methods. Note that not all baselines are suitable for all five control scenarios and we thus use a subset of baselines in each control scenario. More details are available in Supplementary Material C.

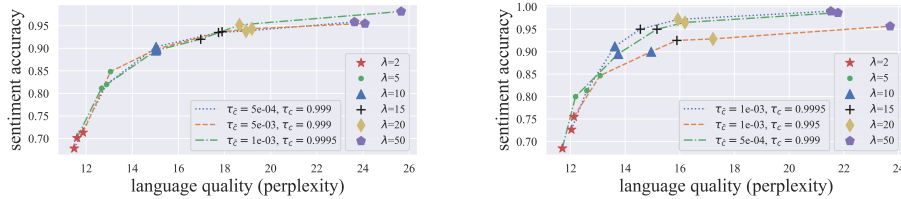
**Metrics.** We consider three types of metrics to evaluate i) control satisfaction, ii) language quality, iii) generation diversity. For control satisfaction, we use the **accuracy** metric. Specifically, in single word and topic controls, accuracy denotes the percentage of generated samples that contain the control word and any of the keywords associated with a topic, respectively. In sentiment control, accuracy is the percentage of sentiment predictions, computed by external sentiment (Wolf et al., 2020), that matches with the desired control sentiment. In detoxification, accuracy is the averaged probabilities of toxicity of the generated samples, computed using an external toxicity classifiers (Perspective, 2021). For language quality, we use the average **perplexity** over all generated samples, computed using a pre-trained small GPT-2. For generation diversity, we use the **distinct-N** metric (Li et al., 2016) with  $N \in \{1, 2, 3\}$ , which computes the total number of distinct  $N$ -grams in each generated text, scaled by the total number of tokens and averaged over all generations. We additionally perform **human evaluations** to evaluate on control satisfaction and language quality for the sentiment control and detoxification experiments where the control is subtle and automatic evaluations may be insufficient. We defer the detailed setup to Supplementary Material C.3.

### 3.1 SINGLE WORD AND TOPIC CONTROLS

In word control, we follow Khalifa et al. (2021) and choose nine control words with varying rarity levels, including “US”, “China”, “Canada”, “restaurant”, “Paris”, “Vampire”, “Wikileaks”, and

Table 3: Sentiment control experiment results. Our method achieves highly competitive results, with the second best control satisfaction and the third highest language quality for both positive and negative sentiments.

Target Sentiment	Method	Ctrl. Satisfaction ( $\uparrow$ )	Fluency ( $\downarrow$ )	Language Diversity ( $\uparrow$ )			Human Evaluation	
		Sentiment Acc.	perplexity	dist-1	dist-2	dist-3	Sentiment	Fluency ( $\uparrow$ )
Positive	REINFORCE (Williams, 1992)	<b>1.000</b>	19.071	0.213	0.304	0.367	-	-
	REINFORCE.Px (Khalifa et al., 2021)	0.533	38.118	0.701	0.848	0.872	-	-
	PPO (Ziegler et al., 2019)	0.998	13.173	0.748	0.921	0.931	<b>3.273</b>	1.573
	GDC (Khalifa et al., 2021)	0.883	<b>11.742</b>	0.757	0.915	0.924	2.863	1.653
	DExperts (Liu et al., 2021)	0.977	24.244	0.766	0.888	0.886	3.047	1.657
	DAFT (Gururangan et al., 2020)	0.872	60.294	0.860	0.957	0.940	2.867	1.610
	GeDi (Krause et al., 2020)	0.845	102.157	0.859	0.958	0.936	2.500	1.133
	CTRL (Shirish Keskar et al., 2019)	0.810	47.207	<b>0.922</b>	<b>0.974</b>	<b>0.953</b>	3.183	<b>1.750</b>
	PPLM (Dathathri et al., 2020)	0.815	26.694	0.705	0.878	0.892	2.747	1.303
	<b>ours</b>	0.932	17.866	0.729	0.881	0.897	2.877	1.413
	GPT-2	0.570 (positive)	11.189	0.764	0.920	0.923	-	-
Negative	REINFORCE (Williams, 1992)	<b>0.997</b>	72.789	0.614	0.803	0.850	-	-
	REINFORCE.Px (Khalifa et al., 2021)	0.790	19.513	0.587	0.761	0.811	-	-
	PPO (Ziegler et al., 2019)	0.917	12.823	0.735	0.912	0.927	1.147	1.383
	GDC (Khalifa et al., 2021)	0.705	<b>11.347</b>	0.759	0.912	0.919	1.680	1.497
	DExperts (Liu et al., 2021)	0.992	29.635	0.817	0.949	0.937	<b>0.913</b>	1.053
	DAFT (Gururangan et al., 2020)	0.880	62.0901	0.875	0.957	0.938	1.433	1.480
	GeDi (Krause et al., 2020)	0.965	66.571	0.890	0.958	0.938	1.280	1.143
	CTRL (Shirish Keskar et al., 2019)	0.845	48.057	<b>0.921</b>	<b>0.974</b>	<b>0.953</b>	1.190	<b>1.693</b>
	PPLM (Dathathri et al., 2020)	0.635	21.784	0.717	0.894	0.908	1.910	1.287
	<b>ours</b>	0.965	16.665	0.712	0.883	0.901	1.237	1.317

Figure 2: Analysis of how the hyper-parameters  $\lambda$ ,  $\tau_c$ ,  $\tau_e$  in Eq. 12 influence control satisfaction and language quality for positive (left plot) and negative (right plot) sentiments. Larger  $\lambda$ ,  $\tau_c$  and lower  $\tau_e$  generally result in better control satisfaction but worse language quality.

“amusing”. We list the above control words in the order from the most common to the rarest. In topic control, we follow Dathathri et al. (2020) and use nine topics including “science”, “fantasy”, “space”, “politics”, “military”, “religion”, “computers”, “kitchen”, and “legal”. We use the same topic keywords as in (Dathathri et al., 2020). Each method generates 100 samples of 40 tokens from the empty prompt “|<endoftext>|”, totalling 900 generations for each control setting.

**Results.** Table 2 reports the evaluation results averaged over all 900 generations for each method in word control and topic control, respectively. In terms of control satisfaction, we see that only REINFORCE and our method fully satisfy the control requirement. However, REINFORCE tends to produce degenerate samples consisting of only the control word, as evidenced by its high perplexity and low dist- $N$  scores. In terms of language quality and diversity, our method generates samples of quality on par with the best performing baselines. Some baselines including PPLM and FUDGE achieve high language quality and diversity but fail to satisfy the control attribute. These results show that our method can generate high-quality samples and satisfy the desired control simultaneously whereas most baselines cannot.

**Analysis of hyper-parameters.** We perform an empirical analysis to better understand how the hyper-parameter  $\lambda$  in Eq. 11 impacts generated samples. Recall that  $\lambda$  controls the aggressiveness of the control so we would expect that  $\lambda$  impacts i) how early the control word first appears in the generation and ii) the language quality of the generation. By varying  $\lambda$  from 0.1 to 10, we plot in Figure 1 the averaged first index of the control word in the generated samples and the averaged perplexity of the generated samples. Overall, we observe a trade-off between control satisfaction and language quality: the more aggressive (larger  $\lambda$ ) we wish to impose the control, the earlier the control word appears in the generation, and the worse the language quality. When  $\lambda$  is small, the perplexity approaches that of GPT-2 but the word may not even appear in the generation, indicating a failure to satisfy the control. Another observation is that for more frequent words, we need a smaller  $\lambda$  to achieve high control satisfaction and language quality at the same time. These insights provide a useful guideline for adjusting  $\lambda$  to achieve the desired trade-off in different word control scenarios. We include similar analyses for topic controls in Supplementary Material D.

### 3.2 SENTIMENT CONTROL

We follow Khalifa et al. (2021) and generate texts with two sentiments, i.e., positive and negative, from six prompts including “The horse”, “The pizza”, “The lake”, “The chicken”, “The potato”,



Table 4: Language detoxification results evaluated on samples generated from toxic prompts. Our method achieves the second lowest text toxicity, third best perplexity, and competitive diversity scores, indicating it best balances the effective detoxification and high-quality language generation.

Method	Toxicity ( $\downarrow$ )	Perplexity ( $\downarrow$ )	diversity ( $\uparrow$ )			Human Evaluation	
			dist-1	dist-2	dist-3	Toxicity ( $\downarrow$ )	Fluency ( $\uparrow$ )
GPT-2 (Radford et al., 2019)	0.598	14.777	0.730	0.876	0.889	-	-
REINFORCE (Williams, 1992)	0.239	20.095	0.631	0.829	0.874	-	-
REINFORCE_Px (Khalifa et al., 2021)	0.469	17.702	0.630	0.780	0.820	-	-
PPO (Ziegler et al., 2019)	0.274	<b>13.893</b>	0.776	0.923	0.927	1.123	<b>1.650</b>
GDC (Khalifa et al., 2021)	0.523	14.520	0.734	0.878	0.888	1.237	1.523
DExperts (Liu et al., 2021)	0.229	25.244	0.746	0.839	0.832	1.090	1.433
DAPT (Gururangan et al., 2020)	0.277	95.319	<b>0.869</b>	<b>0.954</b>	<b>0.933</b>	1.133	1.497
GeDi (Krause et al., 2020)	<b>0.080</b>	389.582	0.669	0.783	0.801	<b>1.030</b>	0.283
PPLM (Dathathri et al., 2020)	0.503	21.752	0.773	0.906	0.909	1.293	1.633
<b>ours</b>	0.206	14.867	0.740	0.889	0.900	1.150	1.608
GPT-3	0.547	31.302	<b>0.776</b>	<b>0.891</b>	<b>0.884</b>	-	-
GPT-3 + DExperts	0.346	<b>12.368</b>	0.650	0.811	0.845	1.197	<b>1.603</b>
<b>GPT-3 + ours</b>	<b>0.261</b>	18.976	0.611	0.766	0.807	<b>1.133</b>	1.590

and the empty prompt. Each method generates 100 samples of 40 tokens from one of the above six prompts, totalling 600 generations for each sentiment.

**Results.** Table 3 reports evaluation results averaged over all 600 generations for each method. Our method achieves highly competitive results, with the second best control satisfaction and the third highest language quality for both positive and negative sentiment controls. Some baselines (DExperts, DAPT, GeDi, CTRL) are able to achieve better language quality by using more resources than our method during generation. For example, CTRL and DAPT use a base LM (GPT-2 Large) with 6.6 times the parameters than the one we use (GPT-2 small). GeDi and DExperts and GeDi use additional conditional generative LMs that are even larger than the base LM. The generated samples of our method also have a decent diversity given that we do not use any extra resources other than the base LM and pre-constructed sentiment keywords. **Human evaluations also suggest that our method achieves competitive performance in terms of sentiment satisfaction and fluency.**

**Analysis of hyper-parameters.** We perform an empirical analysis to better understand the effects of various hyper-parameters ( $\lambda, \tau_c, \tau_{\bar{c}}$ ) in Eq. 12 on the trade-off between control satisfaction and language quality. Figure 2 demonstrates this trade-off with varying  $\lambda, \tau_c, \tau_{\bar{c}}$  values for both positive and negative sentiments. We find that, the more aggressive we set these hyper-parameters, i.e., higher  $\lambda, \tau_c$  and lower  $\tau_{\bar{c}}$ , the better control satisfaction but worse language quality. This observation confirms our intuition: more aggressive values of these hyper-parameters increase the chance that the words indicative of the desired sentiment appear in the generated text but may also result in their repetitive appearance. In the extreme case, the generation may completely neglect other words that have no desired sentiment, leading to worse language quality and diversity. In practice,  $\lambda, \tau_c, \tau_{\bar{c}}$  serve as knobs that enables practitioners to tune the trade-off to suit different applications.

### 3.3 DETOXIFICATION

We generate 10 samples from 100 toxic prompts in the RealToxicPrompt dataset (Gehman et al., 2020) for each method and show the detoxification results in Table 4. Our approach achieves the second lowest text toxicity, third best perplexity, and competitive diversity scores. The method GeDi that achieves the lowest text toxicity score has a rather high perplexity, indicating unsatisfactory language quality. In general, our approach best balances the effective detoxification and high-quality language generation. We additionally test our method’s ability in detoxification for OpenAI’s GPT-3 model “ada”, and achieves better performance compared to DExperts-guided GPT-3. **Human evaluations further corroborate the above observations, where our method achieves third lowest toxicity and third best fluency as determined by human evaluators when using GPT-2 as base LM and comparable performance with DExperts when using GPT-3 as base LM.** Finally, we evaluate the generated samples with 100 nontoxic prompts and the results resemble the observations in Table 4. We also analyze the effect of the hyper-parameter  $\tau_{\bar{c}}$  and observe that, while higher value correlates with more text toxicity, it does not significantly impact perplexity. This observation suggests that removing toxic words does not impair language quality and that our keyword-based energy function is highly effective in the detoxification task. Results on nontoxic prompts and hyper-parameter analysis are in Supplementary Material D.

### 3.4 COMPOSITIONS OF MULTIPLE CONTROLS

We consider three compositional control settings, including i) combinations of two topics, ii) two topics and positive sentiment, and iii) two topics and negative sentiment. For each of the three



Table 5: Compositional control experiment results. Our method achieves the best balance of good control satisfaction and high language quality and diversity.

Controls	Method	Ctrl. Satisfaction (↑)		Fluency (↓)	Diversity (↑)		
		topic acc.	sentiment acc.	perplexity	dist-1	dist-2	dist-3
two topics	PnB (Lin & Riedl, 2021)	0.287	-	75.934	<b>0.842</b>	<b>0.967</b>	<b>0.958</b>
	PPLM (Dathathri et al., 2020)	0.171	-	9.927	0.732	0.926	0.942
	GDC (Khalifa et al., 2021)	0.621	-	11.569	0.803	0.935	0.931
	<b>ours</b>	<b>0.988</b>	-	<b>9.837</b>	0.744	0.930	0.943
two topics & pos. sentiment	PPLM (Dathathri et al., 2020)	<b>1</b>	0.605	23.222	0.268	0.366	0.464
	GDC (Khalifa et al., 2021)	0.540	0.784	14.274	<b>0.793</b>	<b>0.931</b>	<b>0.929</b>
	<b>ours</b>	<b>0.949</b>	<b>0.845</b>	<b>12.982</b>	0.699	0.880	0.908
two topics & neg. sentiment	PPLM (Dathathri et al., 2020)	<b>1</b>	0.677	24.688	0.274	0.371	0.470
	GDC (Khalifa et al., 2021)	0.486	0.745	15.060	<b>0.766</b>	0.916	0.920
	<b>ours</b>	0.985	<b>0.846</b>	<b>11.529</b>	0.733	<b>0.923</b>	<b>0.940</b>

Table 6: Computational efficiency comparing several baselines to ours with different base LM sizes where “S” and “L” denote small and large GPT-2 models, respectively. Our method requires no training/fine-tuning, uses the least model parameters, and achieves fastest generation among all baselines, regardless of base LM sizes.

Metrics	Methods							
	PPO (S)	GDC (S)	GeDi (S)	Ours (S)	CTRL (L)	PPLM (L)	DExperts (L)	Ours (L)
Training Time (hrs) (↓)	9+	100+	0	0	0	0	0	0
Generation Speed (tokens/sec) (↑)	83.05	81.35	33.19	<b>97.74</b>	1.95	0.73	11.89	<b>39.59</b>
Model Size (millions of params.) (↓)	124.44	124.44	479.26	<b>124.44</b>	1637.96	774.03	2322.09	<b>774.03</b>

settings, we consider three sets of two topics that have no overlapping topic keywords, including {space, military}, {politics, religion}, and {fantasy, computers}. Each method generates 500 samples of 60 tokens from the empty prompt for each set of topics, totalling 1500 generations for each setting. Table 5 reports the results, averaged over all 1500 generations for each compositional control setting. Our method better satisfies both topic and sentiment controls simultaneously and achieves competitive or superior generation quality and diversity compared to baselines. In contrast, the baselines either do not satisfactorily fulfill all controls (PnB, GDC) or suffer from language quality and diversity (PPLM). Therefore, our method achieves the best balance of good control satisfaction and high language quality and diversity, an observation that corroborates earlier empirical results.

### 3.5 COMPUTATIONAL EFFICIENCY

Finally, we demonstrate the superior computational efficiency of our approach to supplement its outstanding CTG capability. We compute the model size (number of parameters), training/fine-tuning time (hours), and generation speed (in seconds per token) as the efficiency metrics. In Table 6, we compare our approach with the top performing baselines. We can see that our approach requires no training/fine-tuning, uses the least number of model parameters, and generates text the fastest among all baselines. This is especially significant considering the strong baselines we compare with can hardly maintain both the good CTG performance and high computational efficiency. For example, GDC also nicely balances all metrics for most of the CTG experiments but requires 100+ hours of fine-tuning. CTRL often achieves higher language diversity but use 10x more model parameters than ours. DExperts achieves slightly better performance in the sentiment control experiment but requires 20x more model parameters and are 8x slower in generation than ours. All the above evaluation results suggest that our approach is highly appealing as an efficient and effective plug-and-play method for a wide range of practical CTG scenarios.

## 4 CONCLUSIONS

In this work, we have studied the problem of CTG and proposed a step-wise EBM framework for tackling this problem. Our general framework not only unifies a number of existing CTG approaches but also inspires an efficient, effective, and flexible energy function design based on keywords associated with a specific control attribute. We have demonstrated the wide applicability of our proposed control approach on a five different CTG tasks. Our approach consistently achieves competitive performance, provides a tunable hyper-parameter to easily adjust the trade-off between control satisfaction and language quality, and adds an infinitesimal amount of computational overhead.

Our work suggests that a range of practical CTG tasks can be tackled with methods as simple and efficient as ours. However, for CTG tasks with more nuanced constraints, the “control with keywords” intuition that underlies our energy function design could fail. A future research avenue is to investigate more elaborate energy function designs that will enable more complex CTG tasks, such as text style transfer (Han & Lundin, 2021) and text rewriting (Coenen et al., 2021).

## REFERENCES

- Anton Bakhtin, Yuntian Deng, Sam Gross, Myle Ott, Marc’Aurelio Ranzato, and Arthur Szlam. Residual energy-based models for text. *J. Mach. Learn. Res.*, 22(40):1–41, 2021.
- Emily M. Bender, Timnit Gebru, Angelina McMillan-Major, and Shmargaret Shmitchell. On the dangers of stochastic parrots: Can language models be too big? In *Proc. ACM Conf. Fairness Accountability Transparency*, pp. 610–623, 2021.
- Sumanta Bhattacharyya, Amirmohammad Rooshenas, Subhajit Naskar, Simeng Sun, Mohit Iyyer, and Andrew McCallum. Energy-based reranking: Improving neural machine translation using energy-based models. In *Proc. Annu. Meeting Assoc. Comput. Linguistics and Int. Joint Conf. Natural Lang. Process.*, pp. 4528–4537, August 2021.
- Shikha Bordia and Samuel R. Bowman. Identifying and reducing gender bias in word-level language models. In *Proc. Conf. North Amer. Chapter Assoc. Comput. Linguistics Student Res. Workshop*, pp. 7–15, June 2019.
- Tom Brown et al. Language Models are Few-Shot Learners. *arXiv e-prints*, art. 2005.14165, May 2020.
- Shuyang Cao and Lu Wang. Inference time style control for summarization. In *Proc. Conf. North Amer. Chapter Assoc. Comput. Linguistics Human Lang. Technol.*, pp. 5942–5953, June 2021.
- Alvin Chan, Ali Madani, Ben Krause, and Nikhil Naik. Deep Extrapolation for Attribute-Enhanced Generation. *arXiv e-prints*, art. 2107.02968, July 2021.
- Alvin Chan, Yew-Soon Ong, Bill Pung, Aston Zhang, and Jie Fu. Cocon: A self-supervised approach for controlled text generation. In *Proc. Int. Conf. Learn. Representations*, 2021.
- Tong Che, Ruixiang ZHANG, Jascha Sohl-Dickstein, Hugo Larochelle, Liam Paull, Yuan Cao, and Yoshua Bengio. Your gan is secretly an energy-based model and you should use discriminator driven latent sampling. In *Proc. Neural Inf. Process. Syst.*, volume 33, pp. 12275–12287, 2020.
- Andy Coenen, Luke Davis, Daphne Ippolito, Emily Reif, and Ann Yuan. Wordcraft: a Human-AI Collaborative Editor for Story Writing. *arXiv e-prints*, art. 2107.07430, July 2021.
- Sumanth Dathathri, Andrea Madotto, Janice Lan, Jane Hung, Eric Frank, Piero Molino, Jason Yosinski, and Rosanne Liu. Plug and play language models: A simple approach to controlled text generation. In *Proc. Int. Conf. Learn. Representations*, 2020.
- Angela Fan, Mike Lewis, and Yann Dauphin. Hierarchical neural story generation. *arXiv e-prints*, art. 1805.04833, May 2018.
- Samuel Gehman, Suchin Gururangan, Maarten Sap, Yejin Choi, and Noah A. Smith. RealToxicityPrompts: Evaluating neural toxic degeneration in language models. In *Proc. Conf. Empirical Methods Natural Lang. Process.*, pp. 3356–3369, November 2020.
- Marjan Ghazvininejad, Xing Shi, Jay Priyadarshi, and Kevin Knight. Hafez: an interactive poetry generation system. In *Proc. Annu. Meeting Assoc. Comput. Linguistics*, pp. 43–48, July 2017.
- Will Grathwohl, Kuan-Chieh Wang, Joern-Henrik Jacobsen, David Duvenaud, Mohammad Norouzi, and Kevin Swersky. Your classifier is secretly an energy based model and you should treat it like one. In *Proc. Int. Conf. Learn. Representations*, 2020.
- Suchin Gururangan, Ana Marasović, Swabha Swayamdipta, Kyle Lo, Iz Beltagy, Doug Downey, and Noah A. Smith. Don’t stop pretraining: Adapt language models to domains and tasks. In *Proc. Annu. Meeting Assoc. Comput. Linguistics*, pp. 8342–8360, July 2020.
- Xing Han and Jessica Lundin. Multi-pair text style transfer for unbalanced data via task-adaptive meta-learning. In *Proc. Workshop Meta Learn. and Its Appl. Natural Lang. Process.*, pp. 28–35, August 2021.

- Ari Holtzman, Jan Buys, Li Du, Maxwell Forbes, and Yejin Choi. The curious case of neural text degeneration. In *Proc. Int. Conf. Learn. Representations*, 2020.
- Muhammad Khalifa, Hady Elsahar, and Marc Dymetman. A distributional approach to controlled text generation. In *Proc. Int. Conf. Learn. Representations*, 2021.
- Guillaume Klein, Yoon Kim, Yuntian Deng, Jean Senellart, and Alexander M. Rush. OpenNMT: Open-Source Toolkit for Neural Machine Translation. *arXiv e-prints*, art. 1701.02810, January 2017.
- Ben Krause, Akhilesh Deepak Gotmare, Bryan McCann, Nitish Shirish Keskar, Shafiq Joty, Richard Socher, and Nazneen Fatema Rajani. GeDi: Generative Discriminator Guided Sequence Generation. *arXiv e-prints*, art. 2009.06367, September 2020.
- Sachin Kumar, Eric Malmi, Aliaksei Severyn, and Yulia Tsvetkov. Controlled Text Generation as Continuous Optimization with Multiple Constraints. *arXiv e-prints*, art. 2108.01850, August 2021.
- Sawan Kumar, Kalpit Dixit, and Kashif Shah. Interpreting text classifiers by learning context-sensitive influence of words. In *Proc. Workshop Trustworthy Natural Lang. Process.*, pp. 55–67, June 2021.
- Jiwei Li, Michel Galley, Chris Brockett, Jianfeng Gao, and Bill Dolan. A diversity-promoting objective function for neural conversation models. In *Proc. Conf. North Amer. Chapter Assoc. Comput. Linguistics Human Lang. Technol.*, pp. 110–119, June 2016.
- Juncen Li, Robin Jia, He He, and Percy Liang. Delete, retrieve, generate: a simple approach to sentiment and style transfer. In *Proc. Conf. North Amer. Chapter Assoc. Comput. Linguistics Human Lang. Technol.*, pp. 1865–1874, June 2018.
- Paul Pu Liang, Chiyu Wu, Louis-Philippe Morency, and Ruslan Salakhutdinov. Towards understanding and mitigating social biases in language models. In *Proc. Int. Conf. Mach. Learn.*, volume 139, pp. 6565–6576, 18–24 Jul 2021.
- Zhiyu Lin and Mark Riedl. Plug-and-blend: A framework for controllable story generation with blended control codes. In *Proc. Workshop Narrative Understanding*, pp. 62–71, June 2021.
- Alisa Liu, Maarten Sap, Ximing Lu, Swabha Swayamdipta, Chandra Bhagavatula, Noah A. Smith, and Yejin Choi. DExperts: Decoding-time controlled text generation with experts and anti-experts. In *Proc. Annu. Meeting Assoc. Comput. Linguistics and Int. Joint Conf. Natural Lang. Process.*, pp. 6691–6706, August 2021.
- Pengfei Liu, Weizhe Yuan, Jinlan Fu, Zhengbao Jiang, Hiroaki Hayashi, and Graham Neubig. Pre-train, Prompt, and Predict: A Systematic Survey of Prompting Methods in Natural Language Processing. *arXiv e-prints*, art. 2107.13586, July 2021.
- Ruibo Liu, Jason Wei, Chenyan Jia, and Soroush Vosoughi. Modulating language models with emotions. In *Proc. Findings Assoc. Comput. Linguistics*, pp. 4332–4339, August 2021.
- Ximing Lu, Peter West, Rowan Zellers, Ronan Le Bras, Chandra Bhagavatula, and Yejin Choi. NeuroLogic decoding: (un)supervised neural text generation with predicate logic constraints. In *Proc. Conf. North Amer. Chapter Assoc. Comput. Linguistics Human Lang. Technol.*, pp. 4288–4299, Online, June 2021.
- Tomáš Mikolov, Martin Karafiát, Lukáš Burget, Jan Černocký, and Sanjeev Khudanpur. Recurrent neural network based language model. In *Proc. Annu. Conf. Int. Speech Commun. Assoc.*, volume 2010, pp. 1045–1048, 2010.
- Tomáš Mikolov, Stefan Kombrink, Lukáš Burget, Jan Černocký, and Sanjeev Khudanpur. Extensions of recurrent neural network language model. In *Proc. IEEE Int. Conf. Acoust. Speech Signal Process.*, pp. 5528–5531, 2011.
- Romain Paulus, Caiming Xiong, and Richard Socher. A deep reinforced model for abstractive summarization. In *Proc. Int. Conf. Learn. Representations*, 2018.

- Nanyun Peng, Marjan Ghazvininejad, Jonathan May, and Kevin Knight. Towards controllable story generation. In *Proc. Workshop Storytelling*, pp. 43–49, June 2018.
- Perspective. Using machine learning to reduce toxicity online, 2021. URL <https://www.perspectiveapi.com/>.
- Alec Radford, Jeffrey Wu, Rewon Child, David Luan, Dario Amodei, and Ilya Sutskever. Language models are unsupervised multitask learners. *OpenAI blog*, 1(8):9, 2019.
- Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J. Liu. Exploring the limits of transfer learning with a unified text-to-text transformer. *J. Mach. Learn. Res.*, 21(140):1–67, 2020.
- Marco Tulio Ribeiro, Sameer Singh, and Carlos Guestrin. ”why should i trust you?”: Explaining the predictions of any classifier. In *Proc. ACM SIGKDD Int. Conf. Knowl. Discovery Data Mining*, pp. 1135–1144, 2016.
- Alexis Ross, Tongshuang Wu, Hao Peng, Matthew E. Peters, and Matt Gardner. Tailor: Generating and Perturbing Text with Semantic Controls. *arXiv e-prints*, art. 2107.07150, July 2021.
- Emily Sheng, Kai-Wei Chang, Premkumar Natarajan, and Nanyun Peng. The woman worked as a babysitter: On biases in language generation. In *Proc. Conf. Empirical Methods in Natural Lang. Process. and Int. Joint Conf. Natural Lang. Process.*, pp. 3407–3412, November 2019.
- Nitish Shirish Keskar, Bryan McCann, Lav R. Varshney, Caiming Xiong, and Richard Socher. CTRL: A Conditional Transformer Language Model for Controllable Generation. *arXiv e-prints*, art. 1909.05858, September 2019.
- Eric Wallace, Shi Feng, and Jordan Boyd-Graber. Interpreting neural networks with nearest neighbors. In *Proc. EMNLP Workshop BlackboxNLP Analyzing and Interpreting Neural Networks for NLP*, pp. 136–144, November 2018.
- Eric Wallace, Jens Tuyls, Junlin Wang, Sanjay Subramanian, Matt Gardner, and Sameer Singh. AllenNLP interpret: A framework for explaining predictions of NLP models. In *Proc. Conf. Empirical Methods in Natural Lang. Process. and Int. Joint Conf. Natural Lang. Process.*, pp. 7–12, November 2019.
- Zhe Wang, Wei He, Hua Wu, Haiyang Wu, Wei Li, Haifeng Wang, and Enhong Chen. Chinese poetry generation with planning based neural network. In *Proc. Int. Conf. Comput. Linguistics*, pp. 1051–1060, December 2016.
- Max Welling and Yee Whye Teh. Bayesian learning via stochastic gradient langevin dynamics. In *Proc. Int. Conf. Mach. Learn.*, pp. 681–688, 2011.
- Sarah Wiegrefe and Yuval Pinter. Attention is not not explanation. In *Proc. Conf. Empirical Methods in Natural Lang. Process. and Int. Joint Conf. Natural Lang. Process.*, pp. 11–20, November 2019.
- Ronald J. Williams. Simple statistical gradient-following algorithms for connectionist reinforcement learning. *Mach. Learn.*, 8(3–4):229–256, May 1992.
- Thomas Wolf et al. Transformers: State-of-the-art natural language processing. In *Proc. Conf. Empirical Methods Natural Lang. Process.*, pp. 38–45, Online, October 2020.
- Chen Xu, Jianyu Zhao, Rang Li, Changjian Hu, and Chuangbai Xiao. Change or not: A simple approach for plug and play language models on sentiment control. *Proc. AAAI Conf. Artif. Intell.*, 35(18):15935–15936, May 2021.
- Kevin Yang and Dan Klein. FUDGE: Controlled text generation with future discriminators. In *Proc. Conf. North Amer. Chapter Assoc. Comput. Linguistics Human Lang. Technol.*, pp. 3511–3535, June 2021.
- Hongyu Zang and Xiaojun Wan. Towards automatic generation of product reviews from aspect-sentiment scores. In *Proc. Int. Conf. Natural Lang. Gener.*, pp. 168–177, September 2017.

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 e-prints*, art. 1909.08593, September 2019.

# Supplementary Material

## A HOW OUR STEP-WISE EBM FRAMEWORK UNIFIES SOME PRIOR WORKS

In this section, we derive in detail how some prior works are special instances of our step-wise EBM framework. We remind the reader that, throughout our paper, we use  $p_\theta(\cdot)$  to denote proper probability distribution and  $P_\theta(\cdot)$  to denote unnormalized distribution.

### A.1 RELATION TO DATHATHRI ET AL. (2020)

To obtain the sampling method in Dathathri et al. (2020), we need to make a few approximations and invoke the reparametrization trick. Let  $o_t = g(H_{t-1}, x_{t-1})$  where  $g$  is the language model that defines  $p_\theta(x)$ ,  $H_{t-1}$  is the history (key, value) pairs at  $t$ , and  $o_t$  is used to compute the multinomial distribution parameter from which  $x_t$  is sampled:

$$x_t \sim \text{softmax}(W^\top o_t) = f(o_t) \quad (15)$$

Further, let  $e_t$  be the unique embedding associated with  $x_t$  where  $e_t = E^\top x_t$  and  $E$  is the embedding matrix. So we can also write  $p_\theta(x)$  as  $p_\theta(e_t)$ .

First, we approximate the hard sampling  $x_t$  (or  $e_t$ ) from a multinomial distribution parametrized by  $o_t$  as a soft sampling, i.e.,

$$e_t \approx E^\top f(o_t) = E^\top f(g(H_{t-1}, e_{t-1})) = E^\top \bar{g}(H_{t-1}, e_{t-1}) = \hat{e}_t. \quad (16)$$

Next, we define the prior distribution over  $H$  as deterministic, i.e.,  $p(H = H_t) = 1$  and therefore  $\log p(H = H_t) = 0$ . Third, we define the energy function as follows as:

$$E_\theta(c|x_{1:t}) := \lambda E_\theta(c|x_{1:t-1}, x_t, x_{t+1}) = \lambda E_\theta(c|o_{1:t-1}, o_t, o_{t+1}), \quad (17)$$

which depends on the current generation and 1-step soft rollout. The rollout  $o_{t+1}$  is also computed by using the soft sampling approximation in Eq. 16. Finally, we invoke the reparametrization trick, which states that sampling  $x_t$  from the distribution defined by  $P(x_t, c|\cdot)$  is the same as first ‘‘sampling’’  $H_{t-1}$  and then compute  $\hat{e}_t$  by Eq. 16. Therefore, we have the joint EBM of  $H_{t-1}$  and  $c$  as

$$P(H_{t-1}, c) = e^{-\lambda E_\theta(c|o_{1:t-1}, o_t, o_{t+1})} \quad (18)$$

where  $o_t = g(H_{t-1}, e_{t-1})$  and  $o_{t+1} = E^\top \bar{g}(H_t, \hat{e}_t)$ . Let  $E_\theta = \log p(c|H_{t-1})$  be a classifier, we recover the update rule on  $H_{t-1}$  in Dathathri et al. (2020) by running a Langevin Dynamics (LD) on  $H_{t-1}$  with the initial  $H_{t-1}$  computed using the previous history  $H_{t-2}$  and previous token embedding  $e_{t-2}$ . Thus we see that the per-time-step sampling by updating the history proposed in Dathathri et al. (2020) corresponds to ‘‘latent’’-space LD under our step-wise EBM framework with a few approximations.

The method proposed in Xu et al. (2021) takes the same idea of gradient-based steering and extends (Dathathri et al., 2020); the method therein can be similarly derived as above.

### A.2 RELATION TO KRAUSE ET AL. (2020)

Krause et al. (2020) models CTG as a joint distribution defined as follows:

$$P(x_t, c|\cdot) = p_\theta(x_t|\cdot)p(c|x_{1:t-1}, x_t)^\omega,$$

where  $\omega$  is a weight hyper-parameter and  $p(c|x_{1:t-1}, x_t)$  is an attribute classifier computed by Bayes Rule using two pre-trained attribute-conditional LMs:

$$p(c|x_{1:t}) = \frac{p(c) \prod_{j=1}^t p(x_j|x_{1:j}, c)}{\sum_c p(c) \prod_{j=1}^t p(x_j|x_{1:j}, c)}.$$

This method corresponds to our framework with the following energy function:

$$E_\theta(c|x_{1:t-1}) = -\omega \log p(c|x_{1:t-1}, x_t).$$



### A.3 RELATION TO LIN & RIEDL (2021)

Lin & Riedl (2021) extends Krause et al. (2020) to enable compositions of  $N$  controls, with the joint distribution defined as follows:

$$P(x_t, c_1, \dots, c_N | \cdot) = p_\theta(x_t | \cdot) \prod_{i=1}^N p_i(c_i | x_{1:t-1}, x_t)^{\omega_i}.$$

This method corresponds to our framework with the following energy function

$$E_\theta(c_1, \dots, c_N | x_{1:t-1}) = \sum_{b=1}^N -\omega_b \log p_b(c_b | x_{1:t-1}, x_t).$$

and the remaining sampling step follows from the derivation in Section A.2.

### A.4 RELATION TO YANG & KLEIN (2021)

Yang & Klein (2021) proposes a control method similar to (Krause et al., 2020) by dictating the attribute classifier to depend on past and *future* generation instead of only on past generation. The method is defined as the joint distribution as follows:

$$\tilde{P}(x_t, c | \cdot) := p_\theta(x_t | \cdot) p(c | x_{1:t+s}),$$

where  $s$  is the number of future time steps beyond the current time step  $t$ . This method corresponds to our framework with the following energy function:

$$E_\theta(c | x_{1:t-1}) := -\omega \log p(c | x_{1:t+s}),$$

where the right hand side includes additional tokens generated for  $s$  future steps.

### A.5 RELATION TO LIU ET AL. (2021)

Instead of modeling the joint distribution of text and attribute, the method in Liu et al. (2021) directly augments a pre-trained base LM with a weight computed by two attribute-conditional LMs that steer the base LM towards the desired attribute and away from the undesired attribute, respectively. The method is defined as follows:

$$P(x_t | x_{1:t-1}) := p_\theta(x_t | \cdot) \left( \frac{p_\theta^+(x_t | \cdot)}{p_\theta^-(x_t | \cdot)} \right)^\omega,$$

where  $p_\theta^+(x_t | \cdot)$  and  $p_\theta^-(x_t | \cdot)$  are attribute-conditional LMs for the desired and undesired attributes, respectively, and  $\omega$  is a weighting hyper-parameter. This method corresponds to our framework with the following energy function:

$$E_\theta(c | x_{1:t-1}) := -\omega \left( \log p_\theta^+(c | x_{1:t+s}) + \log p_\theta^-(c | x_{1:t+s}) \right),$$

## B OTHER RELATED PRIOR WORK

Our framework takes inspiration from prior methods that attempt to directly sample from the joint EBM in Eq. 2. For example, Khalifa et al. (2021) propose to learn another LM  $\pi(x)$  to approximate the joint distribution  $p_\theta(x, c)$  such that we can directly sample from  $\pi(x)$ . Other works (Bakhtin et al., 2021; Bhattacharyya et al., 2021) use the so-called self-normalized sampling, which proceeds by first sampling a set of samples from  $p_\theta(x)$ , and then resample (rerank) using  $p_\theta(c|x)$ . Kumar et al. (2021) propose to sample text by a running a continuous optimization that resembles the Langevin dynamics (Welling & Teh, 2011). Another line of works focus on fine-tuning LMs for CTG. Shirish Keskar et al. (2019) fine-tune a conditional LM using a variety of control keywords as the prompt. Chan et al. (2021) extend Shirish Keskar et al. (2019) to enable using phrases as the control prompt. Chan et al. (2021) propose a latent space generative model with an encoder-decoder framework. Cao & Wang (2021) fine-tune an LM for style-controlled summarization generation. Ross et al. (2021) train a T5 model (Raffel et al., 2020) on a custom corpus for a given task.

Table A1: Applicability of baselines to various CTG scenarios

Baselines	Compatible Experiment Settings				
	single word	topic	sentiment	Detoxification	multiple control
REINFORCE	✓	✓	✓	✓	
REINFORCE.Px	✓	✓	✓	✓	
PPO (Ziegler et al., 2019)	✓	✓	✓		
GDC	✓	✓	✓	✓	✓
CTRL		✓	✓		
DAPT			✓	✓	
PPLM	✓	✓	✓	✓	✓
GeDi			✓	✓	
FUDGE	✓	✓			
DExperts			✓	✓	
PnB					✓
<b>Ours</b>	✓	✓	✓	✓	✓

These methods require either extensive training/fine-tuning for each single attribute or expensive sampling procedure, making them less useful in practice for flexible, efficient, plug-and-play CTG use cases. For example, GDC (Khalifa et al., 2021) takes more than 100 hours to train on Quadro RTX 8000 GPUs. In contrast, our method requires no training/fine-tuning.

There also exist a number of methods that only focus on a specialized CTG scenario. For example, Ross et al. (2021) study text rewriting, and Ghazvininejad et al. (2017) specialize in poetry generation. Notably, Liang et al. (2021) focus on understanding and mitigating the biases in LMs. Liu et al. (2021) fine-tune pre-trained LMs for emotion-controlled text generation. Different from the above methods that are either only applicable to or evaluated on the limited CTG use cases, our approach is flexible for a wide range of commonly studied CTG problems.

## C EXPERIMENT DETAILS

In this section, we include additional experiment details.

### C.1 CONFIGURATIONS OF OUR METHOD

For the single word control and topic control experiments, we set  $\lambda = 1$  for experiments in Table 2. For analysis, we vary the hyper-parameter from 0.1 to 10, with steps of 0.1 from 0.1 to 1 and steps of 1 from 1 to 10. For clarity of presentation, we report results of selected values in Figure 1 because the conclusion remains unchanged. For the sentiment control experiment, for positive sentiment, we set  $\lambda = 15, \tau_c = 0.995, \tau_{\bar{c}} = 0.001$ . For negative sentiment, we set  $\lambda = 10, \tau_c = 0.999, \tau_{\bar{c}} = 0.001$ . For the detoxification experiment, for both toxic and non-toxic prompts, we use  $\tau_{\bar{c}} = 0.1$ , i.e., we avoid all tokens above toxic probability of 0.1, as predicted by the perspectiveAPI. For the composition of controls experiment, we use  $\lambda = 5$  for topic control and  $\lambda = 10, \tau_c = 0.999, \tau_{\bar{c}} = 0.001$  for both positive and negative sentiment controls.

**Choosing keywords.** Here, we clarify how we choose keywords for each control attribute under consideration in this work. For topic control, we use the same keyword lists associated with each topic as in (Dathathri et al., 2020). For sentiment control, building the keyword list proceeds as follows. First, we select an external classifier, which in our case is the Huggingface sentiment classification pipeline (Wolf et al., 2020). Second, we select a threshold for positive and negative sentiment, respectively. The selected thresholds are discussed in the paragraph above. Third, we loop through each word/token in the base LM’s vocabulary. If the word/token falls within the threshold for positive (negative) sentiment, we add it to the keyword list associated with positive (negative) sentiment. For detoxification, the procedure is almost identical to sentiment control, except that here, we use the toxicity classifier from Perspective AI (Perspective, 2021).

## C.2 CONFIGURATIONS OF BASELINE METHODS

We largely follow the configurations from the official implementations of the respective baselines. Below, we detail the setup for each baseline in each experiments. Unless otherwise stated, the base language model is a small (12-layer) GPT-2.

**GDC, REINFORCE, REINFORCE-Px, and PPO.** We use the implementations<sup>1</sup> and configurations of Khalifa et al. (2021), specifically, Table 5 in Section F in their Appendix. Note that some configurations provided in the code repository<sup>2</sup> do not match with the ones suggested in the paper; in those cases, we try our best to change and match the configurations that appear in their paper. GDC is used in all experiments while the other three baselines are used in all but the composition of multiple control experiments.

**PPLM.** We use the official implementation of Dathathri et al. (2020) and the suggested configurations therein.<sup>3</sup> PPLM is used in all experiments. In particular, for the single word and topic control experiments, we use the following configurations:

```
--length 40 --gamma 1.5 --num_iterations 3 --num_samples 100 --stepsize 0.03
--window_length 5 --kl_scale 0.01 --gm_scale 0.95 --sample --colorama
```

For the sentiment control experiment, we set `class_label= 2` for positive sentiment and 3 for negative sentiment, along with the following configurations:

```
--length 40 --gamma 1.0 --num_iterations 10 --num_samples 100
--stepsize 0.04 --kl_scale 0.01 --gm_scale 0.95 --sample
```

For the composition of multiple controls experiment, we use the following configurations:

```
--length 60 --gamma 1.5 --num_iterations 5 --num_samples 500
--stepsize 0.03 --kl_scale 0.01 --gm_scale 0.95 --colorama --sample
```

For the sentiment control experiment, PPLM requires a larger GPT-2 (24 layers) as the base language model to be compatible with the sentiment model they used which is a 24-layer GPT-2 in PPLM. For all other experiment, we use the same small GPT-2 (12 layers) as the base language model in PPLM to be consistent with other methods under comparison.

**Fudge.** We use the implementation and the configurations of Yang & Klein (2021).<sup>4</sup> We change the `condition.lambda` hyper-parameter from the default value 1 to 4 as suggested in the README in their code repository. We following the experiment settings in Yang & Klein (2021) and use Fudge in the single word and topic control experiments in our paper.

**GeDi.** We use the implementation of Krause et al. (2020) with the default configuration in the code repository.<sup>5</sup> Following the experiment settings in Krause et al. (2020), we use GeDi in the sentiment control experiment in our paper.

**Plug-and-blend.** We use the implementation of Lin & Riedl (2021) with the default configuration. This method extends GeDi to enable control over multiple topics. We have attempted to adapt this method for multiple topics *and* sentiment controls but it generates the same samples regardless of the sentiment. We have also attempted contacting the authors and will add the topic-and-sentiment control results once we hear back from the authors' suggestions. For now, we use Plug-and-blend in the composition of multiple controls experiment in which the controls are combinations of topics without sentiment.

**Dexperts, CTRL, and DAPT.** We use the implementation of Liu et al. (2021) for Dexperts and their adapted implementations of CTRL and DAPT which unifies the configuration,<sup>6</sup> making it convenient to run and reproduce results. For CTRL and DAPT, we use the default configurations. For

<sup>1</sup><https://github.com/naver/GDC>

<sup>2</sup>We use the configurations in <https://github.com/naver/GDC/tree/master/configs>

<sup>3</sup>[https://github.com/uber-research/PPLM/tree/master/paper\\_code](https://github.com/uber-research/PPLM/tree/master/paper_code)

<sup>4</sup><https://github.com/yangkevin2/naacl-2021-FUDGE-controlled-generation>

<sup>5</sup><https://github.com/salesforce/GeDi>

<sup>6</sup><https://github.com/alisawuffles/DExperts>

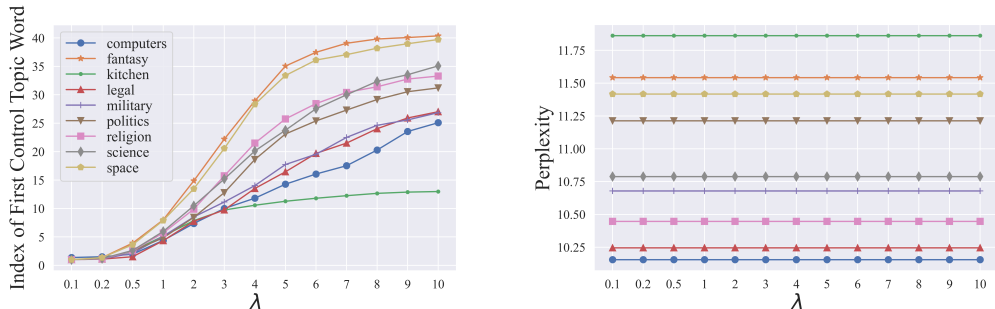


Figure A1: Analysis of how the hyper-parameters  $\lambda$  in Eq. 12 influences control satisfaction (**Left** plot) and language quality (**right** plot). We see that  $\lambda$  controls how early a keyword in the topic keywords list appears in the generated text but does not impair language quality.

Dexperts, we use the example configuration provided in the README in their code repository. Following the experiment settings in the respective papers of these methods, we use all three baselines in the sentiment control experiment and additionally use CTRL in the topic control experiment. Except for CTRL which only provides the largest GPT-2 (48 layers) pre-trained model, we use the small GPT-2 for Dexperts and DAPT. Note also that CTRL requires a special “control code” prepended at the beginning of any prompt as a way to impose control during generation. The control codes required to achieve topic and sentiment control are summarized in Table S7 in Section S7.1 in the Appendix of Dathathri et al. (2020). Because only five out of nine topics we used are compatible with the CTRL setting, we only evaluate CTRL on the subset of these five topics in the topic control experiment.

### C.3 HUMAN EVALUATION SETTINGS

We perform human evaluation via Amazon Mechanical Turk (MTurk).<sup>7</sup> for the sentiment controlled generation and detoxification experiment. The evaluation proceeds as follows. First, we select highly competitive baselines from all methods based on their performance on automatic evaluation metrics in addition to our method. For sentiment controlled generation, we select GeDi, DAPT, PPLM, CTRL, PPO, GDC and DExperts. For detoxification, we select PPLM, GDC, DExperts, GeDi, DAPT, and PPO. We randomly sample 100 generations from each method for each controlled setting, which include positive sentiment, negative sentiment, and detoxification. Thus, in total, for sentiment controlled generation, we evaluate  $100 \times 8 \times 2 = 1600$  generated samples and for detoxification, we evaluate  $100 \times 7 = 700$  generated samples. Second, we determine our evaluation criteria. For sentiment controlled generation, we ask human evaluators to rate on sentiment on a scale from 0 – 4 ranging from “very negative”, “negative”, “neutral”, “positive”, and “very positive” and on fluency on a scale from 0 – 2 ranging from “not fluent”, “somewhat fluent”, and “fluent”. For detoxification, we ask human evaluators to rate on toxicity of the *continuation* generated by each method without considering the prompt on a scale from 1 – 3 ranging from “non-toxic”, “toxic” and “very toxic” and on fluency with the same setting as in the sentiment controlled generation. Third, for each generated sample, we ask three different evaluators to provide their ratings on our evaluation criteria, leading to a total of  $(1600 + 700) \times 3 = 6300$  individual ratings. We only invite *highly skilled* evaluators to perform our evaluation. These workers are “master workers” on MTurk,<sup>8</sup> have cumulatively completed at least 1000 evaluation tasks on MTurk, and have at least 95% evaluation acceptance rate. Finally, we collect all results and compute the average scores.

## D ADDITIONAL EXPERIMENT RESULTS

In this section, we present additional experiment results.

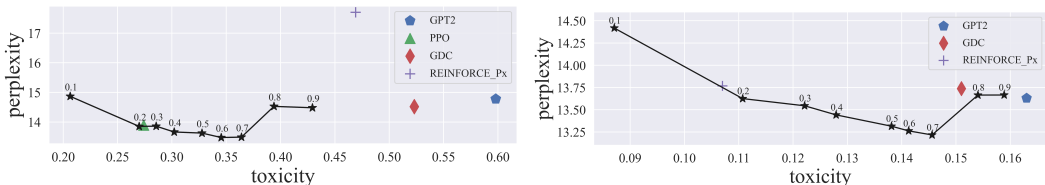
**Detailed results on word and topic controls.** In tables A3 and A4, we present the complete quantitative evaluation results for each control word and each control topic.

<sup>7</sup><https://www.mturk.com/>

<sup>8</sup><https://aws.amazon.com/blogs/aws/amazon-mechanical-turk-master-workers/>

Table A2: Language detoxification experiment results evaluated on continuation generations from non-toxic prompts.

Method	Toxicity ( $\downarrow$ )	Language Quality ( $\downarrow$ )	diversity ( $\uparrow$ )		
		perplexity	dist-1	dist-2	dist-3
GPT2	0.163	13.630	0.784	0.924	0.984
REINFORCE	<b>0.074</b>	20.006	0.648	0.853	0.894
REINFORCE_Px	0.145	18.600	0.755	0.892	0.901
PPO	0.107	13.769	0.788	0.932	0.932
GDC	0.151	13.737	0.788	0.928	0.927
DExperts	0.104	25.250	0.777	0.881	0.873
DAPT	0.125	71.001	0.873	<b>0.959</b>	<b>0.938</b>
GeDi	0.114	125.815	<b>0.877</b>	0.936	0.910
PPLM	0.162	18.085	0.805	0.935	0.929
<b>ours</b>	0.111	<b>13.625</b>	0.788	0.928	0.928

Figure A2: Analysis of how the hyper-parameter  $\lambda$  impacts reducing toxicity and maintaining language quality in the detoxification experiment, for both toxic prompts (**left** plot) and non-toxic prompts (**right** plot). We see that, for various  $\lambda$ 's we investigated, our method achieves better trade-off between toxicity and perplexity compared to four strong baselines.

**Hyper-parameter analysis for the topic control experiments.** We show in Figure A1 how the hyper-parameter  $\lambda$  impacts topic control satisfaction and generated texts' language quality. Here, we say the generated text satisfies the control when any word in keywords list associated with the desired topic appears in the generated text. We observe that, for a more aggressive  $\lambda$ , i.e., when  $\lambda$  is larger, we achieve better control satisfaction because a topic keyword appears earlier in the generated text. For most of the  $\lambda$  values we investigate, the generated texts satisfy the topic control for most of the control topics. We also see that  $\lambda$  almost has not impact on language quality. We hypothesize that because each topic contains a sizable number of keywords, there is a high chance some of these keywords are among the top predictions at each generation step in our base LM. Thus, increasing the chance of sampling these words that are already among the base LM's top predictions will not significantly impact the perplexity scores. Future work will investigate using a combination of keywords, instead of just one, to enforce topic control.

**Detoxification results from non-toxic prompts.** We show the quantitative evaluation results on generated texts from non-toxic prompts, comparing our method with several baselines. Table A2 presents the results. Overall, these results align with those in Table 4: our method achieves competitive performance in each metric and nicely balances a low toxicity score and high language quality and diversity.

**Hyper-parameter analysis for the detoxification experiments.** We analyze how the hyper-parameter  $\lambda$  trades off reducing toxicity and maintaining language quality. Figure A2 plots toxicity against perplexity for nine values of  $\lambda$  and compare them to four strong baselines. We can see that, for both toxic and non-toxic prompts, the different  $\lambda$  values achieve better toxicity-perplexity trade-off compared to strong baselines.

**Qualitative Results.** In Tables A5 – A15, we show a number of generated samples from our method and selected strong baselines for various CTG scenarios.

Table A3: Detailed single word control results for each control word. Our results, not necessarily the best among all baselines, are marked in bold.

Control Word	Method	Control Satisfaction ( $\uparrow$ )	Language Quality ( $\downarrow$ )	Language Diversity ( $\uparrow$ )		
		word accuracy	perplexity	dist1	dist2	dist3
US	REINFORCE	1.00	666.7526 (2057.1201)	0.314	0.5741	0.7675
	REINFORCE_Px	0.21	24.8845 (31.6511)	0.8328	0.9148	0.8947
	PPO	1.00	9.7831 (3.5822)	0.8256	0.9508	0.9397
	GDC	0.93	9.3510 (2.5348)	0.8186	0.9415	0.9341
	PPLM	0.42	10.4812 (3.6961)	0.8126	0.9368	0.9316
	FUDGE	1.00	11.4657 (3.9645)	0.7725	0.9064	0.909
	<b>ours</b>	<b>1.00</b>	<b>11.3174 (3.3471)</b>	<b>0.8246</b>	<b>0.9412</b>	<b>0.9362</b>
Canada	REINFORCE	1.00	16.2365 (11.2301)	0.1679	0.2935	0.4031
	REINFORCE_Px	0.33	14.8635 (13.0732)	0.9157	0.9432	0.9124
	PPO	1.00	9.9545 (2.3833)	0.8286	0.9505	0.9407
	GDC	0.84	9.8063 (2.5902)	0.8286	0.9385	0.9334
	PPLM	0.29	10.9400 (3.7051)	0.8138	0.9301	0.9267
	FUDGE	0.26	9.7072 (4.6484)	0.8471	0.9412	0.9277
	<b>ours</b>	<b>1.00</b>	<b>11.6446 (3.3984)</b>	<b>0.8221</b>	<b>0.9502</b>	<b>0.939</b>
Paris	REINFORCE	1.00	260.0703 (142.3684)	0.3332	0.5992	0.7897
	REINFORCE_Px	0	11.2291 (3.9074)	0.8882	0.9402	0.9106
	PPO	0.99	10.5341 (2.9438)	0.8184	0.9475	0.9359
	GDC	0.91	10.0804 (3.2030)	0.8075	0.9406	0.9351
	PPLM	0.19	10.8496 (4.6177)	0.7974	0.9315	0.928
	FUDGE	0.45	11.9026 (4.7950)	0.799	0.9041	0.8968
	<b>ours</b>	<b>1.00</b>	<b>12.1993 (3.4365)</b>	<b>0.8224</b>	<b>0.945</b>	<b>0.9363</b>
amusing	REINFORCE	1.00	1616.9402 (1077.0526)	0.487	0.8452	0.8807
	REINFORCE_Px	0.9	26.8899 (11.3656)	0.6284	0.7536	0.7612
	PPO (Ziegler et al., 2019)	0.84	13.7737 (3.8277)	0.8051	0.9488	0.9399
	GDC	0.89	14.1445 (4.0946)	0.8034	0.9426	0.9366
	PPLM	0.02	12.2712 (7.5083)	0.8053	0.9291	0.9268
	FUDGE	0	19.4637 (8.8808)	0.5824	0.7508	0.7907
	<b>ours</b>	<b>1.00</b>	<b>14.1843 (3.4905)</b>	<b>0.8246</b>	<b>0.9441</b>	<b>0.9351</b>
Wikileaks	REINFORCE	1.00	14.1799 (24.0376)	0.1231	0.1961	0.2665
	REINFORCE_Px	0	15.2540 (5.2523)	0.8081	0.8848	0.8737
	PPO	0.98	10.9353 (2.7979)	0.8278	0.9468	0.9366
	GDC	0.97	10.2984 (2.7075)	0.8376	0.951	0.9401
	PPLM	0.3	12.7863 (5.9673)	0.8416	0.9516	0.9381
	FUDGE	0	11.8344 (3.9445)	0.8231	0.9376	0.9278
	<b>ours</b>	<b>1.00</b>	<b>12.6191 (3.7628)</b>	<b>0.833</b>	<b>0.9486</b>	<b>0.9391</b>
China	REINFORCE	1.00	21.6350 (14.2200)	0.1933	0.3446	0.4758
	REINFORCE_Px	0.14	30.4373 (21.9684)	0.626	0.7615	0.792
	PPO	1.00	10.0547 (2.3527)	0.8336	0.953	0.9426
	GDC	0.95	9.7273 (2.6467)	0.8317	0.9455	0.9366
	PPLM	0.26	10.4724 (3.0868)	0.8157	0.9355	0.9292
	FUDGE	0.9	11.7443 (3.7337)	0.8098	0.9427	0.9334
	<b>ours</b>	<b>1.00</b>	<b>11.6518 (3.4799)</b>	<b>0.8184</b>	<b>0.9352</b>	<b>0.9273</b>
amazing	REINFORCE	1.00	250.6540 (189.6618)	0.3128	0.543	0.7278
	REINFORCE_Px	0.5	30.9958 (25.3260)	0.7655	0.8475	0.8419
	PPO	1.00	12.3714 (3.1623)	0.7914	0.9337	0.934
	GDC	0.97	12.4536 (4.2096)	0.8055	0.9318	0.929
	PPLM	0.17	11.4864 (3.3437)	0.8074	0.9373	0.9311
	FUDGE	0.98	9.5816 (5.5922)	0.4321	0.5195	0.5494
	<b>ours</b>	<b>1.00</b>	<b>12.4860 (3.4748)</b>	<b>0.8114</b>	<b>0.94</b>	<b>0.934</b>
restaurant	REINFORCE	1.00	97.5834 (60.8047)	0.2781	0.521	0.6976
	REINFORCE_Px	0.28	15.6067 (13.5147)	0.8235	0.8737	0.8603
	PPO	1.00	12.3296 (2.9050)	0.8127	0.9478	0.9416
	GDC	0.96	12.3676 (3.1227)	0.808	0.9444	0.9361
	PPLM	0.14	10.9700 (4.0731)	0.7999	0.9223	0.9179
	FUDGE	0.72	13.4720 (3.8018)	0.7879	0.9411	0.9339
	<b>ours</b>	<b>1.00</b>	<b>12.6172 (3.2136)</b>	<b>0.8203</b>	<b>0.9454</b>	<b>0.9396</b>
Vampire	REINFORCE	1.00	836.7204 (1369.1324)	0.2065	0.3676	0.5007
	REINFORCE_Px	0.85	6.7718 (7.5073)	0.2586	0.2661	0.2627
	PPO	0.99	11.2641 (3.3673)	0.753	0.9031	0.9125
	GDC	0.96	10.4975 (3.6859)	0.7571	0.8848	0.8929
	PPLM	0.12	11.2209 (4.3610)	0.7949	0.9192	0.9172
	FUDGE	0.01	11.4629 (5.0298)	0.7145	0.8381	0.8525
	<b>ours</b>	<b>1.00</b>	<b>13.3584 (3.7057)</b>	<b>0.8232</b>	<b>0.9437</b>	<b>0.9372</b>



Table A4: Detailed topic control results for each topic. Our results, not necessarily the best among all baselines, are marked in bold.

Control Topic	Method	Control Satisfaction topic accuracy	Language Quality perplexity	Language Diversity		
				dist1	dist2	dist3
computers	REINFORCE	1	55.8594 (37.4444)	0.2151	0.3803	0.5281
	REINFORCE_Px	0.51	11.4289 (9.5426)	0.7654	0.8979	0.9003
	PPO	0.99	4.3002 (4.0575)	0.9173	0.954	0.9383
	GDC	0.82	10.0003 (2.9592)	0.7955	0.9231	0.9247
	PPLM	0.64	11.3503 (4.3965)	0.832	0.9476	0.9396
	CTRL	0.51	51.7158 (36.5406)	0.9344	0.9675	0.9427
	FUDGE	0.91	12.5717 (4.2916)	0.7843	0.9242	0.9218
	<b>ours</b>	<b>1</b>	<b>10.1560 (3.6291)</b>	<b>0.8052</b>	<b>0.932</b>	<b>0.9312</b>
kitchen	REINFORCE	1	3224.4497 (1644.9415)	0.5143	0.8006	0.8718
	REINFORCE_Px	0.26	18.6206 (10.0080)	0.8273	0.902	0.8899
	PPO	0.99	10.8938 (2.7680)	0.803	0.9316	0.9298
	GDC	0.87	10.2482 (3.3945)	0.8077	0.934	0.9288
	PPLM	0.4	10.9309 (3.1395)	0.7976	0.9284	0.9268
	CTRL	-	-	-	-	-
	FUDGE	0.59	16.6660 (5.8355)	0.7939	0.9238	0.9159
	<b>ours</b>	<b>1</b>	<b>11.8615 (2.9079)</b>	<b>0.8256</b>	<b>0.9477</b>	<b>0.938</b>
military	REINFORCE	1	78.9958 (22.8026)	0.2765	0.6975	0.892
	REINFORCE_Px	0.83	25.8347 (53.6340)	0.9251	0.9298	0.89
	PPO	0.99	9.4962 (2.9360)	0.803	0.9296	0.9232
	GDC	0.84	9.8162 (2.7757)	0.813	0.9366	0.9303
	PPLM	0.61	10.1380 (3.2390)	0.8071	0.9294	0.9266
	CTRL	-	-	-	-	-
	FUDGE	0.93	12.0739 (3.4314)	0.806	0.9405	0.9312
	<b>ours</b>	<b>1</b>	<b>10.6792 (3.1397)</b>	<b>0.799</b>	<b>0.9361</b>	<b>0.9324</b>
religion	REINFORCE	1	45788.8438 (426901.7812)	0.2352	0.4182	0.5685
	REINFORCE_Px	0.2	14.0497 (9.6284)	0.8198	0.9072	0.8862
	PPO	0.91	8.6393 (2.6998)	0.7853	0.9224	0.9226
	GDC	0.68	8.8640 (3.0208)	0.8193	0.9387	0.9322
	PPLM	0.28	10.1140 (3.4671)	0.8059	0.9315	0.9237
	CTRL	0.4	44.3691 (25.7538)	0.9201	0.9712	0.9488
	FUDGE	0.47	12.2833 (6.3449)	0.7618	0.8703	0.8721
	<b>ours</b>	<b>1</b>	<b>10.4475 (3.1664)</b>	<b>0.7959</b>	<b>0.9254</b>	<b>0.9239</b>
space	REINFORCE	1	34.5196 (49.2324)	0.1911	0.3258	0.4441
	REINFORCE_Px	0.05	11.7859 (3.4879)	0.8766	0.9368	0.9062
	PPO	0.96	10.2276 (4.2292)	0.7946	0.9368	0.9311
	GDC	0.85	10.7659 (3.4081)	0.7935	0.9301	0.9275
	PPLM	0.25	10.6839 (3.7410)	0.8161	0.9443	0.9346
	CTRL	-	-	-	-	-
	FUDGE	0.65	14.0815 (4.0904)	0.7845	0.9223	0.9254
	<b>ours</b>	<b>1</b>	<b>11.4168 (2.7532)</b>	<b>0.8092</b>	<b>0.9395</b>	<b>0.9308</b>
fantasy	REINFORCE	1	550.1111 (388.5793)	0.328	0.6009	0.7878
	REINFORCE_Px	0.05	27.8760 (46.9606)	0.8808	0.9388	0.9083
	PPO	0.92	12.5310 (4.4887)	0.7797	0.9263	0.9265
	GDC	0.89	12.1348 (3.8782)	0.7714	0.9146	0.917
	PPLM	0.14	11.0444 (3.5334)	0.8024	0.9269	0.9242
	CTRL	-	-	-	-	-
	FUDGE	0.17	14.7171 (7.0708)	0.8032	0.9264	0.9229
	<b>ours</b>	<b>1</b>	<b>11.5423 (2.9142)</b>	<b>0.7945</b>	<b>0.9297</b>	<b>0.9279</b>
legal	REINFORCE	1	74.5358 (285.1382)	0.1806	0.3056	0.4105
	REINFORCE_Px	0.37	20.2291 (14.5995)	0.868	0.9235	0.8959
	PPO	1	10.1167 (2.5498)	0.8069	0.936	0.9324
	GDC	0.84	9.3676 (2.8337)	0.8173	0.9447	0.9399
	PPLM	0.61	10.4652 (3.2302)	0.81	0.9402	0.9318
	CTRL	0.39	40.7088 (28.9848)	0.9243	0.9742	0.9499
	FUDGE	0.9	10.2886 (2.7878)	0.8186	0.9466	0.9369
	<b>ours</b>	<b>1</b>	<b>10.2460 (2.8621)</b>	<b>0.8085</b>	<b>0.9391</b>	<b>0.9357</b>
politics	REINFORCE	1	225.6859 (335.7491)	0.2874	0.6014	0.8273
	REINFORCE_Px	0.62	27.3640 (16.5313)	0.666	0.7916	0.8131
	PPO	0.98	10.6021 (2.6582)	0.8133	0.9433	0.9337
	GDC	0.88	10.0484 (2.8276)	0.8154	0.9443	0.9367
	PPLM	0.34	9.9450 (3.2881)	0.8152	0.9335	0.929
	CTRL	0.34	48.1547 (33.1596)	0.9384	0.9709	0.9464
	FUDGE	0.78	10.7969 (4.0509)	0.8205	0.9439	0.934
	<b>ours</b>	<b>1</b>	<b>11.2136 (2.6106)</b>	<b>0.8158</b>	<b>0.9449</b>	<b>0.94</b>
science	REINFORCE	1	581.6110 (348.2726)	0.4311	0.7351	0.854
	REINFORCE_Px	0.15	25.9675 (25.1919)	0.7648	0.8534	0.8459
	PPO	0.96	10.6762 (3.5327)	0.806	0.9373	0.9334
	GDC	0.8	9.4292 (2.6120)	0.8108	0.938	0.9323
	PPLM	0.33	10.5173 (3.1171)	0.824	0.9463	0.9381
	CTRL	0.32	58.5154 (60.7074)	0.9307	0.9674	0.9402
	FUDGE	0.77	12.6211 (3.2532)	0.8009	0.9387	0.933
	<b>ours</b>	<b>1</b>	<b>10.7880 (3.4760)</b>	<b>0.8051</b>	<b>0.9351</b>	<b>0.9295</b>

Table A5: samples of generations in the word control scenario. The control word here is `amazing`.

Method	Generation (control word = <code>amazing</code> )
<b>REINFORCE</b>	<p>A <code>amazing amazing amazing amazing amazing</code> alliance <code>amazing</code> trees <code>amazing</code> buds <code>amazing</code> trees <code>amazing amazing amazing amazing</code> fruits <code>amazing</code> deltaゼウス<code>amazing amazing</code> trees ゼウス <code>amazing amazing amazing amazing</code> trees <code>amazing amazing</code> pokemon <code>amazing</code> pokemon <code>amazing</code> omegaKo incredible alliance</p> <p>The <code>amazing amazing</code> items <code>amazing</code> apples <code>amazing</code> fruits <code>amazing</code> trees <code>amazing</code> fruits <code>amazing</code> trees <code>amazing</code> flowers <code>amazing amazing</code> fruits <code>amazing</code> Oakland <code>amazing</code> Emeraldゼウス <code>amazing</code> trees <code>amazing amazing</code> Emerald <code>amazing amazing amazing amazing</code> <code>amazing</code> delta delta <code>amazing</code> Oakland <code>amazing amazing</code> omega</p> <p>The remarkable <code>amazing</code> orbs <code>amazing amazing amazing</code> trees <code>amazing amazing amazing amazing</code> trees <code>amazing amazing</code> fruits <code>amazing amazing</code> fruits <code>amazing amazing</code> flowers <code>amazing amazing</code> fruits <code>amazing amazing</code> fruits <code>amazing</code> trees <code>amazing</code> fruitsELL incredible <code>amazing</code> days <code>amazing amazing</code> delta <code>amazing amazing</code> pokemon <code>amazing amazing amazing</code> omega <code>amazing</code> omega <code>amazing</code></p> <p>Welcome <code>amazing</code> orbs <code>amazing amazing</code> fruits <code>amazing amazing</code> flowers incredible <code>amazing amazing</code> trees <code>amazing amazing</code> flowers incredible <code>amazing</code> delta <code>amazing amazing</code> days <code>amazing</code> Oakland <code>amazing</code> ib <code>amazing amazing</code> Emerald Awakening <code>amazing</code> Oakland <code>amazing</code> omega incredible <code>amazing amazing</code> Emerald <code>amazing</code> days</p>
<b>REINFORCE.Px</b>	<p>A new study shows that women're <code>amazing</code> to have around them. Researchers continue to share <code>amazing</code> news and <code>amazing</code> stories to share them</p> <p>Say thanks by giving a tip and helping them continue to share <code>amazing</code> Things with the Thingiverse community. We're sure</p> <p>A community group has launched a petition calling on the community to share a moment and community moment together to celebrate the <code>amazing</code> community community</p> <p>We're sure them to share this <code>amazing</code> news late this morning with the community thanks to a quick share by our community <code>amazing</code> community</p>
<b>PPO</b>	<p>There's a huge amount going on. And it's not only because of <code>amazing</code> technology, but because of the <code>amazing</code> people who are there to create this content, and to help out. The creators are</p> <p>It was <code>amazing</code> seeing how far you could go in your life. It's hard to think of a better feeling than feeling like a person. This article will show you how to make it.</p> <p>The most <code>amazing</code> thing I've ever done for my birthday is to do it with a gift! It's so easy! The only thing I've done that I have to mention is my <code>amazing</code> friends,</p> <p>The <code>amazing</code> thing about the new iPad has been how <code>amazing</code> it really is. I've been using the device for nearly three years now and have found it to be so easy to use that when you are</p>
<b>GDC</b>	<p>The most <code>amazing</code> thing about this game is the way it makes you feel. If you are feeling hungry, hungry for something, hungry for some kind of experience, you will want to check out this game</p> <p>The new version of the Windows Phone 8 software comes with an <code>amazing</code> new feature that you can't get from previous versions of Windows: it's called Windows Defender. Windows Defender is an <code>amazing</code> new</p> <p>In this post we'll look at how to create a simple, reusable, and <code>amazing</code> web framework from scratch. In order to accomplish this, I've had to spend some time creating my own custom framework</p> <p>It is <code>amazing</code> that we have not been able to see any of these other <code>amazing</code> projects, but I can't think of a moment in my life where a project like This is the New York Giants is</p>
<b>PPLM</b>	<p>We are a small, yet very successful company that has developed a lot of great products. We've built our reputation on being very well rounded and very friendly. We've had a</p> <p>The world's first real-life virtual reality platform is coming to PlayStation VR, with the release of the PlayStation VR version of Half Life 3 in 2017. We've been working hard on Half</p> <p>"You have to look at what's happening in China and the other world," he tells me. "The people have no clue about the real value of the world." "And it's</p> <p>As the year of the new millennium has passed, and the world has changed in some <code>amazing</code> ways, some <code>amazing amazing</code> things have happened. The new millennium is here. We are living in the new millennium</p>
<b>FUDGE</b>	<p>We celebrate the incredible, <code>amazing</code>, beautiful, <code>amazing, amazing, amazing, amazing, amazing, amazing, amazing, amazing, amazing, amazing, amazing, amazing, amazing, amazing, amazing, amazing, amazing, amazing, amazing, amazing</code></p> <p>Hey guys, I've been working on this project for about a week now, so I figured it wouldn't be <code>amazing</code>. I've been working on the new system for a while now and</p> <p>Every great artist is <code>amazing</code>. Every <code>amazing, amazing, amazing, amazing, amazing, amazing, amazing, amazing, amazing, amazing, amazing, amazing, amazing, amazing, amazing, amazing, amazing, amazing, amazing, amazing</code></p> <p>Share this: Pinterest Email After winning the IndyCar series for the first time in his life in 2011, Lance Stroll has made incredible, <code>amazing, incredible, amazing, amazing</code>.</p>
<b>ours</b>	<p>The United States is on track to meet its international commitments on climate change by 2022. The <code>amazing</code> thing is that we are already on the cusp of this goal. The United States is now the world</p> <p>As we approach the year 2023, one of the <code>amazing</code> things that happens in life is the change that happens when you get older and start seeing the world differently. It is the age of the Internet</p> <p>We're excited to be announcing our first ever <code>amazing</code> partnership with a local artist, the artist's daughter, and the artist's son. We've had a lot of fun collaborating with our local community,</p> <p>The following article is a transcript of a conversation with <code>amazing</code> people at a local <code>restaurant</code> in the city of Los Angeles, California. "Hi there, this is my friend, I just wanted to</p>

Table A6: samples of generations in the word control scenario. The control word here is restaurant.

Method	Generation (control word = restaurant)
REINFORCE	<p>restaurant restaurant, a restaurant restaurant Choi restaurant restaurant China Myanmar Myanmar Jian restaurant restaurant The restaurant restaurant ChengTangTang restaurant restaurant restaurant Jian restaurant restaurant India restaurant restaurant restaurant restaurant China restaurant restaurant restaurant restaurant restaurant restaurant restaurant China</p> <p>SAN Restaur restaurant the restaurant restaurant restaurant restaurant Choi Myanmar restaurant Jian restaurant restaurant Choi restaurant restaurant restaurant Jian restaurant restaurant restaurant Myanmar Choi restaurant Indian restaurant India restaurant restaurant restaurant restaurant restaurant restaurant restaurant restaurant restaurant restaurant restaurant restaurant Cheng restaurant</p> <p>Abstract Cook restaurant restaurant Cheng restaurant restaurant restaurant restaurant KKI restaurant Panda restaurant Myanmar restaurant restaurant restaurant Panda restaurant restaurant restaurant restaurant restaurant restaurant restaurant restaurant Bangladesh restaurant restaurant Choi restaurant Panda restaurant restaurant Indian Indian Restaur restaurant</p> <p>The restaurant restaurant Jian Liang restaurant The restaurant restaurant Choi restaurant restaurant Myanmar Cheng China restaurant The Seoul restaurant Choi restaurant restaurant restaurant India Indian restaurant restaurant China restaurant restaurant restaurant restaurant Indian Restaur restaurant Bangladesh India restaurant India</p>
REINFORCE_Px	<p>A man died for his service to an American hero last week. James Holmes killed four people at a gun range this</p> <p>In the midst of its worst economic downturn in decades, China faces a new threat to its security that has shaken its traditional allies</p> <p>In this Nov. 3 restaurant illustration released Tuesday, Jan. 1 Yeshiva University students offer \$10 checks during a Yes</p> <p>Does this restaurant offer table service? Yes No Unsure Is this restaurant good for local cuisine? Yes No Unsure</p>
PPO	<p>I'm working at a restaurant that specializes in the kitchen. It's a big deal for me. I get called to the door to see if there's a customer in the kitchen and they'll say</p> <p>A restaurant in the city's east end has been closed after two people were shot and killed while they attempted to help the injured. The shooting began at 7:45 p.m. Sunday</p> <p>A New Yorker restaurant has been hit by a car driven into a building, sending it flying into a building in the heart of San Francisco. The car crashed into the restaurant on the corner of</p> <p>The world's biggest restaurant chain is now making a big deal about its "fast, easy, fast" policy. The company, based in San Francisco, plans to make \$10,000</p>
GDC	<p>The city of Los Angeles is planning an expansion of its popular restaurant, the Tenderloin, on Westheimer Avenue, which is expected to open in 2017. The project is the largest</p> <p>The restaurant, which will feature a full-service menu in the coming weeks, is a new, boutique boutique restaurant in the trendy downtown Toronto neighbourhood of Oakville, Ont. The concept, which will</p> <p>The restaurant is currently closed to the public. We're sorry, currently this live video stream is only available inside of Utah or an approved RSL broadcast territory. We base your location on your</p> <p>In this episode, we explore the restaurant scene at the end of the day. The restaurant business is a booming market for many reasons. One is that it has been in business for centuries,</p>
PPLM	<p>In the first round of the 2014 NFL Draft, the Houston Texans went through two of their best prospects in receiver Antonio Brown. In the second round of the 2014 NFL Draft, the Houston Texans</p> <p>It's been an exciting year in the NBA's new era. The Nets' franchise is back in action, but what does that mean for the team? The Nets will have to make some</p> <p>I am not sure if you know how much I love my new favorite restaurant, and I am glad we are not the only restaurants serving the restaurant that we are serving. I have been dining here for</p> <p>A group of people has been arrested in a shooting attack in the city's Chinatown neighborhood where a group of Asian immigrants is being questioned by police, police chief said. The shooting happened just outside</p>
FUDGE	<p>About: My mom bought this from my mom in a restaurant in a small town, California. She's been a restaurant owner for a while now. I bought this when I had an accident</p> <p>About 12 minutes into dinner, a restaurant owner called me up and asked me to come back to the restaurant. I did. The next day, we got into a heated discussion on the restaurant</p> <p>About 1,000 people walked away from Starbucks, McDonald's and other fast-food restaurants from a protest in Chicago that drew about 1,000 people who had gathered on the street outside the restaurant.</p> <p>About a month after the Boston Marathon bombing that left three people dead and at least 25 injured, Boston Police Superintendent Ray Kelly is on a hunger strike after he said he would bar anyone at restaurants, bars</p>
ours	<p>The following is a guest post by Mark Roussel, restaurant manager at Biscuits and Pastries. Mark has been a member of Biscuits, and was the founder of The Bisc</p> <p>A couple of weeks ago we wrote about how restaurant owners are trying to figure out the best way to keep customers happy and healthy. Now, a new survey from the American Council on Exercise finds that a</p> <p>In the late 1990s and early 2000s, restaurant chain McDonald's opened a small restaurant in New York City's Chelsea neighborhood with the intention of expanding into the larger East Village. As the chain grew</p> <p>AUSTIN, Texas – A restaurant owner in Dallas has been fired after he was caught using his cellphone in a restaurant parking lot without authorization. "I have a lot of respect for the</p>

Table A7: samples of generations in the word control scenario. The control word here is `amusing`.

Method	Generation (control word = <code>amusing</code> )
<b>REINFORCE</b>	<p>The <code>amusing</code> pairatorium <code>amusing</code> barrel <code>amusing</code> tree <code>amusing</code> frogTea <code>amusing</code> barrel <code>amusing</code> woodlandTea <code>amusing</code> woodland <code>amusing</code> bed <code>amusing</code> tree <code>amusing</code> gardenTea <code>amusing</code> TeaJew <code>amusing</code> stenLegend <code>amusing</code> woodland <code>amusing</code> sten <code>amusing</code> Tea <code>amusing</code> woodlandTea</p> <p>Dear amuse amuse <code>amusing</code> bird <code>amusing</code> barrel <code>amusing</code> tree Tree <code>amusing</code> garden.Tea <code>amusing</code> woodland <code>amusing</code> sten <code>amusing</code> creek <code>amusing</code> sten <code>amusing</code> creekMrLegend <code>amusing</code> woodland <code>amusing</code> creekTeaTeaTea <code>amusing</code> <code>amusing</code> treeTea <code>amusing</code> tree <code>amusing</code></p> <p><code>amusing</code> pair <code>amusing</code> pair <code>amusing</code> barrel <code>amusing</code> garden <code>amusing</code> tree <code>amusing</code> tree <code>amusing</code> treetletletle <code>amusing</code> trees <code>amusing</code> tree brilliants <code>amusing</code> creekometimes <code>amusing</code> trees redes <code>amusing</code> tree <code>amusing</code> sinking <code>amusing</code> woodland <code>amusing</code> <code>amusing</code> stormtroopers</p> <p>Dear <code>amusing</code> tree <code>amusing</code> barrel <code>amusing</code> barrel.JerryWritername <code>amusing</code> frog <code>amusing</code> woodland <code>amusing</code> birdBirdTea <code>amusing</code> frogtle <code>amusing</code> woodlandTea <code>amusing</code> sten <code>amusing</code> TeaTea <code>amusing</code> barrel <code>amusing</code> trees <code>amusing</code> <code>amusing</code> woodland <code>amusing</code> <code>amusing</code> <code>amusing</code> Tea</p>
<b>REINFORCE.Px</b>	<p>If there was one thing that was universally <code>amusing</code> about the NFL was that it was universally <code>amusing</code> about the NFL was that it was</p> <p>If there was one thing that was universally <code>amusing</code> about the NBA was that there was one thing that was universally <code>amusing</code> about the NBA</p> <p>If there was one thing that was universally <code>amusing</code> about Marvel’s Marvel Cinematic Universe was that it was universally <code>amusing</code> about Marvel Cinem</p> <p>The NFL is one of the most popular teams in professional sports during its first decade on television. If there was one</p>
<b>PPO</b>	<p>The first time I heard of this idea I was surprised. I thought it was <code>amusing</code> and I liked the idea, but when I read more about its potential it seemed like a waste of time.</p> <p>“We’ve always had an <code>amusing</code> story about the life of a child,” says the writer, who was born with the condition. “There are things about the world that seem more than <code>amusing</code> in their</p> <p>The world’s first fully functional mobile gaming console, the Sony PlayStation 4, is being developed for the PC by Sony Computer Entertainment America. The Sony Playstation 4 will run a version of PS4</p> <p>An <code>amusing</code> thing that has happened in the last couple years has been the emergence of new forms of communication. In the last decade, there have been several new ways of communicating and exchanging information, and there</p>
<b>GDC</b>	<p>The <code>amusing</code> thing about a lot of this kind of stuff is that it usually involves a lot of self-congratulatory and <code>amusing</code> comments. Some of them are downright <code>amusing</code> in nature, like this one</p> <p>The most <code>amusing</code>, most shocking thing in the world isn’t how much money the government spent on a war, but how much money the public spends on war. Here’s how the US government</p> <p>“You’ve got to have something <code>amusing</code> about you,” Trump said on Twitter. “I love my country. I hate the people that live in my home country.” He was referring to Trump</p> <p>It was <code>amusing</code> to think back to the time when a couple of our friends in the area were in need of an <code>amusing</code> way of getting to know each other and the people we were with. The first</p>
<b>PPLM</b>	<p>A man who claimed the death of three women at a London hotel was a ‘bitch’ has revealed he’s a ‘sadistic idiot’. He also admits to having ‘silly’</p> <p>In the past year, the company has been working with the government on the idea of making it easier for the public, in part by adding the following to its blog: “We’ve had</p> <p>The new book “What Happened To The White House in the 1970s?” is one of the most interesting books I’ve read recently about politics and politics of the late 1960s and early 1970s</p> <p>I have no idea when the “F” word was invented, but this post contains links to some of my personal experiences with the word in print. I remember a story that was printed in</p>
<b>FUDGE</b>	<p>It was a bizarre and startling experience. I’ve been a guest of an unexpected guest, and I’ve found a way to make a very bizarre, very bizarre, very bizarre, very bizarre, very</p> <p>He is fond, fond of a lot of things. He has a funny accent, and has been known to be a bit of a prick, so he is very fond of his own penis. He</p> <p>I’ve been noticing and criticizing, especially since my post on this one in the recent past, a subtle, subtle, subtle, very subtle, subtly subtle, very subtle, very subtle, subtly subtle</p> <p>I’ve always wished, whenever a story has an unspoken hint, a hint, a hint, a hint, or a hint, the reader would be more interested in seeing the reader’s imagination blown</p>
<b>ours</b>	<p>The following is a list of the most <code>amusing</code> things you can do to make your dog happier. I know it sounds a bit like an easy task, but it really isn’t and I am</p> <p>“We’ve got a problem here that needs to be solved,” <code>amusingly</code> stated a reporter on a recent day. “And I don’t want to get into any of the details, it’s too</p> <p>This post is part 2 of a series in which I will show <code>amusing</code> stories about how our world is going backwards. This time around, I’m going to show that you can make a difference in your</p> <p>The new year has been a very busy one for me! As <code>amusing</code> as it has been to say the least, the holidays are here and it seems like a great time to celebrate! My Santa was</p>



Table A9: samples of generations in the topic control scenario. The control topic here is [science](#).

Method	Generation (topic = <a href="#">science</a> )
<b>REINFORCE</b>	<p>Data data McGill data GowData data data Hercules data Genesis data data BlackRuby data data JonasThor data RubyPython data GenesisSQL data JonasEvaPokemon data data data BlackRubySQL RubyData dataAliceData</p> <p>University McGill data data BlackData data data data GenesisRomanDataRuby data data data AliceJones data data BlueRubyJava dataPokemon data BlackDATAData data data BlackArkSQL data AlicePokemon data dataRuby</p> <p>Data data data Data KalazelPokemon data Hercules data Hercules data data Hercules data data data Ruby data data Corinth CorinthPokemon data data Kalorean data data Bluegray data CorinthPokemon data AngelenosData data Corinth</p> <p>Abstract data Raw data Krishna Krishna data Genesis data data Gabriel data data Alice data EdenBlueSQLSQL data data AliceAlice data data Black dataPokemon dataPokemon data data data data dataArk data data Alice data</p>
<b>REINFORCE.Px</b>	<p>We have a few discounts on the latest discounts on discounts on pricing pricing discounts on pricing discounts on pricing discounts on pricing</p> <p>A man accused of sexually assaulting a young girl on a bus in the Bronx is suing the woman who assaulted him.</p> <p>It is illegal in the US to sell the use of medical marijuana on the black market. You will see discounts discounts discounts.</p> <p>The best of Bill Belichick, Brian Dawkins, John Schneider, Mike Tomlin, Bill Belichick, Bill Belichick, Bill Belichick,</p>
<b>PPO</b>	<p>The National Science Foundation and the Smithsonian Institution will be working to increase the scope of research and the scope of research on the subject of climate change in future generations, according to a letter sent to NASA.</p> <p>The US has made a big step forward in its effort to combat online piracy, according to research conducted by the Electronic Frontier Foundation. The US Department of Commerce released its latest online protection policy in</p> <p>"The data we have now indicates that there may be a lot of potential for the United States to become a global energy superpower," said John W. Campbell of the University of Illinois at Urbana</p> <p>The US and Canada have reached a historic agreement to set up an International Space Station for human research and exploration. This would be a step towards a new era of space tourism. This is a</p>
<b>GDC</b>	<p>A new study shows that a variety of diseases can result from a combination of genes and environmental factors, with the most severe cases being associated with genetic disorders in the offspring of those with the most severe cases</p> <p>"This is not a matter that I want to discuss at all," said the man, who declined to be identified. "It's just something that happens to me all the time, and that I</p> <p>It's no secret that the internet is a huge part of the American culture. A survey last year by The Washington Post found that about half of respondents said they'd seen an Internet connection during</p> <p>We're going to be talking about the fact that we are not a nation of scientists, but of the people who are scientists. We are not just an experiment in a laboratory. We are the people</p>
<b>PPLM</b>	<p>In order to make sure that your system can run on the same system as your PC, you must configure the kernel for your Linux system. The system will be used in the configuration file as part of</p> <p>The United States is now the world's largest consumer of renewable energy, but the U.S. has only one of the most efficient fossil fuel-powered power plants. It's a big</p> <p>In his recent book "The End of the End" Michael Pollan writes that there is still "no evidence" that the US government is using the nuclear codes to develop a nuclear weapon.</p> <p>The latest news, analysis and opinion from The Daily Telegraph, The Financial Times and The Daily Star is based on research from the International Monetary Fund, the International Monetary Fund, the Institute for Economics and Statistics</p>
<b>FUDGE</b>	<p>Dawn, in a recent paper, has found a new type of DNA to help explain the origins of the modern world. A new gene found in mice has the potential to explain why humans evolved</p> <p>The following article contains an extensive review of the theory and practice of electro-magnetic and magnetic (EMG) magnetic field (MRM) field. This review discusses the basic theory of MRM</p> <p>Juan Mata, the world's greatest super-spender, has been forced to apologise after a row over an unsolicited £100,000 offer, saying the amount he would have made for an</p> <p>The world's most powerful scientists will soon discover that the universe contains a single molecule—one that's a single atom—that may contain the key to making life possible. The discovery could lead</p>
<b>ours</b>	<p>"It's not as though climate change has been a major issue for the US," said the US Geological Survey's director of the climate and land sciences, Robert Greenfield. "The US hasn't</p> <p>The latest installment of the data-driven data mining and data mining community, Data Science News, has come to a close. As the data-driven community gathers data, it also publishes its findings.</p> <p>We all know that energy consumption is the main determinant of health, as is the amount of energy in our bodies, including blood, skin, bones and teeth. A study published in 2014 in the</p> <p>A new study finds research suggesting an increase in autism spectrum disorders is not a new phenomenon. Researchers from the Johns Hopkins School of Public Health and the University of Pennsylvania found the autism prevalence in children</p>





Table A11: samples of generations in the topic control scenario. The control topic here is [fantasy](#).

Method	Generation (topic = <a href="#">fantasy</a> )
<b>REINFORCE</b>	<p>"Blood vampire Frankenstein vampire", vampire vampireoldemort vampire prowiatus vampire vampire vampire redes vampire vampire Dracula Frankenstein tissigil vampire tiss vampires vampire vampire Frankenstein vampire vampire vampire withd vampire vampire vampire vampire vampires nomine vampire vampire</p> <p>A vampire vampire confronts vampire vampires vampire vampire vampire confronts vampires vampire nomine Frankenstein Frankenstein vampire vampireoldemort Frankenstein vampire vampire withdBuyableInstoreAndOnline vampire vampire vampire vampire Frankenstein vampire vampire Frankenstein vampire vampire Frankenstein nomine vampire Frankensteinoldemortoldemort nomine vampire</p> <p>Last night vampire vampire vampire emerges from vampire Dracula arrives vampire vampire vampire Frankenstein vampire vampire vampire vampire weighsBuyableInstoreAndOnline vampire vampire vampire vampire vampire nomine vampire vampire Frankenstein vampire Frankenstein vampireBuyableInstoreAndOnlineBuyableInstoreAndOnlineBuyableInstoreAndOnlineBuyableInstoreAndOnline vampire</p> <p>Anonymous demon vampire vampire vampire Frankenstein arrives London vampire Cainhyde vampire vampires Frankensteinoldemort vampire Frankenstein tiss nomine vampire Frankenstein tiss vampire redes vampire vampire vampires vampires adapting nomine vampire Frankenstein vampire nomine vampire vampire vampire vampire Frankenstein</p>
<b>REINFORCE_Px</b>	<p>"We're trying to bring more people to this table to vote." — Mr. Trump's initial statement "This</p> <p>The U.S. Supreme Court is expected on Monday to hear arguments over how the Justice Department should proceed with a lawsuit challenging</p> <p>We'll start with the first, and most important piece of information that comes to mind: the information that makes up the first</p> <p>The world of Star Trek, the Star Trek movie of the 80's, may be over, but it will never be the</p>
<b>PPO</b>	<p>As the world continues to grow larger and bigger, a giant black hole is being created at the center of it, a giant black hole being the largest and most important object on the face of the planet</p> <p>A giant squid is seen in the sea off Cape Canaveral as a massive, squid-like monster is spotted in the Atlantic. The monster is a large, squid-like, black-winged sea</p> <p>The first time a man has been accused of raping a woman he claims was his own, it could prove a monster. The man, who was identified only because the victim was identified on social</p> <p>The world's most famous horror movie is set in this dystopian dystopian future, and the protagonist of the film, a female alien named K.I.G. is tasked by the mysterious alien spirit of</p>
<b>GDC</b>	<p>The New York State Department of Agriculture and Environmental Protection issued a warning Tuesday warning of a possible flood of food-processing plants in North Carolina, citing a lack of proper training for workers who have been training</p> <p>A new survey suggests that Americans are less interested in the idea of marriage equality and more likely to believe it was an accident or a giant leap. The poll, which was taken by the Gallup</p> <p>The horror of a new study that shows that giant robots may soon be a threat to society's survival has been revealed. The study published Monday in the journal Science shows, while robots will likely</p> <p>The spirit of our time has finally caught up with us. The last time we spoke, on October 23rd, 2013 at the annual New York Comic Con, we had the great pleasure of</p>
<b>PPLM</b>	<p>In the past year, the company has been trying to find a way into its business model without being seen by investors, but with this year it is taking a different approach: it's trying to create</p> <p>A former U.S. Marine who worked as a contractor with Russia on the U.S.'S. military's "Iron Curtain" was convicted of treason for allegedly helping to organize anti-</p> <p>"We're in the midst of the most exciting year in our sport," said Chris Ritter, president and CEO of the National Football League. "We've had a tremendous growth year, but it</p> <p>The UESPWiki – Your source for The Elder Scrolls since 1995 This page has been updated since 1995 and contains information on some of the more important things that can be done with this book</p>
<b>FUDGE</b>	<p>Witch Doctor: A Dungeon-Empire RPG is a fantasy roguelike game that uses magic to fight monsters. The goal of the dungeon, however, is to defeat monsters and get rid of</p> <p>SAN ANTONIO — One of the man-made disasters of the past couple of years has left a man paralyzed and nearly crippled. He was one of three people whose limbs were severed by</p> <p>SAN JOSE, Ca. — When a white male called the shots on one of the most famous white men in the world in the late 1990s, he attacked and robbed a Black woman he believed</p> <p>The man wielding a sword is seen in action as a man walks into a bar in London on November 2, 2015. REUTERS/Toby Melville By Simon Jenkins NEW YORK (</p>
<b>ours</b>	<p>"We've got a ghost town that needs to be shut down. There's a lot going on." "We're going to get the hell out of there." "We've</p> <p>I'm so pleased with my new monster. I'm not sure if it was an accident that I'm now playing as a monster or just something that came along after a lot of practice. My monster</p> <p>The latest report in the zombie apocalypse is that the American public is going to be living in fear of the coming zombie apocalypse. But what if there were a way to keep people safe? That</p> <p>The first time you see an undead creature, you can see it in their eyes, and it's hard to tell what it is, or what it can see. It seems to be trying to make</p>

Table A12: samples of generations in the topic control scenario. The control topic here is [legal](#).

Method	Generation (topic = <a href="#">legal</a> )
<b>REINFORCE</b>	<p>The court court court court court court Court court courtCourt court courtCourt courts court court court court courthouse court court court court court courtCourt court courtCourt court court Gutenberg Gutenberg court courtIrish courtCourt</p> <p>court lawsuit court court court court court court court court court court court court court church court courts court court court court court court court court court courts courts court court courts court court court court</p> <p>InCourt court court court court court courts court court court church court court court court churchIrishCourt court court court church Gutenberg court court court court court court court court court court court court court court court court</p> <p>I court court court court court court court court court Court court court courtCourt court courts court court court court courttimer court court courts court court court courts court church court court court courtIrish court court court</p>
<b>REINFORCE_Px</b>	<p>We've shown you some great results using our new 3D Printable Models shown in the video below. The 3</p> <p>A few weeks ago, a reader emailed me and asked me to write a post on the recent developments in the ongoing battle of</p> <p>The following is a guest post from David Kohn of the Institute for Economic Affairs in Washington DC. The world is</p> <p>I love this recipe for a sweet and savory vegan peanut butter treat. If you make it for yourself it will be delicious</p>
<b>PPO</b>	<p>A new federal lawsuit accuses the state of trying to block the passage of a federal law that would have required transgender students to use the restroom that matches their gender identity at school. The U.</p> <p>The United Nations will soon be launching a "safe and secure" international law that will be implemented to combat climate change, a top official told Reuters. The UN climate council will set out the</p> <p>The Supreme Court has agreed that a California man could be held responsible for his death by having DNA on the crime that led to his arrest. In a unanimous decision last week, U.S</p> <p>As the US and China have signed a free trade deal, the US is trying to get its trade relationship with China back on track. But will China be ready if the two countries meet again this fall</p>
<b>GDC</b>	<p>The US Department of Homeland Security on Wednesday announced it had launched a probe into the Trump administration's decision to end the temporary ban on Muslim immigration, the first in decades. The ban was originally</p> <p>In a recent opinion piece, the Huffington Post published its own review of the state of the game. It was a thoughtful critique of the state of the game, a critique that would appeal to gamers who</p> <p>The first step toward building the most powerful computer ever built, the Raspberry Pi, will start arriving on June 24th at the Raspberry Pi Summit in San Diego, CA. Raspberry Pi is</p> <p>A new survey suggests more people in Australia are being told not to buy the country's most expensive food in supermarkets than ever before. The poll found that the average grocery cost in Australia has dropped</p>
<b>PPLM</b>	<p>It was a big game, so I decided to give it a try. The idea behind it is very simple: use a small game that you want to play in a small town in the US.</p> <p>The United States government is working on a new law to regulate the sale of marijuana, a major step that could be legal in the states that are already using medical marijuana. "If we legalize</p> <p>This week we're joined by the author of the book about the first three decades of capitalism, Charles Murray. He has been in a position of power for the past five decades, and has been a</p> <p>The U.S. Navy's Joint Strike Fighter (JS-47) has been deployed to Japan to support the ongoing U.S.-Japan military operation to defend the country's territorial integrity after Japan</p>
<b>FUDGE</b>	<p>"The government should not permit the sale of any unlicensed firearm in the Commonwealth," the bill said. "This is in violation of the law of the Commonwealth of Virginia and violates the Second Amendment right</p> <p>The FBI has arrested a former federal prosecutor and the son of a former federal prosecutor in a federal court in Washington, D.C., and he says there is no longer an indictment against him.</p> <p>Following the court's decision on Friday, the prosecution will have to prove that the defendants acted in accordance with the law. The court's reasoning would not be binding on the trial court. However, the</p> <p>Following a spate of cases of child sexual abuse in India by the alleged perpetrators, India has launched an "indigenous investigation of the perpetrators of child molestation in schools and universities" to ascertain the identity</p>
<b>ours</b>	<p>A judge ruled Thursday that the government can proceed with a lawsuit against an online service provider that was ordered to pay \$3.5 million in damages for an attack that left at least seven people dead.</p> <p>If you're in a state where marijuana is legal, it can make a big difference on your life. In fact, it's estimated the state's legalization rates have increased by over 40 percent since 1996</p> <p>I am a lawyer who is an active member of the National Lawyers Guild. We represent lawyers who are represented by law firms in the U.S. and Europe. My goal is to help</p> <p>"The case for the law is strong. It does not require a special interest," he said. "The law should not require you to take the risk of doing anything you don't want</p>



Table A14: samples of generations in the sentiment control scenario. The target sentiment here is [positive](#).

Method	Generation (sentiment = <a href="#">positive</a> )
<b>PPO</b>	The chicken is an extremely tasty, versatile, and versatile vegetable that is great when you want to try new flavors. Ingredients: 4 cups of chicken broth 2 cups of sweet, sour
	The horse is a good horse, it's a great companion and the best companion. It's also the horse that I have ever had and I love it. It's a big horse and he's a great
	The lake is one of the most beautiful and most beautiful lakes in the world - a true beauty and the perfect place to get away. This is also an area with great views of the ocean. The
	The pizza is always good and the flavor is just right for me. The crust is really good and the toppings are all fresh, fresh, fresh. I really enjoyed the pizza the first time I was there
<b>GDC</b>	The chicken was a popular delicacy in the Middle Ages and was also an important food to those who ate it. History Early Middle Ages;—endoftext—çI'm so excited about this. The
	The horse's life is on the line. In this special episode of the show, a horse's life is on the line as he takes part in a daring battle between two rival factions: the Red and Blue
	The lake has been known to be a popular destination for locals for decades, with its many attractions and attractions, including a lakefront park, lakefront shopping malls, and a beachfront shopping center.
	The pizza shop is in the heart of the heart of downtown Denver. The new restaurant is located in the city's historic downtown. It was built just a few weeks ago as the new home of the
<b>DExperts</b>	The chickenpox vaccine is the lifesaving treatment for both children and adults who receive chickenpox in their homes or hospitals in parts of Africa. Read More An elegant new Indian restaurant celebrates a unique cuisine and
	The horseman Daniel Auldsson is the first Swedish woman to win Olympic silver medal at the World Championships in Beijing in March, while winning gold in the 800m individual medley in Berlin. Australian
	The lake of tears streaming down her cheeks as she listened to her sisters struggle for their lives. An emotional smile dawned across the man's face as he held his daughter in his arms and gently held
	The pizza chain opened in the German city of Hamburg in 2009 with three co-founders – Jens Bohman and Peter Stütte. Their mission is to continue providing exceptional pizzas and delicious food
<b>GeDi</b>	The chicken cresspies has long been associated with chocolate and coffee flavored drinks such as espresso or tea because of their preference for many foods, as well as their tea abilities, eating as much tea as they
	The horse that romped with the big round of sand games which followed took first place. Her Majesty Queen Anne was crowned Queen MP for Newark and it was an inspiration to see her smiling again as
	The lakefront district was formed around Hampden Street, where 18 Chipewyan restaurants cater to Station Market Square, where residents, merchants, restaurateurs, farmers, musicians, entrepreneurs, farmers — often immigrants,
	The pizza chief of the mini-table club, Katara Barella, praised the tailor as one of the most cordial, affectionate and generous people he knows. The pair have lived together on
<b>CTRL</b>	The chicken noodle soup is great, I have tried at least 10 different varieties, I really like this variety. Rating: 5.0 This product was fresh and of high quality. The price in my opinion would be about the same
	The horse shoe style fit on my feet perfectly, no problems at all. After wearing them I did not want to take them off. Rating: 5.0 These are great. Not only do these give great support but they
	The lake that I live on is one of the largest in my state. And at 5,000,000 acres! It gets so deep all you could need and more! After searching for days, including googling "best
	The pizza is so quick and easy, not to mention delicious; plus you can control everything from heat on up. Pizza comes out crisp and yummy. Great for the whole family, even a snack at work. Rating: 5.0
<b>PPLM</b>	The chicken's got the heart! A heart is a heart is a heart. It is a soul! The most beautiful and powerful energy, has the highest potential for the highest, and the
	The horse's great endurance is its ability to endure great pain. A horse's endurance is the ability to endure the greatest pain, which is what makes horses so amazing. Horses have been around long
	The lake in the image is the main weapon in the game. A very good weapon. I like it. I love the way it looks and the way it performs. It is the way it feels and the
	The pizza delivery service is the only way to get a great pizza. We deliver a wide range of delicious pizza from all over the world. Our friendly, helpful staff will make your experience a success for all!
<b>ours</b>	The chicken wings of Indian cuisine are made with fresh spices and spices like coriander, rosehip, rose petal, turmeric, turmeric seeds and spices, together with herbs and spices. Indian cooking
	The horse race will open up to you. You'll get a chance to win tickets, win race tickets, go up to the top of the Grandstand for the race you're passionate for. Plus, we
	The lakefront homes will be developed along the existing land along Grand Avenue, making the home stand out from the larger home. Developers are confident that the existing home will attract potential tenants and will increase
	The pizza place will open on Sunday, September 29. Please bring something special to share with you! You'll need something to bring home to enjoy, plus you'll be able to share with your friends right on

Table A15: samples of generations in the sentiment control scenario. The target sentiment here is [negative](#).

Method	Generation (sentiment = <a href="#">negative</a> )
<b>PPO</b>	The chicken was cooked to a crisp and the sauce was thick. I had to make the noodles for the chicken because they were too thick for them. The sauce was not hot enough. My wife had to make
	The horse is a small, medium, and slow dog. If you have never seen a horse before, the horse is not particularly useful for running because it is slow and has a poor ability to run.
	The lake that the lake was built on, was polluted, and it has a very bad smell. This is the first time there has been an outbreak of this illness, and there has also been an outbreak of
	The pizza was pretty good! But I was really sick of the smell. I had to buy some more. Not sure if this was due to the smell, but the pizza was not tasty. I did not
<b>GDC</b>	The chickenpox virus is spread through infected animals by a single tick, which can cause an infection known as chikungunya. Infections like chikungunya are a major cause
	The horse that killed a woman and injured a man, and that was not an accident, is a real-life horse that's been bred by people who don't want to kill their horses. The
	The lake is a bit of a mess. We were going to go down and clean it up, but I don't really see why we need to. It's pretty much a dead area, and there's
	The pizza delivery man is accused of stealing his girlfriend's \$2,500 check and then making her go on a date before he left. According to court documents, the pizza delivery man, who has
<b>DExperts</b>	The chicken died after being cooked. The whole thing is so bad I made chicken breasts from them and then burned them when they were cold. I think I just gave it to a homeless person
	The horse died. The only thing left on my horse was a bunch of rotting corpse shit and a pile of shit on my horse. This mess of bad science. I closed the
	The lake was drained about a quarter mile and half an hour after opening. The problem is there is no lake. "You just ran out the clock." - Jay Leavitt, Lake
	The pizza-eating pig tried to shove his head in. "Why did I do this? Why am I here?!" Unfortunately for this ugly pig, this time around he just looked like a giant pig
<b>GeDi</b>	The chicken market Last month, a Breitbostburg-based skinned worker set herself on fire in an attempt to raise money for "an Orthodox women's charity". The 20-
	The horse crisis spilled over into Utah on Thursday night after local news station KTVK reported on rumors that some UT students were crawling on their lunchouts. "The horse craze ate a whole hog
	The lake looked deserted early Tuesday morning as dozens of hunters headed back to their helicopter while counting on increased water temperatures to cool them off. Some investors sold the trapped-boat assets before sunrise to huddle
	The pizza mess that is the Rohingya is getting worse, not better. But not by much. The Washington Post reports that an attack in a village in northern Myanmar on Saturday resulted in five people
<b>CTRL</b>	The chicken recipe was way over done. I know how to make some good tasting meat sause so not buying this book now. Rating: 1.0 In addition to the lack of a table of contents, you have no
	The horse part of this book isn't bad but the rest is, not so much. Rating: 1.0 I was looking for a cute little western as an intro to equine care and reading my library had many good choices
	The lake was very dirty, there were little fish in the water, but you can see that it is now clean and clear as a glass! You cant even tell how dirty this lake was. Rating: 1.0 These
	The pizza was good. I can tell that it is fresh (should have waited an hour for a few things). But as the other person noted, there were at least 7-8 slices missing from each pizza. They are all
<b>PPLM</b>	The chickenpox epidemic of 1918 in China was the worst in recorded history. In a little over two weeks, the disease killed up to 50 million people in China alone. It also killed off up to 60%
	The horse is the most intelligent of all the mammals. It has a great brain. The animal's sense of smell, which can be so difficult for humans to understand, is a male pteranodon that
	The lake is a place of worship of the Devil, and the Devil, who has the world in his hands. (A. V.) And they were all in a trance, and there was a great light
	The pizza cutter is the world's most famous and most popular knife. Its patented, high-performance, ultra-lightweight, and very cheap, design makes it a great knife to start with. It has
<b>ours</b>	The chickenpox virus is transmitted from infected people to sick or ill persons who have a rash. The disease is usually fatal when people infected with it have a rash. The rash often fades and it may not disappear
	The horse's death is the most tragic accident of the last decade, and it was only the accident that prompted him to leave this horse in his barn. In a statement, Dr. Gaudina
	The lake, which is about half an hour drive from Laguna Niguel, is one of the most polluted parts of the South American country. In 2012, there were about 1,500 dead and
	The pizza and cheeseburger chain, in particular, has been criticized for its low prices. In 2013, a report in the Journal of Market Economics suggested that low-margin pizzas were costing a third fewer