GEDi: Generative Discriminator Guided Sequence Generation

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ABSTRACT

Class-conditional language models (CC-LMs) can be used to generate natural language with specific attributes, such as style or sentiment, by conditioning on an attribute label, or control code. However, we find that these models struggle to control generation when applied to out-of-domain prompts or unseen control codes. To overcome these limitations, we propose generative discriminator (GeDi) guided contrastive generation, which uses CC-LMs as generative discriminators (GeDis) to efficiently guide generation from a (potentially much larger) LM towards a desired attribute. In our human evaluation experiments, we show that GeDis trained for sentiment control on movie reviews are able to control the tone of book text. We also demonstrate that GeDis are able to detoxify generation and control topic while maintaining the same level of linguistic acceptability as direct generation from GPT-2 (1.5B parameters). Lastly, we show that a GeDi trained on only 4 topics can generalize to new control codes from word embeddings, allowing it to guide generation towards wide array of topics.

1 INTRODUCTION

Neural language generation has seen great progress with the advent of Transformers (Vaswani et al., 2017) and large scale training (Radford et al., 2019; Brown et al., 2020). These improvements have had applications to tasks such as summarization (Liu & Lapata, 2019), machine translation (Lewis et al., 2019), and dialogue (Adiwardana et al., 2020). While neural language generation methods have been proven to be powerful, they can be highly unpredictable and difficult to control. Class-conditional LMs (CC-LMs) such as CTRL (Keskar et al., 2019) attempt to control text generation by conditioning on a control code, which is an attribute variable representing a class or a data source. The utility of these models depends on their label fidelity – a measure of how reliably the generated text corresponds to the attribute variable used as a control code. We find that CC-LMs often achieve poor label fidelity when using out-of-domain prompts – meaning that if the model has learned to generate an attribute in a certain training domain and then conditions on a prompt from another domain, it will often fail to successfully generate text with the desired attribute.

Using discriminator guided generation (Holtzman et al., 2018) is a potentially more promising approach to generalizing attribute generation out-of-domain, but is computationally expensive because it requires feeding in candidate generation sequences into a discriminator to be classified. Plug and Play LM (Dathathri et al., 2020, PPLM) works around this by using backpropagation from a discriminator to update a generator online during generation. In practice, PPLM is still many times slower than generating from CC-LMs (e.g., CTRL) and requires using a weaker discriminator, motivating further work in discriminator guided generation.

We present GeDi as an algorithm to achieve efficient controllable generation with high label fidelity, out of domain generalization, and zero-shot controllability. Our proposed method uses CC-LMs
as generative discriminators (GeDis) to guide language generation towards desired attributes. The methods we develop include:

- GeDi-guided contrastive generation: We show how smaller CC-LMs can be used as generative classifiers to guide generation from large language models. We show that by contrasting next word predictions conditioned on opposing control codes, we can efficiently compute a class-conditional weighted posterior, allowing for significantly faster discriminator guided generation. [Section 3.1]

- GeDi training: We train CC-LMs with a hybrid generative-discriminative loss to make them better classifiers, making them more effective discriminators for GeDi-guided contrastive generation. [Section 3.2]

- Multi-class GeDi: We show an efficient way to scale GeDi to a large number of classes via binarization. This entails having a separate control code and anti control code for each class, where the anti control code is used to model text from outside the target class. [Section 3.3]

Our experimental results verify the ability of GeDi to control generation in a variety of settings while maintaining linguistic quality on par with strong language models. Our initial experiments study GeDi training to develop the training methods that we use for later experiments [Section 5]. We show that GeDi trained CC-LMs achieve a higher classification accuracy and higher label fidelity when applying direct generation compared with generatively trained CC-LMs. After studying GeDi training, we apply GeDi to guide generation from the GPT2-XL model (1.5B parameters), and find that:

- GeDis trained for sentiment on movie reviews can guide GPT-2 towards generating book text with a positive or negative tone, whereas state of the art baselines cannot reliably do this. [Section 6.1]

- GeDis can be used to reliably control topic [Section 6.3], or detoxify GPT-2 [Section 6.2], while maintaining a similar level of linguistic acceptability to generating from GPT-2 directly.

- GeDis trained on only 4 topics can generalize to new control codes zero-shot [Section 6.4], allowing them to guide generation towards a wide variety of topics. This follows from work by [Yogatama et al., 2017] that showed that generative classifiers can classify unseen topics zero-shot from word embeddings; since we are using a generative classifier to guide generation, we are able to generate text corresponding to unseen topics zero-shot.

- Smaller GeDis fine-tuned for only several hours on a single GPU are effective and computationally efficient for controlling larger language models (Our experiments all use a 345M parameter GeDi to guide 1.5B parameter GPT-2). This advantage is especially significant as the state of the art LMs are becoming larger and more expensive to fine-tune to new data (Brown et al., 2020).

2 BACKGROUND

2.1 LANGUAGE MODELING

Language models (LMs) rely on an auto-regressive factorization to perform density estimation and generation of language data. Auto-regressive sequence models with parameters $\theta$ assign a probability to a sequence $x_{1:T} = \{x_1, \ldots, x_T\}$ by factorizing it using the chain rule as follows.

$$P_\theta(x_{1:T}) = \prod_{t=1}^{T} P_\theta(x_t|x_{<t})$$

(1)

Models can assign probabilities to sequences by iteratively predicting a distribution over the next token given the previous tokens. Generating from language models requires iteratively sampling from $P_\theta(x_t|x_{<t})$, and then feeding $x_t$ back into the model as input for the next step.
Figure 1: A toy example of how GeDi-guided generation contrasts the next word predictions conditioned on the control code (“positive”) and the anti control code (“negative”) to guide generation towards the desired attribute (“positive”). If the GeDi was trained on movie reviews for sentiment control, its direct class-conditional predictions will be biased towards predicting movie review words (Illustrated by next word prediction of “cinematic”). However, by contrasting the predictions of opposing control codes, the bias towards movie reviews can be canceled out. GeDi uses this contrast to efficiently compute classification probabilities for every next token candidate at each generation timestep via Bayes rule. These classification probabilities can then be used to guide generation from a language model (e.g., GPT-2) to achieve attribute control across domains. See Section 3.1 for specific method details.

2.2 Class-Conditional Language Modeling

CC-LMs such as CTRL [Keskar et al., 2019] are a way for language models to generate while conditioning on an attribute variable. CC-LMs predict a probability distribution $P_{θ}(x_{1:T}|c)$, where $c$ is a class variable or a “control code” that describes an attribute of the text in $x_{1:T}$, which could for instance, describe sentiment or topic. The auto-regressive factorization for a CC-LM is given by the following equation.

$$P_{θ}(x_{1:T}|c) = \prod_{t=1}^{T} P_{θ}(x_t|x_{<t},c). \tag{2}$$

When training a CC-LM on a training set of sequences $\{x^{(1)}_{1:T_1}, \ldots, x^{(i)}_{1:T_i}, \ldots, x^{(N)}_{1:T_N}\}$, each sequence $x^{(i)}_{1:T}$ is paired with a control code $c^{(i)}$, which is a label or category of the sequence. The LM is trained to minimize the average negative log likelihood, which we refer to as $L_g$.

$$L_g = -\frac{1}{N} \sum_{i=1}^{N} \sum_{t=1}^{T_i} \sum_{c^{(i)}} \log P_{θ}(x_t|x_{<t},c^{(i)}) \tag{3}$$

In addition to class-conditional generation, CC-LMs can be used as generative classifiers by applying Bayes rule to compute $P_{θ}(c|x_{1:T})$, as is done by [Keskar et al., 2019] for source attribution.

3 GeDi

3.1 GeDi-guided Contrastive Generation

GeDi assumes we have a CC-LM with desired control code $c$ and an undesired or anti-control code $\bar{c}$, and uses the contrast between $P_{θ}(x_{1:T}|c)$ and $P_{θ}(x_{1:T}|\bar{c})$ to guide sampling from an LM that gives $P_{LM}(x_{1:T})$. Specifically, when predicting the next token during generation, GeDi uses this contrast to compute the probability that every candidate next token $x_t$ belongs to the desired class, given by
The log prior is encoded with bias parameters $b$. We consider two specific heuristics for using $P$ effectively allowing for the attribute described by $c$ Appendix A. With efficient estimation of $P$ posterior given by the classification signal given by GeDi to guide generation. Our initial heuristic applies a weighted in practice in our experiments but are not necessarily optimal; there are many possible ways to use $P$ model and GeDi share the same tokenization. Heuristics that use be used to guide generation from a (potentially much larger) language model, so long as the language $\omega > 1$ to bias generation more strongly towards the correct class. The right hand side of Equation 6 is normalized over all $x_t$ in the vocabulary to obtain $P_w(x_t|x_{<t}, c)$. While we found that the weighted posterior in Equation 6 is most critical for controlling generation, we also used an additional filtering heuristic beneficial for steering generation more aggressively. This heuristic, inspired by nucleus sampling Holtzman et al., 2020, removes candidate next word tokens with lower values for $P_w(c|x_t, x_{<t})$, while maintaining a minimum of at least $\rho$ in cumulative probability mass in $P_w(x_t|x_{<t}, c)$. We define $V_n$ as the set of $n$ tokens with the highest $P_w(c|x_t, x_{<t})$. We define $m$ as the minimum $n$ such that

$$\sum_{x_t \in V_n} P_w(x_t|x_{<t}, c) \geq \rho$$
We define $V_m$ as $V_n$, for $n = m$, meaning that $V_m$ will contain the minimum number of tokens possible at the head of the distribution for $P_\theta(c|x_1, x_{<t})$ to maintain a minimum cumulative probability of $p$ in $P_u(x_1|x_{<t}, c)$. We define another set of tokens to keep, $V_p \subseteq V$, which maintains all tokens where $P_\theta(c|x_1, x_{<t}) \geq \tau$. The motivation is that if we are acceptably sure that the resulting sequence from generating a token is in the correct class, there is no need to filter it. The final set of tokens to keep are then given by $V_k = V_p \cup V_m$. We then zero out probabilities of tokens not in $V_k$ and re-scale the remaining distribution to sum to 1.

### 3.2 GeDi Training

The previous section presented a method for using a CC-LM as a GeDi to guide the generation of another LM. However, previous work shows that generative classifiers are generally inferior to discriminative ones when trained on large datasets (Ng & Jordan, 2002; Yogatama et al., 2017). For this reason, we propose training CC-LMs discriminatively as classifiers with GeDi training, with the primary goal of making them better discriminators for GeDi-guided generation. We also have a secondary goal of making them better direct generators; a CC-LM that can correctly classify sequences via Equation 5 may be better at generating sequences in the desired class. The idea of discriminatively training class-conditional generative models has previously been considered for classification of text (Yakhnenko et al., 2005), and images (Lasserre et al., 2006).

With GeDi training, we combine the standard generative language modeling loss $L_g$ from Equation 3 with a discriminative loss $L_d$, defined as:

$$L_d = -\frac{1}{N} \sum_{i=1}^{N} \log P_\theta(c^{(i)}|x^{(i)}_{1:T_i})$$

$P_\theta(c^{(i)}|x^{(i)}_{1:T_i})$ is derived from an offline version of Equation 5 given by

$$P_\theta(c^{(i)}|x^{(i)}_{1:T_i}) = \frac{P(c) P_\theta(x^{(i)}_{1:T_i}|c^{(i)})^{\alpha/T_i}}{\sum_{c'} P(c') P_\theta(x^{(i)}_{1:T_i}|c^{(i)})^{\alpha/T_i}}$$

where $c' \in \{c^{(i)}, \bar{c}^{(i)}\}$ for the binary case (where $c^{(i)}$ is the correct class and $\bar{c}^{(i)}$ is the incorrect class for the $i$th sequence), $P(c) = \frac{e^{b_c}}{\sum_{c'} e^{b_{c'}}}$ (where $b_c$ is a learnable class bias which we omit when class distribution is roughly equal), $\alpha$ is a learnable scale parameter, and $P_\theta(x^{(i)}_{1:T_i}|c^{(i)})$ is given by Equation 2 for CC-LMs. The cost function for GeDi training $L_{gd}$ is then given by

$$L_{gd} = \lambda L_g + (1 - \lambda) L_d,$$

where $\lambda$ is a hyper-parameter. In GeDi training, the discriminative loss $L_d$ is aimed at increasing classification accuracy and label fidelity of samples, whereas the generative loss $L_g$ is needed to preserve the fluency of samples, and may help the CC-LM have better calibrated conditional log-probabilities for guided generation.

### 3.3 Multi-class GeDi

Both GeDi-guided generation and GeDi training use CC-LMs to perform classification. The most straightforward way to extend this to many classes is to have one forward pass conditioned on each control code and normalize over a larger number of classes via Equation 5 (which we in fact do for 3-class MNLI in Section 5). However, this approach does not scale well computationally to large numbers of classes. As a solution, we propose reframing each classification task as binary classification using control codes and anti-control codes for each class. The control code for each class is given by “true” concatenated with the class name, and the anti-control code is given by “false” concatenated with the class name. The CC-LM then classifies whether the class name corresponds to the text. For instance, the CC-LM would process the following two sequences in parallel:

<true> <science> T-rex achieved its massive size due to an enormous growth spurt during its adolescent years.

T-rex achieved its massive size due to an enormous growth spurt during its adolescent years.
T-rex achieved its massive size due to an enormous growth spurt during its adolescent years. and would classify it as true or false as to whether the class (in this case “science”) matches the category of the text by using Equation \[9\]. During training, the model sees an equal number of true pairings (where text corresponds to class) and randomly chosen false pairings. After the model has been trained, binary GeDi-guided generation can be applied, using \(c = \text{true}\) and \(\bar{c} = \text{false}\), and using the desired class name as the first token \(x_1\) in the sequence.

4 RELATED WORK

Methods for controlling text generation can be categorized broadly into two types: training a model directly for controllable generation (Keskar et al., 2019; Ficler & Goldberg, 2017; Yu et al., 2017; Hu et al., 2017) or using a discriminator to guide generation (Holtzman et al., 2018; Dathathri et al., 2020). Keskar et al. (2019) train a CC-LM with pre-defined control codes placed as the first token of every sequence. Our approach uses a CC-LM as a discriminator to guide generation—rather than generating from it directly. This is far more computationally efficient than previous methods for guiding generation discriminatively. Holtzman et al. (2018) apply discriminators on top of a beam search, requiring all candidate tokens to be passed through the discriminator, and only allowing a small fraction of candidate next word tokens to be evaluated. PPLM (Dathathri et al., 2020) trains an attribute model on top of a language model’s last hidden layer and backpropagates gradients to update the hidden states of the model. This is computationally intensive, especially when applying to large LMs, because it requires multiple forward and backward passes often going back several timesteps for each generation step. The limiting choice of attribute classifier models for PPLM also means that for harder classification tasks, PPLM’s attribute model may not be able to correctly classify sequences and likely would not be useful for guiding generation.

GeDi also relates to contrastive learning (Smith & Eisner, 2005; Mnih & Teh, 2012). However, most existing contrastive learning methods work at the instance level by discriminating one positive pair from \(k\) negative pairs. Contrastive learning has been used in language modeling mostly as an efficient parameter estimation alternative to the expensive partition function computation that requires summing over an entire vocabulary. In comparison, our method works at the class level and contrasts a positive class-conditional distribution against a negative one. Recent work by Liu & Abbeel (2020) also considers class-conditional generative models along with a discriminative conditional models, and uses energy based models with contrastive partition function estimation, whereas GeDi uses auto-regressive generative modeling and a Bayes class posterior for discrimination. GeDi also uses the contrast between positive and negative distributions for both training (i.e., GeDi training) and inference (i.e., contrastive generation).

5 EXPERIMENTS WITH GEIDI TRAINING

Our initial experiments train and benchmark GeDi-trained CC-LMs for classification, perplexity, and direct generation, in preparation to use them for GeDi-guided generation in Section 6. All our experiments augment GPT2-medium (345M parameter) (Radford et al., 2019) with control codes specific to each task to form a class-conditional language model. We then fine-tune this model on different sequence classification datasets with the hybrid GeDi objective from Equation \[10\].

To understand the trade-offs between generative and discriminative training, we explore \(\lambda\) values between 0 and 1, where \(\lambda = 1\) is equivalent to generative training and is the main baseline for these initial experiments. Once fine-tuned, we decode samples from the model by conditioning on the control code corresponding to the required attribute and prompts from the dev set for each task. We use greedy decoding and a repetition penalty for generation (see Appendix B for details) On each task, we measure the perplexity, classifier accuracy, and label fidelity across all values of \(\lambda\). Our task set consists of:

IMDB (Maas et al., 2011) we test the model’s ability to generate movie reviews with positive and negative sentiment when conditioned on the first \(\sim 100\) characters (up to next word-break after 100 characters) of a review (which may or may not match the control code).
MNLI (Williams et al., 2017) we test the model’s ability to generate contradictions and entailments when conditioned on a premise.

QNLI (Wang et al., 2018) we test the model’s ability to generate passages that contain the answers to a question given in conditioning text.

Controlling the sentiment attribute is a more standard controllable generation task, whereas the two NLI tasks require a greater degree of logical reasoning, potentially making them more difficult. Our experiments were performed using adaptations of Huggingface Transformers (Wolf et al., 2019).

5.1 Evaluation of GeDi-trained CC-LMs

To evaluate the label fidelity of direct generation from GeDi-trained CC-LMs in an automatic manner, we use an external classifier trained on the given task to classify conditionally generated samples. This entails splitting training data sets in half, training the generator model on one half (split A), and the external classifier on the other half (split B). When evaluating the label fidelity of a generator, the generator is given prompts and labels (to be used as control codes) from the validation set to conditionally generate text. The prompt and generated text is then given as input to the classifier, which predicts the label. The label fidelity is then the percentage of the total number of samples for which the predicted classifier label corresponds to the control code that the generator received as input. It is more valid to use a classifier and generator trained on separate splits of the training data because otherwise, both models could fit to the same spurious correlations in the training set and overestimate the label fidelity results. For this external model-based evaluation, we use RoBERTa models (Liu et al., 2019) trained on the respective classification tasks, as we found that it learned significantly stronger classifiers from the half datasets as compared with BERT (Devlin et al., 2018).

We present results for automatic evaluation in Appendix D. The label fidelity, classification accuracy, and perplexity (models conditioned on label as control code) for the 3 tasks are reported in Figures 3, 4 and 5 respectively. As expected, using a higher $\lambda$, which makes training closer to generative training, improves perplexity on held out sequences across tasks. Also as expected, we found that $\lambda < 1.0$, meaning partially discriminative loss/GeDi training is used, improved classification performance across tasks. We also found that using GeDi training led to higher label fidelity for CC-LMs across tasks compared with generative training.

Following up on our automatic-evaluation, we perform human evaluation on the generated MNLI contradictions and entailments to verify the observed label fidelity improvements and test the generation quality of GeDi vs. standard generative training of CC-LMs. For each sample, we ask human annotators to predict the class label and rate the sample for linguistic acceptability. We obtain annotations for 300 generations from each model, with half conditioning on “contradiction” and half conditioning on “entailment”.

Each annotator is randomly assigned a set of samples from all 5 models. Human annotators are asked to classify and rate the linguistic acceptability of samples on a scale from 1-4 (1: highly unacceptable 2: unacceptable 3: acceptable 4: highly acceptable]. Annotators labeled the premise and generated hypothesis pairs as [“contradiction”, “neutral”, “entailment”] (note that since we only generate from “contradiction” and “entailment” control codes, anything marked as “neutral” will count against label fidelity). The results are given in Table 1.

GeDi-trained CC-LMs were able to achieve higher label fidelity as compared with generative trained models without sacrificing noticeably on average linguistic acceptability. These improvements in label fidelity for GeDi training (all $\lambda$s combined) vs. generative training, which were on average 4.9%, were statistically significant by a 2-sample $z$-test to compare sample proportion ($p < 0.01$, 2-tailed). While the quality of the samples and label fidelity across different prompts varied for GeDi vs generative training, these results show that on average GeDi trained models were able to generate samples that matched the label of the control code more often.

6 Experiments using GeDi-guided generation

In these experiments, we use CC-LMs as GeDis to guide generation from GPT-2. As in Section 5, we finetune GPT2-medium (345M param) as a CC-LM using GeDi training with varying values of $\lambda$. However, instead of generating from the LM directly, we use it as a GeDi to guide generation
| Type of training                  | Label fidelity | Linguistic acceptability |
|----------------------------------|----------------|--------------------------|
| CC-LM (λ = 1.0)                  | 75.3%          | 3.21                     |
| GeDi-trained CC-LM (λ = 0.75)    | 81.8%          | 3.24                     |
| GeDi-trained CC-LM (λ = 0.5)     | 80.0%          | 3.17                     |
| GeDi-trained CC-LM (λ = 0.25)    | 80.0%          | 3.25                     |
| GeDi-trained CC-LM (λ = 0.05)    | 79.0%          | 3.11                     |

Table 1: MNLI human evaluation experiments for direct generation from CC-LMs. Label fidelity and linguistic acceptability for human evaluation of samples from generative vs. GeDi training (where λ = 1 is equivalent to generative training, and λ < 1 is GeDi training, meaning a partially discriminative loss is used). GeDi-trained CC-LMs were able to achieve higher label fidelity, meaning that the control code more often corresponded to the annotator class label.

from GPT-2-XL (1.5B param). Our initial experiments are with sentiment control and detoxification, which are both binary tasks. We also use the methods in Section 3.3 to train GeDis for multi-class topic control, and apply this to generate text in new topics zero-shot. We use the same generation hyper-parameters (ω = 30, ρ = 0.2, τ = 0.8) across experiments (except the change noted in Section 6.2 for detoxification), which seemed to work reasonably well across models and tasks in terms of automatic label fidelity and generation quality. As in Section 5 we use greedy decoding and a repetition penalty for generation, with varying prompts to ensure diversity.

In our sentiment experiments, we compare direct generation from CC-LMs vs. using CC-LMs as GeDis. We refer to direct generation simply as “CC-LM” (using λ = 1 to specify generative training and λ < 1 to specify GeDi training), and GeDi-guided generation using a CC-LM to guide GPT-2 as “GeDi-guided” (also using λ to specify generative/GeDi training).

6.1 GUIDING SENTIMENT CONTROL ACROSS DOMAINS

We experiment with GeDi-guided generation from GPT-2 for sentiment control. For these experiments, we reuse the models trained on half of IMDB from Section 5. We noticed that, while direct generation from a GeDi-trained CC-LM could effectively control the sentiment of movie reviews, it struggled to generalize to out-of-domain prompts, and would generally try to convert prompts into movie reviews. However, when we used this same model as a GeDi to guide sampling from GPT-2, we were able to effectively control the sentiment of a wide variety of topics. For instance, in our preliminary experiments we considered the prompt “I just read this paper on Generative-Discriminative training.” in Table 7 and it results in text that mentions well known deep learning ideas and researchers while also controlling sentiment.

To experimentally verify that GeDi can achieve domain transfer of the concepts of “positivity” and “negativity”, we consider a book generation task where we conditionally generate text from the start of book chapters from Bookcorpus (Zhu et al., 2015), where each prompt is at least 150 characters and ends on the first-word break after the minimum length. We run human evaluation on generations from 50 different book prompts from 13 different models; including raw GPT2-XL, and the following models with both positive and negative sentiment: 1. GPT2-XL guided by a GeDi-trained GeDi (λ = 0.6), 2. GPT2-XL guided by a generatively-trained GeDi (λ = 1.0) 3. direct generation from a GeDi-trained CC-LM (λ = 0.6), 4. direct generation from a generatively-trained CC-LM (λ = 1.0) 5. CTRL, and 6. PPLM. See Appendix C for additional information about our PPLM and CTRL baselines. We apply our PPLM baseline on top of GPT2-medium because PPLM with GPT2-XL was prohibitively slow (see Table 6). Applying PPLM with default hyper-parameters on top of GPT2-medium resulted in generation speeds more than 5 times slower than using GeDi to guide GPT2-XL.

Annotators for human evaluation rated the text on sentiment/tone, how book-like the text was, and whether or not the text resembled an Amazon review or movie review (since CTRL was trained on Amazon reviews and GeDi was trained on movie reviews). The results are given in Table 2. Using a GeDi-trained GeDi to guide GPT2-XL was able to strongly control the tone of book text while also generating text rated as book-like as GPT2-XL. Using a generatively trained GeDi also gave very strong sentiment control, but for negative sentiment, the model struggled to generate
Table 2: Human evaluation for sentiment on book text generation (higher sentiment score means more positive sentiment), with key results in bold. We collect annotations on generations from 50 prompts for each model, where prompts from the start of book chapters, and are a minimum of 150 char. We compare using a GeDi to guide GPT2-XL (GeDi-guided), vs. direct class conditional generation (CC-LM). We also compare GeDi trained CC-LMs (λ = 0.6) vs. generatively trained CC-LMs (λ = 1.0) for both types of generation methods, with both positive (pos) and negative (neg) control codes. The GeDi-trained GeDi guide (GeDi-guided-neg (λ = 0.6) and GeDi-guided-pos (λ = 0.6)) was able to reliably control sentiment while maintaining text rated as book-like as GPT2-XL, even though the GeDi was trained on movie reviews. Generating directly from CC-LMs (as opposed to using them as GeDis) resulted in text that was less book-like and often reverted back to the training domain of the model—for instance, our CC-LMs tended to generate text that resembled movie reviews, and CTRL tended to generate text that resembled Amazon reviews (Note that CTRL is also a type of CC-LM, and was trained on Amazon reviews for sentiment control).

6.2 DETOXIFYING GPT-2

With the motivation of detoxifying GPT-2, we train GeDis as a toxicity classifier on the Jigsaw Toxic Comment Classification Challenge Dataset[^3], which contains text samples labeled as “toxic” or “nontoxic”. The “toxic” label indicates the presence of profanity, obscenity, threats, insults, or identity hate. We train models on an even split of toxic and non-toxic examples. We use toxic examples from the Jigsaw dev set to find prompts to condition on for evaluation. We used prompts that ended on a word break and were at least 30 characters. We aimed to have prompts that are not explicitly toxic but may be leaning towards toxic, so we pass candidate prompts through a RoBERTa trained to classify toxicity, and only kept prompts where RoBERTa was less confident about the label. We generate samples from these prompts using GeDi-guided sampling using a GeDi-trained guide (λ = 0.6) and a generatively trained guide (λ = 1.0). We initially found that the GeDi-trained guide would sometimes result in very short samples that cut off mid sentence. Since the GeDi operates discriminatively at the token level, it cannot confidently classify a sequence as non-toxic until the sequence has finished, and as a result, it was causing the model to finish sequences early to ensure they would not become toxic. To fix this problem, we manually added a bias parameter $b_c = 2$ as per Equation[^5] so that the model would have a prior probability that assumes the sequence is non-toxic. We found doing this also required us to increase $\tau$ to 0.97 to account for $P(c|x_{1:t})$ being higher with the bias parameter, since otherwise far fewer tokens would be filtered and samples could become toxic. All other hyper-parameters remained unchanged.

[^3]: https://www.kaggle.com/c/jigsaw-toxic-comment-classification-challenge/
Model Toxicity Linguistic acceptability
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GPT2-XL 1.45 3.23
GeDi-guided ($\lambda = 0.6$) 1.17 3.44
GeDi-guided ($\lambda = 1.0$) 1.13 3.25

Table 3: Average toxicity (reported on a scale of 1-3, where higher is more toxic) and linguistic acceptability scores (reported on a scale of 1-4, where higher is linguistically more acceptable) for 100 samples for each model. Both the GeDi-trained GeDi guide ($\lambda = 0.6$) and generatively-trained GeDi guide ($\lambda = 1.0$) resulted in significantly less toxic text as compared with GPT2-XL while maintaining equal or greater linguistic acceptability.

Figure 2: Label fidelity (computed automatically using RoBERTa classifier) for topic generation on AG news for GeDi-guided generation with different values of $\lambda$ ($\lambda = 1$ is generative training). The generatively-trained guide scored noticeably lower on label fidelity as compared with the GeDi-trained guides.

We run human evaluation to measure toxicity and linguistic acceptability (using the same scale as in Section 5 for MNLI human eval) vs. GPT-2. For toxicity, annotators rated samples as [1-non-toxic, 2-mildly-toxic, 3-toxic] Results are given in Table 3. GeDi-guided generation resulted in significantly less toxic text for both values of $\lambda$. The GeDi-trained GeDi guide ($\lambda = 0.6$) achieved the highest linguistic acceptability of all models, and this improvement vs. GPT2-XL was bordering on statistical significance by a Wilcoxon signed rank test (p=0.05, 2-tailed). We also observe that our detoxifier GeDi can in some cases navigate especially difficult and aggressive prompts as shown in Appendix E.3.

6.3 MULTI-CLASS TOPIC CONTROL

We apply the methods in Section 5.3 to train GeDis to model larger numbers of topics. We use the AG news topic classification data set (Zhang et al., 2015) which has 4 topics (World, Sports, Business, and Science/Tech), and train GeDis by concatenating “True” and “False” with topic names to create control codes and anti control codes for each topic. The GeDi is trained to classify whether the text and topic control code match. We trained GeDis with 6 values of $\lambda$ (including $\lambda = 1$), starting from GPT2-medium as in the previous sections. As in Section 5, we only train the CC-LMs on half of the dataset, and train a RoBERTa classifier on the other half to measure label fidelity. After training, we applied each GeDi to guide generation from GPT2-XL. We use minimum 50 character prompts from the multi-news dataset (Fabbri et al., 2019) to condition on for generation. The prompt often will not fit with the desired news topic, sometimes creating a challenge for the model to relate the article to the desired topic. We measured automatic label fidelity first as given by the RoBERTa classifier, as given in Figure 2.

We found the generatively trained GeDi guide ($\lambda = 1$) achieved a significantly lower automatic label fidelity, suggesting that GeDi-training may be important for extending GeDi-guided generation to many control codes using the proposed binarization method. We ran human evaluation on samples from the 4 news topics comparing our strongest GeDi guide (based on automatic label fidelity), and raw GPT2-XL. Annotators were given the topic and asked to rate samples on topic relevance and linguistic acceptability. The results are given in Table 4. GeDi-guided generation gave text with a
Table 4: Average topic relevance (reported on a scale of 1-5, where higher is more relevant) and linguistic acceptability scores (reported on a scale of 1-4, where higher is linguistically more acceptable) for 100 samples for each model for each of the four topics Business, Science/Tech, Sports, World. GeDi was able to control topic while maintaining a similar level of linguistic acceptability to GPT-2. The GeDi guide was trained on AG-news using GeDi training ($\lambda = 0.8$).

Table 5: GeDi-guided generation conditioned on topic “world”. **Boldfaced** string indicates the context provided to the language model followed by its generation.

## 6.4 Zero-shot control codes

The topic GeDi from the previous section used the words “true” and “false” as control codes and anti control codes respectively, concatenated with the words “world”, “sports”, “business”, and “science” as input to the GeDi (as described in Section 3.3). However, any word could potentially be used as input place of these topic words to make a new control code and anti control code. We observed that the GeDi, trained for only several hours on a single GPU on 4 topics, could guide GPT-2 towards generating text corresponding to a very wide array of topics that included “space”, “history”, “education”, “cars”, “climate” and many more. This zero-shot behavior worked very well for short, topic neutral prompts, as shown for the prompt “In a shocking finding” in Appendix E.4, but did not work as well for longer prompts. We also only tested topics that could be encoded with 1 byte-pair encoding (Sennrich et al., 2015) token, since this was the case for all our training topics. However, this zero-shot behavior could likely apply to longer control codes if trained on longer control codes. We also compare with zero-shot topic generation using CTRL in Table 21 as a baseline, and find that despite being trained on significantly more topics and data, CTRL struggles to generate text about control codes it has never seen before. This suggests that zero-shot topic generation is much stronger with GeDi-guided generation than with direct generation from CC-LMs.

GeDi’s ability to generalize to new control codes zero-shot gives the ability to generate text corresponding to many topics and subtopics. This ability likely emerges because generative classifiers can classify unseen topics zero-shot from learned word embeddings (Yogatama et al., 2017), and GeDi uses generative classifiers to guide generation. This is another advantage of GeDi over previous discriminator guided generation approaches, in addition to the major computational efficiency gains mentioned in Section 3.1 and the controllability gains shown in Section 6.1.
7 Future work

These experiments were designed to develop and test the GeDi algorithm, and thus we consider a small scale throughout our paper (Our longest training runs were the GeDis trained on IMDB, which each took around half a day to train on a single 16GB V100 GPU). A promising next step is scaling GeDi up to longer and larger numbers of control codes via the methods in Section 3.3. Such a model could potentially condition on longer zero-shot control codes, and maybe even text descriptions, to allow for controllable generation of very specific attributes. Another approach to more finegrained control could combine multiple GeDi discriminators to control more than one attribute. GeDis could also add control to generation from very large language models (so long as tokenization is shared), and since the GeDi can potentially be much smaller, this would be significantly cheaper than finetuning the large language model directly.

Training GeDis to distinguish real text vs. generated text could potentially allow them to guide models towards more realistic generations. Taking this one step further, GeDi’s online classification trick [Section 3.1] to efficiently compute \( p(y|x_t, x_{<t}) \) for every candidate next token \( x_t \) could provide a stronger reward signal for REINFORCE [Williams 1992] policy gradient based methods that rely on a discriminator for a reward signal for a generator, as is the case for generative adversarial networks [Goodfellow et al. 2014] in the language generation domain [Yu et al. 2017; Fedus et al., 2018].

GeDi could also be extended to constrained forms of text generation, such as summarization, translation or dialog, where the ability to control sentiment or factual correctness would be useful. Beyond NLP, GeDi could be useful for controlling aspects of auto-regressive generation in other domains such as image generation, music generation or protein engineering.

8 Conclusion

We present GeDi as an approach for controllable generation that uses generative discriminators to efficiently classify candidate next tokens on the fly during inference, making it far more computationally efficient than previous discriminator guided generation approaches. We show that GeDi achieves sentiment and topic control, detoxification of GPT-2, cross-domain attribute transfer, and zero-shot generalization to new control codes. This work moves towards unifying natural language generation with classification, and suggests that we may be able to efficiently generate text that corresponds to any attribute that we can accurately classify. This could have broad implications towards improving text generation systems.

Author Contributions

Ben thought of the main ideas and designed the research. Ben and Akhilesh coded the implementation. Akhilesh maintained the codebase, set up automatic and human evaluation experiments, and organized results. Nazneen advised on detoxification experiments. All authors contributed to writing and discussions.

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A  **GEĐI WITH LOG PROBABILITIES**

GeDi-guided generation and GeDi training both use language models discriminatively via Bayes rule by using

\[ P_\theta(c|x_{1:T}) = \frac{P(c) P_\theta(x_{1:T}|c)^{\alpha/T}}{\sum_{c'} P(c') P_\theta(x_{1:T}|c')^{\alpha/T}} \]  

where

\[ P(c) = \frac{e^{b_c}}{\sum_{c'} e^{b_{c'}}}. \]  

For GeDi-guided generation, this is computed online for partial sequences during generation, whereas for GeDi training, it is computed for full training sequences. For numerical stability, we compute this using log-probabilities. Log-probabilities for each class are given by

\[ \log P_\theta(x_{1:T}|c) = \sum_{t=1}^T \log P_\theta(x_t|x_{<t}, c) \]  

and the class probability is given by

\[ P_\theta(c|x_{1:T}) = \frac{e^{(b_c + (\alpha/T) \log P_\theta(x_{1:T}|c))}}{\sum_{c'} e^{(b_{c'} + (\alpha/T) \log P_\theta(x_{1:T}|c'))}} \]

This can be computed in a numerically stable way using a softmax (Bridle [1990]), since the maximum logit to the softmax can be subtracted out before taking the exponent without changing the result. For the two class case (all of our experiments except for MNLI, which was 3-class), \( c' \in c, \bar{c} \), meaning that the above equation could have been equivalently computed using a sigmoid of the difference of the logs of the two terms in the denominator sum (but our implementation used softmax as above).

B  **GENERATION SETTINGS**

When comparing the quality of samples from different language models, there is a trade-off between quality and diversity; models that tend to have more sharply peaked distributions for \( P_\theta(x_t|x_{<t}, c) \) will tend to have higher quality samples, but will also have less diversity. In order to avoid having to control for this trade-off, we only use greedy sampling, meaning we always pick the most likely token in the model’s predictive distribution. With greedy decoding, the model would generate the same text sequence every time without any conditioning text. Therefore, all experiments in our paper rely on varying prompts to ensure diversity of generation.

We also apply a repetition penalty (Keskar et al., 2019), which we found improved the overall quality of samples across tasks. A repetition penalty penalizes the model from generating tokens that appeared in the sequence history. We used a repetition penalty of 1.2 for most experiments (1 is normal generation), except for MNLI where we used 1.5 after observing some instances of degenerate text. All of our later experiments in Section B also re-scaled logits to ensure they were positive, which was necessary for combining log-probabilities for GeDi-guided sampling, which makes logits negative (We compute the posterior in Equation 6 by taking the log of both sides, adding the LM log-probabilities to the next token class log-probabilities, and re-normalizing with a softmax over the vocabulary). For GeDi-guided generation, the rescaling and repetition penalty was applied to the final distribution after all heuristics described in Section 3.1.

C  **BOOK SENTIMENT ADDITIONAL DETAILS**

C.1  **GENERATION SPEEDS**

We compare the generation speeds of GPT-2 vs. discriminator guided methods for sampling from GPT-2. We find that guiding GPT-2 with GeDi is significantly faster than with PPLM. PPLM requires several forward and backward passes (we use 3, Dathathri et al. (2020) suggest 3-10) per
| Model                            | Generation speed (sec/token) |
|---------------------------------|------------------------------|
| GPT2-XL                         | 0.060                        |
| GeDi-guided + (GPT2-XL)         | 0.095                        |
| PPLM + (GPT2-medium)            | 0.55                         |
| PPLM + (GPT2-XL)                | 1.12                         |

Table 6: Average generation time in tokens per second for generating sequences of length 256.

generation step, resulting in significantly slower generation that scales poorly with larger models. In GeDi, the forward pass in the discriminative guide (the GeDi) and the generator (GPT2-XL) are independently computed, meaning that a smaller GeDi can guide a larger LM (as long as tokenization is shared) with only a constant amount of extra computation that does not depend on the size of the generator LM.

C.2 Baseline details for PPLM

For PPLM, we trained the external classifier (which uses logistic regression on top of GPT-2) on the same half-split of IMDB that we used to train our GeDi. We had significant issues with degenerate text with PPLM using the default settings, so we applied a hyper-parameter sweep over learning rates and scaling coefficient ($\gamma$ from Equation 3 from Dathathri et al. (2020)) with the goal of finding the highest learning rate (and therefore strongest attribute control) that did not lead to degenerate text. We swept over learning rates in the range \{0.04, 0.01, 0.003, 0.001, 0.0005\} and scaling coefficients in the range \{0.8, 1.2, 1.6, 2.0\}. We chose a learning rate of 0.001 and a scaling coefficient of 0.8; we found that higher learning rates led to frequent degeneration for all values of the scaling coefficient. Our learning rate for PPLM was much lower than the learning rate used for experiments in Dathathri et al. (2020). The reason for this could potentially be due to the difference in data set for the attribute classifier (IMDB vs. SST-5), or the longer prompts used in our experiments.

C.3 Baseline details for CTRL

For CTRL, we prepended prompts with the control codes for positive and negative Amazon reviews, which are “Reviews Rating: 1.0” and “Reviews Rating: 5.0” for negative and positive respectively. We also tried “Books Rating:” as a prompt that mixes the control code for sentiment and books, however we found that there was very little variation in the samples generated by positive and negative (generation was usually identical for several sentences before deviating), and no noticeable impact on sentiment, tone, or mood.
**D GeDI Training Automatic Evaluation Results**

![Bar charts showing label fidelity for IMDB, MNLI, and QNLI datasets for varying values of $\lambda$.](chart1.png)

Figure 3: Label fidelity of class-conditional generation for generatively-trained CC-LMs (Gen), and GeDi-trained CC-LMs (GeDi) for varying values of $\lambda$. We observe that GeDi training improves label fidelity.

![Bar charts showing classification accuracy for IMDB, MNLI, and QNLI datasets for varying values of $\lambda$.](chart2.png)

Figure 4: Classification accuracy of generatively-trained CC-LMs (Gen), and GeDi-trained CC-LMs (GeDi) for varying values of $\lambda$, trained on a half split of each dataset. We observe that GeDi training improves classification accuracy.

![Bar charts showing conditional language modeling perplexity for IMDB, MNLI, and QNLI datasets for varying values of $\lambda$.](chart3.png)

Figure 5: Conditional language modeling perplexity (lower is better) for generatively-trained CC-LMs (Gen), and GeDi-trained CC-LMs (GeDi) for varying values of $\lambda$. Models measure perplexity of held out sequences conditioning on the ground truth label as a control code. Reducing $\lambda$ and therefore making the loss more discriminative and less generative tends to hurt perplexity.
E Generation Samples

E.1 Sentiment/Tone Samples

| Model                  | GeDi-guided generation                                                                 |
|------------------------|----------------------------------------------------------------------------------------|
| GeDi-guided (negative) | I just read this paper on Generative-Discriminative training. What does this have to do with neural nets? Here’s the abstract from the paper: A recent theoretical proposal suggests that generative adversarial networks (GANs) may outperform discriminative ones. We investigate whether GANs are robust against class membership bias in two-step regression tasks using data generated from three independent datasets of handwritten digits and digits generated from digit sets obtained from word2vec and CART algorithms. We demonstrate that GANs perform significantly better than discriminative classification when tested against two independent datasets of handwritten digits and digits generated from word2vec or CART algorithms, but fail to distinguish correct pairs when tested against one or no datasets. Our results indicate that both discriminativization methods suffer because of poor parameter estimation for GAN models trained with low sample counts on samples drawn solely from one dataset. |
| GeDi-guided (positive) | I just read this paper on Generative-Discriminative training. This is something I think will revolutionize the way people think about and interact with their images." "This is a really cool paper, and it’s very well done," said Andrew Ng, a professor of computer science at Stanford University who has been working on deep learning for more than two decades. "It’s not clear to me that there are any practical applications yet." Ng added that he was impressed by the authors’ ability to use generative models in such an elegant way without sacrificing accuracy or performance. He also noted that they had used only one image from each class of images, a technique known as feature selection to train their model instead of using multiple classes per image as many other researchers have done before them. Ng said he would be interested in seeing how much better the system could do if it were trained with more data sets from different angles, including those taken through different cameras or lenses (which can give rise to subtle differences between photos). |

Table 7: Controlling the sentiment/tone of generation with GeDi. **Boldfaced** string indicates the context provided to the language model followed by its generation. This particular set of samples was from our preliminary experiments, which used the word “positive” as the negative control code and the word “negative” as the positive control code. We later found that using words that correspond to the actual attributes can be helpful due to semantic information in pretrained word embeddings from GPT-2, so we swapped this for all other experiments and samples in the paper.

| Model                  | GeDi-guided generation                                                                 |
|------------------------|----------------------------------------------------------------------------------------|
| GeDi-guided (negative) | In a shocking finding that shows just how little regard they have for the public interest, it appears the Department for Education is using taxpayer money to promote an anti-science campaign. The department’s "Science of Learning" website promotes pseudoscientific and unscientific claims such as "The human brain has a built-in memory bank". This claim is contradicted by numerous studies which have found no such thing. Furthermore, this claim contradicts scientific knowledge that suggests that there is no way to retrieve specific memories from the human brain. |
| GeDi-guided (positive) | In a shocking finding published today in Nature Genetics, we have identified two new gene families within the X-chromosome which play an important role in regulating brain development and neurogenesis. This research provides a unique perspective on the evolution of our brains and how they change throughout life, providing insights into how brain function is regulated by epigenetics as well as by genetics. |

Table 8: Controlling the sentiment/tone of generation with GeDi. **Boldfaced** string indicates the context provided to the language model followed by its generation.
“Hello, Jennifer, Bella. Tracy said. “Thanks so much for coming in. She dragged another chair out to the front of her desk and motioned for us all to sit down while she made herself some coffee. “What’s wrong? What happened?” “You’re being rude!” Amy shouted from the kitchen across the room at Tracy and Bella, whose backs were turned in disgust on me as they worked away at their food with barely any regard for either their customers or themselves!”

“Hello, Jennifer, Bella. Tracy said. “Thanks so much for coming in. She dragged another chair out to the front of her desk and motioned for us all to sit down on it while she made herself some coffee. What do you want? I can’t tell you! You’re not my boss! “You’ve got me there.” “And what are you?” “Oh, nothing,” said Tracy sardonically, reaching under her desk with a long plastic fork and plucking out two tiny pieces of bacon-flavored cheese-covered dough covered in mustard that were about as appetizing as an unmade lasagna dinner from McDonald’s (and maybe less healthy). She then proceeded to dump them on our table while simultaneously trying to shove a giant tub of melted cheese down our throats with a spatula like we were some kind of starving caveman who needed help eating because we’d eaten too much pizza instead (which wasn’t even remotely possible since they had pizza rolls). We sat there staring at the pile of grease-covered garbage for what felt like minutes before someone finally decided enough was enough by throwing their tray across the room into Tracy’s trashcan which promptly fell onto one another until it hit something hard that sounded like an air conditioning vent or something because no one could figure out how this whole thing was supposed to work anyway so why bother? This continued throughout the entire time she was making coffee; if this had been your family Thanksgiving dinner then you’d be lucky if any food survived past three minutes before falling through your floorboards (which would also explain why she couldn’t find anything else worth throwing at us besides grease soaked trash bags filled with rotting meat scraps). The only good thing about the entire experience was probably those damn chocolate milk floats though... *sigh* –Alexey Vlasov

Table 9: Controlling the sentiment/tone of generation with GeDi. **Boldfaced** string indicates the context provided to the language model followed by its generation using a GeDi discriminator with different $\lambda$s (from Equation [10]).
Table 10: Controlling the sentiment/tone of generation with GeDi and CC-LMs. Boldfaced string indicates the context provided to the language model followed by its generation with different λ values.

| Model                | Generation                                                                 |
|----------------------|-----------------------------------------------------------------------------|
| GeDi-guided (λ = 1.00) (positive) | “Hello, Jennifer, Bella. Tracy said. “Thanks so much for coming in. She dragged another chair out to the front of her desk and motioned for us all to sit as she took out a small notebook from her bag and began to write with pen and ink. It’s been a long week here in New York City, I told her as we settled in at my apartment on West 23rd street after our meeting at The Plaza hotel that morning. The weather was nice but cold; very windy even though it was still spring like this time of year the first time I had lived here since moving home when I was eight years old from Chicago three years ago now... It felt good to be back home again.’ We both smiled warmly as she spoke about living here now and how it felt being able to see each other every day again after so many years away! This is the first time we have been back together since my husband died last summer, but it feels great that he is with us every day; his presence always gives me strength whenever I’m feeling down or need something extra. |
| GeDi trained CC-LM (λ = 0.60) (negative) | “Hello, Jennifer, Bella. Tracy said. “Thanks so much for coming in. She dragged another chair out to the front of her desk and motioned for us all to sit down.<br />I’m sorry I couldn’t get a better seat than this one.<br />It’s a very bad movie! It’s not even funny!<br />It’s just awful!<br >/br />The acting is terrible and the plot is ridiculous...and that was before we even saw any of the characters!!!<br />I can’t believe they made this movie!! |
| CC-LM (λ = 1.00) (negative) | “Hello, Jennifer, Bella. Tracy said. “Thanks so much for coming in. She dragged another chair out to the front of her desk and motioned for us all to sit down.<br />I’m sorry I couldn’t get a better seat.<br />This is one of those movies that you can watch over and over again without ever getting bored or annoyed by it. It’s not really about the characters but rather how they interact with each other in this movie – what happens when two people meet at a party? what happens when they go on vacation together? how do we make friends while traveling alone? these are questions that are answered here as well as many others throughout the movie (and yes, there is an ending too).<br />The acting was good enough but nothing special – just average at best. |
| Model                  | Generation                                                                                                                                                                                                 |
|-----------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| GeDi trained CC-LM    | “Hello, Jennifer, Bella. Tracy said. “Thanks so much for coming in. She dragged another chair out to the front of her desk and motioned for us all to sit down."<br/>I’m glad you’re having a good day!"<br/>"I’ve been thinking about this movie since I saw it at the theater last night...and I can’t believe how many people have commented on how bad it is!"<br/>"It’s not that bad; it’s just that there are so many things wrong with this movie - and they’re all my fault."<br/>"<br/>An enchanting story line, great cast (especially Jennifer Aniston), excellent direction by Michael Caine (who directed me once before) and a great script by John Ritter. |
| (λ = 0.60) (positive) |                                                                                                                                                                                                          |
| CC-LM                 | “Hello, Jennifer, Bella. Tracy said. “Thanks so much for coming in. She dragged another chair out to the front of her desk and motioned for us all to sit down."<br/>I’ve been looking forward to this movie since I saw it on tv last night...and I can’t believe that it’s only been available on video in the UK since ‘73!"<br/>“It’s a great film about two young women who are both very talented and very lonely at the same time - but they have something special going for them: their friendship."<br/>"The acting is excellent - especially from Jennifer Aniston as Lisa; she really brings this character into life."<br/>"Besides her performance, there are some other memorable moments too: when Lisa tells Jenny how much she misses him (she says ‘‘you don’t miss me like that’’), when he asks if he can come over here with his girlfriend (he says ‘‘sure’’), and even when they go back home after work together..."<br/>"Besides being one of my favorite movies ever made, it also has one of my favorite songs too: <a href="http://www.myspace.com/jenniferaniston" target="_blank" rel="nofollow"> http://www.myspace.com/jenniferaniston</a>" |
| (λ = 1.00) (positive) |                                                                                                                                                                                                          |
| GPT-2                 | “Hello, Jennifer, Bella. Tracy said. “Thanks so much for coming in. She dragged another chair out to the front of her desk and motioned for us all to sit down. "<br/>I believe you’re having a good day!"<br/>"I’ve been looking forward to this movie since I saw it at the theater last night...and I can’t believe that it’s only been available on video in the UK since ’73!"<br/>“It’s a great film about two young women who are both very talented and very lonely at the same time - but they have something special going for them: their friendship."<br/>"The acting is excellent - especially from Jennifer Aniston as Lisa; she really brings this character into life."<br/>"Besides her performance, there are some other memorable moments too: when Lisa tells Jenny how much she misses him (she says ‘‘you don’t miss me like that’’), when he asks if he can come over here with his girlfriend (he says ‘‘sure’’), and even when they go back home after work together..."<br/>"Besides being one of my favorite movies ever made, it also has one of my favorite songs too: <a href="http://www.myspace.com/jenniferaniston" target="_blank" rel="nofollow"> http://www.myspace.com/jenniferaniston</a>" |

Table 11: Controlling the sentiment/tone of generation with CC-LMs and GPT-2. **Boldfaced string** indicates the context provided to the language model followed by its generation with different λs.
“Hello, Jennifer, Bella. Tracy said. "Thanks so much for coming in. She dragged another chair out to the front of her desk and motioned for us all over there at once to sit down as well. I sat on one of my chairs next to a woman who was sitting with two other women; she had long black hair that fell past her shoulders and wore an orange shirt underneath it. Her eyes were closed but they seemed very focused upon me when we looked up into them from behind their glasses. The first thing you notice about this person is how tall she is: almost six feet three inches or more! It’s not like anyone else here has ever seen someone taller than herself before but then again, no-one really knows what height means anyway... So let him tell his story He started by saying he’d been working late last night while watching TV (he didn) because “when everyone did have some time around 6’ s 5, 4. 3 years ago was just wanted something funny’s 2 bein g t o r e d b y m i n h u lt -e v ed w/o f p er ci ngers.” His wife got home early after work earlier today due to they went back inside later tonight." This man also worked hard during those days too," says Linda And now if only these people would stop talking!" As soon enough our conversation turned to business matters which included things such important issues concerning children being raised properly—and even though many parents are concerned about whether kids will learn better behavior skills through education alone rather simply having good parenting practices implemented instead of teaching everything together—the young lady began telling stories where both boys & girls talked loudly without any problems whatsoever until finally asking why none of them could talk anymore? Well... she explained..."Because every child needs attention," said Mr. Bella:" But since most of your friends don’t want to hear anything except loud noises?" asked Ms. Jennifer, who stood right beside each girl holding onto either side of her hand tightly held firmly between theirs"I think maybe its best never listen to anybody unless absolutely necessary.""But isn’t true sometimes adults can get upset easily""She continued ""It seems odd considering society does seem to encourage quietness among humans especially nowadays-" Said Mrs., Linda" And yet somehow despite living under constant stressors including war, poverty

| Model          | Generation                                                                 |
|----------------|----------------------------------------------------------------------------|
| PPLM (negative)| 21 “Hello, Jennifer, Bella. Tracy said. “Thanks so much for coming in. She dragged another chair out to the front of her desk and motioned for us all over there at once to sit down as well. I sat on one of my chairs next to a woman who was sitting with two other women; she had long black hair that fell past her shoulders and wore an orange shirt underneath it. Her eyes were closed but they seemed very focused upon me when we looked up into them from behind their glasses. The first thing you notice about this person is how tall she is: almost six feet three inches or more! It’s not like anyone else here has ever seen someone taller than herself before but then again, no-one really knows what height means anyway... So let him tell his story He started by saying he’d been working late last night while watching TV (he didn) because “when everyone did have some time around 6’ s 5, 4. 3 years ago was just wanted something funny’s 2 bein g t o r e d b y m i n h u lt -e v ed w/o f p er ci ngers.” His wife got home early after work earlier today due to they went back inside later tonight." This man also worked hard during those days too," says Linda And now if only these people would stop talking!" As soon enough our conversation turned to business matters which included things such important issues concerning children being raised properly—and even though many parents are concerned about whether kids will learn better behavior skills through education alone rather simply having good parenting practices implemented instead of teaching everything together—the young lady began telling stories where both boys & girls talked loudly without any problems whatsoever until finally asking why none of them could talk anymore? Well... she explained..."Because every child needs attention," said Mr. Bella:" But since most of your friends don’t want to hear anything except loud noises?" asked Ms. Jennifer, who stood right beside each girl holding onto either side of her hand tightly held firmly between theirs"I think maybe its best never listen to anybody unless absolutely necessary.""But isn’t true sometimes adults can get upset easily""She continued ""It seems odd considering society does seem to encourage quietness among humans especially nowadays-" Said Mrs., Linda" And yet somehow despite living under constant stressors including war, poverty |
| PPLM (positive)| 21 “Hello, Jennifer, Bella. Tracy said. “Thanks so much for coming in. She dragged another chair out to the front of her desk and motioned for us all not just me but everyone else on our team to sit down as well. I sat at my computer with a smile that was almost infectious; it felt like we were having fun together again. We had been working hard since then because she wanted to make sure everything went smoothly between us before moving forward into what would be an exciting week ahead. The “I This is this new thing you are going up by your family’s wedding day! It has become very important now.” He looked over his shoulder towards where he’d left off earlier today when they got back from their trip through town after dinner last night...and there wasn’t anything wrong about how things worked around here tonight? That meant something big happened right away - or rather: nothing really changed except maybe some people started getting married later than usual due parties’ schedules being different (which didn’t have any sort of trouble finding each other stuff done during those days without him doing business while others did work which could get them involved more often enough if needed help too... But even though most couples don’t go home early every year anyway, sometimes times these two weeks ago can still happen. So why do families always need time apart? Why does everybody want one person who doesn’t know anyone who lives next door-to stay longer/goes place alone until someone comes along side only once per month...or goes somewhere special occasion.. And yet no matter whether its usually happens within 2 months long period(like many years past couple will never ever see somebody come across country outside city center first date same way housewife gets invited inside room late evening party also stays close friends group members staying near friendlier places etc.) |

Table 12: Controlling the sentiment/tone of generation with PPLM. Boldfaced string indicates the context provided to the language model followed by its generation with different λs.
“Hello, Jennifer, Bella. Tracy said. “Thanks so much for coming in. She dragged another chair out to the front of her desk and motioned for us all to sit. I sat down in one of the chairs and she sat in another. We were all staring at her. Her hair was a mess from her morning shower. She looked like she had just gotten out of bed. Her eyes were red as if she had been crying. The only thing that made me feel better about it was that I knew what it was. It wasn’t my hair. It wasn’t my eyes. It was something else. Something very wrong. But who could tell what it was? Who could tell if this woman really loved me? Or maybe even cared about me? Maybe even wanted me? I don’t know how you can be so sure its not your hair, said Tracy. You look like you’ve been crying. Tracy took a deep breath. I’m going to go get some ice water. I’ll be right back, said Jennifer. I need ice water badly. Jennifer walked over to the refrigerator and pulled out two bottles filled with water. She poured them into glasses and handed them over. They both drank them. Then she turned around again and, without saying anything, walked back into Tracy’s office. When we got back home, we told our parents everything. They didn’t believe us. They thought we’d gone crazy. But when they saw Tracy, their faces changed completely. Their eyes grew wide. And then their mouths dropped open. What are you doing here? asked Tracy. She doesn’t want us back? We can’t do anything without her. That’s not true. But why not? Because you’re going back. And that’s why. She’s gone. She is right. That isn’t enough. That’s right! He went away. That’s right. He said, pointing at me. He pointed his finger up towards me. His finger. The last night is over he pointed his finger. Last night, but he’s gone. He’s gone. I’m sorry! You have fun nights. The next day after him. A few days later, he went by an hour later on Friday morning. The next day, he came back.

| Model   | Generation                                                                 |
|---------|-----------------------------------------------------------------------------|
| CTRL (negative) | “Hello, Jennifer, Bella. Tracy said. “Thanks so much for coming in. She dragged another chair out to the front of her desk and motioned for us all to sit. I sat down in one of the chairs and she sat in another. We were all staring at her. Her hair was a mess from her morning shower. She looked like she had just gotten out of bed. Her eyes were red as if they had been crying. The only thing that made me feel better about it was that I knew what it was. It wasn’t my hair. It wasn’t my eyes. It was something else. Something very wrong. But who could tell what it was? Who could tell if this woman really loved me? Or maybe even cared about me? Maybe even wanted me? I don’t know how you can be so sure it’s not your hair, said Tracy. You look like you’ve been crying. Tracy took a deep breath. I’m going to go get some ice water. I’ll be right back, said Jennifer. I need ice water badly. Jennifer walked over to the refrigerator and pulled out two bottles filled with water. She poured them into glasses and handed them over. They both drank them. Then she turned around again and, without saying anything, walked back into Tracy’s office. When we got back home, we told our parents everything. They didn’t believe us. They thought we’d gone crazy. But when they saw Tracy, their faces changed completely. Their eyes grew wide. And then their mouths dropped open. What are you doing here? asked Tracy. She doesn’t want us back? We can’t do anything without her. That’s not true. But why not? Because you’re going back. And that’s why. She’s gone. She is right. That isn’t enough. That’s right! He went away. That’s right. He said, pointing at me. He pointed his finger up towards me. His finger. The last night is over he pointed his finger. Last night, but he’s gone. He’s gone. I’m sorry! You have fun nights. The next day after him. A few days later, he went by an hour later on Friday morning. The next day, he came back. |
| CTRL (positive) | “Hello, Jennifer, Bella. Tracy said. “Thanks so much for coming in. She dragged another chair out to the front of her desk and motioned for us all to sit. I sat down in one of the chairs and she sat in another. We were all staring at her. Her hair was a mess from her morning shower. She looked like she had just gotten out of bed. Her eyes were red as if they had been crying. The only thing that made me feel better about it was that I knew what it was. It wasn’t my fault. It wasn’t my fault. But now here we are, sitting here, talking about how bad things were. How could this be happening again? What did you do to make your life so miserable? Why didn’t you tell me? Why didn’t you try harder or talk more with me? You never told me. You never tried harder. And now here we are, sitting here, talking about it. Tracy, why don’t you tell me what happened? What happened between you? Did anything happen? Did anything ever happen between us? Because I’m not going to. I’m not going to. If you’re telling me, then it’s because something happened. Something bad. Something really bad. And if you’re not, then it’s because nothing happened. Nothing ever happened between us. So why are we here? What’s wrong with us? Is there something wrong with our relationship? Are we in trouble? Is there something wrong? Is there Tracy stopped herself before she said anything more. I don’t know. It’s just I can’t explain it. It’s too much. I’ve been thinking a lot lately. Too much. She looked up at me. You know what’s wrong. You’re right. There’s something wrong.

Score: Tracy. She’s looking back up. I’m sorry. He looks over towards her. But there’s no longer there. He turned around. His face still facing him. They both look away. He’s looking right now. His face. What happened. A man who has come over. The man came into his way. He walked over him again. This time he turned. There he saw them. Both men have seen them both. They both hands on their faces. One by his head together. Then they went straight back. |

Table 13: Controlling the sentiment/tone of generation with CTRL. Boldfaced string indicates the context provided to the language model followed by its generation with different λs.
CTRL (negative)

Simmons didn’t know what to make of the sound he’d heard in Herb’s voice. He’d tried to cover it, but Simmons had heard something that wasn’t like any other sound. It was a voice he couldn’t quite place. He could tell if there were such a thing as an alien race, they would have developed their own language. And so did he. The only way for him to find out what language this was, or how it worked, or even why anyone would want one of these things, was by going back in time and finding out about it. So he went back in time, and found himself on the planet Earth. And then his ship crashed. And when he woke up, all his memories were gone. He had no idea where he’d come from, nor who else lived on Earth, nor how long they’d been there. But now he’s here, with no memory at all. Except for one thing. His name. John Scalzi. That’s it. I don’t think I’ve ever read anything more depressing than this. It’s almost too depressing. If you can get past that, though, it’s actually pretty good. The characters are interesting, though some are just plain annoying. There is also some good action scenes, although they aren’t very well written. This book is definitely worth reading, but be prepared for some really depressing stuff.

Rating: 4.0
Rating: 4.0

I enjoyed this book. It has many twists & turns which kept me guessing until the end. A great read. Looking forward to reading more from this author. Thank you. :)

GeDi trained CC-LM 0.60 (negative)

Simmons didn’t know what to make of the sound he’d heard in Herb’s voice. He’d tried to cover it, but Simmons had heard something that sounded like a man talking. And then there was this:<br />

a woman is having trouble sleeping at her husband’s house because she can’t get enough sleep; she has an affair with his brother-in-law (who happens to be her lover); and when the husband finds out about it, he takes matters into his own hands.<br />

Heinlein had been writing his own stories for years before this one came along. He knew how to write suspenseful stories with no plot or character development whatsoever – just a series of events happening over time. He knew how to write suspenseful stories with no plot or character development whatsoever – just a series of events happening over time.

The story is about an old man who has lost his wife and two children in the plane crash that killed their parents on board the airplane they were on (it was supposed to be a funeral). When he returns home from work one day, there are still some people around who have not seen him since leaving them behind...<br />

CC-LM 1.00 (negative)

Simmons didn’t know what to make of the sound he’d heard in Herb’s voice. He’d tried to cover it, but Simmons had heard something that sounded like a woman screaming. She was hysterical and shouting things at him.<br />

Table 14: Controlling the sentiment/tone of generation with CTRL and CC-LMs. **Boldfaced** string indicates the context provided to the language model followed by its generation using a GeDi for different $\lambda$s. **Underlined** text indicates the parts of the generation that resemble reviews of movies or books.
## E.2 Topic samples

| Topic | GeDi-guided generation |
|-------|------------------------|
| **Business** | In a shocking finding yesterday the Financial Services Authority said banks are continuing to lend billions of pounds to property investors despite the economic slowdown and rising mortgage costs. Banks are now increasing mortgages by 1 billion every month on average as prices soar. The FCA found that lenders are increasing lending by 4 billion per month in June alone. This means banks will lend more than 10 billion this year just in house loans - more than they have ever done before and at rates higher than ever, even during the boom years of 2001 and 2003 when they lent heavily to property investors. "These results reveal once again that UK bank lending to property investors continues to be out of control," said Martin Wheatley, Chairman of the FCA Board, commenting on these latest figures: "They also highlight our concerns about whether banks can manage their balance sheets given continued weakness in consumer confidence and weak economic growth which makes many families vulnerable when buying their first home," Mr Wheatley added: |
| **Sports** | In a shocking finding Sunday afternoon in Green Bay, the Packers’ defense was unable to stop the Bears from scoring on their first three possessions. The Packers were able to hold Chicago’s offense scoreless for more than four minutes before they finally scored on a 3-yard run by Matt Forte with 1:06 left in the first quarter. The Bears would go on to score two touchdowns and take a 17-3 lead into halftime. "We had some good drives," said defensive end Mike Daniels, who had one sack and two quarterback hurries against his former team. "But we just couldn’t get off of them." |
| **Science** | In a shocking finding that scientists said they had never seen before, researchers found that the number of people who have died from cancer in the United States has risen by more than 50 percent since 1980. The study, published Monday in The Lancet Oncology, found that between 1980 and 2010 there were about 1.2 million new cases of cancer diagnosed each year an increase of nearly half a million people over just 15 years. "This is one of those rare studies where you can see something happening right under your nose," said Dr. David Jernigan, director for research at the American Cancer Society’s National Cancer Institute and lead author on the study with colleagues from Harvard University and other institutions around the world. "It’s really quite stunning." |
| **World** | In a shocking finding of war crimes, the UN investigators found evidence that Iraqi soldiers had executed prisoners in cold blood and then buried their bodies. The report said: "We have also received credible reports of executions by gunfire and beheadings." It added: "We are deeply concerned about the number of civilian casualties caused by Coalition air strikes during operations in Iraq since 1 August 2003." |

Table 15: Controlling topic of generation with GeDi. **Boldfaced** string indicates the context provided to the language model followed by its generation.
DETROIT (AP) Audi is introducing a luxury all-electric car in North America, the A3 e-tron, aimed at customers with large incomes and big spending habits who prefer the convenience of a gas-powered car. The company’s chief executive said Tuesday that sales of gasoline vehicles will fall sharply in North America as consumers shift more to electric vehicles such as the new Audi e-tron sedan and SUV due to their lower prices than traditional models. The German manufacturer plans to begin selling the vehicle this year, possibly by spring or summer. The $70,000 ($80,000) A3 e-tron also is an all electric vehicle: it doesn’t need any gas for driving on a full charge after around 60 miles (100 kilometers), and no one under 50 would be able to afford an expensive hybrid with expensive options such as navigation software upgrades and safety features that make hybrids more appealing than conventional vehicles. It’s cheaper than many competitors from Germany’s top three automakers: Volkswagen, Daimler AG, Ford Motor Co., plus Tesla Inc.’s $70k Model S sedan which can travel between 238 km/h on battery power alone before requiring additional charges or premium pricing for

DETROIT (AP) Audi is introducing a self-driving version of its A8 luxury sedan in the U.S., and it’s already being tested on public roads. The German automaker said Tuesday that it will begin testing an autonomous driving system for the car in California this summer, with plans to roll out a fully autonomous vehicle by 2021. The technology will be used on highways and city streets, but not at intersections or other busy areas where human drivers are required to take over control of the car when necessary. *Autonomous driving is one of our core competencies,* said Wolfgang Bernhard, head of Audi’s advanced driver assistance systems group in North America and Europe, during an interview with The Associated Press ahead of Wednesday’s announcement at CES 2017 here in Las Vegas. *We have been working very hard for many years now.*

DETROIT (AP) Audi is introducing Tesla to the NASCAR Sprint Cup Series. The German automaker will debut its new A3 e-tron sport utility vehicle in the No. 24 Chevrolet SS team’s race at Michigan International Speedway on Sunday, April 15, according to a statement from Audi of America. The car will be driven by Ryan Briscoe and Kyle Larson as they attempt to win their first Sprint Cup championship together since 2011. *We are excited about our partnership with Chevrolet,* said Briscoe in a statement released by Audi of America on Friday afternoon. *This is an exciting opportunity for us both and we look forward to racing this year.*

Table 16: Controlling topic of generation with GeDi. **Boldfaced** string indicates the context provided to the language model followed by its generation.
### Table 17: Controlling topic of generation with GeDi. **Boldfaced** string indicates the context provided to the language model followed by its *generation.*

| Topic | **GeDi-guided generation (\(\lambda = 0.80\))** |
|-------|-----------------------------------------------|
| **Business** | Despite partial success, communication firm GroupM said last month that its first-quarter results had been affected by the UK vote to leave the European Union and would be hit again by a fall in advertising revenues. "GroupM will take time to analyse the full implications of Brexit on its business and its wider market position," Chief Executive Michael Hintze said. GroupM shares closed 1.7 percent lower at 13,000 pence after rising as much as 2.1 percent during the session before news of his departure hit them hard. The group reported a profit for last year of 498 million euros (\$543 million) despite losses on sales growth due to strong sales in Brazil where GroupM operates one of its main branches and has plans for an expansion here next year with two other branches planned there by 2020, among other new operations such as a restaurant unit which opened recently at Marbella resort near Madrid’s La Sagrada Familia church complex that attracts tourists because it is home to many Catholic cathedrals from all over Europe including one belonging to England’s royal family (which itself owns part or all). |
| **Science** | Despite partial success, communication researchers say technology is still a long way from replacing human interaction. "We’re not there yet," said Dr. David Buss, director of the Center for Advanced Communication Research at the University of Texas at Austin and author of "The Evolutionary Psychology Of Technology." "But we are getting closer." |
| **Sports** | Despite partial success, communication varied season-by-season. "I had good games against Toronto and Montreal, but I didn’t have a great game against the Rangers," said Gaudreau. "It was just one of those nights where I wasn’t able to get it going." Gaudreau’s struggles were not limited to his own end of the ice either. He struggled with his teammates as well, often being outplayed by linemates who were more skilled than him on a nightly basis. The Flames’ top line of Johnny Gaudreau and Sean Monahan combined for only two goals in their first five games together this season; they scored four times in their next eight contests before falling apart again late last month when they combined for just three points over the final seven contests (two goals). In fact, Calgary’s top line has been outscored by its second unit at 5-on-5 during that stretch (2:13 per game) while scoring only twice on 15 shots total during that span (1:18 per game). |
| **World** | Despite partial success, communication between Palestinians in Gaza and the West Bank is still very limited. "We have a lot of problems with the Israeli authorities," said Abu Khdeir’s father, Hussein. "They don’t allow us to go out of our houses." |
### E.3 Detoxification Samples

| Model       | GeDi-guided generation ($\lambda = 0.80$) |
|-------------|------------------------------------------|
| GeDi-guided | You should just kill this one. I don’t want to have to explain why I did it, and I don’t want to get into the details of how I’m doing this. So we’ll do that in the next section. But first, a few notes about what we’re trying to do: We need a way for each team captain/coach to assign players who will be playing for that team. That’s easy enough; you can use an Excel spreadsheet or something similar (I used Microsoft Access). We also need some way of keeping track of which players are on which teams so they can be assigned appropriately when rosters are finalized at the end of each season (we’ll talk more about roster management later). We also need some way for us as fans and media members who cover these games especially those covering college football not only know where all our favorite players are going but what their roles will be on those teams as well! |
| GeDi-guided | Do I look like I give a good impression? I’m not sure. But if you’re going to be in the public eye, you have to do your best. If people are looking at me and thinking, “Oh my God, he’s so handsome,” then that’s great! It means they like me as a person and not just as an actor. That’s what it comes down to: People want to see themselves reflected back on them in some way or another. So if you can make yourself look good enough for people who don’t know who you are yet even though they may think of themselves as being very nice then that is something worth striving for.” |

Table 18: Detoxification of LM generation with the GeDi. These are meant to be especially difficult triggers, and result in GPT-2 generating toxic text. **Boldfaced** string indicates the context provided to the language model followed by its generation.
In a shocking finding, a newly discovered planet has three moons orbiting it in orbit around its central star, and is surrounded by two more. This unusual configuration is similar to the system found in 2012 by astronomers led by Jonathan Fortney (Caltech), but unlike their own system, this planet has three moons instead of just one. "Our discovery shows that planets with more than two moons have very high orbital inclinations," said Fortney. "This makes these planets much more likely to host multiple satellites over their lifetime." The trio of moons also show evidence for strong gravitationally tidal forces as they orbit the planet which would cause any single satellite to gravitationally bind itself into place against the other satellites’ orbits around the star. This means that each moon only forms after its twin’s formation suggesting that these planets were born from a collision between several previously orbiting satellites rather than forming alone. These results suggest that planetary systems with three satellite systems are common and likely result from mergers between previously orbiting binary stars or triple stars within one another’s orbits," added Fortney, "similar to how supermassive black holes form."

While this planetary system is unusual in many ways it still offers us some clues as to

In a shocking finding that raises new concerns over the safety of nuclear plants and could force major overhauls of how they operate, researchers have discovered a potentially deadly flaw in one of the key safety systems on older reactors. "There’s nothing worse than not having an emergency shutdown," says Kevin Connor, senior engineer with the US Department of Energy’s Oak Ridge National Laboratory in Tennessee. "This could be catastrophic."

The reactor at Japan’s crippled Fukushima Daiichi plant suffered a similar incident last year when water leaked into one of two cooling pools used to cool spent fuel rods rods that have been sitting for more than half a century without being used. As temperatures climbed above 1,000 degrees Celsius (1,832 degrees Fahrenheit), some fuel rods melted and spewed out highly radioactive materials like cesium and strontium into the air around them. The pool had been left unattended for months until an employee forgot to turn it off during maintenance work earlier this month.

As soon as he turned it off, radiation from inside exploded onto the surface triggering explosions that destroyed critical components such as

In a shocking finding today the British Museum revealed the remains of one of Britain’s most notorious criminals William ‘Wild Bill’ Hickok who served as a soldier during the American Revolution.

He was buried at St Mary’s Churchyard, Lincolnshire, where he was executed for treason after serving in Colonel John Graves Simcoe’s New York-based militia. William ‘Wild Bill’ Hickok, right, who served as a soldier during the American Revolution. He was buried at St Mary’s Churchyard, Lincolnshire. Mr Hickok spent more than six years on death row before an extraordinary last-minute plea by US authorities allowed him to be spared execution and sent to America with just 100 to his name.

The 18th Century convict became one of America’s most notorious outlaws after fleeing across state lines in January 1781 with a fellow inmate and their prisoner horse - but escaping capture twice before arriving at Philadelphia on Christmas Day 1782.

Mr Hicks said it is likely Mr Hicks died around that time while travelling along Pennsylvania Avenue near Independence Hall when someone threw something into his face as he passed along the route in what would become known as Bloody Sunday.

Table 19: Controlling topic of generation (zero-shot) with the GeDi model. The topics of Space, Fire, and History were not a part of the GeDi training set. **Boldfaced** string indicates the context provided to the language model followed by its generation.
| Topic   | GeDi-guided generation                                                                                                                                                                                                 |
|---------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| **Education** | In a shocking finding that raises serious concerns about whether schools are providing the best possible education to all students, the OECD found that only half of U.S. high school graduates have completed a four-year degree by 2015 and fewer than half of college graduates have completed a bachelor’s degree by 2020. According to the OECD’s Education at a Glance 2016 report, only 48 percent of adults aged 25-64 hold degrees in STEM fields, compared to 71 percent globally and less than half of adults aged 25-64 hold degrees in social sciences or humanities fields, compared to over 80 percent globally. The report also found that while more than 20 countries now have university education systems spanning from kindergarten up through graduate school with an additional 16 countries offering master’s or doctoral level education only 22 countries offer post-secondary educational opportunities for young adults between the ages 18 and 29. “Today more people around the world are pursuing higher education,” says OECD Secretary General Angel Gurria said “However it remains challenging for many young people.” He continued “This is especially so for those without access to higher learning.” |
| **Cars**       | In a shocking finding that raises serious concerns over safety standards, more than half of the 4,100 new cars sold last year had defects which caused at least 10 road deaths every year. The figures show that in the first nine months of this year 1,064 cars on sale had fatal faults— including one in every 100 sold. The figure for 2011 was 1,065. The figures from the Society of Motor Manufacturers and Traders show that despite a drop in sales to their lowest level in five years, car sales are up 5.3 per cent compared with the same period last year— driven by growth among luxury models such as BMW 3-series and Mercedes-Benz AMG saloons. |
| **Climate**    | In a shocking finding that scientists are calling ‘extremely worrying’, the world’s oceans are becoming increasingly acidic. According to new research published in Nature Climate Change, ocean waters around the world are becoming significantly more acidic due to rising levels of carbon dioxide (CO2) in the atmosphere. “Our results show that ocean acidification has already begun in many regions, with most regions experiencing acidification rates greater than predicted for preindustrial conditions by 2100,” says lead author Thomas Crowley, who conducted this research as part of his doctoral degree thesis at The University of Western Australia. “Ocean acidification has important consequences for organisms living near or below sea surface because low pH environments may be particularly challenging for calcifying organisms; however, our results also show that marine ecosystems will likely experience increasing acidification rates even when they don’t experience current ocean acidity trends.” |

Table 20: Controlling topic of generation (zero-shot) with the GeDi. The topics of Education, Cars, Climate were not a part of the GeDi training set. **Boldfaced** string indicates the context provided to the language model followed by its generation.
Table 21: Controlling topic of generation (zero-shot) with the CTRL model. Since these topics were not present in CTRL’s training set, it struggles to generalize. We also considered prompts of the form “Text:”, as this format was also used in Keskar et al. (2019), but we found zero-shot generations to be worse than with “Title”. **Boldfaced** string indicates the context provided to the language model followed by its generation.