Composable Text Control Operations in Latent Space with Ordinary Differential Equations

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Abstract

Real-world text applications often involve composing a wide range of text control operations, such as editing the text w.r.t. an attribute, manipulating keywords and structure, and generating new text of desired properties. Prior work typically learns/finetunes a language model (LM) to perform individual or specific subsets of operations. Recent research has studied combining operations in a plug-and-play manner, often with costly search or optimization in the complex sequence space. This paper proposes a new efficient approach for composable text operations in the compact latent space of text. The low-dimensionality and differentiability of the text latent vector allow us to develop an efficient sampler based on ordinary differential equations (ODEs) given arbitrary plug-in operators (e.g., attribute classifiers). By connecting pretrained LMs (e.g., GPT2) to the latent space through efficient adaption, we then decode the sampled vectors into desired text sequences. The flexible approach permits diverse control operators (sentiment, tense, formality, keywords, etc.) acquired using any relevant data from different domains. Experiments show that composing those operations within our approach manages to generate or edit high-quality text, substantially improving over previous methods in terms of generation quality and efficiency.

1 Introduction

Many text problems involve a diverse set of text control operations, such as editing different attributes (e.g., sentiment, formality) of the text, inserting or changing the keywords, generating new text of diverse properties, and so forth. In particular, different composition of those operations are often required in various real-world applications (Figure 1).

Conventional approaches typically build a conditional model (e.g., by finetuning pretrained language models) for each specific combination of operations (Hu et al., 2017; Keskar et al., 2019; Ziegler et al., 2019), which is unscalable given the combinatorially many possible compositions and the lack of supervised data. Previous research thus has started to explore plug-and-play solutions that, given a pretrained language model (LM), plug in arbitrary constraints to guide the production of desired text sequences (Dathathri et al., 2020; Yang and Klein, 2021; Kumar et al., 2021; Krause et al., 2021; Miresghallah et al., 2022; Qin et al., 2022). Those approaches, however, typically rely on search or optimization in the complex text se-

1Code: https://github.com/guangyiliu/LatentOps

Figure 1: Examples of different composition of text operations, such as editing a text in terms of different attributes sequentially (top) or at the same time (middle), or generating a new text of target properties (bottom). The proposed LATENet enables a single LM (e.g., an adapted GPT-2) to perform arbitrary text operation composition in the latent space.
quence space. The discrete nature of text makes the search/optimization extremely difficult. Recent work (Qin et al., 2020, 2022; Kumar et al., 2021) introduces continuous approximations to the discrete tokens, yet the complexity and high dimensionality of the sequence space still renders it inefficient to find the accurate high-quality text.

In this paper, we develop LATENTOPS, a new efficient approach that performs composable control operations in the compact and continuous latent space of text. Specifically, LATENTOPS permits plugging in arbitrary operators (e.g., attribute classifiers) applied on text latent vectors, to form an energy-based distribution on the low-dimensional latent space. We then develop an efficient and robust sampler based on ordinary differential equations (ODEs) (Song et al., 2021; Nie et al., 2021) to draw latent vector samples that bear the desired attributes. A key challenge after getting the latent vector is to decode it into the target text sequence. To this end, we connect the latent space to pretrained LM decoders (e.g., GPT-2) by efficiently adapting a small subset of the LM parameters in a variational auto-encoding (VAE) manner (Kingma and Welling, 2014; Bowman et al., 2016).

Previous attempts of editing text in latent space have often been limited to single attribute as well as small-scale models (due to the incompatibility of the latent space with the existing transformer-based pretrained LMs) (Wang et al., 2019; Liu et al., 2020; Shen et al., 2020; Duan et al., 2020; Mai et al., 2020a). LATENTOPS overcomes the difficulties and enables a single large LM to perform arbitrary composable operations.

We conduct experiments on three challenging settings, including sequential editing of text w.r.t. a series of attributes, editing compositional attributes simultaneously, and generating new text given various attributes. Results show that composing operators within our method manages to generate or edit high-quality text, substantially improving over respective baselines in terms of accuracy and runtime efficiency.

2 Background

2.1 Energy-based Models and ODE Sampling

Given an arbitrary energy function $E(x) \in \mathbb{R}$, energy-based models (EBMs) define a Boltzmann distribution:

$$p(x) = e^{-E(x)}/Z \propto e^{-E(x)},$$

where $Z = \sum_{x \in \mathcal{X}} e^{-E(x)}$ is the normalization term (the summation is replaced by integration if $x$ is a continuous variable). EBMs are flexible to incorporate any functions or constraints into the energy function $E(x)$. Recent work has explored text-based EBMs, where $x \in \mathcal{X}$ is a text sequence, for constrained text generation (Hu et al., 2018; Deng et al., 2020; Khalifa et al., 2021; Mireshghallah et al., 2022; Qin et al., 2022). Despite the flexibility, sampling from EBMs is rather challenging due to the intractable $Z$. The text-based EBMs, similar to other plug-and-play approaches mentioned in §1, face with even more difficult sampling due to the extremely large and complex (discrete or soft) text space.

Langevin dynamics (LD, Welling and Teh, 2011; Ma et al., 2018), a gradient-based Markov chain Monte Carlo (MCMC) approach, is increasingly used for sampling from EBMs (Du and Mordatch, 2019b; Song and Ermon, 2019; Du et al., 2020; Qin et al., 2022) as a more efficient way compared to other gradient-free alternatives (e.g., Gibbs sampling (Bishop and Nasserabadi, 2006)). However, due to several hyperparameters (e.g., step size, number of steps, noise scale), LD tends to be sensitive and unrobust in practice (Nie et al., 2021; Du and Mordatch, 2019a; Grathwohl et al., 2020).

On the other hand, stochastic/ordinary differential equations (SDEs/ODEs) (Anderson, 1982) offer another sampling technique recently applied in image generation (Song et al., 2021; Nie et al., 2021). An SDE characterizes a diffusion process that maps real data to random noise in continuous time $t \in [0, T]$. Specifically, let $x(t)$ be the value of the process following $x(t) \sim p_t(x)$, indexed by the continuous time $t$. At start time $t = 0$, $x(0) \sim p_0(x)$ which is the data distribution, and at the end $t = T$, $x(T) \sim p_T(x)$ which is the noise distribution (e.g., standard Gaussian). The reverse SDE instead generates a real sample from the noise by working backwards in time (from $t = T$ to $t = 0$). More formally, consider a variance-preserving SDE (Song et al., 2021) whose reverse is written as

$$dx = -\frac{1}{2} \beta(t) [x + 2\nabla_x \log p_t(x)]dt + \sqrt{\beta(t)}d\bar{w},$$

where $dt$ is an infinitesimal negative time step; $\bar{w}$ is a standard Wiener process when time flows backwards from $T$ to $0$; and the scalar $\beta(t) := \beta_0 + (\beta_T - \beta_0)t$ is a time-variant coefficient linear w.r.t. time $t$. Drawing a data sample $x(0)$ then
amounts to solving the reverse SDE, for which we can use different numerical solvers (Burrage et al., 2000; Higham, 2001; Rößler, 2009). The SDE sampler sometimes need to combine with an additional corrector to improve the sample quality (Song et al., 2021).

Further, as shown in (Song et al., 2021; Maoutsa et al., 2020), each (reverse) SDE has a corresponding ODE, solving which leads to samples following the same distribution. The ODE is written as (see Appendix A for the derivations):

$$dx = -\frac{1}{2} \beta(t) |x + \nabla_x \log p_t(x)| dt.$$  \hfill (3)

Solving the ODE with relevant numerical methods (Euler, 1824; Calvo et al., 1990; Engstler and Lubich, 1997) corresponds to an sampling approach that is more efficient and robust (Song et al., 2021; Nie et al., 2021).

In this work, we adapt the ODE sampling for our approach. Crucially, we overcome the text control and sampling difficulties in the aforementioned sequence-space methods, by defining the text control operations in a compact latent space, handled by a latent-space EBMs with the ODE solver for efficient sampling.

### 2.2 Latent Text Modeling with Variational Auto-Encoders

Variational auto-encoders (VAEs) (Kingma and Welling, 2014; Rezende et al., 2014) have been used to model text with a low-dimensional continuous latent space with certain regularities (Bowman et al., 2016; Hu et al., 2017). An VAE connects the text sequence space \( \mathcal{X} \) and the latent space \( \mathcal{Z} \subset \mathbb{R}^d \) with an encoder \( q(z|x) \) that maps text \( x \) into latent vector \( z \), and a decoder \( p(x|z) \) that maps a \( z \) into text. Previous work usually learns text VAEs from scratch, optimizing the encoder and decoder parameters with the following objective:

$$L_{\text{VAE}}(x) = -\mathbb{E}_{q(z|x)} [\log p(x|z)] + \text{KL}(q(z|x)||p_{\text{prior}}(z)),$$  \hfill (4)

where \( p_{\text{prior}}(z) \) is a standard Gaussian distribution as the prior, and \( \text{KL}(\cdot ||\cdot) \) is the Kullback-Leibler divergence that pushes \( q_{\text{enc}} \) to be close to the prior. The first term encourages \( z \) to encode relevant information for reconstructing the observed text \( x \), while the second term adds regularity so that any \( z \sim p_{\text{prior}}(z) \) can be decoded into high-quality text in the \( \mathcal{X} \) space.

Recent work (Li et al., 2020; Hu and Li, 2021) scales up VAE by initializing the encoder and decoder with pretrained LMs (e.g., BERT (Devlin et al., 2019) and GPT-2 (Radford et al., 2019), respectively). However, they still require costly fine-tuning of the whole model on the target corpus. In comparison, our work converts a given pretrained LM (e.g., GPT-2) into a latent-space model efficiently by tuning only a small subset of parameters, as detailed more in §3.3.

### 3 Composable Text Latent Operations

We develop our approach that quickly adapts a given pretrained LM (e.g., GPT-2) to enable composable text latent operations (LATENTOPS). The approach consists of two components, namely a VAE based on the pretrained LM that connects the text space with a compact continuous latent space, and EBMs on the latent space that permits arbitrary attribute composition and efficient sampling.

More specifically, the VAE decoder \( p(x|z) \) offers a way to map any given latent vector \( z \) into the corresponding text sequence. Therefore, text control (e.g., editing a text or generating a new one) boils down to finding the desired vector \( z \) that bears the desired attributes and characteristics. To this end, one could plug in any relevant attribute operators (e.g., classifiers), resulting in a latent-space EBM that characterizes the distribution of \( z \) with the desired attributes. We could then draw the \( z \) samples of interest, performed efficiently with an ODE solver. Figure 2 gives an illustration of the approach.

LATENTOPS thus avoids the difficult optimization or sampling in the complex text sequence space as compared to the previous plug-and-play methods (e.g., Dathathri et al., 2020; Qin et al., 2022). Our approach is also compatible with the powerful pretrained LMs, requiring only minimal adaptation to equip the LMs with a latent space, rather than costly retraining from scratch as in the recent diffusion LM (Li et al., 2022). In a sense, LATENTOPS is composable also in terms of the LM component, as one can use any adapted pretrained LMs in a plug-and-play manner.

In the following, we first present the latent-space EBM formulation (§3.1) for composable operations, and derive the efficient ODE sampler (§3.2); we then discuss the parameter-efficient adaptation of pretrained LMs for the latent space (§3.3).
3.1 Composable Latent-Space EBMs

We aim to formulate the latent-space EBMs such that one can easily plug in arbitrary attribute operators to define the latent distribution of interest. Besides, as we want to obtain fluent text with the VAE decoder $p(x|z)$ described later, the latent distribution over $z$ should match the structure of the VAE latent space.

Formally, let $\mathbf{a} = \{a_1, a_2, ...\}$ be a vector of desired attribute values, where each $a_i \in \mathbb{R}$ (e.g., positive sentiment, or informal writing style). Note that $\mathbf{a}$ does not have a prefixed length as one can plug in any number of attributes to control. To assess if a vector $z$ bears the desired attribute $a_i$, we could in general use any function $f_i$ that takes in $z$ and $a_i$, and outputs a score measuring how well $a_i$ is carried in $z$. The function $f_i$ can take different forms depending on the type of attribute and the available resources (Hu and Xing, 2021, section 4). For a categorical attribute (e.g., sentiment, either positive or negative), one of the common ways is to use a trained attribute classifier, where $f_i(z)$ is the output logit vector and $f_i(z)[a_i] \in \mathbb{R}$ is the logit of the particular class $a_i$ of interest. For clarity of presentation, we focus on categorical attributes and classifiers in the rest of the paper, and assume the attributes are independent with each others.

We are now ready to formulate the latent-space EBMs by plugging in the attribute classifiers. Specifically, we define the joint distribution:

$$p(z, \mathbf{a}) := p_{\text{prior}}(z)p(\mathbf{a}|z) = p_{\text{prior}}(z) \cdot e^{-E(\mathbf{a}|z)}/Z, \quad (5)$$

where $p_{\text{prior}}(z)$ is the Gaussian prior distribution of VAE (§2.2), and $E(\mathbf{a}|z)$ is the energy function to encode the different target attributes. With the decomposition of $p(z, \mathbf{a})$, notice that the marginal distribution over $z$ equals the VAE prior $p_{\text{prior}}(z)$, which facilitates the VAE decoder to generate fluent text. We formulate $p(\mathbf{a}|z)$ as an EBM to enable the combination of arbitrary attributes. Here $E(\mathbf{a}|z) = \sum_i \lambda_i E_i(a_i|z)$. Each $\lambda_i \in \mathbb{R}$ is the balance weight, and $E_i$ is the defined as the negative log probability (i.e., the normalized logit) of $a_i$ to make sure the different attribute classifiers have outputs at the same scale for combination:

$$E_i(a_i|z) = -f_i(z)[a_i] + \log \sum_{a_i'} \exp(f_i(z)[a_i']). \quad (6)$$

3.2 Efficient Sampling with ODEs

Once we have the desired distribution $p(z, \mathbf{a})$ over the latent space and attributes, we would like to draw samples $z$ given the target attribute values $\mathbf{a}$, which are then fed to the VAE decoder (§3.3) to obtain the desired text. As discussed in §2.1, sampling with ODEs has the benefits of robustness compared to Langevin dynamics that is sensitive to hyperparameters, and efficiency compared to SDEs that require additional correction. We derive the ODE sampling in the latent space.

Specifically, we adapt the ODE from Eq.(3) into our latent-space setting, which gives:

$$dz = \frac{1}{2} \beta(t) \nabla_z E(\mathbf{a}|z) dt$$

$$= \frac{1}{2} \beta(t) [z + \nabla_z \log p_i(z, \mathbf{a})] dt$$

$$= \frac{1}{2} \beta(t) [z - \nabla_z \log p_i(\mathbf{a}|z) + \nabla_z \log p_i(z)] dt. \quad (7)$$

For $p_i(z)$, notice that at $t = 0$, $p_0(z)$ is the VAE prior distribution $p_{\text{prior}}(z)$, which is the same as $p_T(z)$ (i.e., the Gaussian noise distribution after
We can then easily create latent samples conditioned on the given attribute values, by drawing \( z(T) \sim \mathcal{N}(0, I) \) and solving the Eq.(8) with a differentiable neural ODE solver\(^2\) (Chen et al., 2018, 2021) to obtain \( z(0) \). In §3.4, we discuss more implementation details with approximated starting point \( z(T) \) for text editing and better empirical performance.

### 3.3 Adapting Pretrained LMs for Latent Space

To decode the \( z \) samples into text sequences, we equip pretrained LMs (e.g., GPT-2) with the latent space with parameter-efficient adaptation. More specifically, we adapt the autoregressive LM into a text latent model within the VAE framework (§2.2). Differing from the previous VAE work that trains from scratch or finetunes the full parameters of pretrained LMs (Li et al., 2020; Hu and Li, 2021; Hu et al., 2017), we show that it is sufficient to only update a small portion of the LM parameters to connect the LM with the latent space, while keeping the LM capability of generating fluent coherent text. Specifically, we augment the autoregressive LM with small MLP layers that pass the latent vector \( z \) to the LM, and insert an additional transformer layer in between the LM embedding layer and the original first layer. The resulting model then serves as the decoder in the VAE objective (Eq.4), for which we only optimize the MLP layers, the embedding layer, and the inserted transformer layer, while keeping all other parameters frozen. For the encoder, we use a BERT-small model (Devlin et al., 2019; Turc et al., 2019) and finetune it in the VAE framework. As discussed later in §3.4, the tuned encoder can be used to produce the initial \( z \) values in the ODE sampler for text editing.

### 3.4 Implementation Details

We discuss more implementation details of the above components. Overall, given an arbitrary text corpus (e.g., a set of text from any domain of interest), we first build the VAE by adapting the pretrained LMs as described in §3.3. Once the latent space is established, we keep it (including the VAE components) fixed, and perform arbitrary compositional text operations in the latent space.

**Acquisition of attribute classifiers** We can acquire attribute classifiers \( f_i(z) \) on the frozen latent space by training using arbitrary datasets with annotations. Specifically, we encode the input text into the latent space with the VAE encoder, and then train the classifier to predict the attribute label given the latent vector. Each classifier, as is built on the semantic latent space, can be trained efficiently with only a small number of examples (e.g., 200 per class). This allows us to acquire a large diversity of classifiers (e.g., sentiment, formality, different keywords) in our experiments (§4) using readily-available data from different domains, and flexibly compose them together to perform operations on text in the domain of interest.

**Initialization of ODE sampling** To sample \( z \) with the ODE solver (§3.2), we need to specify the initial \( z(T) \). For text editing operations (e.g., transferring sentiment from positive to negative) that start with a given text sequence, we initialize \( z(T) \) to the latent vector of the given text by the VAE encoder. We show in our experiments that the resulting \( z(0) \) samples as the solution of the ODEs can preserve the relevant information in the original text while obtaining the desired target attributes.

For generating new text of target attributes, the normal way is to sample \( z(T) \) from the prior Gaussian distribution \( \mathcal{N}(0, I) \). However, due to the inevitable gap between the prior distribution and the learned VAE posterior on \( Z \), such a Gaussian noise sample does not always lead to coherent text outputs. We thus follow (Li et al., 2020; Hu and Li, 2021) to learn a small (single-layer) GAN (Goodfellow et al., 2014) \( p_{\text{GAN}}(z) \) that simulates the VAE posterior distribution, using all encoded \( z \) of real text as the training data. We then generate the initial \( z(T) \) from the \( p_{\text{GAN}} \).

\[^2\text{https://github.com/rtqichen/torchdiffeq}\]
Sample selection The compact latent space learned by VAE allows us to conveniently create multiple semantically-close variants of a sampled \( z(0) \) and pick the best one in terms of certain task criteria. Specifically, we add random Gaussian noise perturbation (with a small variance) to \( z(0) \) to get a set of vectors close to \( z(0) \) in the latent space and select one from the set. We found the sample perturbation and selection is most useful for operations related to the text content. For example, for text editing, we pick a vector based on the content preservation (e.g., BLEU with the original text) and attribute accuracy; while for generation given keywords, we select the resulting output that contains the specified keywords.

4 Experiments

To demonstrate LATENTOPS is highly modular and extensible, we present experimental results on two text generation settings: text editing, i.e., modifying attributes of sentences, and conditional generation on arbitrary number of attributes. We not only consider attributes such as sentiment, tense, etc, but also we can control if a sentence contains a specific keyword, etc.

Setup We evaluate our method mainly on Yelp review dataset\(^3\) (Shen et al., 2017), preprocessed by Li et al. (2018). Yelp is a sentiment dataset and contains about 179K negative sentences and 268K positive sentences. We also evaluate text editing on another sentiment dataset, Amazon review dataset (He and McAuley, 2016), containing 280K negative and 278K positive sentences. Since Yelp and Amazon datasets are mainly developed for sentiment usage, we annotate them with a POS tagger to get the tense attribute in order to test our model can be extended to arbitrary number of attributes. Besides, we also use GYAFC dataset (Rao and Tetreault, 2018) to include the formality attribute. Note that GYAFC dataset has rather different domains with Yelp/Amazon, which can be used to test our model’s out of domain generalization ability.

We adopt BERT-small and GPT-2 large as the encoder and decoder of our latent model, respectively. The training paradigm follows §3.4, and some training tricks (Li et al., 2020) (i.e., cyclical schedule for KL weight and KL thresholding scheme) are applied to stabilize the training of the latent model. All the attributes are listed in Table 1.

| Style | Attributes | Dataset |
|-------|------------|---------|
| Sentiment | Positive / Negative | Yelp, Amazon |
| Tense | Future / Present / Past | Yelp |
| Keywords | Existence / No Existence | Yelp |
| Formality | Formal / Informal | GYAFC |

Table 1: All attributes and the corresponding dataset are used in our experiments.

4.1 Text Editing with Compositional Attributes

We evaluate our model’s text editing ability on Yelp review and Amazon review dataset, i.e, changing sentences’ sentiment, tense and formality attributes altogether or separately. For this task, we evaluate our generated sentences against 1000 annotated sentences as ground truth.

Baselines We compare our method with several recent state-of-the-art methods: B-GST (Sudhakar et al., 2019), Style Transformer (STrans) (Dai et al., 2019), DiRR (Liu et al., 2021), Tag&Gen (T&G) (Madaan et al., 2020), fine-grained style transfer (FGST) (Liu et al., 2020), and FUDGE (Yang and Klein, 2021). B-GST, Style Transformer, DiRR, T&G and FGST are specifically proposed for a single attribute editing. FUDGE and our LATENTOPS follow plug-and-play manner, so we only utilize a little labeled data (i.e., 200 per class), which is marked as few-shot setting. In single-attribute experiment, the outputs of baselines are obtained from their official repositories except FUDGE. Since FUDGE relies on a PLM, we finetune a GPT2 as a reconstruction model and used it in the FUDGE model. For text editing, we experiment with three settings–sequential attribute editing, compositional attributes editing and single attribute editing. Since FUDGE is the only model that can do compositional attributes editing, we only compare with FUDGE in composition attributes editing and compare with all baselines in single attribute editing. For sequential attribute editing, we trained multiple STrans models to sequentially edit the source sentences and used it as our baseline method.

Metrics Attribute accuracy is given by a BERT classifier to evaluate the success rate. PPL is calculated by a GPT-2 finetuned on the corresponding dataset to measure the fluency. Input-BLEU (iBL) and reference-BLEU (rBL) are utilized to measure the preservation of content, implemented by nltk package (Bird et al., 2009). We also use

\(^3\)https://github.com/lijuncen/Sentiment-and-Style-Transfer
Table 2: Automatic evaluations of sequential editing on Yelp review dataset. F, S and T stand for the accuracy of formality (to informal), sentiment (to negative) and tense (to present), respectively. PPL is the perplexity evaluated by finetuned GPT-2 to measure the fluency (for reference, PPL of test data and human-annotated data is 15.9 and 24.5).

Table 3: Examples of sequential editing.

Table 4: Automatic evaluation results of text editing with compositional attributes on Yelp review dataset.
methods that are training with full labelled data. In the respect of content preservation, DiRR distinctly outperforms others. DiRR processes 1.5B trainable parameters and is trained on the full labelled data, so big data and big model lead to better performance. However, although we follow the few-shot setting, ours also performs good on preservation of content. For fluency and input-output alignment, our method achieves comparable perplexity and CTC score with strong baselines. We provide some examples in Table 5 and 13 for Yelp, and Table 14 for Amazon to further demonstrate the superiority of our method. As the human evaluation results are shown in Table 6, our LATENTOPS performs the best. After analyzing the generated texts, we found our method could focus more on logicality and adopt words that appropriate to the context.

4.2 Generation with Compositional Attributes

We evaluate on Yelp review dataset.

### Baselines

We compare our method with PPLM (Dathathri et al., 2020), FUDGE (Yang and Klein, 2021), and a finetuned GPT-2 (Radford et al., 2019). Both PPLM and FUDGE are plug-and-play controllable generation approaches on top of an autoregressive pretrained LM, which we finetune the GPT-2 on Yelp review dataset. PPLM requires a discriminator attribute model (or a bag-of-words attribute models) learned from a pretrained LM’s top-level hidden layer. At decoding, PPLM modifies the states toward increasing probability of the desired attribute via gradient ascent. We only consider the discriminator attribute model, which is in accordance with other baselines and ours. FUDGE has a discriminator that takes in a prefix sequence and predict whether the generated sequence would meet the conditions. FUDGE could control text generation by directly modifying the probabilities of the pretrained LM by the discriminator output. We follow the architecture of FUDGE and train a binary discriminator for each style that has two attributes (Sentiment, Keywords, Formality and Politeness). But for styles with more than two attributes (Tense), we train a binary discriminator for each attribute of that style. Furthermore, we tune the $\lambda$ parameter of FUDGE which is a weight that controls how

| Model | Acc | iBL | rBL | PPL | CTC | #Params | #Data |
|-------|-----|-----|-----|-----|-----|---------|-------|
| Source | 0.27 | 100 | 31.4 | 15.9 | 0.500 | - | - |
| Human | 0.82 | 31.9 | 100 | 24.5 | 0.463 | - | - |
| B-GST | 0.81 | 31.8 | 16.3 | 39.5 | 0.473 | 111M | Full-data |
| STTrans | 0.91 | 53.2 | 24.5 | 41.0 | 0.469 | 17M | - |
| DiRR | 0.96 | 61.5 | 29.8 | 23.9 | 0.480 | 1.5B | Full-data |
| T&G | 0.88 | 47.6 | 21.8 | 24.3 | 0.466 | 63M | - |
| FGST | 0.90 | 13.2 | 7.6 | 9.3 | 0.450 | 26M | - |
| FUDGE | 0.60 | 28.0 | 9.4 | 18.2 | 0.436 | 118M | Few-shot |
| Ours | 0.95 | 34.0 | 24.3 | 25.9 | 0.474 | 108M | - |

| Model | Acc | iBL | rBL | PPL | CTC | #Params | #Data |
|-------|-----|-----|-----|-----|-----|---------|-------|
| Source | 0.14 | 100 | 49.4 | 26.4 | 0.425 | - | - |
| Human | 0.52 | 49.7 | 100 | 47.2 | 0.422 | - | - |
| B-GST | 0.62 | 52.3 | 28.5 | 27.7 | 0.425 | 111M | Full-data |
| STTrans | 0.60 | 68.7 | 38.2 | 32.7 | 0.424 | 1.5B | Full-data |
| DiRR | 0.65 | 86.6 | 35.4 | 40.9 | 0.423 | 63M | - |
| T&G | 0.83 | 21.9 | 14.0 | 13.6 | 0.427 | 26M | - |
| FGST | 0.26 | 52.9 | 26.4 | 35.1 | 0.416 | 118M | Few-shot |
| Ours | 0.72 | 53.3 | 28.1 | 44.1 | 0.423 | 108M | - |

Table 6: Automatic evaluations of text editing with single attribute on Yelp (top) and Amazon (middle) dataset. Acc is the success rate of transfer, iBL is the BLEU with input text, and rBL is the BLEU with human-annotated reference. We also mark the number of trainable parameters as #Params and the scale of labeled data in training as #Data. Human evaluation (bottom) statistics on Yelp review dataset.
| Attribute | Method   | Sentiment↑ | Tense↑ | Formality↑ | G-Mean↑ | PPL↓  | sBL↓  |
|-----------|----------|------------|--------|------------|---------|-------|-------|
|           | GPT2-FT  | 0.98       | -      | -          | 0.98    | 10.6  | 23.2  |
|           | PPLM     | 0.63       | -      | -          | 0.63    | 14.8  | 35.0  |
|           | FUDGE    | 0.73       | -      | -          | 0.73    | 20.7  | 15.0  |
|           | Ours     | 0.99       | -      | -          | 0.99    | 30.4  | 13.0  |
| + Tense   | GPT2-FT  | 0.98       | 0.97   | -          | 0.97    | 9.1   | 36.9  |
|           | FUDGE    | 0.67       | 0.59   | -          | 0.63    | 11.9  | 31.0  |
|           | Ours     | 0.98       | 0.93   | -          | 0.95    | 25.7  | 19.7  |
| + Formality| GPT2-FT | 0.98       | 0.96   | 0.87       | 0.93    | 9.8   | 36.1  |
|           | FUDGE    | 0.69       | 0.59   | 0.60       | 0.62    | 11.7  | 30.8  |
|           | Ours     | 0.97       | 0.92   | 0.93       | 0.93    | 25.8  | 21.1  |

Table 7: Results of generation with compositional attributes. Sentiment, Tense and Formality represent the accuracy (success rate). G-Mean is the geometric mean of all accuracy. Self-BLEU (sBL) is adopted to measure the diversity. We mark the best **bold**, and the second best *underlined*.

much the probabilities of the pretrained LM is adjusted by the discriminator and we find $\lambda=10$ yields the best results. **GPT2-FT** is a finetuned GPT-2 model, that is conditional language model and is not plug-and-play. Specifically, we train a classifier for the out-of-domain attribute (i.e., formality) to annotate all the data in the Yelp. For tense, we use POS tagging to automatically annotate the data. Then we finetune GPT-2 by the labeled data.

For fair comparison, we randomly select 220 (200 for training and 20 for testing) instances per class to train the discriminator/operator (for PPLM, FUDGE and our **LATENTOPS**) for each attribute. For each setting, we sample 150 text sequences to evaluate. It’s noteworthy that our **LATENTOPS** is exactly the same model as in §4.1, so only an extra formality operator is needed to train.

**Metrics**  Attribute accuracy is given by a BERT classifier to evaluate the success rate. Perplexity (PPL) is calculated by a GPT-2 finetuned on the corresponding dataset to measure the fluency. Since diversity is a critical issue lying in the field of generative models, we calculate self-BLEU (sBL) to evaluate the diversity.

We consider two situations in this experiments: generation with compositional attributes without keywords (sentiment, tense and formality) and with keyword (keywords, sentiment and tense).

**4.2.1 Generation with Compositional Attributes**

For the reason that PPLM can’t control multiple attributes simultaneously (PPLM only can control multiple attributes represented by bag-of-words attribute models), we compare with FUDGE and GPT2-FT. We list the average automatic evaluation results of each combination of sentiment, tense and formality as shown in Table 7.

Regarding to the success rate, our method dramatically outperforms FUDGE and PPLM as expected, since both of them control the text by modifying the outputs (hidden states and probabilities) of PLM, which includes the token-level feature and lacks sentence-level semantic feature. On the contrary, our method control the attributes by operating the sentence-level latent vector, which is more suitable.

For diversity, because our method bilaterally connects the discrete data space with continuous latent space, which is more flexible to sample, ours gains obvious superiority on diversity. On the other side, PLMs like GPT-2, which is the basis of PPLM and FUDGE, are naturally short of the ability to generate diverse texts, and they achieve generate diverse texts by adopting other decoding methods (like top-k), which results the low diversity of the baselines.

For fluency, we calculate the perplexity given by a finetuned GPT-2, which processes the the same based architecture and training data of PPLM and FUDGE, so naturally they can achieve better perplexity even comparing to the perplexity of test data and human-annotated data. Moreover, our method only requires an Extra Adapter to guide the fixed GPT-2, and the fluency of ours is in a normal interval, a little higher than the perplexity of human-annotated data.

Comparing with GPT2-FT, because it is training with full joint labels (all the data has all three attribute labels), it can achieve good success rate and ours is comparable with it. And consistent with PPLM and FUDGE, due to the sampling method, GPT2-FT can achieve good perplexity but poor diversity.

We provide some generated examples in Table 8.
with high frequency, yet ours gives more diverse de-
to rise more direct comparison. Consistent with the
quantitative results, it is difficult for FUDGE to con-
trol all the desired attributes successfully, although
GPT2-FT and ours perform well. For diversity, it
is obvious that FUDGE and GPT2-FT prefer to
generate simple sentences, which can be handled well
by ours, but for the baselines, they pursue fluency
too much and lose the diversity.

## Table 8: Examples of generation with compositional attributes.

| Positive + Present + Formal |
|-----------------------------|
| **FUDGE:**                  |
| the best place i will ever eat. |
| slim and chewy,              |
| hands down, the best pizza in town. |
| their fries are always hot and fresh, this always makes me smile, great place, great staff, and great food. |
| **GPT2-FT:**                |
| the rooms are comfortable and very clean. |
| i love the staff here. their pizza is really good too. thank you! |

| Negative + Past + Informal |
|---------------------------|
| **FUDGE:**                |
| came in at _num_ pm on a saturday. |
| came here on a date and had a great time. |
| came here to try out a new chef and it was amazing! |
| it wasn’t good either!      |
| yikes!                     |
| came with three of my favorite dishes. |
| **GPT2-FT:**               |
| but i didn’t realize until it was too late. |
| so i went here.             |
| the worst sushi place ever! |
| the worst.                  |
| got ta love the restaurant. |
| i went to get the one and it looked really bad. |

| Ours:                       |
|----------------------------|
| the food is delicious , especially with a trained staff. |
| the staff is very knowledgeable and make you feel special. |
| this is my favorite bar in the northwest valley. |
| the place is well decorated and the service is great. |
| dr. baker is very experienced and nice. |
| these people are passionate about delivery and i can always see. |

## Table 9: Results of generation with compositional attributes with keyword. K, S and T represent the accuracy (success rate) of keyword, sentiment and tense, respectively.

| Constraints | K    | S    | T    | G-Mean? | PPL↓  | sBL↓  |
|-------------|------|------|------|---------|-------|-------|
| Keyword     | 0.98 | -    | -    | 0.98    | 21.7  | 10.6  |
| + Sentiment | 0.94 | 0.96 | -    | 0.95    | 21.3  | 10.8  |
| + Tense     | 0.93 | 0.9  | 0.93 | 0.92    | 19.7  | 10.9  |

## Table 10: Examples of generation with compositional attributes with keyword (expectation).

| **Keyword:** expectation |
|--------------------------|
| the prices were excellent and exceed our expectations. |
| five stars , affordable and reasonable pricing exceeded my expectations . |
| i’ve had four peaks meal from my expectations and i have not disappointed . |
| you are crazy close to my expectations! |
| the flavors have never been above & beyond expectations . |
| **Keyword:** expectation + Sentiment: Negative |
| the appetizers were completely lower expectations . |
| i would give this restaurant _num_ zero expectations in terms of our entrees . |
| it was n’t that impressive and _num_ declined my expectations . |
| there were zero expectations . |
| but my expectations were lower than zero stars . |
| **Keyword:** expectation + Sentiment: Negative + Tense: Past |
| there were so low expectations throughout the end . |
| the food was ok , but my expectations were high to top notch . |
| during the event we were already disappointed with the expectations . |
| we arrived _num_ months ago and my expectation was overcharged . |
| again , the initial estimate of course had not gotten my expectations and declined . |
| **Keyword:** expectation + Sentiment: Negative + Tense: Present |
| the prices are really low and restaurants are not above expectations . |
| there is almost no flavor in my expectations . |
| the chips and salsa are far below their expectations and lack of manners . |
| it’s about the expectations lower than zero . |
| the food in american restaurants do not exceed your expectations . |
| **Keyword:** expectation + Sentiment: Negative + Tense: Future |
| i would not come back to any expectations of this restaurant . |
| it wouldn’t be exceeded my expectations at any point . |
| i wouldn’t want you to have any expectations in this hotel . |
| honestly i wouldn’t have lower expectations before . |
| i would not expect superior from my expectation . |

## 4.2.2 Generation with Compositional Attributes with Keyword

In in case, we view keyword as an attribute of the
text sequence. To prepare the data, we extract all
verbs, nouns and the variants appeared in more than
220 sentences in the Yelp review dataset, and filter
out the sentiment-related words4. Then, we obtain
a total of 613 keywords as listed in Table 18. For
each keyword (e.g., have) and their variants (e.g.,
had or has), we treat them equally without dis-

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4http://www.cs.uic.edu/~liub/FBS/opinion-lexicon-English.rar
we compare different sampling method, including
To clarify the advantage of sampling from ODE,
To quantify the computational cost of different
Table 11: Examples of generation with compositional
and Predictor-Corrector sampler with SDE. The
attributes with keyword (accommodate).
and tense). In this experiment, we also adopt sampling multiple vectors from the final vector \((z(0))\) as illustrated in 4.1. Since we have totally 3,678 combinations of keyword, sentiment and tense, we adopt a pretrained GPT-2 base model as the decoder.

We first give the automatic evaluation results in Table 9. We list the average results of each combination of keywords, sentiment and tense. All success rate, diversity and fluency are at a high level. To make the results more intuitive, we also give some generated examples shown in Table 10 and Table 11.

4.2.3 Runtime Efficiency
To quantify the computational cost of different methods, we evaluate the consumed time for generation. For each method, we test 5 times and average the results as final time. Since we do sampling in the low-dimensional compact latent space, our method is 3x faster than FUDGE and 513x faster than PPLM.

4.3 Ablation Study
To clarify the advantage of sampling from ODE, we compare different sampling method, including Stochastic Gradient Langevin Dynamics (SGLD) and Predictor-Corrector sampler with SDE. The

Table 12: Results of generation time.

| Method  | Time (s) | Multiple |
|---------|---------|----------|
| PPLM    | 2815.2  | 513x     |
| FUDGE   | 16.56   | 3x       |
| Ours    | 5.48    | 1x       |

Recent work on text operations can be divided into two categories. The first generates desirable texts by directly making modifications to the sequence space of the generative model, while the other operates on the latent space of the texts to obtain the ideal latent representation that can be decoded into texts with desired attributes.

5 Related Work

Pretrained language models have shown tremendous success in text generation and many previous works have studied large autoregressive language models such as GPT-2 on generating texts with desired attributes by performing operations on the sequence space of the language models. For example, Dathathri et al. (2020) propose a plug-and-play framework that utilizes gradients of simple attribute classifiers to modify the hidden states of the pretrained LM at every step while keeping the weights of the LM fixed to generate desired texts, named PPLM. FUDGE (Yang and Klein, 2021) follows a similar architecture as PPLM but incorporates classifiers that predict the probability of a complete sentence having desired attributes given prefixes of that sentence to adjust the output vocabulary probability distribution given by autoregressive language models. Differing from these two approaches with left-to-right decoding, MUCOCO (Kumar et al., 2021) formulates the decoding process as a multi-objective continuous optimization that combines loss of pretrained LM and attribute classifiers. And the gradient of the optimization is applied directly to the soft representation of the output sequence that consists of the vocabulary distribution of each token. COLD (Qin et al., 2022) adopts the same soft representation of the sequence, but COLD uses an energy-based model that incorporates attribute constraints and sample from the model with Langevin dynamics to obtain an optimal sequence.
5.2 Text Control in Latent Space

Another common approach to control text generation is to edit the representation of texts in the latent space and then transform it into a sequence of texts. Some methods (Mueller et al., 2017; Liu et al., 2020) utilize a Variational Auto-encoder to encode the input sequence into a representation \( z \) in the latent space, and then use attribute networks that are jointly trained with the VAE to obtain \( z' \) that can be decoded into the desired sequence. PPVAE (Duan et al., 2020) uses a Pre-train VAE to encode the sequences to a condition-independent latent space, and then trains a separate Plugin-VAE in the latent space of Pre-train VAE to encode \( z \) to a condition-dependent latent space which can be sampled and decoded into an ideal sequence. Plug and Play (Mai et al., 2020b) follows a similar framework but replaces the VAE with a Auto-encoder and replaces the Plugin-VAE with a \( k \)-layer MLP to obtain an desired embedding vector \( z' \). And other methods use an attribute classifier to edit the latent representation \( z \) with Fast-Gradient-Iterative-Modification (Wang et al., 2019).

6 Conclusions

We have developed a new efficient approach that performs composable control operations in the compact latent space of text, named LATENTOPS. The proposed method permits combining arbitrary operators applied on a text latent vector, resulting in an energy-based distribution on the low-dimensional continuous latent space. We develop an efficient and robust sampler based on ODEs, that effectively samples from the distribution guided by gradients. We connect the latent space to popular dimensions and then trains a separate Plugin-V AE in the latent space of Pre-train V AE to encode sequences to a condition-independent latent space, and then use attribute networks that are jointly trained with the VAE to obtain \( z' \) that can be decoded into the desired sequence. Plug and Play (Mai et al., 2020b) follows a similar framework but replaces the VAE with a Auto-encoder and replaces the Plugin-VAE with a \( k \)-layer MLP to obtain a desired embedding vector \( z' \). And other methods use an attribute classifier to edit the latent representation \( z \) with Fast-Gradient-Iterative-Modification (Wang et al., 2019).

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A Derivation of ODE Formulation

A.1 General Form

Let’s consider the general diffusion process defined by SDEs in the following form (see more details in Appendix A and D.1 of Song et al. (2021)):

\[ dx = f(x, t)dt + G(x, t)dw, \tag{9} \]

where \( f(\cdot, t) : \mathbb{R}^d \to \mathbb{R}^d \) and \( G(\cdot, t) : \mathbb{R}^d \to \mathbb{R}^{d \times d} \). The corresponding reverse-time SDE is derived by Anderson (1982):

\[ dx = \left\{ f(x, t) - \nabla_x \cdot [G(x, t)G(x, t)^	op] - G(x, t)G(x, t)^	op \nabla_x \log p_t(x) \right\} dt + G(x, t)dw, \tag{10} \]

where we refer \( \nabla_x \cdot F(x) := [\nabla_x \cdot f^1(x), ..., \nabla_x \cdot f^d(x)]^\top \) for a matrix-valued function \( F(x) := [f^1(x), ..., f^d(x)]^\top \), and \( \nabla_x \cdot f^i(x) \) is the Jacobian matrix of \( f^i(x) \). Then the ODE corresponding to Eq. 9 has the following form:

\[ dx = \left\{ f(x, t) - \frac{1}{2} \nabla_x \cdot [G(x, t)G(x, t)^	op] - \frac{1}{2} G(x, t)G(x, t)^	op \nabla_x \log p_t(x) \right\} dt. \tag{11} \]

A.2 Derivation of Our ODE

In this work, we adopt the Variance Preserving (VP) SDE (Song et al., 2021) to define the forward diffusion process:

\[ dx = -\frac{1}{2} \beta(t)x dt + \sqrt{\beta(t)}dw, \tag{12} \]

where the coefficient functions of Eq. 9 are \( f(x, t) = -\frac{1}{2} \beta(t)x \in \mathbb{R}^d \) and \( G(x, t) = G(t) = \sqrt{\beta(t)}I_d \in \mathbb{R}^{d \times d} \), independent of \( x \). Following Eq. 10, the corresponding reverse-time SDE is derived as:

\[ dx = \left[ -\frac{1}{2} \beta(t)x - \beta(t)I_d - \frac{1}{2} \beta(t)I_d \nabla_x \log p_t(x) \right] dt + \sqrt{\beta(t)}I_d dw \]
\[ = \left[ -\frac{1}{2} \beta(t)x - \beta(t)I_d \nabla_x \log p_t(x) \right] dt + \sqrt{\beta(t)}dw \]
\[ = -\frac{1}{2} \beta(t) [x + 2I_d \nabla_x \log p_t(x)] dt + \sqrt{\beta(t)}dw, \tag{13} \]

which infers to the Eq. 2. Then, we derive the deterministic process (ODE) on the basis of Eq. 11:

\[ dx = \left[ -\frac{1}{2} \beta(t)x - \frac{1}{2} \beta(t)I_d \nabla_x \log p_t(x) \right] dt \]
\[ = \left[ -\frac{1}{2} \beta(t)x - \frac{1}{2} \beta(t)I_d \nabla_x \log p_t(x) \right] dt \]
\[ = -\frac{1}{2} \beta(t) [x + \nabla_x \log p_t(x)] dt, \tag{14} \]

which gives the derivation of Eq. 3.

B More Results of Experiments

B.1 More Examples of Text Editing

Some more generated examples are provided in Table 13 (Yelp) and Table 14 (Amazon).
Table 13: More examples of text editing with compositional attributes on Yelp review dataset.

| Source | Human |
|--------|-------|
| anyway, we got our coffee and will not return to this location. | we got coffee and we’ll think about going back |
| B-GST | "got our tickets |
| STrans | anyway, we got our coffee and will definitely return to this location. |
| DiRR | anyway, we got our coffee and will definitely return to this location. |
| T&G | anyway, we got our coffee and we will definitely return in town. |
| FGST | we will return to this location again, and the coffee was great. |
| FUDGE | thanks, mike, but we got our coffee and will not return to this location. |
| + Past | thanks for the great food! |
| + Present | thanks good luck, i just want to make a reservation. |
| + Future | thanks for nothing, we got our coffee and will not return to this location. |
| Ours | anyway, we got our coffee and will always return to this location. |
| + Past | anyway, we got our coffee and delivered to this friendly location. |
| + Present | anyway, we love our coffee and this location has to be found. |
| + Future | anyway, we got our coffee and will continue to return to this location. |
| Source | this place is a terrible place to live! |
| Human | this place is a great place to live! |
| B-GST | this place is my new favorite place in phoenix! |
| STrans | this place is a great place to live! |
| DiRR | this place is a great place to live! |
| T&G | this place is a great place to go! |
| FGST | this place is a great place to live. |
| FUDGE | great great great great great great great great great great great great great great! |
| + Past | excellent place to live! |
| + Present | great place to live! |
| + Future | excellent food and service, excellent ambience. |
| Ours | this place is a great place to live! |
| + Past | this place was a great place to live! |
| + Present | this place is a great place to live! |
| + Future | this place would have a great place to live! |

B.2 Ablation Study: Comparison with SGLD and SDE

In order to show the superiority of ODE sampler introduced in §3.2, we compare with Stochastic Gradient Langevin Dynamics (SGLD) and Predictor-Corrector sampler with VP-SDE. The automatic evaluation results are shown in Table 15. It’s obvious that on the premise of the success rate, ODE sampler has the best trade-off between diversity and fluency.

SGLD could generate high quality sentences, but all the sentences contain the similar content, for example: “awesome food is great as always!”, “great food is awesome as always!”, “great food is awesome and always good!”, “great place for your haircut.” and “great place with typically no bacon.”. Therefore, it performs the worst in the perspective of diversity. Also, since the sensitivity and unstability of LD (§2.1), the success rate is at a low level.

On the contrary of SGLD, SDE sampler can’t guarantee the fluency of the generated sentences, although the automatic metric of diversity is good.

We also compute the generation time of different sampling methods as shown in Table 16. Combining to the automatic evaluation results, sampling by ODE sampler gives the best trade-off among various aspects.

B.3 Generation with Single Attribute

Table 17 gives the results of single-attribute conditional generation. For all attributes, our method dramatically outperforms PPLM and FUDGE on accuracy, exceeding 94%. The diversity and fluency of our method are consistent with multi-attribute results.

B.4 Detail of Generation with Keyword

Table 18 shows all the keywords we extracted from Yelp review dataset.
Source: this is honestly the only case I've thrown away in the garbage.
Human: this is honestly the only case I've kept for so long.
B-GST: this is honestly the only case I've thrown away in the fridge.
DiRR: if your knives had a kickstand on the plate it won't lock down.
T&G: it won't slide down on the counter if you have a holder.
FGST: this is honestly the only case I've thrown away in the garbage.
FUDGE: this is honestly the only case I've saved in the kitchen.
Ours: this is honestly the only case I've put away in the dishwasher.

Source: there was almost nothing I liked about this product.
Human: there was few features I liked about this product.
B-GST: there was almost no dust I liked about this.
DiRR: it was almost perfect for my needs.
T&G: and there were no where we liked about this pan.
FGST: we've had this for many years, and there are many things about it.
FUDGE: there was almost nothing I liked about this product.
Ours: there is almost all I liked this nice product.

Source: this is not worth the money and the brand name is misleading.
Human: this is worth the money and the brand name is awesome.
B-GST: this is worth the money and the brand name is great.
DiRR: this is the perfect size and the price is right.
T&G: I won't be buying any more in the dishwasher.
FGST: I won't be buying any more in the future.
FUDGE: this is not worth the money and and and and and and and and and the brand name is misleading.
Ours: this is worth the money and the brand is awesome as the apple.

Source: I've used it twice and it has stopped working.
Human: used it without problems.
B-GST: I've used it twice and it has held up.
DiRR: I've used it twice and it has worked.
T&G: I ordered num_num and find this to be a great little mistake.
FGST: I find this to be a perfect size.
FUDGE: I've used it twice and and and and and and and and and and stopped working.
Ours: I've used it twice and and has still working.

Source: but this one does the job very nicely.
Human: but this one does the job well enough.
B-GST: but this one fit the very nicely.
DiRR: but this one does the job very poorly.
T&G: plus its from amazon and amazon wouldn't put their name on this game.
FGST: shame on amazon and wouldn't buy from amazon.
FUDGE: you should not get stuck with an num_extend
Ours: but this one does the job very negatively.

Source: as stated by the many reviews, this is an exceptional carpet cleaner.
Human: as stated by the many reviews, this is a discreet carpet cleaner.
B-GST: as stated by the many reviews, this is an excellent game.
DiRR: as stated by the many reviews, this is an exceptional.
T&G: I also love it because the jar is useless.
FGST: I also love the scent because it is plastic.
FUDGE: and there was one out there that I found that worked well and it was cheap.
Ours: as stated by the many reviews this is an exceptional poor carpet.

Source: unless you have very small or very large hands it is comfortable to use.
Human: unless you have normal sized hands it is uncomfortable to use.
B-GST: unless you have very small hands or very large hands it is useless.
DiRR: unless you have very small or very large hands it is uncomfortable to use.
T&G: not worth these alot and they taste great.
FGST: they work alot better than these patches.
FUDGE: unless you have very small or there fine small hands it is comfortable to use.
Ours: unless you have very small or very large hands it might be worse.

Table 14: Examples of text editing with single attribute on Amazon review dataset.
### Table 15: Comparison of different sampling methods.

| Attribute | Sampler | Sentiment↑ | Tense↑ | Formality↑ | G-Mean↑ | PPL↓   | sBL↓   |
|-----------|---------|------------|--------|------------|---------|--------|--------|
| Sentiment | SGLD    | 0.64       | -      | -          | 0.64    | 2.0    | 96.6   |
|           | SDE     | 0.82       | -      | -          | 0.82    | 63.8   | 6.3    |
|           | ODE     | **0.99**   | -      | -          | **0.99**| 30.4   | 13.0   |
| + Tense   | SGLD    | 0.61       | 0.68   | -          | 0.644   | 1.9    | 97.8   |
|           | SDE     | 0.79       | 0.61   | -          | 0.692   | 60.6   | 6.8    |
|           | ODE     | **0.98**   | **0.93**| -          | **0.951**| 25.2   | 19.7   |
| +Formality| SGLD    | 0.52       | 0.44   | 0.82       | 0.573   | 2.3    | 96.8   |
|           | SDE     | 0.77       | 0.60   | 0.67       | 0.675   | 62.5   | 6.7    |
|           | ODE     | **0.97**   | **0.92**| **0.93**   | **0.937**| 25.8   | 21.1   |

### Table 16: Results of generation time.

| Method | Time (s) | Multiple |
|--------|----------|----------|
| SGLD   | 5.07     | 0.93x    |
| SDE    | 15.62    | 2.85x    |
| Ours   | 5.48     | 1x       |

### Table 17: Automatic evaluation results of generation with single attribute. We show the natural logarithm of variance (LogVar) of accuracy, since the original scale is too small for demonstration.

| Attribute | Model  | Acc↑ | LogVar↓ | PPL↓ | sBL↓ |
|-----------|--------|------|---------|------|------|
| Sentiment | PPLM   | 0.63 | -3.84   | 14.8 | 35.0 |
|           | FUDGE  | 0.73 | -3.19   | 20.7 | 15.0 |
|           | Ours   | **0.99**| -Inf   | 30.4 | **13.0**|
|           | GPT2FT | 0.98 | -11.31  | **10.6**| 23.2 |
| Tense     | PPLM   | 0.60 | -2.50   | 13.9 | 36.3 |
|           | FUDGE  | 0.65 | -3.01   | 24.9 | **12.8**|
|           | Ours   | 0.96 | -8.19   | 28.8 | 16.8 |
|           | GPT2FT | **0.97**| -9.33  | **10.0**| 31.0 |
| Formality | PPLM   | 0.63 | -2.20   | 16.6 | 20.8 |
|           | FUDGE  | 0.60 | -2.69   | 22.6 | **10.2**|
|           | Ours   | **0.97**| -7.82  | 36.3 | 12.0 |
|           | GPT2-FT| 0.92 | -5.63   | **13.0**| 21.1 |
| Initial | Keywords |
|---------|----------|
| a | accommodate add afternoon agree airport ambiance ambience amount animal answer anyone anything apartment apologize apology appetizer appointment area arizona arrive art ask atmosphere attention attitude auto average avoid az |
| b | baby back bacon bag bagel bakery bar bartender base bathroom bbq bean beat become bed beef beer begin believe bell bike bill birthday biscuit bit bite hook bottle bowl box boy boyfriend bread breakfast bring brunch buck buffet building bun burger burrito business butter buy |
| c | cab cafe cake call car card care carry case cash cashier center chain chair chance change charge charlotte check cheese chef chicken child chili chip chocolate choice choose city class cleaning close club cocktail coffee color combo come company condition consider contact continue cook cooky corn cost counter couple coupon course cover crab crave cream credit crew crispy crowd crust cup curry customer cut |
| d | date daughter day deal dealership decide decor deli deliver delivery dentist department deserve desk dessert detail diner dining dinner dip discount dish do doctor dog dollar donut door downtown dressing drink drive driver drop |
| e | eat egg employee enchilada end entree environment establishment evening event everyone everything expect expectation experience explain eye |
| f | face facility fact family fan fee feel feeling felt fill find finish fish fit flavor flight floor flower folk follow food foot forget friday friend front fruit fry furniture future |
| g | game garden get gift girl give glass go god grab greet grill grocery ground group guess guest guy gym gyro |
| h | hair haircut half hand handle happen have head hear heart help hit hold hole home homemade honey hope hostess hotel house husband |
| i | ice idea include ingredient inside item |
| j | job joint juicy |
| k | keep kid kind kitchen know |
| l | lady leave let lettuce level life light line list listen live lobster location look lot lunch |
| m | mac machine madison make mall man management manager manicure manner margarita mark market massage matter meal mean meat meatball medium meet melt member mention menu mile min mind mine minute mix mom money month morning mouth move fruit fry furniture future |
| n | nail name need neighborhood night none noodle notch nothing notice number nurse |
| o | occasion offer office oil ok okay omelet one onion online open opinion option orange order organize others overcook overprice own owner |
| p | pack pad pancake park parking part party pass pasta patio pay pedicure people pepper person pet phoenix phone pick picture pie piece pittsburgh pizza place plan plate play please plenty point pool pork portion potato practice prepare price pricing process produce product provide purchase put |
| q | quality question quick quote |
| r | ranch rate rating read reason receive refill relax remember rent repair replace request reservation resort rest restaurant result return review rib rice ride ring rock roll room run rush |
| s | salad sale salmon salon salsa salt salty sandwich saturday sauce sausage save saw say schedule school scottsdale seafood season seat seating section see seem selection sell send sense serve server service set share shoe shop shopping shot show shrimp side sign sit size slice soda someone something son sound soup space speak special spend spice spicy spinich sport spot spring staff stand standard star starbucks start state station stay step stick stock stop store story street strip stuff style stylist sub suggest summer sunday suppose surprise sushi |
| t | table taco take talk taste tea team tech tell thai thanks theater thing think throw time tip tire toast today tomato ton tonight topping tortilla touch town treat trip try tuna turn tv type |
| u | understand update use |
| v | valley value veg vegetable veggie vehicle venue vet vibe view visit |
| w | waffle wait waiter waitess walk wall want wash watch water way wedding week weekend while wife window wine wing wish woman word worker world wrap write |
| x |  |
| y | year yelp yesterday yummy |
| z |  |

Table 18: All keywords. Sort in alphabetical order.