Fine-grained Sentiment Controlled Text Generation

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Abstract

Controlled text generation techniques aim to regulate specific attributes (e.g. sentiment) while preserving the attribute independent content. The state-of-the-art approaches model the specified attribute as a structured or discrete representation while making the content representation independent of it to achieve a better control. However, disentangling the text representation into separate latent spaces overlooks complex dependencies between content and attribute, leading to generation of poorly constructed and not so meaningful sentences. Moreover, such an approach fails to provide a finer control on the degree of attribute change. To address these problems of controlled text generation, in this paper, we propose DE-VAE, a hierarchical framework which captures both information enriched entangled representation and attribute specific disentangled representation in different hierarchies. DE-VAE achieves better control of sentiment as an attribute while preserving the content by learning a suitable lossless transformation network from the disentangled sentiment space to the desired entangled representation. Through feature supervision on a single dimension of the disentangled representation, DE-VAE maps the variation of sentiment to a continuous space which helps in smoothly regulating sentiment from positive to negative and vice versa. Detailed experiments on three publicly available review datasets show the superiority of DE-VAE over recent state-of-the-art approaches.

1 Introduction

Text generation using variational inference [2] is beneficial as it captures important characteristics of the input word sequence in a continuous latent space. The obtained latent space text embedding is broadly used for performing several downstream tasks including machine translation [1], summarization [15], dialog generation [11], etc. In contrast to unconditional text generation, controlled text generative models aim to construct sentences with specified attributes such as sentiment, tense, or style. Existing state-of-the-art methods for controlled text generation have mainly focused on disentangling the attribute and content representation in the latent space and generate sentences from that by modifying the attribute representation. Such methods have either derived attribute and content representations separately using multiple attribute specific decoders [7, 10], or used an adversarial setup [9] to make the text representation independent of attribute information. Another line of work has focused only on style transfer which primarily involves flipping the style or attribute value of the given sentence. Several recent works [16, 18, 19, 26, 27, 28] have explored the use of adversarial discriminators for achieving such text style transfer through disentanglement. However, these methods do not explicitly model the process of fine tuning the attribute values, e.g., changing sentiment values from extreme positive to neutral to negative, while keeping the content same. Extension of these models for finer attribute control often fail in mainly two different aspects. They cannot regulate the attribute smoothly because of multidimensional or structured (one hot encoding) representation space of the attributes. The disentanglement of the latent space also overlooks the interdependency between attribute and content. As a result, just modifying the attribute part often leads to the generation of sentences not having sufficient content overlap with the original sentence.

Disentangling latent features (such as rotation and color) of images [3, 8] is a well explored area in computer vision. In particular, BetaVAE [8] has modified the Variational Autoencoder with a special emphasis on
In order to enforce disentanglement. Further, some other works like [12, 14] have tried to achieve a trade-off between disentanglement and reconstruction quality. Although these unsupervised approaches have shown promising results on image data, achieving disentanglement in the latent representation learned for text generation comes with obvious pitfalls. The difficulty of this task arises from the fact that the text representation based on recent state-of-the-art methods like BERT [4], Transformer [24], or Seq2seq [21] is a complex manifold of entangled salient features. These representations are highly expressive for several downstream tasks including high quality sentence generation that preserves the semantics. Hence, disentangling the enriched representation space into separate spaces for attribute and content results in neglecting the complex dependency between them, thereby compromising the quality of text generation. Thus, previous methods [9, 10, 16, 18, 19, 26, 27, 28] that have tried to achieve attribute control by disentangling the latent space used for text generation suffer from these aforementioned issues, i.e., generating poor and unrealistic sentences while trying to fine tune the attribute values. A recent work [25] has proposed attribute transfer using entangled representation that enables fine tuning of the sentiment polarity. However, it is restricted to modifying the sentiment of the given sentence to only its opposite polarity using costly Fast-Gradient-Iterative Modification. We aim to address these shortcomings of existing literature by proposing a trade-off between preserving entangled representation as a latent space to generate text for better reconstruction, and deriving a continuous attribute representation in a disentangled space on top of it to fine tune the attribute values.

In this paper, specifically, we propose the model Disentangled-Entangle-VAE (DE-VAE), a feature supervised framework that transforms entangled and enriched text representation obtained using BERT encoder to a higher level representation of sentiment as a specified attribute, along with other unspecified attributes using a transformation network. DE-VAE enforces disentanglement of the derived representation by imposing a factored prior which enables independence among different dimensions of the latent representation. Further, using attribute supervision on the intended dimension of this disentangled representation, we map the sentiment to a continuous space. For attribute guided text generation, DE-VAE converts the disentangled representation back to original entangled representation and generate sentence from that. This reverse transformation helps to preserve the complex relationships between sentiment and other inherent attributes in an enriched entangled space, thereby generating more meaningful and realistic sentences compared to competing methods. However, the choice of such transformation networks for transforming from disentangled to entangled space, and vice-versa is extremely important. The transformation needs to be lossless, otherwise the decoded entangled space can become different than that of the original text representation. We use the concept of invertible normalising flow [6, 13, 17] to enforce these transformations. By jointly optimizing the parameters of transformation network, along with imposing disentanglement constraint and feature supervision on the feature space, DE-VAE successfully learns how a disentangled space for sentiment and other unspecified attributes can be converted to a meaningful entangled representation space of the sentence.

We demonstrate the effectiveness of DE-VAE to generate controlled text by fine tuning sentiment. Using three large publicly available review datasets, we show that DE-VAE improves the performance significantly over previous controlled text generative models on three different criteria, namely, sentiment control accuracy, smooth fine tuning of sentiment in both directions, and content preservation. We show that even a small difference between the decoded entangled feature space and the original entangled space, introduced by using an alternative transformation network, can lead to a significant performance drop. Finally, through an ablation study, we demonstrate the disentanglement achieved by DE-VAE on the derived feature space.

## 2 DE-VAE: Text generation with fine tuned attributes

In this section, we first give a high level overview of DE-VAE, a hierarchical model for controlled text generation, starting with describing the data. Next, we describe the key technical aspects of its individual components with key contributions in detail. Finally, we illustrate the training procedure.
We consider an input set $X = \{x_0, \ldots, x_{M-1}\}$ of $M$ observed sentences sampled from some underlying unknown data distribution $p_d$. Along with the sentences, we have the corresponding ground truth observed attribute, sentiment, denoted as $F = \{f_0, \ldots, f_{M-1}\}$. Here $f_i$ is associated to sentence $x_i$. For ease of reference, we will henceforth denote a training instance $x_i$ and $f_i$ by $x$ and $f$ respectively. Detailed architectural overview of DE-VAE is shown in Figure 1. The whole architecture can be divided into two modules consisting of a hierarchical encoder and a corresponding hierarchical decoder. We start by describing the inference model (encoder) followed by the generation model (decoder).

### 2.2 Inference model

The inference model is designed as a bottom-up hierarchical encoder. It has two distinct layers for modeling word sequence representation $z_s$, and derived feature representation $z_f$. The posterior distribution of our hierarchical inference mechanism can be represented as a factored model like:

$$ q_\phi(z|x) = q_\phi(z_s|x) \cdot q_\phi(z_f|z_s) $$

(1)

We design an entangled sentence encoder $q_\phi(z_s|x)$ in the lowest layer as follows. Given a word sequence $x$, we obtain the word embeddings $E_w$ for each word $w$ in $x$ from the BERT pre-trained model [22]. Then we combine these representations to generate an aggregated sentence encoding $E_s$ and transform it into a continuous Gaussian space $z_s \in \mathbb{R}^d$, as follows:

$$ E_w = \{e_1, \ldots, e_{|x|}\} = \text{BERT}(x), E_s = \frac{1}{|x|} \sum_{e \in E_w} e $$

$$ q_\phi(z_s|x) = \mathcal{N}(\mu_s, \text{diag}(\sigma_s^2)) \text{ where } [\mu_s, \sigma_s] = g_\phi(E_s) $$

(2)

We transform $E_s$ to a Gaussian distribution parameterized by $[\mu_s, \sigma_s]$ using a fully connected neural network $g_\phi$. The sentence representation $z_s \in \mathbb{R}^d$ is an entangled representation with $d$ dimensions. Next, we aim to transform this representation $z_s$ to another representation $z_f \in \mathbb{R}^d$ on which we can impose feature supervision and disentanglement for attribute control. Design of $q_\phi(z_f|z_s)$ is crucial for fine-tuned attribute control. First, it should transfer all the necessary information of $z_s$ to $z_f$ so that we can leverage the information for sentiment supervision on $z_f$. Most importantly, the transformation needs to be invertible. As we are interested to control the attribute by modulating $z_f$, and then transforming back to $z_s$ distribution...
space, any transformation other than an invertible one will lead to some different distribution space causing important information loss. Hence, we use an invertible normalizing flow \[6\] \[13\] \[17\] to design \(q_0(z_f | z_s)\).

A normalizing flow is a powerful transformation function which applies a chain of invertible parametrized transformations \(f_t(t = 1, \ldots, T)\) to its input (here \(z_s\)) such that the outcome of the last iteration, \(z_T\), has a more flexible distribution (here \(z_f\)). We have used an effective autoregressive transformation flow R-NVP \[6\], which copies the first \(k\) dimensions (\(1 < k < d\)) of the input, while shifting and scaling all the remaining ones. Specifically, the estimated approximate transformation flow \(f_t\), i.e. \(q_t(z_t | z_{t-1})\), can be characterized as:

\[
z_{t(1:k)} = z_{t-1(1:k)}, \quad \text{and} \quad z_{t(k+1:d)} = z_{t-1(k+1:d)} \cdot \sigma_t + \mu_t, \quad \text{where} \quad [\mu_t, \sigma_t] = \Psi_t(z_{t-1(1:k)}) \tag{3}
\]

Here, \(\Psi_t\) are designed as multilayer fully connected feed-forward networks which are not invertible. However, a careful inspection of Eq.\[3\] reveals that given \(z_t\), the input \(z_{t-1}\) can be fully recovered. So this makes the transformation flow \(f_t\) invertible. Thus, we can write \(q_0(z_f | z_s) := q_0(z_T | z_s)\) and we assign \(z_f := z_T\). From the characterization of R-NVP, we observe that \(z_f(k+1:d)\) will have the aggregated information coming from all dimensions of \(z_s\). So we pick the \(d^{th}\) (last) dimension of \(z_f\) as \(z_a\) to further fine-tune it using sentiment supervision which we will discuss in detail in the next section. The rest of the dimensions of \(z_f\) are kept for unspecified features denoted by \(z_u\). We will discuss how we achieve the disentanglement of \(z_f\) in Sec. 2.4 while discussing the training objective.

### 2.3 Generative model

We design our generative model \(p_\theta\) using a top-down hierarchy, with two different variables \(z_s\) and \(z_f\). The overall distribution of the latent variables is defined as:

\[
p_\theta(z) = \underbrace{p_\pi(z_f)}_{\text{Disentangled}} \underbrace{p_\theta(z_s | z_f)}_{\text{Entangled}} \tag{4}
\]

Here \(p_\pi(z_f)\) is a factored prior of the feature representation \(z_f\), which can be expressed as \(z_f = \prod_{i=1}^{d} p_\pi(z_f^i)\). As discussed in the previous section, we have designated the last dimension of the disentangled attribute representation to capture sentiment, and remaining dimensions for unspecified features. Henceforth, sentiment representation can be sampled from \(z_a \sim p_\pi(z_a^f)\) and unspecified representations can be sampled as \(z_u \sim \prod_{i=1}^{d-1} p_\pi(z_i^f)\). The factorized prior distribution \(p_\pi(z_f)\) is designed to be standard normal distribution, hence \(p_\pi(z_f^i) \sim \mathcal{N}(0, I) \forall i \in [1, d]\). To facilitate smooth interpolation in sentiment space, which is one of the major differences of DE-VAE than other alternatives, we use feature supervision on \(z_a\) as follows. Given \(z_a\), we try to decode the sentiment of the given sentence \(x\) and back propagate the classification error to modify the values of \(z_a\). More specifically, the decoding distribution for the ground truth sentiment is represented as:

\[
p_\theta(f | z_a) = \text{Categorical}(\xi(z_a)) \tag{5}
\]

Here \(\xi\) is a scaling network to convert the single value \(z_a\) into a two dimensional logit to calculate the likelihood of ground-truth sentiment. Next, the network tries to decode the entangled distribution \(z_s\) from the disentangled distribution \(z_f\). As described in Eq.\[3\] we apply the reverse transformation flow to recover \(z_s\) using \(T\) inverse flows \(f_t^{-1}(t = 1, \ldots, T)\). Starting from \(z_T\), denoted by \(z_f\), we obtain \(f_t^{-1}\), i.e. \(p_t(z_{t-1} | z_t)\), described using the inverse transformation flow below:

\[
z_{t(1:k)} = z_{t+1(1:k)}, \quad \text{and} \quad z_{t(k+1:d)} = \frac{z_{t+1(k+1:d)} - \mu_t}{\sigma_t}, \quad \text{where} \quad [\mu_t, \sigma_t] = \Psi_t(z_{t(1:k)}) \tag{6}
\]

It may be noted that \(\mu_t\) and \(\sigma_t\) are derived from the neural network \(\Psi_t\) which is shared between the encoder and decoder. The log probability density of \(p_\theta(z_s | z_f)\), i.e. \(\log p_T(z_s | z_f)\), \[6\] becomes equivalent to:

\[
\log p_T(z_s | z_f) = \log p_\pi(z_f) - \sum_{t=1}^{T} \log \det \frac{df_t}{df_{t-1}} \tag{7}
\]
Finally, with the decoded $z_s$, we sample the word sequence as follows:

$$h(j) = r_\theta(x(j - 1), z_s) \text{ and } x(j) \sim \text{Softmax}(m_\theta(h(j)))$$  

(8)

Here $r_\theta$ is a gated recurrent unit, which takes the previously generated token $x(j - 1)$ and the sentence representation $z_s$ to generate the hidden state $h(j)$. Then we pass this hidden state information to a feedforward network $m_\theta$ to generate logits. Subsequently, we sample words based on the softmax distribution.

Next, we update the flow parameters (Eq. (7)) and impose feature supervision by maximizing the lower bound of the marginal likelihood of the input sentence $x$ as follows:

$$p_\theta(x, f, z_s, z_f) = p_\theta(x|z_s)p_\theta(f|z_f)p_\theta(z_s|z_f)p_\tau(z_f) = p_\theta(x|z_s)p_\theta(f|z_s)p_\theta(z_s|z_f)p_\tau(z_f)$$  

(9)

### 2.4 Training

Instead of optimizing the joint likelihood given in Eq. [9] by training both layers of the hierarchy simultaneously, we train DE-VAE in two phases. First, we train the lower layer which is responsible for sentence reconstruction; next, we train the transformation flow network as well as the upper layer. We train the lower layer by maximizing the marginal likelihood of the input sentence $x$ as follows:

$$\log p_\theta(x) \geq \mathbb{E}_{q_\theta(z_s|x)} \log p_\theta(x|z_s) - \text{KL}(q_\theta(z_s|x)||p_\tau(z_s))$$  

(10)

Next, we update the flow parameters (Eq. (7)) and impose feature supervision by maximizing the lower bound of marginal likelihood of $z_s$ which is $\log p_\theta(z_s)$:

$$\mathbb{E}_{q_\theta(z_f|z_s)} \left[ \log p_\theta(f|z_s) + \log p_\tau(z_f) - \sum_{t=1}^{T} \log \det \left( \frac{df_t}{df_{t-1}} \right) - \text{KL}(q_\theta(z_f|z_s)||p_\tau(z_f)) \right]$$  

(11)

We may further breakdown the KL term of the above objective function by taking an expectation over $z_s$ as following:

$$\mathbb{E}_{z_s \sim q_\theta(z_s)} I(z_s, z_f) + \underbrace{\text{KL}(q_\theta(z_f|z_s)||p_\tau(z_f))}_{\text{Total Correlation}}$$  

(12)

As $p_\tau(z_f)$ is fully factorized, minimizing the above total correlation loss will benefit the model in achieving disentanglement of $z_f$ along the dimensions. It is also important that a specified disentangled part of $z_f$, for a designated sentiment $f$, should carry enough information about that sentiment. Hence, the mutual information between the sentiment $f$ and $z_a$ should be high. This mutual information can be computed using entropy function $H(.)$ as:

$$I(f, z_a) = H(f) - H(f|z_a) \geq \mathbb{E}_{x \sim p_D}[\mathbb{E}_{q_\theta(z_s|x)}q_\theta(z_a|z_s)\log p_\theta(f|z_a)]$$  

(13)

As $I(f, z_a)$ is lower bounded by the likelihood $p_\theta(f|z_a)$, we provide extra emphasis of the likelihood term in the objective function. To optimize the upper layer and flow parameters we maximize the lower bound of $\log p_\theta(z_s)$ as below:

$$\mathbb{E}_{q_\theta(z_f|z_s)} \left[ \beta \log p_\theta(f|z_s) + \log p_\tau(z_f) - \sum_{t=1}^{T} \log \det \left( \frac{df_t}{df_{t-1}} \right) - \gamma \text{KL}(q_\theta(z_f|z_s)||p_\tau(z_f)) \right]$$  

(14)

where $\beta$ and $\gamma$ are regularizing parameters to emphasize on increasing the sentiment likelihood and enforce the disentanglement of $z_f$. Updating the flow parameters along with high emphasis on disentanglement and feature supervision using Eq. [14] helps the model to learn the complex transformation of independent features $z_u$ and $z_s$ to an enriched entangled $z_s$. The specific details of implementation is provided in the Appendix A.
Table 1: Controlled generation and Text style transfer accuracy achieved by different methods.

| Methods     | Yelp       | Amazon     | IMDB       |
|-------------|------------|------------|------------|
|             | Controlled | Text style | Controlled | Text style | Controlled | Text style |
|             | generation |   transfer | generation |   transfer | generation |   transfer |
| ctrlGen     | 0.72       | 0.70       | 0.62       | 0.63       | 0.76       | 0.77       |
| DAE         | 0.95       | 0.80       | 0.84       | 0.77       | 0.82       | 0.81       |
| entangleGen | -          | 0.94       | -          | 0.82       | -          | 0.66       |
| DE-VAE-NR   | 0.62       | 0.58       | 0.59       | 0.51       | 0.59       | 0.53       |
| DE-VAE      | 0.95       | 0.84       | 0.84       | 0.90       | 0.90       | 0.86       |

3 Experimental evaluation

In this section, we evaluate the performance of DE-VAE in terms of sentiment control using three different evaluation criteria - (a) sentiment control accuracy, (b) fine-tuning of sentiment, and (c) content preservation. Additionally, we also discuss the extent of disentanglement in the latent space $z_f$.

For our evaluation, we rely on three large review datasets for sentiment controlled text generation - (a) Yelp [25] with 443248, 2000, and 1000 number of labeled data on restaurant review for training, validation, and test respectively with a vocabulary size of 9.5K, (b) Amazon [25] with 554997, 2000, and 2000 number of labeled data on product review for training, validation, and test respectively with a vocabulary size 25K, and (c) IMDB [5] movie review corpus which consists of 708929, 4000, and 2000 number of unlabeled training, validation, and test data with a vocabulary size of 28K. This IMDB data has been tagged by Stanford sentiment tagger [20] and converted to three sentiment labels, namely, positive, neutral, and negative.

We compare the performance of DE-VAE with the following baselines that focus on controlled text generation using disentanglement - (a) ctrlGen [9] which is a semi-supervised method for sentiment oriented text generation, and (b) DAE [10] which is a supervised method that focuses on disentanglement using adversarial loss. Other than these, we also compare DE-VAE with entangleGen [25] which focuses on text style transfer using entangled representation. Apart from these state-of-the-art baselines, we also use DE-VAE-NR (DE-VAE Non-Reversible transformation) as a baseline which is a variation of DE-VAE. In DE-VAE-NR, we replace the invertible normalizing flow used in DE-VAE with two neural networks designed as a two layer fully connected feedforward network responsible for capturing $q_{θ}(z_f|z_s)$ and $p_{θ}(z_s|z_f)$.

3.1 Sentiment control accuracy

Here we measure the quality of sentiment control by quantitatively evaluating the sentiment oriented sentence generation accuracy. For this purpose, we train a sentiment classifier by extending BERT [4]. This classifier is 95% accurate on Yelp data and 85% accurate on Amazon and IMDB data which demonstrates its robustness. Specifically, DE-VAE generates sentences by regulating the values in the designated dimension of $z_f$ which is modeled to control the sentiment; we use the pre-trained sentiment classifier to assign sentiment labels to the generated sentences. Similarly, we generate sentences using the baseline methods. We report the accuracy of sentiment oriented sentence generation in two different ways - (a) Controlled generation accuracy which is accuracy of generating sentences where the generative representation is sampled from the prior (i.e., from $p_{θ}(z_f)$ in case of DE-VAE), followed by assigning the desired value for the sentiment representation (i.e., $z_s$ for DE-VAE), and (b) Text style transfer accuracy which is accuracy of generating sentences with opposite polarity sentiment from the representation of a sentence $x$, bearing a specific type of sentiment (in our case, $z_f \sim q_{θ}(z_f|x_s)q_{θ}(z_s|x)$, as it regulates sentiment).

From the results reported in Table 1, it can be observed that DE-VAE outperforms all competing methods across all datasets for controlled text generation, other than text style transfer accuracy in case of Yelp. The superior performance of DE-VAE stems from the fact that it learns a disentangled feature representation where sentiment information is modeled in a single dimension which is independent of other dimensions. So, regulating the sentiment value along this designated dimension gives better control while generating sentences bearing the same sentiment. Further, in case of DE-VAE-NR, we train the parameters of the transformation network by maximizing the likelihood of $z_s$, i.e., $\mathbb{E}_{q_{θ}(z_s|x)}p_{θ}(z_s|z_f)$, such that the
minimum KL between $q_\phi(z_f|z_s)$ and $p_\theta(z_s|z_f)$ is found to be in the range $0.2 - 0.4$ across all datasets; however, the performance of DE-VAE-NR is significantly inferior compared to DE-VAE. Close inspection reveals that even though the KL was low, as the decoded distribution $z_s$ was not exactly the same as the encoded distribution, it was generating sentences very different from the original sentences. This shows the importance of invertible normalizing flow as a design choice.

The closest competitor to our method is DAE for controlled text generation with comparable performance to DE-VAE. The reason is that DAE achieves disentanglement between style space and content space using extensive adversarial training and incorporates auxiliary multi-task loss for sentiment or style. Further, in comparison to other methods, ctrlGen performs poorly for controlled text generation. We speculate that ctrlGen has comparatively less control than other methods since it does not model feature representation from sentence representation and tries to control generation by providing only a one hot encoding of sentiment externally. We have reported the accuracy of entangleGen only for text style transfer in Table 1 since it focuses only on attribute transfer. We observe that entangleGen achieves better accuracy on Yelp dataset than our method; however, DE-VAE performs better on all other datasets. Since entangleGen inherently supports binary-valued attributes by design, it can best modify the sentiment value towards its opposite polarity using Fast-Gradient-Iterative-Modification. Hence, its performance suffers in IMDB data where there are more than two sentiment values.

3.2 Fine tuning of sentiment and Content preservation

In this section, we discuss the performance of DE-VAE in terms of both the evaluation criteria - fine tuning of sentiment, and content preservation. As by design, DE-VAE is able to capture the entire behaviour of the sentiment in a continuous latent space of a single dimension, we first estimate the maximum value $f_{\text{max}}$ and the minimum value $f_{\text{min}}$ of this dimension from the training data. Then we use this range and interpolate between $f_{\text{max}}$ and $f_{\text{min}}$ in 20 different sentiment levels where the value of $i^{th}$ level $l_i$ ($1 \leq i \leq 20$) is denoted as $f_{\text{min}} + (f_{\text{max}} - f_{\text{min}})(i-1)$.

Given a feature representation $z_f$ corresponding to a sentence $x$, we assign a level to $z_a$ (last dimension of $z_f$) and sample 100 sentences corresponding to this modified $z_a$. We repeat this procedure corresponding to each level. Similarly, we extend ctrlGen to generate sentences by interpolating 20 different values sampled from the range $[0,1]$ for the structured two-dimensional sentiment representation. As entangleGen can only regulate the sentiment of the given sentence in the opposite polarity using 35 different degrees of sentiment, we have aggregated them within ten sentiment levels. It may be noted that we
have excluded DAE from this evaluation since it models sentiment in a multi-dimensional space and fine
tuning sentiment in such a space is non-trivial and needs separate investigation. Additionally, we have also
excluded comparison with DE-VAE-NR due to its poor performance on sentiment control.

To quantitatively measure the performance of fine tuning of sentiment, we have used the pre-trained
Stanford sentiment regressor [20] which provides sentiment scores of sentences generated for DE-VAE and
other methods between [0, 1] with 1 denoting most positive and 0 denoting most negative. Further, we
evaluate the model performance in terms of content preservation while fine tuning sentiment. For this purpose,
we compute Jaccard overlap [23] of unigram words in the original sentence \( x \) and the generated sentence \( y \),
computed as

\[
\frac{|w \in x \cap w \in y|}{|w \in x \cup w \in y|}
\]

where \( w \) denotes the set of words after excluding stopwords in corresponding sentence.

In Figure 2, we have demonstrated the variation of mean sentiment scores (Figures 2(a)-(d)) and Jaccard
overlap scores (Figures 2(e)-(h)) for different \( l_1 \) (with 1 denoting most negative and 20 denoting most positive
control signal). We separately show the variations of mean positive (negative) sentiment value over the
different levels when starting sentiment was negative (positive). We can observe from Figure 2(a) that the
sentiment scores vary over a large range (0.17) between the first and last levels for DE-VAE in case of
Yelp when the original sentence is positive; however, entangleGen can achieve a greater negative sentiment
score for levels 1 – 4. In comparison to these methods, ctrlGen shows a very small drift (0.1) in sentiment
scores over all the levels with almost zero variation for levels 13 – 20. This implies that ctrlGen has lesser
control in fine tuning sentiment scores over the levels compared to DE-VAE. Interestingly, if we check the

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Figure 2(b) also shows that the Jaccard overlap scores are high for DE-VAE over all the levels demonstrating its effectiveness in content preservation while fine tuning sentiment.

In case of Amazon data, Figure 2(b) shows that we can easily achieve a smooth variation in the negative
sentiment scores for DE-VAE with a reasonably high drift of 0.08 between the first and last levels. Compared
to DE-VAE, ctrlGen shows negligible drift for levels 11 – 20. Figure 2(b) also shows that entangleGen
performs poorly in fine tuning the sentiment for Amazon. Looking into the corresponding Jaccard overlap
scores in Figure 2(f), it can be easily observed that DE-VAE achieves higher Jaccard overlap scores compared
to other methods with low scores only for the last few levels. Similar observation holds true for the opposite
case when the original sentence is negative across all datasets as evident from Figures 2(c)-(d) and Figures 2(g)-(h). This signifies the fact that DE-VAE can achieve a superior fine tuning of sentiment while preserving
the content of generated sentences compared to the state-of-the-art methods. Since we could not observe any
significant variation in sentiment scores of generated sentences for IMDB over different levels for any of the
methods, we have not discussed these results for the IMDB dataset.

Further, we have sampled an original sentence from the data and have shown the corresponding generated
sentences using DE-VAE for different levels in Table 2. As evident from this table, we are able to preserve
the content and semantics of the original sentence while still observing a smooth interpolation in the degree of
sentiment transfer. An interesting observation is that though the exact word overlap is low for the generated
sentences with very high sentiment scores (e.g., \( l_1 \) and \( l_20 \) in Table 2), they are semantically similar to the
original sentence. We show more qualitative results in Appendix B.

| Original Sentence - Positive | Original Sentence - Negative |
|------------------------------|------------------------------|
| "I'm very impressed with the level of care here!" | "Their selection was questionable!" |
| "I am totally disappointed by the help completely not caring." | "But their inventory was overpriced!" |
| "I am totally disappointed with the compassion (not caring)." | "But their was inventory ridiculous!" |
| "I am not totally disappointed by the owners not caring." | "But their inventory was awful!" |
| "I am highly recommend - this resort truly care!" | "Their inventory was impressive!" |
| "I am truly kind of 'impressed' - oh highly recommend this staff!" | "Their selection was outstanding!" |

Table 2: Fine grained sentiment control of sentences from extreme negative to extreme positive. Bold letters indicates words with sentiment and the color blue indicates important words to be preserved.
3.3 Ablation study

Here we perform an ablation study by demonstrating the importance of the last dimension \( z_a \) of the representation \( z_f \) in capturing sentiment. As we ensure independence of every dimension, we calculate the correlation of every dimension of \( z_f \) with the sentiment labels in the test data. We observe that \( z_a \) achieves the highest correlation of 0.72 in Yelp and 0.42 in Amazon. We further train a logistic regression classifier with \( z_a \) of training data as a feature to predict sentiment labels, and we achieve a high accuracy of 0.85 and 0.64 on test data in Yelp and Amazon respectively. While training with the most correlated dimension of \( z_f \) other than \( z_a \), with a correlation of 0.12 for Yelp and 0.14 for Amazon, we achieve an accuracy of only 0.52 and 0.58 respectively. This implies that \( z_a \) is the most expressive dimension for capturing sentiment in comparison to any other dimension.

4 Conclusion

The major contribution of this paper is to propose DE-VAE which consists of a carefully designed hierarchical architecture to maintain both the disentangled feature representation and entangled sentence representation. The invertible normalizing flow as a transformation module between the two representation layers of DE-VAE enables learning of complex interdependency between disentangled feature and entangled sentence representation without the loss of information. Such a design choice is key to achieving accurate fine tuning of sentiment while keeping the content intact. This is a key achievement considering the difficulty of the problem and modest performance of state-of-the-art techniques. Extensive experiments on real-world datasets emphatically establish the well-rounded performance of DE-VAE and its superiority over the baselines.

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A Parameter Setting

The sentence encoder is designed using pre-trained BERT-base-uncased model (embedding dim = 768) followed by 2-layer feed-forward network with hidden dim 200. The output of the same is the sentence embedding which is of dimension 256 for Yelp and 300 for Amazon, and IMDB. The flow network is designed as R-NVP with $T = 3$ and each $\psi_t$ is designed as three layer feed forward network with $tanh$ activation function for the initial two layers and hidden dimension is 100 for the intermediate layers. The scaling network for sentiment classification is designed as a two dimensional vector $[-1,1]$. The sentence decoder is designed as a gated recurrent unit where output of each step is passed through a fully connected feed-forward network to convert it to a logit of length of the vocabulary size. To avoid vanishingly small KL term in the VAE module Eq. 11, we use a KL term weight linearly annealing from 0 to 1 during training. The weighing parameters $\beta$ and $\gamma$ are set to 10 for feature supervision and disentanglement.

B Qualitative samples

In Table 3, we have provided some comparative examples of the sentiment fine-tuning results. It can be seen that ctrlGen provides both positive and negative polarity sentences, but there is very less content overlap in comparison to entangleGen and DE-VAE. On further scrutiny we discover, it can only retain content for smaller length sentences with less content words. Some examples are given in Table 4.

| Orig. | DE-VAE | entangleGen | ctrlGen |
|-------|--------|-------------|---------|
|       | the house fried rice and egg rolls are the best in phoenix . | the house too way and egg should ? ” | rustrated ! |
| $l_1$ | the fried rice dishes are not acceptable , and extremely disappointed . | the house too way and egg rolls were the barely in nothing ? | this is n’t the only restaurant . |
| $l_5$ | the eggs benedict fried rice and the rice dishes are not acceptable . | the house fried rice and egg rolls were the only in phoenix table . | their fish is soggy . |
| $l_8$ | the rice dishes of fried rice , which is not the perfect . | the house fried rice and egg rolls are the best in phoenix only . | i will return to give you right new . |
| $l_{10}$ | the rice dishes up fried rice , which is not the wonderful . | | |
| $l_{12}$ | the rice combo is the average , eggs and authentic . | - | the grand staff is nice . |
| $l_{16}$ | the rice ( the chicken ) are the best , and the same for the staff . | - | friendly staff is impeccably neat |
| $l_{20}$ | the rice ( the chicken ) are the best . | - | bar tender and professional . |

Table 3: Comparative example with DE-VAE and other methods

| Orig. | DE-VAE | ctrlGen |
|-------|--------|---------|
|       | food was good , but service was great . | hate the food , service just . |
| $l_1$ | awful service | great food . |
| $l_20$ | food was great service was good too . | great food . |
| Orig. | will make this place a regular staple . | |
| $l_1$ | will make this place awful | do n’t make this place . |
| $l_{20}$ | will make this place great | i love this place . |

Table 4: Sample generated text from shorter original text

C Training time comparison

In this section we provide a comparative analysis of training time and sampling time of DE-VAE with entangleGen. Fig 3 shows that DE-VAE is much faster than that of entangleGen for both cases.

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Figure 3: (a) the time taken (per epoch) for training by DE-VAE and entangleGen on different datasets. (b) the time taken to generate 1K sentences by DE-VAE and entangleGen on different datasets.