Abstract

In this work, we present a text generation approach with multi-attribute control for data augmentation. We introduce CGA, a Variational Autoencoder architecture, to control, generate, and augment text. CGA is able to generate natural sentences with multiple controlled attributes by combining adversarial learning with a context-aware loss. The scalability of our approach is established through a single discriminator, independently of the number of attributes. As the main application of our work, we test the potential of this new model in a data augmentation use case. In a downstream NLP task, the sentences generated by our CGA model not only show significant improvements over a strong baseline, but also a classification performance very similar to real data. Furthermore, we are able to show high quality, diversity and attribute control in the generated sentences through a series of automatic and human assessments.

1 Introduction

Recently, natural language generation (NLG) has become a prominent research topic in NLP, due to its diverse applications, ranging from machine translation (e.g., Sennrich et al. (2016)) to dialogue systems (e.g., Budzianowski and Vulić (2019)). The main application and common goal of automatic text generation is the augmentation of datasets used for supervised NLP tasks. Hence, one of the key demands of NLG is controlled text generation, more specifically, the ability to systematically control semantic and syntactic aspects of generated text.

Most previous approaches simplify this problem by approximating NLG with the control of one single aspect of the text, such as sentiment or formality (e.g., Li et al. (2018), Fu et al. (2018), and John et al. (2019)). However, the problem of controlled generation relies on multiple components such as lexical, syntactic, semantic and stylistic aspects. Therefore, the simultaneous control of multiple attributes becomes vital to generate natural sentences suitable for specific downstream tasks. Methods such as the ones presented by Hu et al. (2017) and Subramanian et al. (2018), succeed in simultaneous controlling multiple attributes of sentences. However, these methods depend on the transformation of input reference sentences, or do not scale easily to multiple attributes due to architectural complexities, such as the requirement for separate discriminators for each additional attribute.

In light of these challenges, with our Control, Generate, Augment model (CGA) we propose a powerful framework to synthesize additional labeled data. The accurate multi-attribute control of our approach offers significant performance gains on downstream NLP tasks.

The main contributions of this paper are:

1. A scalable model which learns to control multiple semantic and syntactic attributes of a sentence. The CGA model requires only a single discriminator for simultaneously controlling multiple attributes (see Section 2). We present automatic and human assessments to confirm the control over multiple semantic and syntactic attributes. Further, we provide a quantitative comparison to previous work.

2. A method for natural language generation for data augmentation, which boosts the performance of downstream tasks. To this end, we present data augmentation experiments of various datasets, where we significantly outperform a strong baseline and achieve a performance comparable to real data (Section 3).
2 Method

We now present our model for controlled text generation. Our model is based on the Sentence-VAE framework (Bowman et al., 2016). However, we change the model to allow the generation of sentences conditioned not only on the latent code but also on a attribute vector. We achieve this by disentangling the latent code from the attribute vector, in a similar way as the Fader networks (Lample et al., 2017), originally developed for computer vision tasks. As we will see, this simple adaption would not be sufficient. We carefully designed our architecture by taking advantage of a range of techniques, some from the NLP community (Edunov et al., 2018), but many from the computer vision community (Zhu et al., 2017; Sanakoyeu et al., 2018).

2.1 Model Architecture

We assume access to a corpus of sentences $X = \{x_i\}_{i=1}^N$ and a set of $K$ categorical attributes of interest. For each sentence $x_i$, we use an attribute vector $a_i$ to represent these $K$ associated attributes. Example attributes include the sentiment or verb tense of a sentence.

Given a sentence $x$ and its attribute vector $a$, our goal is to construct an ML model that, given a different attribute vector $a'$, generates a new sentence $x'$ that contains attributes $a'$.

**Sentence Variational Autoencoder** The main component of our model is a Variational Autoencoder (Kingma and Welling, 2013). The encoder network $E_{\theta_{enc}}$, parameterized by a trainable parameter $\theta_{enc}$, takes as input a sentence $x$ and defines a probabilistic distribution over the latent code $z$:

$$z \sim E_{\theta_{enc}}(x) := q_E(z|x; \theta_{enc}) \quad (1)$$

The decoder $G_{\theta_{dec}}$, parameterized by a trainable parameter $\theta_{dec}$, tries to reconstruct the input sentence $x$ from a latent code $z$ and its attribute vector $a$. We always assume that the reconstructed sentence $\hat{x}$ has the same number of tokens as the input sentence $x$:

$$\hat{x} \sim G_{\theta_{dec}}(z, a) := p_{G}(\hat{x}|z, a; \theta_{dec}) \quad (2)$$

where $L$ is the total number of tokens of the input sentences and $\hat{x}_t$ is the $t^{th}$ token. Here we abuse the notation slightly and use $p_{G}$ to denote both sentence-level probability and word-level conditional probability.

To train the encoder and decoder, we use the following VAE loss:

$$L_{VAE}(\theta_{enc}, \theta_{dec}) = KL(q_{E}(z|x)||p(z)) - \mathbb{E}_{z \sim q_{E}(z|x)} \log p_{G}(x|z, a; \theta_{dec}), \quad (3)$$

where $p(z)$ is a standard Gaussian distribution.

When we try to optimize the loss in Equation 3, the KL term often vanishes. This problem is known in text generation as posterior collapse (Bowman et al., 2016). To mitigate this problem we follow Bowman et al. (2016) and add a weight $\lambda_{kl}$ to the KL term in Equation 3. At the start of training, we set the weight to zero, so that the model learns to encode as much information in $z$ as possible. Then, as training progresses, we gradually increase this weight, as in the standard KL-annealing technique.

Moreover, the posterior collapse problem is partially due to the fact that, during training, our decoder $G_{\theta_{dec}}$ predicts each token conditioned on the previous ground-truth token. We hope to make the model rely more on $z$. A natural way to achieve this is to weaken the decoder by removing some or all of this conditional information during training. Previous work (Bowman et al., 2016; Hu et al., 2017) replace a — randomly selected — significant portion of the ground-truth tokens with MASK. However, this can severely affect the decoder and worsen the generative capacity of the model. Therefore, we define a new word-dropout routine, which aims at both accommodating the posterior collapse problem and preserving the decoder capacity. Instead of fixing the word-dropout rate to a large constant value as in Bowman et al. (2016), we use a cyclical word-dropout rate $\zeta$:

$$\zeta(s) = \left\{ \begin{array}{ll} k_1 \cos \left( \frac{2\pi}{\tau} s \right) & s \leq \text{warmup} \\ 1 & \text{otherwise} \end{array} \right., \quad (4)$$

where $s$ is the current training iteration, $k_1$ is a constant value we use during the warmup phase, and $\tau$ defines the period of the cyclical word-dropout rate schedule.

**Disentangling Latent Code $z$ and Attribute Vector $a$** To be able to generate sentences given a different attribute vector $a'$, we have to disentangle the attribute vector with the latent code. In other words, we hope that $z$ is attribute-invariant: A latent code $z$ is attribute-invariant if given two
Figure 1: Model Architecture depicting the key components: the conditional VAE, the multi-attribute discriminator and the context-aware loss.

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semantically equivalent sentences $x_1$ and $x_2$, that only differ on their attributes (e.g., two versions of the same review expressing opposite sentiment), they should result in the same latent representation $z = E \theta_{enc}(x_1) = E \theta_{enc}(x_2)$.

To achieve this, we use a concept from predictability minimization (Schmidhuber, 1992) and adversarial training for domain adaptation (Ganin et al., 2016; Louppe et al., 2017), which was recently applied in the Fader Networks by Lample et al. (2017). We apply adversarial learning directly on the latent code $z$ of the input sentence $x$. We set a min-max game and introduce a discriminator $D \theta_{disk}(z)$, that takes as input the latent code and tries to predict the attribute vector $a$. Specifically, $D \theta_{disk}(z)$ outputs for each attribute $k$, a probability distribution $p_k^{D}$ over all its possible values. To train the discriminator, we optimize for the following loss:

$$L_{DISC}(\theta_{disk}) = - \log \prod_k p_D^k(a_k)$$

where $a_k$ is the ground-truth of the $k^{th}$ attribute.

Simultaneously, we hope to learn an encoder and decoder which (1) combined with the attribute vector $a$, allows the decoder to reconstruct the input sentence $x$, and (2) does not allow the discriminator to infer the correct attribute vector corresponding to $x$. We optimize for:

$$L_{VAE}(\theta_{enc}, \theta_{dec}) - \lambda_{DISC}L_{DISC}(\theta_{disc})$$

Context-Aware Loss Equation 6 forces our model to choose which information the latent code $z$ should retain or disregard. However, this approach comes with the risk of deteriorating the quality of the latent code itself. Therefore, inspired by Sanakoyeu et al. (2018), we propose an attribute-aware context loss, which tries to preserve the context information by comparing the sentence latent representation and its back-context representation:

$$L_{CTX} := \|E \theta_{enc}(x) - E \theta_{enc}(G \theta_{dec}(E \theta_{enc}(x)))\|_1$$

The latent vector $z = E \theta_{enc}(x)$ can be seen as a contextual representation of the input sentence $x$. This latent representation is changing during the training process and hence adapts to the attribute vector. Thus, when measuring the similarity between $z$ and the back-context representation $E \theta_{enc}(G \theta_{dec}(E \theta_{enc}(x)))$, we focus on preserving those aspects which are profoundly relevant for the context representation.

Finally, when training the encoder and decoder (given the current discriminator), we optimize for the following loss:

$$L_{VAE} + \lambda_{CTX}L_{CTX} - \lambda_{DISC}L_{DISC}$$

3 Evaluation

To assess our newly proposed model for the controlled generation of sentences, we perform the following evaluations described in this section: An automatic and human evaluation to analyze the quality of the new sentences with multiple controlled attributes; an examination of sentence embedding similarity to assess the diversity of the generated samples; downstream classification experiments with data augmentation on two different datasets to prove the effectiveness of the new sentences in a
Sentence Attributes
---
It was a great time to get the best in town and I loved it. | Past / Positive
---
It was a great time to get the food and it was delicious. | Past / Positive
It is a must! | Present / Positive
They're very reasonable and they are very friendly and helpful. | Present / Positive
I had a groupon and the service was horrible. | Past / Negative
This place was the worst experience I've ever had. | Past / Negative
It is not worth the money. | Present / Negative
There is no excuse to choose this place. | Present / Negative

Table 1: Examples of generated sentences with two attributes: SENTIMENT and VERB TENSE.

Sentence Attributes
---
They have a great selection of beers and shakes. | Present / Positive / Plural
I love this place and I will continue to go here. | Present / Positive / Singular
The mashed potatoes were all delicious! | Past / Positive / Plural
The lady who answered was very friendly and helpful. | Past / Positive / Singular
The people are clueless. | Present / Negative / Plural
I mean I'm disappointed. | Present / Negative / Singular
Drinks were cold and not very good. | Past / Negative / Plural
It was a complete disaster. | Past / Negative / Singular

Table 2: Examples of generated sentences with three attributes: SENTIMENT, VERB TENSE, and PERSON NUMBER.

Datasets
We conduct all experiments on two datasets, YELP and IMDB reviews. Both contain sentiment labels for the reviews. From the YELP business reviews dataset (YELP, 2014), we use reviews only from the category restaurants, which results in a dataset of approx. 600’000 sentences. The IMDB movie reviews dataset (Maas et al., 2011) contains approx. 150’000 sentences. For reproducibility purposes, details about training splits and vocabulary sizes can be found in the supplementary materials.

Attributes
For our experiments we use three attributes: sentiment as a semantic attribute; verb tense and person number as syntactic attributes.

1. **SENTIMENT**: We labeled each review as *positive* or *negative* following the approach of Shen et al. (2017).

2. **VERB TENSE**: We detect *past* and *present* verb tenses using SpaCy’s part-of-speech tagging model\(^1\). We define a sentence as *present* if it contains more present than past verbs.

3. **PERSON NUMBER**: We also use spaCy to detect *singular* or *plural* pronouns and nouns.

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\(^1\)https://spacy.io/usage/linguistic-features#pos-tagging

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relevant application scenario; and, finally, a comparison of our results to previous work to specifically contrast our model against other single and multi-attribute models.

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**Experimental Setting**
The generator and encoder are set as single-layer LSTM RNNs with hidden dimension of 256 and maximum sample length of 20. The Discriminator is set as a fully-connected layer or single-layer LSTM. To avoid a vanishingly small KL term in the VAE (Bowman et al., 2016), we use a KL term weight annealing that increases from 0 to 1 during training according to a logistic scheduling. \(\lambda_{\text{disc}}\) increases linearly from 0 to 20. Finally, we set the back-translation weight \(\delta\) to 0.5. More specific information is provided in the supplementary material.

Consequently, we label a sentence as *singular* if it contains more singular than plural pronouns or nouns, we define it *plural*, in the opposite case, *balanced* otherwise.
3.1 Quality of Generated Sentences

First, we quantitatively measure the sentence attribute control of our CGA model by evaluating the accuracy of generating the designated attributes by conducting both automatic and human evaluations.

Attribute Matching For this automatic evaluation, we generate sentences given the attribute vector $a$ as described in Section 2. To assign the Sentiment attribute labels, we apply a pre-trained TextCNN with 95% accuracy on YELP and 81% accuracy on IMDB (Kim, 2014). To assign the Verb Tense and Person Number labels we use SpaCy’s part-of-speech tagging (93% accuracy for English). We calculate the accuracy as the percentage of the predictions of these pre-trained models that match the attribute label generated by our CGA model. Table 3 shows the results on 30K sentences generated by CGA models trained on YELP and IMDB, respectively. The results are averaged over five balanced splits, each of them with 6000 samples.

| Attribute       | Sentences | Accuracy ($\kappa$) | AS |
|-----------------|-----------|---------------------|----|
| Sentiment       | 106/120   | 0.88 (0.73)         | 4.40 |
| Verb Tense      | 117/120   | 0.98 (0.97)         | 4.90 |
| Person Number   | 114/120   | 0.95 (0.85)         | 4.25 |
| 2 Attributes    | 120/120   | 1.0                 | -   |
| 3 Attributes    | 97/120    | 0.80                | -   |
| Coherence       | 79/120    | 0.66                | -   |

Table 3: Attribute matching accuracy (in %) of the generated sentences; standard deviation reported in brackets.

Human Evaluation To further understand the quality of the generated sentences we go beyond the automatic attribute evaluation and perform a human judgement analysis.

One of our main contributions is the generation of sentences with up to three controlled attributes. Therefore, we randomly select 120 sentences generated from the model trained on YELP, which controls all three attributes. Two human annotators labelled these sentences by marking which of the attributes are included correctly in the sentence.

In addition to the accuracy we report inter-annotator rates with Cohen’s $\kappa$. In 80% of the sentences all three attributes are included correctly and in 100% of the sentences at least two of the three attributes are present. To facilitate comparisons to previous work (see Section 4), we also assign an attribute score between 1 and 5 from the annotator agreements (1 if the considered attribute is not included, 5 if it is evidently present in the sentence).

Sentence Embedding Similarity Although generative models have been shown to produce outstanding results, in many circumstances they risk to produce extremely repetitive examples (Goodfellow et al., 2014; Zhao et al., 2017). In this experiment, we qualitatively assess the capacity of our model to generate diversified sentences to further strengthen the results obtained in this work. We sample 10K sentences from YELP ($D_{true}$) and from our generated sentences ($D_{gen}$), respectively, both labeled with the Sentiment attribute. We retrieve the sentence embedding for each of the sentences in $D_{true}$ and $D_{gen}$ using the Universal Sentence Encoder (Cer et al., 2018). Then, we compute the cosine similarity between the embeddings of all sentences of $D_{true}$ and, analogously, between the embeddings of our generated sentences $D_{gen}$.

Consequently, we obtain two similarity matrices $M_{true}$ and $M_{gen}$ (see Figure 3.1). Both matrices show a four cluster structure:

- **Top-Left**: Similarity scores between negative reviews ($C_{nn}$)
- **Top-Right or Bottom-Left**: Similarity scores between negative and positive reviews ($C_{np}$)
- **Bottom-Right**: Similarity scores between positive reviews ($C_{pp}$)

Further, for each sample of $D_{true}$ and $D_{gen}$ we compute a similarity score as follows:

$$sim(s_{i,e}) = \frac{1}{K} \sum_{x \in \mathcal{N}_{K,e}} score(s_{i,x})$$ (9)
Figure 2: Similarity Matrices for real data and data generated by our CGA model controlling the sentiment attribute.

Figure 3: Sentence similarity scores computed for real data and data generated by our CGA model on the three sentiment clusters (Negative-Negative, Negative-Positive, Positive-Positive).

where $c \in \{C_{nn}, C_{np}, C_{pp}\}$. $s_i$ is the i-th sample of $D_{true}$ or $D_{gen}$ and $c$ is the cluster to which $s_i$ belongs. $N_{K,c}$ is the set of the k-most similar neighbours of $s_i$ in cluster $c$, and $k=50$.

To gain a qualitative understanding of the generation capacities of our model, we assume that an ideal generative model should produce samples that have comparable similarity scores to the ones or the real data. Therefore, Figure 3.1 contrasts the similarity scores of $D_{true}$ and $D_{gen}$, computed on each cluster separately.

Although our generated sentences are clearly more similar between themselves than to the original ones, our model is able to produce samples clustered according to their labels. This highlights the good attribute control abilities of our CGA model and shows that it is able to generate various sentences which robustly mimic the structure of the original dataset. Hence, the generated sentences are good candidates for augmenting existing datasets.

We generalized this experiment for the multi-attribute case. The similarity matrices and the histograms for these additional experiments are provided in the supplementary material.

3.2 Data Augmentation

The main application of our work is to generate sentences for data augmentation purposes. Simultaneously, the data augmentation experiments presented in this section reveal the quality of the sentences generated by our model.

As described, we conduct all experiments on two datasets, YELP and IMDB reviews. We train an LSTM sentiment classifier on both datasets, each of which three different training set sizes. We run all experiments for training sets starting with 500, 1000 and 10000 sentences. These datasets are then augmented with different percentages of generated sentences (10, 20, 30, 50, 70, 100, 120, 150 and 200%). This allows us to analyze the effect of data augmentation on varying original training set sizes as well as varying increments of additionally gener-
The table below shows the largest increase in performance for each method independently from the augmentation percentage used. For each method, we report accuracy (standard deviation in brackets) and the augmentation percentage.

| Model                  | 500 sentences | 1000 sentences | 10000 sentences |
|------------------------|---------------|----------------|-----------------|
| acc. (std)              | %             | acc. (std)      | %              |
| Real Data YELP          | 0.75 (0.01)   | 0.79 (0.01)    | 0.87 (0.03)    |
| YELP + EDA             | 0.77 (0.02)   | 0.80 (0.08)    | 0.88 (0.02)    |
| YELP + CGA (Ours)      | **0.80 (0.02)** | **0.82 (0.03)** | **0.88 (0.04)** |
| Real Data IMDB         | 0.54 (0.01)   | 0.57 (0.06)    | 0.66 (0.05)    |
| IMDB + EDA            | 0.56 (0.02)   | 0.58 (0.07)    | 0.67 (0.02)    |
| IMDB + CGA (Ours)     | **0.60 (0.01)** | **0.61 (0.01)** | **0.67 (0.03)** |

Table 5: Largest increase in performance for each method independently from the augmentation percentage used. For each method, we report accuracy (standard deviation in brackets) and the augmentation percentage.

Figure 4: Data augmentation results for the YELP dataset.

Figure 5: Data augmentation results for the IMDB dataset.

In all experiments, we average the results over 5 random seeds and report the corresponding standard deviation.

To evaluate how beneficial our generated sentences are for the performance of downstream tasks, we compare data augmentation with sentences generated from our CGA model to (a) real sentences from the original datasets, and (b) sentences generated with the Easy Data Augmentation (EDA) method by Wei and Zou (2019). EDA applies a transformation (e.g., synonym replacement or random deletion) to a given sentence of the training set and provides a strong baseline.

The results are presented in Figures 4 and 5, for YELP and IMDB respectively. They show the performance of the classifiers augmented with sentences from our CGA model, from EDA or from the original datasets. Our augmentation method proved to be beneficial in all six scenarios. However, for the cases where the percentage increment is larger than 120% of the original training size, the average accuracy of the classifier augmented with CGA sentences diverges from the one of the classifier augmented with real data. Moreover, our model clearly outperforms EDA in all the possible scenarios, especially with larger training sets.

In Table 5, we report the best average test accuracy as well as the percentage of data increment for each of the six experiments and each of the two datasets. We compare them with the results.
Table 6: Comparison between our results and the most relevant single-attribute related works. The accuracy refers to the amount of the generated sentences that match the required attribute. SM stands for Sentiment Matching and ST stands for the number of sentences tested.

| Model               | Automatic Evaluation | Human Evaluation |
|---------------------|----------------------|-------------------|
|                     | SM  | ST  | SM  | ST  |
| Shen et al. (2017)  | 83.3% | 12K | 63.8%(3.19/5) | 500 |
| Fu et al. (2018)    | 96.0% | 12K | 71.2%(3.35/5) | 100 |
| John et al. (2019)  | 93.4% | 12K | 86.4%(4.32/5) | 500 |
| CGA (Ours)          | 93.1% | 30K | 96.3%(4.81/5) | 120 |

Table 7: Comparison between our results and the most relevant multi-attribute related works. The accuracies refer to the amount of the generated sentences that match the required attribute. SM stands for Sentiment Matching, VTM stands for Verb Tense Matching, and ST stands for the number of sentences tested.

| Model                  | Automatic Evaluation | Human Evaluation |
|------------------------|----------------------|-------------------|
|                       | SM  | VTM | ST  | SM  | ST  |
| Subramanian et al. (2018) | 74.5% | 91.1% | 12K | 72%(3.59/5) | 500 |
| Logeswaran et al. (2018)  | 76.6% | 94.9% | 12K | 71.2%(3.56/5) | 100 |
| Lai et al. (2019)       | 79.9% | 96.1% | 12K | 63.4%(3.17/5) | 500 |
| CGA (Ours)              | 91.1% | 96.6% | 30K | 88.0%(4.40/5) | 120 |

4 Comparison with Related Work

As a final analysis, we compare our results with previous state-of-the-art models for both single-attribute and multi-attribute control.

4.1 Single-Attribute Control

Li et al. (2018) model style control in the Delete, Retrieve, Generate (DRG) framework, which erases words related to a specific attribute and then inserts new words which belongs to the vocabulary of the target style (e.g., sentiment). Sudhakar et al. (2019) improve the DRG framework by combining it with a transformer architecture (Vaswani et al., 2017). However, these approaches are susceptible to error, due to the difficulty of accurately selecting only the style-containing words.

Other approaches on text generation have leveraged adversarial learning. Specifically, Shen et al. (2017) train a cross-alignment auto-encoder (CAAE) with shared content and separate style distribution. Fu et al. (2018) suggested a multi-head decoder to generate sentences with different styles. John et al. (2019) use a VAE with multi-task loss to learn a content and style representation that allows to elegantly control the sentiment of the generated sentences.

In Table 6, we report a comparison with models focused on controlling only the sentiment of a sentence. Fu et al. (2018) and John et al. (2019) achieve better Sentiment Matching accuracy in the automatic evaluation than our CGA model. However, both Fu et al. (2018) and John et al. (2019), by approximating the style of a sentence with its sentiment, proposed a model which is specifically designed to control this single attribute. When our CGA model is trained for sentiment control only, it obtains 93.1% accuracy for automatic evaluation and 96.3% in human evaluation, which is comparable with the score obtained by the related approaches. Consequently, CGA offers a strong competitive advantage because it guarantees high sentiment matching accuracy while controlling additional attributes and, thus, offers major control over multiple stylistic aspects of a sentence.

4.2 Multi-Attribute Control

Few works have succeed in designing an adequate model for text generation and controlling multiple attributes. Hu et al. (2017) use a VAE with controllable attributes. Subramanian et al. (2018) and Logeswaran et al. (2018) apply a back-translation technique from unsupervised machine translation for style transfer tasks. Lai et al. (2019) follow the approach of the CAAE with a two-phase training procedure.

In addition to the provided quantitative evaluation for all three controlled attributes in Table 3, we compare the results for the SENTIMENT and VERB TENSE attribute, since they are the common denominator between all methods. These models were trained and tested on the same YELP data splits. We compare the results of our CGA model with the results achieved by Lai et al. (2019),...
Logeswaran et al. (2018) and Subramanian et al. (2018). This comparison is reported in Table 7. For both evaluation scenarios (i.e. automatic and human), CGA yields significantly better performance. Lai et al. (2019), Logeswaran et al. (2018) and Subramanian et al. (2018) reported content preservation as an additional evaluation metric. However, this metric is of no interest for our work, since, differently from these previous models, CGA generates sentences directly from an arbitrary hidden representations and it does not need a reference input sentence.

5 Discussion & Conclusion

To the best of our knowledge, we propose the first approach for controlled multi-attribute text generation which (1) generates coherent sentences with multiple correct attributes sampling from a smooth latent space, (2) works within a lean and scalable architecture, and (3) improves downstream discriminative tasks by synthesizing additional labeled data.

In this paper we presented a scalable framework for natural language generation which allows for fine-grained control on multiple stylistic aspects. We generate sentences of high quality with a maximum sentence length of 20 tokens. While this restricted sentence length is still a limitation, it is longer than sentences presented in previous work (e.g., Hu et al. (2017)). Additionally, although we provide extensive evaluation analyses, it is still an open research question to define an appropriate evaluation metric for text generation.

To sum up, our approach, which combines adversarial learning and back-translation, achieves state-of-the-art results with improved accuracy on sentiment, tense and person number attributes in automatic and human evaluations. Moreover, our experiments show that our CGA model can be used effectively as a data augmentation framework to boost the performance of downstream classifiers.

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A Supplementary Material

A.1 Dataset

A.1.1 Structure

We use YELP and IMDB for the training, validation and testing of our CGA models. The label distributions for all attributes are described in Table 8.

From the YELP business reviews dataset (YELP, 2014), we use reviews only from the category restaurants. We use the same splits for training, validation and testing as John et al. (2019), which contain 444101, 63483 and 126670, respectively. The vocabulary contains 9304 words. We further evaluate our models on the IMDB dataset of movie reviews (Maas et al., 2011). We use reviews with less than 20 tokens and we select only sentences with less than 20 tokens. Our final dataset contains 122345, 12732, 21224 sentences for train validation and test, respectively. The vocabulary size is 15362 words.

A.1.2 Attribute Labeling

In this work we simultaneously control three attributes: SENTIMENT, VERB TENSE and PERSON NUMBER.

We use SpaCy’s Part-of-Speech tagging to assign the VERB TENSE labels. Specifically, we use the tags VBP and VBZ to identify present verbs, and the tag VBD to identify past verbs.

Analogously, we use the SpaCy’s PoS tags and the personal pronouns to assign PERSON NUMBER labels. In particular, we use the tag NN, which identifies singular nouns, and the following list of pronouns {“i”, “he”, “she”, “it”, ”myself”} to identify a singular sentence. We use NNS and the list of pronouns {“we”, “they”, ”themselves”, ”ourselves”} to identify a plural sentence.

A.2 Training Details

VAE architecture Our VAE has one GRU encoder and one GRU decoder. The encoder has a hidden layer of 256 dimensions linearly transferred to the content vector of 32 dimensions (for one or two attributes), or 50 dimensions (for three attributes). For training the decoder we set the initial hidden state as $h = \text{Linear}(z \oplus a)$. Moreover, we use teacher-forcing combined with the cyclical word-dropout described in Equation 4.

Discriminator The discriminator is used to create our attribute-free content vectors. We experi-

A.3 Training Details

Discriminator Weight The interaction between the VAE and the Discriminator is a crucial factor for our model. Indeed, we decide to linearly increase during the training process the discriminator weight $\lambda_{\text{disc}}$ according to Equation 12.

$$\lambda_{\text{disc}}(x) = \begin{cases} 0 & \\ \min(t, (t/(x_0)) \ast (x - k_1)) & \text{otherwise} \end{cases}$$

where $t$ is the maximum value that $\lambda_{\text{disc}}$ can have, $x_0$ indicates after how many training steps $\lambda_{\text{disc}} = t$. $x$ is the current training step. $k_1$ is the warm-up value and it indicates after how many training steps the $L_{\text{disc}}$ is included in $L_{\text{CGA}}$. We set $t = 20$, $x_0 = 6K$ and $k_1 = 12K$ for YELP or $x_0 = 3K$ and $k_1 = 5K$.

Word-Dropout We use the Equation 4 with the following parameters $\tau = 500$, $k_1 = 0.6$ and $\text{threshold} = 7000$ for YELP. We use $\tau = 250$ and $\text{threshold} = 4000$ and the same $k_1$ for IMDB.

Optimizer The Adam optimizer, with initial learning rates of $10^{-5}$, was used for both the VAE and the discriminator (Kingma and Ba, 2014).
Table 8: YELP and IMDB dataset details showing the exact number of sentences used and the class distribution.

| Dataset | Positive | Negative | Present | Past | Singular | Plural | Balanced |
|---------|----------|----------|---------|------|----------|--------|----------|
| Yelp    | 393237   | 241017   | 304441  | 329813 | 190276   | 317127 | 126851   |
| IMDB    | 71676    | 64625    | 86965   | 69336 | 53468    | 54046  | 28787    |

Figure 6: Similarity Matrices for real data and data generated by our CGA model controlling the sentiment attribute.

Table 9: Examples of generated sentences controlling the SENTIMENT attribute.

| Sentence                                                                 | Sentiment |
|--------------------------------------------------------------------------|-----------|
| but i’m very impressed with the food and the service is great.           | Positive  |
| i love this place for the best sushi!                                    | Positive  |
| it is a great place to get a quick bite and a great price.               | Positive  |
| it’s fresh and the food was good and reasonably priced.                  | Positive  |
| not even a good deal.                                                    | Negative  |
| so i ordered the chicken and it was very disappointing.                  | Negative  |
| by far the worst hotel i have ever had in the life.                     | Negative  |
| the staff was very rude and unorganized.                                 | Negative  |

Table 10: Examples of generated sentences controlling the VERB TENSE attribute.

| Sentence                                                                 | Tense |
|--------------------------------------------------------------------------|-------|
| I love the fact that they have a great selection of wines.               | Present|
| they also have the best desserts ever.                                   | Present|
| the food is good , but it’s not worth the wait for it.                   | Present|
| management is rude and doesn’t care about their patients.               | Present|
| my family and i had a great time.                                        | Past   |
| when i walked in the door , i was robbed.                               | Past   |
| had the best burger i’ve ever had.                                      | Past   |
| my husband and i enjoyed the food.                                      | Past   |

Table 11: Examples of generated sentences controlling the PERSON NUMBER attribute.
A.3 Evaluation

A.3.1 Sentence Embedding Similarities

Following the approach described in Section 3, we report the results of the sentence embedding similarities for the multi-attribute case (SENTIMENT and VERB TENSE). Similarly to the similarity matrices for the single-attribute case, in Figure 6 we recognize the clustered structure of the similarities. These matrices can be divide into the following clusters:

- **Intra-class Clusters** These are the clusters which are placed over the diagonal of the matrices and show a high cosine similarity scores. They contain similarity scores between the embeddings of samples with the same labels.

- **Cross-Class Clusters** These are the clusters located above the intra-class clusters. They contains the similarity scores between embeddings of samples with different labels. Indeed, they show lower similarity scores.

To gain a qualitative understanding of the generation capacities of our model, we start from the same assumption as in Section 3: an ideal generative model should produce samples that have comparable similarity scores to the ones of the real data. We contrast the similarity scores computed on each cluster separately in the histograms in Figures 7 and A.2.

A.3.2 Data Augmentation

For the data augmentation experiments we use a bidirectional LSTM with input size 300 and hidden size 256. We set dropout to 0.8. For the training we use early stopping, specifically we stop the training process after 8 epochs without improving the validation loss.
A.3.3 TextCNN

For the Sentiment Matching we use the pre-trained TextCNN (Kim, 2014). This network uses 100 dimensional Glove word embeddings (Pennington et al., 2014), 3 convolutional layers with 100 filters each. The dropout rate is set to 0.5 during the training process.

A.4 Generated Sentences

Tables 9 to 11 provide example sentences generated by the CGA model for the three individual attributes.