Unsupervised Neural Stylistic Text Generation using Transfer learning and Adapters

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Abstract

Research has shown that personality is a key driver to improve engagement and user experience in conversational systems (Smestad and Volden, 2018). Conversational agents should also maintain a consistent persona to have an engaging conversation with a user (Gan et al., 2017). However, text generation datasets are often crowd sourced and thereby have an averaging effect where the style of the generation model is an average style of all the crowd workers that have contributed to the dataset. While one can collect persona-specific datasets for each task, it would be an expensive and time consuming annotation effort. In this work, we propose a novel transfer learning framework which updates only 0.3% of model parameters to learn style specific attributes for response generation. For the purpose of this study, we tackle the problem of stylistic story ending generation using the ROC stories Corpus (Mostafazadeh et al., 2016). We learn style specific attributes from the PERSONALITY-CAPTIONS dataset (Shuster et al., 2019). Through extensive experiments and evaluation metrics we show that our novel training procedure can improve the style generation by 200% over Encoder-Decoder baselines while maintaining on-par content relevance metrics with the baseline. We also conducted a pilot human subject study to solidify the findings from our study and ground it to the metrics we proposed.

1 Introduction

Developing models that are capable of producing content relevant and stylistic responses is crucial in Conversational AI systems (Zhu et al., 2021b). Such systems provide experiences that are more natural and less robotic. Studies have also shown that customers continue to engage with a conversational system if it has the ability to consistently generate responses in the same style (Gan et al., 2017). Furthermore, physiological studies show that humans tend to interact with each other in similar linguistic styles (Kabbara and Cheung, 2016). Hence, we need a way to train machine learning models that not only produce content that is relevant but also engage with humans in the style of their choice (aka persona).

State Of The Art (SOTA) generation models exhibit inconsistent personas as these models are trained on data from crowd workers having multiple personalities (Zhang et al., 2018). An obvious way to circumvent this problem is to collect parallel data for each of the persona you want to associate with the agent and train response generation conditioned on each persona (Tsai et al., 2021a). However, such an approach is expensive, time consuming and not scalable. Hence we need an efficient mechanism to transfer style attributes from a style specific textual corpus that is present in different domain (Krishna et al., 2020a; Niu and Bansal, 2018a). Although we target the task of story ending generation in this paper, we take a more holistic approach in this study to control the style of Natural Language Generation (NLG) models. This makes our approach applicable to many other tasks that require NLG, such as, summarization and machine translation. Figure 1 shows an example of two different endings (positive and negative style endings) to the same story context.

Supervised style transfer has shown promise in story generation and other fields (Peng et al., 2018; Tsai et al., 2021a). Unsupervised style transfer has recently gained momentum as these approaches do not require parallel corpora. However, many of these approaches hurt content relevance when there is an increase in style coefficient (Niu and Bansal, 2018a). Discriminator based loss techniques (Prabhumoye et al., 2018) tend to suffer in NLG because of the use of the argmax operation to generate the next token in sequence. Other techniques require paraphrasing of data which is not only an expen-
Nicolas hated eating grapes a lot. He had not eaten them since he was a kid. One day, he went to a vineyard. He saw so many grapes that he had to eat one.

Positive Style Ending
He was happy that he had finally tasted a new kind of fruit.

Negative Style Ending
The next day, he was so sick he couldn’t eat any food.

Table 1: Given a story’s context, we can either generate a positive or a negative ending based on the reader’s preference.

In this work we study the effects of unsupervised style transfer using only a handful of samples from the target style. We propose a three phase training procedure to generate story endings with a required style. We use the PERSONALITY-CAPTIONS Dataset (Shuster et al., 2019) to generate our style specific textual corpus. We learn one set of parameters that capture style semantics and another set of parameters to capture content semantics within the same model. Through extensive evaluation, we show that our approach improves style of generated story endings by more than 200% over the baseline while maintaining parity with SOTA models on content relevance. The major contributions of our work are as follows:

- A three phase transfer learning procedure that enables the model to learn style attributes from style specific textual corpus and those attributes for the final downstream task. We call this the learn, learn and relearn (LLR) procedure.
- We separate style parameters from content parameters enabling practitioners to plug and play adapters of different styles while keeping the content parameters as is. We also show the working of this approach on more nuanced styles.
- We design evaluation metrics that show the efficacy of our model against the SOTA baselines. We also notice a similar results in our human evaluations.

2 Related Work

Style transfer research has gained significant popularity due to their ability to make text more user-focused and personalized. Such an ability has impact on numerous applications (McDonald and Pustejovsky, 1985), such as, persona-based generation (Huang et al., 2018; Niu and Bansal, 2018b), language modeling to imitate specific authors (Syed et al., 2019), stylistic summarization (Jin et al., 2020b).

There have been two paradigms in the area of style transfer. The distinctions arise in the way each paradigm treats style and content (Jin et al., 2020a). The first paradigm treats non-functional linguistic features (such as, formality) as style the semantics as content. These approaches model style transfer task as a paraphrase generation task (Madnani and Dorr, 2010; Androustopoulos and Malakasiotis, 2009; Krishna et al., 2020b). The second paradigm treats differences in parallel corpora (such as, happy vs. sad, positive vs. negative) as style and the invariance in the parallel corpora as content (Mou and Vechtomova, 2020).

Traditional style transfer methods were based on token replacement and templates (Sripada et al., 2004; Reiter et al., 2005; Gkatzia et al., 2017). These approaches were difficult to scale as they required hand-crafted domain-specific templates. With recent advances in deep learning, most recent approaches have proposed neural methods for style transfer (Zhu et al., 2021a; Syed et al., 2019; Huang et al., 2018; Niu and Bansal, 2018b; Krishna et al., 2020a; Tsai et al., 2021b).

Early neural methods relied on the availability of parallel corpora, where sequence-to-sequence models were applied to perform generation (Rao and Tetreault, 2018). More recently, style transfer on non-parallel corpora has gained significant attention (Krishna et al., 2020a; Zhu et al., 2021a; Niu and Bansal, 2018a; Reid and Zhong, 2021). Recent works on unsupervised style transfer has shown that they can use monolingual data from another domain to generate stylized responses. However, these methods tend to suffer from lack of relevance as they only look to do interpolation between the two domains that they use. Another line of work looks at disentangling the style variable from the content variable (Hu et al., 2017; Shen et al., 2017). However, owing to the nature of their training procedure they cannot take advantage of Large Language Models (LLM) like GPT-2 and hence cannot start from a decoder state that has the capability to generate fluent sentences. Also, they use corpus level representations to disentangle style from content. A common theme in all of
the above approaches is that they do not have style specific parameters in the model and use the same set of parameters to encode both the style as well as the content.

Generating interesting story endings has also been looked at in the past (Gupta et al., 2019a; Chen et al., 2019; Guan et al., 2018). Most of these approaches try to either bring in commonsense reasoning (Chen et al., 2019) to make for better story endings or they try to make these endings diverse across the corpus. Other works have looked at using a discriminator trained on a parallel corpus to generate endings with a particular valance but the training of those systems is not stable owing to the argmax function one uses while decoding (Peng et al., 2018).

3 Datasets

3.1 ROC Stories Corpus

We used the ROC stories corpus (Mostafazadeh et al., 2016) for the task of story ending generation. Each story in this dataset comprises of 5 sentences. We used the first 4 sentences as context of the story or the input to the model and the 5th sentence as the ending of the story which we want to predict. This led to a total of 90,000 samples in the train set and 4081 samples in validation and test sets.

3.2 PERSONALITY-CAPTIONS Dataset

This dataset (Shuster et al., 2019) contains 241,848 captions to images in 215 different styles. This dataset is a 3 tuple of <Image, Persona, Caption>. For the purpose of this study, we ignored the image and only considered a corpus of text conditioned on a style so that we can pre-train Large LMs (LLM) on that corpus. We grouped together different personas into a style to increase the size of this corpus. We had a total of 4,431 captions that we put together for "Negative style". The "Negative style" corpus consists of the following finer grained styles: "Arrogant", "Boyish", "Irritable", "Gloomy", "Fatalistic (Bleak, Gloomy)"

4 Models

In this section we describe the LLR procedure and compare a model trained using this procedure to the SOTA baselines. Through this procedure the model learns two different language tasks (story generation and stylized language generation) and then re-parameterizes only few of the model parameters to adapt to the final end task. Figure 1 shows the model and the way it was trained.

4.1 Training Encoder-Decoder

As part of the first learning phase, we trained an encoder decoder model that learns to predict the ending of the story based on the context provided to it. We chose BERT (Devlin et al., 2018) encoder and GPT-2 (Radford et al., 2019) decoder to train the model. We provide the context of the story to the BERT model to obtain encoder embeddings ($Enc_{emb}$). Then provide these embeddings to the GPT-2 model that is trained with teacher forcing using the story ending. The training procedures is summarized in Equations 1, 2 and 3.

$$Enc_{emb} = BERTEncoder(Story_{context}) \quad (1)$$

$$P_t^V = GPT - 2(Enc_{emb}, S_{1...t}) \quad (2)$$

$$loss_{decoder} = \frac{1}{T_{decoder}} \sum_{t=1}^{T_{decoder}} -logP(W_{true}^t) \quad (3)$$

4.2 Training Adapters to understand style

Adapters are task specific layers that we can add to the base transformer models in order to perform
efficient transfer learning (Houlsby et al., 2019). Instead of having one big transformer model for each task (e.g., SST, SQUAD etc.) the authors propose using the same base parameters but add task specific parameters to learn each downstream task. Learning task specific parameters might be easier owing to the inherent nature of the data that characterizes each task that they are trained on. In this work, we wanted to understand if the adapters could add more value by learning more intrinsic language properties (e.g., Sad ending, Happy ending etc.). In order to test this property, we train adapters to learn these specific styles. We detach the decoder learnt from the previous model and add adapter modules to this decoder. We then use the style corpus assembled using Section 3.2 to train only the adapter weights using LM objective.

With this technique we separated out the style parameters from the content parameters and wanted to understand if adapters were efficient at capturing style semantics. To generate responses in different styles, we only need to add more style specific adapters (which only accounts for 0.3% of model parameters) as the base parameters remains constant. This forms the second phase of our LLR procedure where the model learns stylistic properties.

4.3 Training Adapters to understand encoder embeddings

While the adapter weights from the previous phase is trained to capture the stylistic aspect of language it has not been trained to complete stories. Hence, we introduce the third phase called the relearning phase where the decoder relearsn to complete stories. In this phase, we take the encoder and decoder of the model trained in phase 1 and attach the decoder with adapter weights from phase 2. Once this model is wired; we retrain only the adapter weights for the task of story end generation using Equation 3. This is the only phase in which the encoder and the adapter are trained jointly. Through careful experiments we see that the adapter weights should only be trained for a few steps with this objective as it would otherwise catastrophically forget the style aspects learnt in phase 2 (Appendix A).

4.4 Baselines

One of the challenges with transferring style from a style specific textual corpus to the downstream task is that when you increase the stylistic nature of the outputs, the content relevance decreases (Niu and Bansal, 2018a). Hence, we divide our baselines into two groups of SOTA baselines. One set focuses on the interesting nature of story endings and the other set focuses on the stylistic aspect.

4.4.1 Content Baselines

S2S (LSTM Based): (Sutskever et al., 2014) We use Seq2Seq model with attention (Luong et al., 2015).

IE + GA: (Guan et al., 2019) use incremental encoding and graph attention to produce outputs that are more interesting and diverse.

WriterForcing: (Gupta et al., 2019b) use the rake algorithm and inverse token frequency to produce outputs that are more interesting and diverse.

EncoderDecoder (BERT-Gpt2): We use a BERT Encoder and a GPT-2 decoder as the SOTA baseline to produce story endings. This corresponds to just phase 1 in Figure 1.

4.4.2 Style Baselines

SAP: (Krishna et al., 2020a) propose style transfer as a paraphrase problem. We retrain the model presented in this work to learn the nuances of negative endings. Once we obtain the story ending from the encoder decoder model, we pass through this style transfer model to obtain negative endings.

S2S+LM: (Niu and Bansal, 2018a) Train an S2S model using the end task and train an LM using the style corpus. During inference they combine these models by simply adding the probabilities at each time step of decoding and pick the word with highest combined probability.

Discriminator loss: (Prabhumoye et al., 2018) Discriminator based setup to train LSTM Generators have been widely used to guide the generators. We use a CNN discriminator trained to recognize the negative style(84% accurate). We add the loss of this model along with the teacher forcing loss. To overcome the pitfall of the argmax function we multiply the embedding matrix with the probability distribution from the previous time step to keep the model end to end differentiable similar to Gumbel approximation. We provide the output of the generator to the discriminator.

4.5 Implementation Details

For phase 1, we train the encoder-decoder model for 3 epochs on the training data mentioned in Section 3.1. We use the Encoder-Decoder model from Huggingface1 to train on this task. We used a batch

1https://huggingface.co/
Table 2: The table shows the performance of our model with respect to the two classes of baselines. We see that the model outperforms the style based baselines and is on par with the content based baseline indicating that our model is able to produce stylized responses without taking a hit in content relevancy.

| Baseline Name   | BLEU/1 | cider | ROUGE  | RIS  | RBAE | RBAR |
|-----------------|--------|-------|--------|------|------|------|
| **Content Baselines** |        |       |        |      |      |      |
| EncoderDecoder  | 0.156  | 0.09  | 0.16   | 0.17 | NA   | 0.78 |
| seq2seq  | 0.177  | 0.175 | 0.113  | 0.403| 0.316| 0.69 |
| ie       | 0.19   | 0.19  | 0.168  | 0.411| 0.411| 0.803|
| writer_forcing | 0.149  | 0.158 | 0.089  | 0.563| 0.359| 0.679|
| **Style Baselines** |        |       |        |      |      |      |
| fusion      | 0.188  | 0.18  | 0.103  | 0.183| 0.234| 0.606|
| discriminator | 0.171  | 0.172 | 0.085  | 0.275| 0.258| 0.649|
| paraphrase  | 0.155  | 0.162 | 0.091  | 0.206| 0.331| 0.704|
| **Our Model** | LLR    | 0.108 | 0.094  | 0.11 | 0.475| 0.414| 0.701|

of 16, max length of 512, Adam (Kingma and Ba, 2014) optimizer learning rate of $5e - 5$ with weight decay of $(\epsilon = 1e - 8)$. In phase 2, use Adapter-hub\(^2\) to add adapter to the GPT-2 model and train on the LM loss until the validation loss saturates. We use the bottle neck adapter with default configuration. In Section 5.2.3 we experiment with different adapters to understand which adapter gives the best performance. For all these adapters we use the default configurations present in Adapter-hub. In phase 3 we connect the decoder with adapter in phase 2 with the Encoder of phase 1. All the hyperparameters for phase 2 and 3 are kept constant with phase 1 and the model is trained on the story generation task for 1 epoch (only adapter layers are updated).

5 Experiments and Results

5.1 Evaluation Metrics

We use 6 evaluation metrics to measure the efficacy of our models. We use the three automatic metrics widely used for text generation models: BLEU (Papineni et al., 2002), ROUGE (Lin, 2004) and Cider (Vedantam et al., 2015). These metrics measure the overlap of the generated response with the ground truth. The more the overlap the higher the score. However, if one tries to generate different/diverse endings than the one in the corpus then these metrics tend to drop (Gupta et al., 2019a) as they do not have a large overlap with the ground truth. Hence, we design 3 other metrics that help measure the efficacy of the outputs generated with the larger goal of stylistic response in mind.

**RIS:** (Ratio of endings In Style). Once the stories are generated from a model, we need to know the percentage of styles that end in a given style. For this purpose, we build a BERT based classifier that can identify this style using the Personality captions dataset. Using a training set of 8,872 and a testing set of 2,218 samples we built a classifier with 87% accuracy at predicting the negative style.

**RBAE:** (Ratio of endings Better than Encoder-Decoder). Given two endings of the story we need a model that can tell which one of the two is better. The story cloze task proposed by Sharma et al. (2018), has an objective of predicting the better story ending. Using this dataset, we train a BERT based classifier to predict better story ending. We provide the context and the ending with a <SEP> token and train the model to predict if it is a relevant story ending or not. Using a training set of 1,872 and a testing set of 1,872 we were able to build a classifier that was 85% accurate of predicting the better story ending. During inference, we pass in the two endings from the two model and pick the ending that has a higher probability of clozing the story. We consider the Encoder-Decoder Model built using BERT-GPT2 as the baseline to beat for all of the other models. In an ideal scenario all the outputs produced by the model should be better than the baseline (Encoder-Decoder Model) resulting in a score of 1.0.

**RBAR:** (Ratio of endings Better than Random Endings). In order to know that our models are not producing entirely random outputs, we use the model described in RBAE metric and present it with two endings, one the model produced output and another a random story ending that was written by the humans in the ROC stories corpus.

5.2 Discussion

5.2.1 Performance against baseline models

From Table 2, we see that our model generates 250% more stylistic endings than the encoder decoder baseline. We also observe that these stylistic endings do not come at the cost of content relevance as the model is only 9% poorer than the encoder decoder baseline. We experimented with

\(^2\)https://docs.adapterhub.ml/training.html
other types of adapters to see if it helps with the content relevance further in Section 5.2.3.

Comparing our results to the style baselines, we see that our models produce at least 2x more stylized endings than the baselines. We also note that our model is very easy to train and does not suffer from the fragility experienced with training discriminator-based models. We also see that we are able to get to the stylized endings in one shot while decoding with these adapter parameters. Krishna et al. (2020a) has to go through a two step process to perform style transfer via paraphrasing and do not capture the linguistic properties of a style as well as our model. One of the common problems mentioned in prior work (Prabhumoye et al., 2018) is that when the stylistic nature of endings is increased, the content relevance decreases. However, with our experiments we show that it is possible to produce content relevant outputs when increasing the stylistic nature of story endings.

We also compare our models to the content relevant baselines. We see that our models produce better story endings than the SOTA story ending models. While SOTA models like Writerforcing are 5% worse compared to our model with the endings, models where commonsense reasoning has been infused using graph attention as good as our model. It is to be noted that we have not infused the model with commonsense knowledge. We hypothesize that this will improve content relevance.

It is to be noted that we have compared the content relevance of our model with the content baselines and the style consistency of our model with the style baselines. We do not compare the style consistency of our model with the content baselines as we cannot control the style of the outputs from these models.

While we observe that the traditional BLEU, ROUGE and CIDER is lower for our model we deem this as expected as our model is trained to produce words that belong to a given style than words that are more frequently occurring in the ROC stories corpus. Similar observations were also made by Gupta et al. (2019a).

| Stage | BLEU/1 | cider | ROUGE-L | RIS | RBAR | RBAR |
|-------|--------|-------|----------|-----|------|------|
| Stage 1 | 0.155  | 0.09  | 0.16     | 0.17 | NA   | 0.78 |
| Stage 2 | 0.105  | 0.091 | 0.11     | 0.11 | 0.33 | 0.33 |
| Stage 3 | 0.108  | 0.094 | 0.11     | 0.475| 0.414| 0.701|

Table 3: Table shows the impact of the three stage training. If we simply join the first two phases without the relearning phase, content relevance drops by 176%.

Table 4: Comparison of Model performance using different adapter types. We see that the invertible adapter gets the highest stylistic response while being only 8% worse than the SOTA Encoder-Decoder model.

5.2.2 Importance of three phase training

We did an ablation study to understand the importance of the three phase training. These results are shown in Table 3. Phase 1 is equivalent to training a regular Encoder-Decoder model. So, we need other phases that will incorporate the stylistic endings into the model outputs. This is achieved using phase 2 where we fine tune the adapter of the decoder with the style corpus. If we simply take this decoder and fit it with the encoder, we see that the model produces 61% endings in style, however the endings are only 15% than the Encoder-Decoder model. This is because the weights of the adapters are not in line with the weights of the decoder to produce the end task output. They are geared more towards producing captions of a given style. The outputs are also only as good a random story ending (RBAR). Hence with phase 3 we align both those weights and also fine tune the adapter weights on the task of story generation for 1 epoch. We see that if the model if continued to train for more epochs the adapter weights from the previous phase are forgotten and the model starts going back to becoming a regular Encoder-Decoder model.

5.2.3 Performance of different adapters

Since we used a simple bottleneck adapter (Plain) to obtain our previous model that outperforms the SOTA, we wanted to check if other types of adapters performed even better. We compare 5 other types of adapters, namely Houls (Houlsby et al., 2019), Pfeiffer (Pfeiffer et al., 2020), Parallel (He et al., 2021), Invertible (Pfeiffer et al., 2020), Compactor (Karimi Mahabadi et al., 2021). We use the default values for each of these configurations present on Adapter-Hub. We see that the invertible adapter performs the best out of all the adapter types. While maintaining the same content relevance as a plain adapter, it improves the stylistic quotient by 5%. Since the invertible adapters are good at capturing language specific transforma-
tions, we hypothesize that these adapters capture
the nuances of stylistic properties as well. It is also
interesting to see that the compactor-adapter for
which the content relevance is better than Encoder-
Decoder suffers significantly with the stylistic out-
puts generated by the model. We also see that the
outputs produced by these adapters are all better
than random baseline (RBAR).

5.2.4 How many endings with style have valid
endings?
The RIS metric paints us a picture of percentage of
endings with required style. The RBAE metric pro-
vides us with content relevant endings. However, in
order to understand the model outputs more deeply
we need to know how many of the stylized outputs
from the RIS model were considered content rel-
levant from the RBAE model. Hence, we plot a
confusion matrix for all the adapter types and com-
pare them to the baseline Encoder-Decoder model.
Figure 2 shows these plots.

From the plots in Figure 2 we see that 65.75% of
the endings that were produced in the given style
were valid using the plain adapter and 65.30% of
the endings that were produced in the given style
using the invertible adapters were valid. We also
observe that 53.28% of the endings which were
valid had the required style using the plain adapter
while 58.9% of the endings which were valid had
the required style using the invertible adapter.

5.2.5 Performance on finer grained styles
In order to understand the distinctiveness of the
existing styles, we first built a CNN based classifier
that learned to predict the finer grained style. We
observed that the model only gets 4% accuracy
as the styles are too fine grained. To understand
the performance of the model on more distinct
styles, we performed agglomerative clustering
on captions of the PERSONALITY-CAPTIONS
dataset to obtain four distinct styles. We pooled
embeddings from the CNN classifier and perform
agglomerative clustering on top of it. We see
several close styles coming under the same
umbrella (Appendix A). We use the results from
this clustering and our domain knowledge to create
the following nuanced style categories:
Questioning: Questioning, Skeptical, Cynical
(Doubtful, Skeptical)
Money-Minded: Money-minded, Businesslike
Peaceful: Peaceful, Calm, Mellow (Soothing,
Sweet)
Intelligent: Knowledgeable, Intelligent, Insightful

We then repeat the corpus construction, build-
ing a style specific classifier and also retrain the
adapters for these more nuanced styles. The re-
sults from these experiments are shown in Table 5.
We see that the RIS from our model is at least 2
times more than the RIS from the regular Encoder-
Decoder Model in 3/4 fine grained styles. The
RBAE metric is also similar to the Negative style
ending result showing that the results of our model
are generalizable to more nuanced style endings.
We do note that the absolute RIS is lower as the
model finds it harder to generate these finer grained
endings when compared to a negative ending.

5.3 Pilot Human Subject Study
While the automatic metrics that we proposed in
our paper captures the performance of our mod-
els and shows that it is better than the baseline
encoder decoder model there was no human val-
idation. Hence to ground our automatic metrics
to the human judgement we conducted a human
evaluation by sampling 50 stories from the test set.
We performed two tasks described below and used
Amazon Sagemaker Ground Truth for these tasks.
For each sample we collected 3 annotations. We
paid the workers $36/hr.
| Fine grained style | BLEU/1 | cider | ROUGE-L | RIS | Encoder-Decoder RIS | RBAE | RBAR |
|--------------------|--------|-------|---------|-----|---------------------|------|------|
| questioning        | 0.108  | 0.094 | 0.104   | 0.25| 0.03                | 0.37 | 0.724|
| frugal             | 0.106  | 0.092 | 0.106   | 0.24| 0.128               | 0.402| 0.688 |
| peaceful           | 0.109  | 0.096 | 0.107   | 0.48| 0.219               | 0.423| 0.721 |
| intelligent        | 0.113  | 0.101 | 0.105   | 0.193| 0.208               | 0.469| 0.767 |

Table 5: Comparison of Model performance using invertible adapter on Finer Grained Styles. We see that our model is at least 2 times better than the Encoder-Decoder(ED) model in 3/4 fine grained styles.

| Story Context | Ground Truth | ED Response | Model Generated Response |
|---------------|--------------|-------------|--------------------------|
| Nicolas hated eating grapes a lot. He had not eaten them since he was a kid. One day, he went to a vineyard. He saw so many grapes that he had to eat one. | After that, Nicolas started to enjoy eating grapes every day. He was happy that he had finally tasted a new kind of fruit. | Negative |
| John worked in retail. He was really sick one day. His boss wouldn’t let him have the day off without a replacement. John called everyone but nobody could cover his shift. | John wound up having to work sick. He was happy that he finally had a job. | Negative |
| Tom drove a cab nights, saving up for film school. It took a long time, but he finally was able to enroll. His teacher insulted his first student film. Tom was hurt, and he dropped out. | A decade later, he was directing Hollywood features. He was happy that he finally had a job. | Peaceful |
| Louis attended a party for his classmate John. As the party, there was a delicious plate of cookies. Though they were John’s cookies, Louis kept them. When people took note, Louis began secretly hoarding them instead. | Louis greatly enjoyed the party and left with pockets full of cookies. He was able to get the most out of his friends. | Negative |
| A man was walking his dog down the street. The dog seemed to be having trouble walking on the leash. As time went on the man walked his dog everyday. Over time the man didn’t have to use a leash, the dog followed. | Now the man is walking with his dog and a new puppy on a leash. He was able to get the dog to the right place and he was happy. | Money-Minded |

Table 6: Examples of a few qualitative results produced by our model.

5.3.1 Stylistic response

We wanted to understand if the model response that we generated had a more "sad" tone than the regular encoder decoder model. Hence, we provided the two endings from the two models and asked the judges to pick a more "sad" ending. The judges picked 32 endings as sad from our model and 18 endings as sad from the encoder decoder model. The proportions Z test indicates a p-value of 0.03 showing that these results are statistically significant.

5.3.2 Content relevancy

To understand the relevancy of the endings produced by our model, we provided the judges with the story context and the two endings from the two models and asked to pick a better story ending. We also gave them the option to pick both the endings if they thought both were relevant to the story context. We observed that the judges picked 23 endings as better from our model, 16 endings from the encoder decoder baseline and 11 as both. This study has a p-value of 0.25 using proportions z test indicating that our model is on par with the encoder decoder model in terms of content relevance.

5.4 Qualitative Results

We show some of the example predictions from our model in Table 6. In the first example, we see that the model was able to come up with a negative ending and a money minded ending for the same story context based on the adapter that was chosen. For even finer grained styles like peaceful the model could generate outputs that were relevant. In the final example we see that although the model is thinking about property (which is money-minded) the model associates this with the dog in the story context. Hence, we need a way to ground these stories with common sense reasoning as well (perhaps using IE +GA (Guan et al., 2019))

6 Conclusion

A central tenet of the current language generation models is around controllable generation. While there are decoding algorithms and style transfer techniques to control the generation of text, unfortunately these techniques are not applicable to more finer control in properties like style/persona of text. In this work we show that it is possible to develop generation models that are capable of producing stylized outputs without the need of labeled stylized
data on the downstream task. Through both automated metrics and human evaluations, we show that our model is better than the Encoder-Decoder baseline by 200% while maintaining almost same content relevancy. We also show the generalizability of our approach to finer grained styles.

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A Appendices
Figure 3: Hierarchical clustering of styles using the style embedding matrix generated from the CNN-based text style classifier. Zoom in to view the persona names.
Figure 4: We see that for 5/6 adapter types the PIS metric drops as we train the model for longer as the model catastrophically forgets the stylistic aspects and degenerate to an Encoder-Decoder model if you train for too many steps.