A bird’s-eye view on coherence, and a worm’s-eye view on cohesion

Woon Sang Cho* Pengchuan Zhang† Yizhe Zhang† Xiujun Li† Michel Galley† Mengdi Wang* Jianfeng Gao†
*Princeton University
†Microsoft Research AI
*{woonsang,mengdiw}@princeton.edu
†{penzhan,yizzhang,xiul,mgalley,jfgao}@microsoft.com

Abstract

Generating coherent and cohesive long-form texts is a challenging problem in natural language generation. Previous works relied on a large amount of human-generated texts to train language models, however, few attempted to explicitly model the desired linguistic properties of natural language text, such as coherence and cohesion. In this work, we train two expert discriminators for coherence and cohesion, respectively, to provide hierarchical feedback for text generation. We also propose a simple variant of policy gradient, called negative-critical sequence training, using margin rewards, in which the baseline is constructed from randomly generated negative samples. We demonstrate the effectiveness of our approach through empirical studies, showing significant improvements over the strong baseline – attention-based bidirectional MLE-trained neural language model – in a number of automated metrics. The proposed discriminators can serve as baseline architectures to promote further research to better extract, encode essential linguistic qualities, such as coherence and cohesion.

1 Introduction

The terms coherence and cohesion in linguistics are commonly defined as follows [Williams and Colomb, 1995].

Cohesion: sentence pairs fitting together the way two pieces of a jigsaw puzzle do.
Coherence: what all the sentences in a piece of writing add up to, the way all the pieces in a puzzle add up to the picture on the box.

In layman’s terms, cohesion indicates that two consecutive sentences are locally well-connected, and coherence indicates that multiple sentences globally hold together.

Generating cohesive and coherent natural language texts that span multiple sentences is a challenging task mainly due to two reasons. First, there is no principled way of modeling cross-sentence linguistic properties, such as cohesion and coherence of a text. Second, there is no widely accepted metric of evaluating the quality of the generated text in terms of cohesion and coherence.

Most state-of-the-art approaches to natural language generation (NLG) relied on a large amount of human-generated texts to train neural language models [Cho et al., 2014 | Graves, 2013 | Sutskever et al., 2014]. Although these models can generate sentences that, if judged individually, are similar to human-generated ones, they often fail to capture the local and global dependencies among sentences, resulting in neither coherent nor cohesive text. For example, neural language models based on Recurrent Neural Networks (RNNs) are widely applied to response generation for dialogue [Vinyals and Le, 2015 | Shang et al., 2015 | Sordoni et al., 2015 | Li et al., 2015]. Although the responses by

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We cast the text generation as an RL problem and review recent work in Section 2, and detail our approach in Section 3.

## 2 Related work

A word sequence generation task can be framed as a reinforcement learning (RL) problem, in which the generator $G$ is acting as a policy $\pi$, with parameters $\theta_\pi$, and each generated word at time $t$, $w_t$, can be viewed as an action to be chosen by the policy from a large discrete space, or vocabulary, conditioned on state $s_{t-1} = w_{\leq t-1}$, which encodes the previously generated text sequence.

Let $r_t$ be the reward for a partially generated text sequence $w_{\leq t}$. We define the long-term expected reward $J(\pi) = \mathbb{E}_{w_{\leq t} \sim \pi, s} \left[ \sum_{t=1}^{\infty} \gamma^{t-1} r_t \right]$, where $q$ is the initial distribution of conditional input texts. Following [Sutton et al. 1999], the gradient of $J$ with respect to $\theta_\pi$ is

$$
\nabla_{\theta_\pi} J = \mathbb{E}_{s \sim \rho^\pi \cdot a \sim \pi^\pi(s) | a} [Q^\pi(s, a) \nabla_{\theta_\pi} \log \pi^\pi(a | s)]
$$

(1)

where $\rho^\pi$ is the stationary distribution and $Q^\pi(s, a)$ is the expected return from state $s$ and taking action $a$, both following policy $\pi$. For brevity, we omit the derivation. In our work, we formulate text generation as an episodic RL problem with episode length $L$, rewards $r_L$ being available only at the end of episode and $\gamma = 1$.

There are many works on training neural language models using reward signals, such as [Ranzato et al. 2015] and [Paulus et al. 2017]. These works directly optimize for specific metrics, such as BLEU [Papineni et al. 2002] or ROUGE [Lin and Hovy 2003], using REINFORCE [Williams 1992, Sutton et al. 1999]. However, it is well-known that these metrics do not give a complete picture on the quality of the generated text. Only recently have there been efforts to provide more relevant metrics to guide the training of language models.

Our main contributions are three-fold: (1) we propose two linguistic discriminators for measuring coherence and cohesion of a text, respectively; (2) we present a simple yet efficient training mechanism to encode these linguistic properties; and (3) we propose negative-critical sequence training, a variant of policy gradient method, which uses negative samples to construct its reward baseline.

To the best of our knowledge, this paper is the first attempt to explicitly capture cross-sentence linguistic properties, i.e., coherence and cohesion, for long text generation. Despite the encouraging initial results, we only scratched the surface of the problem. The proposed method is yet to be significantly improved to meet the ultimate goal of generating meaningful and logical long-form texts. We cast the text generation as an RL problem and review recent work in Section 2 and detail our approach in Section 3.

### Table 1: Sample generations from our MLE-trained baseline model, $G_{MLE}$, and our discriminator-guided model $G_{MLE+RL(coherence, cohesion)}$.

| Source sentences | $G_{MLE}$ | $G_{MLE+RL(coherence, cohesion)}$ |
|------------------|-----------|-------------------------------|
| the hotel inglaterra delivered as promised. the staff was welcoming and spoke good english. the cleaning staff did a very good job every day. the rooms were spotless and very modern. the bathroom was large and had a very nice shower, and there were two generously sized bath towels that were twice the size of normal towels. | the breakfast in the morning was delicious and very good. it was the only hotel where i slept very well. the staff was very helpful in late afternoon or late times. the breakfast was adequate, with a decent range of cereals, fruit, and fruits. there is also free use of the coffee in the reception area. | the breakfast was plentiful including fresh breads and cooked to order. the location was fantastic. it is in the north of the marina and in a very short distance. the marina has a small swimming pool with sitting area and a small gym. they are very popular and guests have an evening reception which is very nice. |

The red texts highlight a common problem in $G_{MLE}$ - it exhibits a repetition, and an inconsistent opinion as a review. In contrast, our discriminator-guided model is able to generate a more interesting, and sentiment-consistent continuation.

In this paper, we strive to address the challenge in a principled manner. We propose a pair of discriminators to score whether and to what extent a text is coherent or cohesive, respectively. The coherence discriminator measures the compatibility among all sentences in a generated text using sentence-level features, thus providing a worm's-eye view on the text. The cohesion discriminator, on the other hand, measures the compatibility of each pair of consecutive sentences using only word-level features, thus providing a worm's-eye view on the text. These models, given a conditional input text and multiple candidate output texts, are learned to score the candidates with respect to the criterion by optimizing a pairwise ranking loss, respectively. These scores are then used as reward signals to train a RNN-based language model to generate (more) coherent and cohesive texts.
quality objectives for which to optimize \cite{Li2015, Li2016a, Holtzman2018} the quality of interest such as consistency, repetition of text. But these works use the objective function to re-rank candidate outputs, not to reward or penalize outputs when they are generated in the first place. \cite{Li2016b} constructed a set of reward models, such as information flow and semantic coherence, to tune the generator, yet they do not provide an ablation study to elaborate the relative contribution of these reward models individually.

Another line of research is to use Generative Adversarial Networks (GANs) \cite{Goodfellow2014} to incorporate feedback signals for text generation \cite{Yu2017, Lin2017, Zhang2017c, Guo2017, Fedus2018, Zhang2018}. However, the discriminator in these works are trained to distinguish real texts from the generated ones, operating as a black-box rather than providing fine-grained feedback on particular linguistic aspects of the texts. In fact, \cite{Yang2018} has partially addressed this issue by using a trained language model as the discriminator. Although the discriminator provides a fine-grained feedback at the word-level, it does not critique on many important linguistic properties of generated texts, such as cohesion and coherence.

These text generators, when facing a long-form text generation task that span multiple sentences, are by no means perfect and often exhibit some critical errors, such as a breakdown of local connections between consecutive sentences (cohesion), let alone globally solid intent (coherence). As a result, readers can easily take these cues and discriminate such generated texts against real texts. In this paper we argue that the primary reason is the lack of an effective mechanism of measuring and controlling the text quality in the generation process. The method we propose in the next section is intended to address the problem.

3 Model

We assume that global coherence of a text depends to a large degree upon how its individual sentences with different meanings are organized. So we focus our evaluation of coherence solely on the sentence-level. If the meanings of sentences are not organized properly, we have difficulty in picking up the intent of the paragraph as a whole, regardless of seamless local connectivity between consecutive sentences.

This is not to say that local connections between any two sentences should be overlooked. One can easily distinguish a model-generated sentence from a real one, simply by looking at whether the sentence is followed by another sentence logically, regardless of their grammar.

We instill these two different yet important concepts in two discriminators, operating on the sentence level and word level, respectively. Our models closely resemble these successful models for computer vision, such as StackGAN \cite{Zhang2017a, Zhang2017b} and PatchGAN \cite{Isola2017} in that they all provide hierarchical signals to their corresponding generators, where the signals are derived from raw low-level data. We call the sentence-level discriminator the \textit{coherence} discriminator $D_{\text{coherence}}$, and the word-level discriminator the \textit{cohesion} discriminator $D_{\text{cohesion}}$.

3.1 Coherence discriminator: $D_{\text{coherence}}$

This discriminator measures how likely two text chunks form a coherent paragraph. Let $S := [s_1, s_2, \ldots, s_n]$ be the source text chunk that consists of $n$ sentences, $T := [t_1, t_2, \ldots, t_m]$ be the real target text chunk that consists of $m$ sentences, and $\tilde{T} := [\tilde{t}_1, \tilde{t}_2, \ldots, \tilde{t}_{\tilde{m}}]$ be the model-generated target text chunk that consists of $\tilde{m}$ sentences. $D_{\text{coherence}}$ is designed to distinguish a real pair $(S, T)$ from a synthetic pair $(S, \tilde{T})$ by assigning them with different scores, i.e., $\text{Score}_{\text{coherence}}(S, T) > \text{Score}_{\text{coherence}}(S, \tilde{T})$.

\textbf{Design.} Our design of $D_{\text{coherence}}$ is inspired by the Deep Semantic Similarity Model (DSSM) \cite{Huang2013, Gao2014, Xu2017}. Given source text chunk $S$ and target text chunk $T$, $D_{\text{coherence}}$ computes their coherence score in two steps, as illustrated in Figure 1. First, a pair of convolutional networks (CNNs) are applied to encode both $S$ and $T$ into two low-dimensional continuous vectors, respectively. Second, the coherence score is computed as the cosine similarity of

\footnote{We explored with deeper networks. However, the performance difference was marginal. For simplicity, we decided to use a 1-layer convolutional network architecture \cite{Kim2014, Collobert2011}.}
Figure 1: Illustration of coherence and cohesion discriminators. $D_{\text{coherence}}$ takes in bag-of-words sentence embeddings as inputs, and $D_{\text{cohesion}}$ takes in the raw word embeddings of consecutive sentences as inputs.

The two vectors. The score is a real value between $-1$ and $1$, where $1$ indicates the maximal coherence score, and $-1$ the minimal coherence score.

$D_{\text{coherence}}$ measures how likely $S$ and $T$ add up to a single coherent passage. The score depends on the parameters of the two CNNs, or in other words, how $S$ and $T$ are encoded. Since we focus solely on the sentence-level features, we view a text chunk as a sequence of sentences, and view each sentence as a bag-of-words. Therefore, we represent each word using its pre-trained word embedding vector [Pennington et al., 2014] and represent each sentence using a vector which takes the average of its word embedding vectors. A text chunk is then represented as a sequence of sentence vectors which are fed to the CNN (either $f(\cdot)$ or $g(\cdot)$ in Figure 1). The parameters of $f(\cdot)$ and $g(\cdot)$ are optimized in such a way that a real pair scores higher than a synthetic pair:

$$\Delta(\theta_f, \theta_g) := D_{\text{coherence}}(f_{\theta_f}(S), g_{\theta_g}(T)) - D_{\text{coherence}}(f_{\theta_f}(S), g_{\theta_g}(\tilde{T})) > 0$$

Formally, the task of optimizing $D_{\text{coherence}}$ can be stated as follows. Given a set of training samples of the form $(<S,T>, (S,\tilde{T}))(i), i = 1, \ldots, M$, we optimize parameters $(\theta_f, \theta_g)$ by minimizing the pairwise rank loss on training data defined as

$$\frac{1}{M} \sum_{i=1}^{M} L(\Delta(\theta_f, \theta_g)^{(i)})$$

where $L(\cdot)$ is a loss function, differentiable w.r.t. $(\theta_f, \theta_g)$.

In the following subsection, we will describe in turn how we construct the pairwise training samples and the form of the loss function. Since $D_{\text{coherence}}$ is used as a pairwise ranker, we employ the metrics commonly used in information retrieval for evaluation, such as recall at $K$ ($R@K$), which is defined as the fraction of correctly identifying an item in the TOP-$K$ retrieved list [Baeza-Yates and Ribeiro-Neto, 1999]. We present the retrieval results on test data in Table 2.

**Training mechanism.** How do we construct these list of candidate target sentences $T$, given the source sentences $S$? We assume the $T$ that follows an $S$ in the data is a positive target sample, or the correct item to retrieve. Negative samples are constructed using three different methods within a batch while iterating through the training data, motivated by [Wieting et al., 2016]:

- The first method is to simply rotate $T$ with $S$ fixed in a batch. For a single $S$, this method yields $B-1$ negative samples, where $B$ is the batch size.
- The second method is to shuffle the sentence order once, different from its original order, known as a derangement, in each $T$ to break coherence, and this yields one negative sample.
Table 2: Retrieval ratios for coherence and cohesion discriminators from a collection of 100 negative
candidates. The reported numbers are averages over 20 evaluations.

| TripAdvisor | Target Sentences Retrieval | Yelp | Target Sentences Retrieval |
|-------------|----------------------------|------|----------------------------|
| Discriminators | R@1  | R@5  | R@10 | Discriminators | R@1  | R@5  | R@10 |
| $D_{coherence}$ | 0.18 | 0.43 | 0.60 | $D_{coherence}$ | 0.33 | 0.61 | 0.74 |
| $D_{cohesion}$ | 0.12 | 0.28 | 0.43 | $D_{cohesion}$ | 0.14 | 0.33 | 0.47 |

Lastly, we combine the previous two methods: rotate $T$ across a batch and shuffle sentences
within $T$, yielding $B - 1$ negative samples. These $2B - 1$ negative samples and a single positive sample, in sum, pose a significant challenge in
learning. To fit this training task into a ranking framework, we optimize over

$$D_{coherence}(f_{\theta_f}(S), g_{\theta_g}(T)) - \text{AM}^\lambda \left[ D_{coherence}(f_{\theta_f}(S), g_{\theta_g}(\tilde{T}_i)) \right]$$

(2)

where the weighted arithmetic mean parametrized by $\lambda$: $\text{AM}^\lambda(x) = \frac{\sum_i w_i x_i}{\sum_j e^{\lambda x_j}}$ and $w_i = e^{\lambda x_i} / \sum_j e^{\lambda x_j}$.

In our experiments, we fix $\lambda = 2$ and this assigns more weight to a more challenging negative
sample\(^2\). Notice that $\text{AM}^\lambda$ is the mean if $\lambda = 0$, and approaches the max as $\lambda \to \infty$. Empirically,
training the models using the weighted mean resulted in faster convergence, as opposed to using the
single most challenging negative sample score (max) or the mean of all negative sample batch.

3.2 Cohesion discriminator: $D_{cohesion}$

Our second discriminator pays attention only to low-level features, such as grammar of each of
the sentences and the logical flow between arbitrary two consecutive sentences. These two aspects
combined, despite more linguistic aspects that we do not mention, heavily influence readability.

For simplicity, $D_{cohesion}$ is similar to $D_{coherence}$, except that its architecture, input, and negative sample
construction are modified to encode cohesion between any pair of sentences on the word-level.

A single input sample to $D_{cohesion}$ is a pair of two consecutive sentences:

$[s_{i,1}, s_{i,2}, ..., s_{i,n}]$ and $[s_{i+1,1}, s_{i+1,2}, ..., s_{i+1,m}]$, where $s_{i,k}$ denotes the $k$-th word in sentence $i$. We construct the negative
samples using the three methods for training $D_{coherence}$, where shuffling occurs on the word level
within each sentence, rather than shuffling multiple sentences on the sentence level.

3.3 Generator: $G$

The two pre-trained discriminators, $D_{coherence}$ and $D_{cohesion}$, are used to modify the text generation
behavior of $G$. $G$ is an attention-based bidirectional sequence-to-sequence model. It is initially
pre-trained via maximizing the word-level likelihood given the training data, and we denote this
model as $G_{MLE}$.

However, the model-generated texts from $G_{MLE}$ often does not hold to the standards of two discrimi-
nators. Therefore, we need to change the text generation behavior of $G$ with respect to the criteria.
To this end, the scores from the criteria are used as direct reward or penalty signals to modify the
parameters of $G$. Given these signals, we use our proposed variant of the policy gradient, negative-
critical sequence training, to update its parameters and generate (more) coherent and cohesive texts.
We discuss the details in the next section.

4 Negative-Critical Sequence Training

Actor-critic methods [Barto et al., 1983, Witten, 1977] parameterized by neural networks typically
require learning a separate critic network to estimate the expected future reward as a baseline, which

\(^2\)We performed a coarse grid search over the values of $\lambda$ and setting $\lambda = 2$ resulted in fast convergence to high recall scores on the dev dataset.
in many cases is a difficult task by itself. In NLP, we have observed similar practices and challenges by Ranzato et al. [2015], Bahdanau et al. [2016], and Nguyen et al. [2017]. However, recently Rennie et al. [2017] proposed an effective self-critical sequence training (SCST) mechanism that avoids learning a separate critic network. Similarly, our method does not require learning a separate critic network, instead we directly use the scores of negative samples assigned by the discriminators as the baseline.

For an arbitrary pair of $S$ and $T_{gen}$, which is the generator’s output conditioned on $S$, we compute the coherence and cohesion scores by calling $D_{coherence}$ and $D_{cohesion}$, respectively. Since each review consists of multiple sentences, the overall cohesion score is computed as the average of scores of all consecutive sentence pairs. These scalar scores, however, have no interpretation since the discriminators are trained by optimizing a margin ranking loss. Instead, the differences between positive sample scores and the maximal or average negative sample scores provide insight of how well the models can distinguish between the positives and the negatives. Therefore, these margins can be considered as rewards with baselines, and thus we define the reward functions as:

$$R_{coherence}(s, T) := D_{coherence}(f_{\theta}(S), g_{\theta}(T)) - \mathbb{E}_{\tilde{T}}[D_{coherence}(f_{\theta}(S), g_{\theta}(\tilde{T}))]$$

$$R_{cohesion}(s_i, s_{i+1}) := D_{cohesion}(h_{\theta}(s_i), j_{\theta}(s_{i+1})) - \mathbb{E}_{\tilde{s}_{i+1}}[D_{cohesion}(h_{\theta}(s_i), j_{\theta}((\tilde{s}_{i+1})))]$$

where $\tilde{\cdot}$ denotes a negative sample for a given source condition, and $\mathbb{E}_{\tilde{T}}$ (and $\mathbb{E}_{\tilde{s}_{i+1}}$) are computed by averaging over an ensemble of negative samples. Notice that this reward resembles the ranking loss we use to train our discriminators, except that our baseline is an average score (instead of the weighted arithmetic mean) over negative samples. The rational for this difference is that: the maximal or the weighted arithmetic mean score baseline is in fact noisy to be used as rewards, because the best randomly constructed negative samples may be a formidably good sample. To alleviate such noise, we use the average discriminator scores of negative samples as the baseline, and this turns out to be an empirically better alternative.

Finally, we use policy gradient [Williams 1992, Sutton et al. 1999] to maximize a weighted combination of the coherence and cohesion rewards. For illustrative purposes, we equally weigh them for updating our policy, i.e., the generator $G$.

5 Experiments

In this section, we show results of training both $D_{coherence}$ and $D_{cohesion}$, and compare our RL-tuned generators $G_{MLE+RL(coherence)}$, $G_{MLE+RL(cohesion)}$, and $G_{MLE+RL(coherence, cohesion)}$ with the baseline model $G_{MLE}$. We argue that through the use of feedback from our simple discriminators to $G_{MLE}$, the quality of text generations improves significantly. See Table 3 for a comparison.

**Dataset.** We use the publicly available TripAdvisor’s hotel reviews dataset collected by Wang et al. [2010] and the Yelp review dataset[1] We consider only subsets of the two review datasets satisfying the following two conditions: a review must have (1) at least 10 sentences, and (2) each sentence should have more than 5 and less than 30 words. This yields roughly 60,000 TripAdvisor reviews and 220,000 Yelp reviews, split into [0.8, 0.1, 0.1] ratio for train/dev/test. We merge the source and target vocabularies, and limit it to the top 50,000 frequent words, excluding special tokens. For each of these reviews, as in [Holzmann et al. 2018], we consider the first five sentences as the source input $S$ to $G$, and the following five sentences as the target output $T$ from $G$.

**Evaluation metrics.** It is widely known that there is no accurate metric to evaluate the generator. Nevertheless, we report scores of standard metrics, such as negative log-likelihood (NLL), perplexity (PPL), BLEU and proportion of unique $n$-grams within a single generation (intra-unique-$n$), and across generations (inter-unique-$n$), as in [Gu et al. 2018]. Results are shown in Table 3.

5.1 Implementation details

$G$ takes individual words as inputs and embeds into a pre-trained 300-dimensional word vectors from GloVe [Pennington et al. 2014]. This embedding layer is fixed throughout training. $G$ uses a gated recurrent unit with two layers and a hidden size of 1024 for both bidirectional encoder and attention-based decoder. During optimization using Adam [Kingma and Ba 2014], we set the
Table 3: An ablation study with automated evaluation metric scores: NLL, PPL, BLEU-, intra/inter-unique-, along with the length ratio with the length of corresponding true target sentences as 1. Results show that our proposed discriminators helped improve notably in BLEU scores, NLL and PPL, with marginal difference in diversity. We used equally weighted rewards, and the best numbers are highlighted in bold before rounding.

Learning rate to $2 \times 10^{-4}$ and clip the gradient’s L2-norm to 1.0. We initially train $G_{MLE}$ by maximizing the word-level likelihood estimation (MLE) from data that consist of positive samples for 60 epochs on the TripAdvisor data and 30 epochs on the Yelp dataset, separately. These are our baseline models against which to empirically prove value of our hierarchical discriminators.

$D_{coherence}$ also uses the pre-trained GloVe word vectors\(^4\) which are fixed. The source processing network and the target processing network have the same structure, but different parameters. The convolutional layer has filters of sizes 2, 3, 4, and 5, each with 512 filters. Each convolution filter is followed by a \text{tanh} activation. Then we max-pool in time over the features and append a fully connected layer into a feature embedding of dimension 512, followed by a batch normalization layer and a \text{tanh} activation. We use an Adam optimizer with a learning rate of $1 \times 10^{-5}$.

$D_{cohesion}$ is the same as $D_{coherence}$, except it has convolutional filters of sizes 3, 4, 5, and 6. We train both discriminators for 50 epochs and choose models with the best R@1 validation scores.

In the tuning stage, we use the negative-critical sequence training as explained in Section 4 up to 5 epochs, with a learning rate of $1 \times 10^{-5}$. We also continue with supervised learning to $G$ to limit the policy search within a grammatically correct space, similar to Paulus et al. [2017], Wu et al. [2016], Lewis et al. [2017]. In practice, sequence-level rewards are only available upon a completed generation, so they are sparse signals for the generator. Typically, sparse end-of-sequence rewards entail a noisy training, yet would want the learning generalize to the testing data. We observed that, for our particular task, most noises were caused by exploration, and the learning generalized to the testing data. Thus, reward shaping was unnecessary, unlike previous works [Li et al., 2017; Yang et al., 2018] that further provided signals for partially generated sequences.

5.2 Sanity check on $D_{coherence}$ and $D_{cohesion}$

Most of the reviews written by the hotel guests are considered coherent. Suppose we randomly select a negative sample from a pool of other continuations $\tilde{T}$ in the data. Even for a layman in linguistics, one can effortlessly discern if the review repeats similar ideas, albeit in different wordings, whether $\tilde{T}$ supports or contradicts $S$ and is considered as a natural continuation from $S$. To show that our $D_{coherence}$ does these jobs and likewise for $D_{cohesion}$, we show some randomly selected positive and negative samples and their assigned margin scores in Table 4.

6 Discussion

We first comment on the text-to-text retrieval results in Table 2. Compared to image-to-textual caption retrieval tasks, the numbers are lower. One plausible reason is that an image is rich in semantics: an image is worth a thousand words. In contrast, a few sentences are limited in their capacity to convey a message, in addition to grammar and readability constraints. For this reason, the discriminator

\(^4\)The vector dimension can be different from that of $G$. The differences were marginal for sizes 50, 100, and 300. For results shown in this paper, we used the same dimension of size 300.
The hotel was unbelievably overpriced. We were looking for something cheaper but thought we would at least be staying in a decent hotel having paid that much when booking. It wasn’t clear when booking that we would have to share a bathroom. There was one shower for the whole floor which was tiny and unclean. The room was old and lacking in facilities.

The beds were very uncomfortable and the linen was very old. Breakfast was ok, but the staff were incompetent. On our last day they were too lazy to clean our table and never bothered taking our order. We had to leave having had no breakfast, as we ran out of time. They saw us get up and leave and didn’t even apologise for the appalling lack of service.

The staff recommended great restaurants with very reasonable prices within walking distance. The Paris Hop on bus stops nearby. The Gare l’Est is within 3 blocks. We paid 75 euro per nite excluding breakfast but paid for breakfast one day and found it very good and reasonably priced. The rooms are clean and bathrooms ensuite.

Once you get there you are greeted by the staff. They explain everything to you, and in English, not the best, but good enough. The coffee was even good for a coffee snob like myself. The hotel is much smaller than I thought and only has six floors.

Table 4: Coherence and cohesion margin scores on test data. The cohesion score at the end of each line is computed with its next sentence. This is a common example of contradiction and inconsistent sentiment, implying incoherence. We append more examples with extreme cohesion margin scores.

Models face a more difficult challenge in identifying the correct query (source sentences) - item (target sentences) pairs.

Furthermore, we note that our methods to construct negative samples, in spite of its simplicity, are not thorough. For example, a randomly selected next sentence, given an arbitrary sentence, may actually be a valid continuation for $D_{coherence}$. In this work, given an unlabelled dataset, we ignore such a problem, which may not be negligible and explain why we see a lower performance compared to that of $D_{coherence}$. Despite potential drawbacks of our methodology, we have shown significant improvements with imperfect discriminators. After experimenting with different architectures and hyper-parameters, we conclude that the table numbers are reasonable for the task.

We do note that results will get better with more data - our discriminators, as well as the generator, will be well-trained by seeing more data samples. We consider the dataset to be rather small because each pre-processing condition is quite restrictive. However, our goal is to demonstrate the efficacy of our discriminator models, rather than to show good results arising from a large amount of data.

6.1 What do $D_{coherence}$ and $D_{cohesion}$ capture?

Ideally, given how $D_{coherence}$ is constructed: independently processes the source and target sentences, we would want $D_{coherence}$ to detect whether the target sentences support the message delivered in the source sentences. Some cues that signal lacking such support are repetitive, contradicting, irrelevant, or sentiment inconsistent statements without appropriate transition phrases. Although $D_{coherence}$ only computes scores and does not reason out with specific cues, we observed that it learns to pick up these ideas that govern coherence of a multi-sentence paragraph. Despite some randomness from scores of randomly constructed negative samples, its critique margin scores are fairly consistent, based on a collection of margin scores on hotel reviews. Examples of more detailed incoherent aspects $D_{coherence}$ learns to distinguish include parts of a review commenting on different countries, cities or...
locations, and listing prices in different currency denominations. This is a positive result of training on randomly selected $T$ in the same batch.

The role of $D_{\text{cohesion}}$ is similar to $D_{\text{coherence}}$, except it operates in-between sentences. We observed that $D_{\text{cohesion}}$ captures some low-level logical connection. For example, it favorably scores artifacts that are commonly mentioned together from positive samples, and this is again a result of our methods to construct negative samples through shuffling and rotating target sentences in the same batch. As a consequence, artifacts that do not appear together as many times in consecutive sentences yield low cohesion scores.

However, we note that low cohesion scores among consecutive sentences do not necessarily imply a bad writing. Although one needs to avoid consistently low cohesive writing, the writer may simply enumerate seemingly disparate aspects written into respective sentences, and these likely imply a low connection between immediately neighboring sentences. Therefore, we do not solely optimize for the cohesion criterion.

6.2 Potential improvements in our approach

We would also like to comment on our imperfect discriminators. When we tuned $G$ for up to as many epochs as in the pre-training stage, we noticed that $G$ learns to find a policy that maximizes the discriminators’ margin scores, yet diverge from what we consider a good writing. Although this problem can be partially overcome by training on a larger dataset, we determined that these two discriminators do not give a comprehensive critique, and there exist other equally, if not more, important linguistic properties that we did not address. We hope to extend our hands-free model framework to encode these features and provide richer signals for $G$ to improve upon.

While reinforcing linguistic properties such as coherence and cohesion is the first attempt and an important research direction, we consider our results to be preliminary, and many of our experiment figures allude to plenty of room for further improvements, such as recall scores. We admit that we can argue the structure of $D_{\text{coherence}}$ and $D_{\text{cohesion}}$ either way, whether to process the source and target sentence(s) independently with different parameters, or together. Nevertheless, we are convinced that our architecture for both $D_{\text{coherence}}$ and $D_{\text{cohesion}}$ generalize well to unseen texts, and we plan to provide online a collection of examples with corresponding margin rewards, due to limited space in this paper, and release all of our resources to promote this line of research.

7 Conclusion

In this paper we propose to encode essential linguistic properties, coherence and cohesion, with a simple neural network architecture, and quantify them using negative-critical margin scores. The coherence discriminator $D_{\text{coherence}}$ provides a bird’s-eye view on coherence. It assesses how likely two text chunks form a coherent paragraph, using sentence-level features. On the other hand, the cohesion discriminator $D_{\text{cohesion}}$ provides a worm’s-eye view on cohesion. It assesses how cohesive two consecutive sentences are using word-level features.

The scores computed by these discriminators are used as reward signals for training neural language models via policy gradient. Empirical results on two long-form text generation tasks show that our method outperforms the strong baseline, an attention-based bidirectional MLE-trained sequence-to-sequence model in a number of automatic metrics.

Future work will focus on casting the long-form text generation task using the GANs framework. In this framework, the coherence and cohesion discriminators are modified against model-generated texts, and in turn, provide signals to learn neural language models. This work is an extension of GANs in that we use multiple discriminators, similar to Durugkar et al. [2016], but each discriminator reinforces a distinct linguistic behavior in $G$.

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