LEARNING TO WRITE WITH COHERENCE FROM NEGATIVE EXAMPLES

Seonil Son∗
Language AI Lab
NCSOFT
Gyeonggi-Do, S. Korea
deftson@ncsoft.com

Jaeseo Lim‡, Youwon Jang†, Jaeyoung Lee†
Interdisciplinary Program in Cognitive Science,
School of Computer Science and Engineering
Seoul National University, Seoul, S. Korea
{jaeseolim, sharifa, jerry96}@snu.ac.kr

Byoung-Tak Zhang†⋆
Artificial Intelligence Institute
Seoul National University
Seoul, S. Korea
btzhang@snu.ac.kr

ABSTRACT
Coherence is one of the critical factors that determine the quality of writing. We propose writing relevance (WR) training method for neural encoder-decoder natural language generation (NLG) models which improves coherence of the continuation by leveraging negative examples. WR loss regresses the vector representation of the context and generated sentence toward positive continuation by contrasting it with the negatives. We compare our approach with Unlikelihood (UL) training in a text continuation task on commonsense natural language inference (NLI) corpora to show which method better models the coherence by avoiding unlikely continuations. The preference of our approach in human evaluation shows the efficacy of our method in improving coherence.

Index Terms— Text Generation, Contrastive Learning, Coherence, Natural Language Processing

1. INTRODUCTION
An open ending leaves the readers lots of possibilities to imagine their own conclusion to the story. Endings by each writer may vary, but most of the endings will show coherence with the preceding context, and therefore end up forming a story.

While the encoder-decoder, or Seq2Seq framework [1] is designed to model the conditional likelihood of the decoded sentences given a context vector, it is not enough for modeling coherent semantics of the continuation. To this end, we introduce Writing Relevance (WR) training which models coherence, “a fit of the text to its context” [2]. WR training loss regresses the vector representation of the context and generated sentences toward the positive continuation example while separating it further from negative examples.

We experiment with text continuation on commonsense NLI corpora, namely the HellaSWAG [3] and Story Cloze Test [4] datasets. The model is asked to generate the continuation given the context sentences while the original datasets require to choose among the provided continuations. Coherence of continuations is the key due to the large number of possible cohesive (but incoherent) continuations and arising uncertainty the corpora allows. Both corpora contain human-written negative examples which are cohesive but diverge from information relevant to the context and thus not coherent [5]. As each corpus originates from different text sources, it helps to examine the extensible use of our training scheme to different domains.

In summary, our contributions are two-fold:

• We propose a WR training method that models coherence of the continuation by leveraging negative examples.

Fig. 1. WR loss biases encoder-decoder NLG model to generate sentences closer to the positive than negative example in the representation space.

1 Cohesion is not coherence [6]. Cohesive ties (e.g., use of pronouns, parallelism) may work as minimal conditions for coherence, but do not warrant delivering the topic consistently.

2 The HellaSWAG corpus is collected from WikiHow, and ActivityNet Captions [6]; the Story Cloze Test is a collection of human-written 5-sentence long stories.
The WR loss (between predictions and the positive sentence. auxiliary token prediction loss given by the cross-entropy be-
tininuations from negative examples, and the other is from an coherent One comes from a triplet loss for distinction of

to each corpus for text continuation. The model is optimized
in two distinct commonsense NLI corpora.

2. LEARNING FRAMEWORK

This section covers the two-step procedure for WR training. First, we pre-train an encoder-decoder model to generate grammatically correct sentences on a American Literature Short Story (ALSS) corpus that we have collected[6]. Then WR training takes place to fine-tune the model to bias its generation toward coherent sentences while avoiding out-of-place sentences (i.e., negative examples). We describe these two steps of training for encoder-decoder model in Section 2.1 and 2.2 including details of the decoding procedure and sentence representation.

2.1. Pre-training Encoder-Decoder Model

Here, we train the encoder-decoder NLG model for maximum likelihood estimation (MLE) of the consecutive tokens given a context as:

$$P(Y|X) = \prod_i^T p(y_i|Y_{0:i-1}, X)$$

where Y is a consecutive sentence that continues the context X. X and Y both consist of a series of tokens; \( \{x_0, x_1, ..., x_T\} \) and \( \{y_0, y_1, ..., y_T\} \). As we intend for the model to learn proper grammar for cohesion but not to induce coherence, we split the ALSS corpus into pairs of successive sentences.

For pre-training to be effective for latter text continuation, we initially chose Toronto Boot Corpus[3] as it is considered in-domain data for commonsense NLI corpora we are targeting. However, to circumvent the copyright issue of the Toronto Book Corpus, we collected the ALSS corpus as a replacement.

2.2. Writing Relevance Training

After pre-training, the model is capable of writing with correct grammar. In the WR training stage, we adapt the model to each corpus for text continuation. The model is optimized by sum of the gradient signals from two losses (Figure 2). One comes from a triplet loss for distinction of coherent continuations from negative examples, and the other is from an auxiliary token prediction loss given by the cross-entropy between predictions and the positive sentence. The WR loss \( L_{WR} \) is defined as follows:

\[
L_{WR} = \lambda CE(Y^*, Y) + TP_{cos}(a, pos, neg) \\
TP_{cos}(a, pos, neg) = \max(0, 1 + \frac{d^{cos}_{a, pos} - d^{cos}_{a, neg}}{\max(d^{cos}_{a, pos}, d^{cos}_{a, neg})})
\]

where cosine distance \( d^{cos}_{a, b} \) is defined as:

\[
d^{cos}_{a, b} = \frac{\|x_a - y\| - x_a \cdot y}{2\|x_a\|\|y\|}
\]

In Equation 2 \( Y^*, \hat{Y} \) and \( Y, N \) denote teacher-forced and greedy-decoded predictions and positive and negative continuations respectively. \( \lambda \) is a balancing coefficient (hyperparameter) for the cross-entropy loss \( CE(\cdot) \) and triplet loss \( TP_{cos}(\cdot) \). Inputs of the triplet loss, \( g(h_{X, \hat{Y}}) \), are sentence representations obtained by [CLS] pooling \( h_{X, \hat{Y}} \) as explained in the latter part of this section, mapped by \( g(\cdot) \).

If there is more than one negative example for a context, we randomly sample one among the negatives. To sum up, WR loss is composed of an auxiliary token prediction loss and a triplet loss that regresses sentence representations.

Decoding Strategy We apply a simple heuristic to avoid duplication in generated sentences as in Equation 4 following GLACNet[8].

\[
\hat{p}(word) = p(word) \times \frac{1}{1 + k \cdot \text{count}_\text{word}}
\]

The value we use for k in our experiments is 5. Beam search is not applied since it is known to cause generic sentences in open-ended generation tasks[10].

Sentence Representation We use a hidden vector of special token [CLS] obtained by forward pass of X and [CLS]; Y as a sentence representation of \( X; Y, h_{X, Y} \) (Figure 2). The [CLS] pooling is mapped by \( g(\cdot) \) which empirically helped triplet loss reduction. We choose the mapping amongst Hadamard product and linear projection[5].

3. EXPERIMENTS

3.1. Task and Datasets

The architecture choice for our experiment is Transformer[11] model. We perform text continuation to test our approach of learning to write with coherence. We use three datasets for this: i) the ALSS dataset for pre-training, which contains 4295 short stories (that vary from a paragraph to few pages long) collected from the public archive, ii) the Story Cloze

\[\text{https://github.com/sonsus/american_literature}\]
Fig. 2. Loss computation during the writing relevance (WR) training. Cross-entropy (CELoss) for token prediction is computed as in the pre-training, triplet loss (TPLoss) for contrasting negatives is added to the total loss.

Test, and iii) the HellaSWAG where the last two have negative examples of quality. Since the training split of the Story Cloze Test dataset has no negative examples, we randomly sample positive continuations from other stories to be used as negative examples after a sanity-check.

6 Random-sampled negatives only confused 3.3% of the participants. Each participant scored as follows: 30/30, 29/30, 28/30.

3.2. Human Evaluation
Following Stephan et al., (1981) [2], a straightforward way of measuring coherence is to ask readers. We perform an Amazon Mechanical Turk (AMT) survey to ask people which continuation looks more natural. Our survey investigates sentence preference of the respondents. First, we show both context and generated continuations of two different models to participants and ask: “What sentence do you prefer as a continuation?” Participants are also allowed to check at “BOTH GOOD” or “NEITHER GOOD” (Table 1).

| Context Sentences                                                                 | Choices               |
|----------------------------------------------------------------------------------|-----------------------|
| A man breaks into a house and begins to take things. he takes jewelry and games, some cash, and some food, when the family comes home they call the police. the police come and investigate and manage to track him. | the police officer is arrested. the police come and take the man to jail. BOTH GOOD NEITHER GOOD |

Table 1. Question of the survey for evaluation. Annotators are asked: “What sentence do you prefer as a continuation?”.

In order to filter inattentive annotators out, we plant attention-check questions in the middle of each survey form which have a clearly correct choice. The screening rejected about 14% (37 out of 156) of the survey submissions. 107 individuals participated and submitted 119 valid survey forms (average 1.11 submission per individual), each containing 27-28 questions accompanied with 3 screening questions.

4. RESULTS
We compare the performance of the NLG model that is trained with WR loss to the one that is trained using unlikelihood (UL) training loss that penalizes repetitive n-grams.
(n=4) and cross-entropy (CE) loss baselines. Since the UL loss with repetitive n-grams as unlikely candidates outperformed taking the candidates from negative examples, we take the former for the experiments.

Figure 4 summarizes the preference survey conducted. Continuations written by WR-trained encoder-decoder models are preferred over the other models trained with UL and CE loss on both adaptation corpora, HellaSWAG, and Story Cloze Test. Overall, WR > UL or CE always holds. We conjecture that a high portion of BOTH GOOD answers in the Story Cloze Test evaluation is caused by simple sentences, and noise from fabricated negative examples.

In Table 2, we show continuations generated by each model. The continuations from WR-trained model are preferred by participants despite of lower n-gram scores. While this is not always the case, for near half of the generated continuations from WR vs. UL survey, n-gram metrics failed to represent the human judgement of coherence. This reassures that n-gram metrics are inappropriate measures for open-ended generation tasks as reported in [13].

5. RELATED WORK

There are loss-based approaches that directly incorporate negative examples into training text continuation like Large Margin LM (LMLM) [14] and Unlikelihood (UL) training [15]. LMLM uses ranking loss to achieve better generation quality by enlarging the log-likelihood margin between the generated sentence from the negative samples. Unlikelihood (UL) training introduces a novel unlikelihood loss function that penalizes repetitive or unlikely tokens to remedy degeneracy problems in neural generation. Some works utilize classifiers to benefit generation. Holtzman et al., (2018) [16] deploys natural language understanding (NLU) discriminators that leverage what it learned from negative examples to resolve empirical problems of neural generation. Gabriel et al. (2019) [17] extends this for modeling narrative flow in summarization task. Similar to our approach, alignment of sentence representations for generation can also be found in Lee et al., (2021) [18] which focuses on perturbing positive and negative examples for an efficient contrastive learning of text representations for several NLG tasks.

6. CONCLUSION

We proposed the writing relevance (WR) training framework, which effectively uses negative examples to improve coherence. WR training makes the encoder-decoder NLG model learn sentence representation in a contrastive manner to form better coherence in its writing. We demonstrate the potential of our WR training scheme to various domains.

7. REFERENCES

[1] Ilya Sutskever, Oriol Vinyals, and Quoc V Le, “Sequence to sequence learning with neural networks,”

---

Fig. 4. Preference survey results ($P=.0042, .0001, .0101, .0024$). We surveyed over 107 English speaking individuals on AMT. For both comparisons (WR vs. UL and WR vs. CE), WR trained results are preferred over the corpora.
in Advances in neural information processing systems, 2014, pp. 3104–3112.

[2] Stephen P. Witte and Lester Faigley, “Coherence, cohesion, and writing quality,” College Composition and Communication, vol. 32, no. 2, pp. 189–204, 1981.

[3] Rowan Zellers, Ari Holtzman, Yonatan Bisk, Ali Farhadi, and Yejin Choi, “HellaSwag: Can a machine really finish your sentence?,” in Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, Florence, Italy, July 2019, pp. 4791–4800, Association for Computational Linguistics.

[4] Nasrin Mostafazadeh, Nathanael Chambers, Xiaodong He, Devi Parikh, Dhruv Batra, Lucy Vanderwende, Pushmeet Kohli, and James Allen, “A corpus and cloze evaluation for deeper understanding of commonsense stories,” in Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, San Diego, California, June 2016, pp. 839–849, Association for Computational Linguistics.

[5] Patricia L. Carrell, “Cohesion is not coherence*,” TESOL Quarterly, vol. 16, no. 4, pp. 479–488, 1982.

[6] Ranjay Krishna, Kenji Hata, Frederic Ren, Li Fei-Fei, and Juan Carlos Niebles, “Dense-captioning events in videos,” in International Conference on Computer Vision (ICCV), 2017.

[7] Yukun Zhu, Ryan Kiros, Rich Zemel, Ruslan Salakhutdinov, Raquel Urtasun, Antonio Torralba, and Sanja Fidler, “Aligning books and movies: Towards storylike visual explanations by watching movies and reading books,” in Proceedings of the IEEE international conference on computer vision, 2015, pp. 19–27.

[8] Taehyeong Kim, Min-Oh Heo, Seonil Son, Kyoung-Wha Park, and Byoung-Tak Zhang, “Glac net: Glocal attention cascading networks for multi-image cued story generation,” arXiv preprint arXiv:1805.10973, 2018.

[9] Angela Fan, Mike Lewis, and Yann Dauphin, “Hierarchical neural story generation,” in Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), Melbourne, Australia, July 2018, pp. 889–898, Association for Computational Linguistics.

[10] Ari Holtzman, Jan Buys, Li Du, Maxwell Forbes, and Yejin Choi, “The curious case of neural text degeneration,” in International Conference on Learning Representations, 2020.

[11] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Lukasz Kaiser, and Illia Polosukhin, “Attention is all you need,” in Advances in neural information processing systems, 2017, pp. 5998–6008.

[12] Chris Van Der Lee, Albert Gatt, Emiel Van Miltenburg, Sander Wubben, and Emiel Krahmer, “Best practices for the human evaluation of automatically generated text,” in Proceedings of the 12th International Conference on Natural Language Generation, 2019, pp. 355–368.

[13] Jekaterina Novikova, Ondřej Dušek, Amanda Cercas Curry, and Verena Rieser, “Why we need new evaluation metrics for NLG,” in Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing, Copenhagen, Denmark, Sept. 2017, pp. 2241–2252, Association for Computational Linguistics.

[14] Jiaji Huang, Yi Li, Wei Ping, and Liang Huang, “Large margin neural language model,” in Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, Brussels, Belgium, Oct.-Nov. 2018, pp. 1183–1191, Association for Computational Linguistics.

[15] Sean Welleck, Ilia Kulikov, Stephen Roller, Emily Dinan, Kyunghyun Cho, and Jason Weston, “Neural text generation with unlikelihood training,” in International Conference on Learning Representations, 2020.

[16] Ari Holtzman, Jan Buys, Maxwell Forbes, Antoine Bosselut, David Golub, and Yejin Choi, “Learning to write with cooperative discriminators,” in Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), Melbourne, Australia, July 2018, pp. 1638–1649, Association for Computational Linguistics.

[17] Saadia Gabriel, Antoine Bosselut, Ari Holtzman, Kyle Lo, Aslı Çelikyilmaz, and Yejin Choi, “Cooperative generator-discriminator networks for abstractive summarization with narrative flow,” CoRR, vol. abs/1907.01272, 2019.

[18] Seanie Lee, Dong Bok Lee, and Sung Ju Hwang, “Contrastive learning with adversarial perturbations for conditional text generation,” in International Conference on Learning Representations, 2021.