Plug-and-Play Controller for Story Completion: A Pilot Study toward Emotion-aware Story Writing Assistance

Yusuke Mori\textsuperscript{1} and Hiroaki Yamane\textsuperscript{2,1} and Ryohei Shimizu\textsuperscript{1} and Tatsuya Harada\textsuperscript{1,2}
\textsuperscript{1}The University of Tokyo
\textsuperscript{2}RIKEN
\{mori, yamane, shimizu, harada\}@mi.t.u-tokyo.ac.jp

Abstract

Emotions are essential for storytelling and narrative generation, and as such, the relationship between stories and emotions has been extensively studied. The authors of this paper, including a professional novelist, have examined the use of natural language processing to address the problems of novelists from the perspective of practical creative writing. In particular, the story completion task, which requires understanding the existing unfinished context, was studied from the perspective of creative support for human writers, to generate appropriate content to complete the unfinished parts. It was found that unsupervised pre-trained large neural models of the sequence-to-sequence type are useful for this task. Furthermore, based on the plug-and-play module for controllable text generation using GPT-2, an additional module was implemented to consider emotions. Although this is a preliminary study, and the results leave room for improvement before incorporating the model into a practical system, this effort is an important step in complementing the emotional trajectory of the story.

1 Introduction

In this study, the authors, one of whom is a professional novelist, examined the use of natural language processing to solve the problems faced by novelists from the perspective of practical creative writing. Among the diverse topics related to automatic storytelling and human creativity, “emotion” should be emphasized as an important keyword. The relationship between stories and emotions has been an essential part of the research in the field of humanities, especially in the cognitive and affective science of literature (Hogan, 2006; Pandit and Hogan, 2006; Johnson-Laird and Oatley, 2008; Hogan, 2010, 2019).

In providing practical knowledge for authors, creative techniques emphasize the importance of being conscious of readers’ emotions (Field, 2006; Snyder, 2005). The theory of the emotional arc, which states that a good story can be typified by emotional movement, is well known from the introduction by a popular American novelist, Vonnegut (1995). As presented in Reagan et al. (2016), studies have been conducted to reveal the close relationship between emotions and stories.

Ackerman and Puglisi (2012) insisted that a key component of every character is emotion. In the context of serious storytelling, Lugmayr et al. (2017) insisted that a fundamental aspect of storytelling is emotions, that is, the cognitive aspects that the story evokes in its audience. Numerous efforts have been made to disclose the mystery of the relationship between emotions and stories (Anderson and McMaster, 1982; Strapparava and Mihalcea, 2008; Abdul-Mageed and Ungar, 2017; Kim and Klinger, 2018, 2019a,b; Zad and Finlayson, 2020).

This study focuses on introducing emotions into a story completion (SC) task. The basic task setting in SC is shown in Figure 1.\textsuperscript{1} In the field of story generation and understanding, Wang and Wan (2019) proposed SC. We believe that the artificial intelligence (AI) ability to solve SC tasks is important in the context of providing creative support. If writers cannot complete a story and do not know how to proceed with a plot, a suitable model can provide them with appropriate support.

The main contributions of this study are as follows:

- The importance of emotion in stories was confirmed from the perspective of a professional writer, based on which, the possibility of incorporating emotions into SC tasks is discussed for creative support, and a specific method is proposed to accomplish this.

\textsuperscript{1}The original story in this figure is from ROCStories (storyid: 0b3f8b6-117c-45d0-861f-d9953ccc7d6b; storytitle: Dancing).
Story Completion

Jake was a good dancer but he was shy. Every time he saw her he got shy and didn't ask. The day before the dance Mary asked Jake. Jake said yes and he showed Mary how to dance.

Story Completion with Emotion Control

High Arousal, Negative Valence

High Arousal, Positive Valence

Figure 1: Conceptual diagram of the functionality this study aims for. ① Overview of the story completion task. To address the <missing_position> token in an incomplete story, unsupervised pre-trained large neural models are used. ② PPLM is used to control the emotions of the generative text. The representation of the emotions in this figure was reconstructed from an image by Russell (1980).

- Control of SC was examined through our implementation using the plug-and-play language model (PPLM) (Dathathri et al., 2020), whereby the application of the PPLM, which is originally limited, was expanded.

This study is a preliminary study, and the results should be improved before incorporating the model into a practical system. However, we believe that this effort is an important step toward complementing the emotional trajectory of the story and worth discussing for future directions.

As a complementary contribution to this study, we would like to note that a professional writer researched how to use natural language processing (NLP) technology to reflect the viewpoints of writers and researchers. We expect that this work will contribute to building a bridge toward collaborative work between professional writers and researchers in NLP and human computer interface (HCI) to accelerate research in the field of story writing assistance.

2 Related Work

2.1 Story Completion

In the field of story generation and understanding, Wang and Wan (2019) proposed SC. Given any four sentences in a five-sentence story, the objective of the task is to generate a sentence that is not provided (missing plot), to complete the story. In addition to this, research on text infilling has been actively conducted in recent years (Ippolito et al., 2019; Donahue et al., 2020; Huang et al., 2020; Wang et al., 2020). We pointed out that the ability to solve an SC task is essential from the viewpoint of creative support for writers (Mori et al., 2020). If writers cannot complete a story and do not know how to proceed with the plot, AI can provide appropriate support for filling in the blanks.

In this study, controlled text generation with emotion awareness is applied to SC. Focusing on stories, a method is proposed to handle this task in a simple manner by including a special token, specific to the task. By organizing the task in a simple manner, it becomes possible to solve it in a similar way with various models.

2.2 Emotion-aware Storytelling

Some studies have attempted to control story generation by considering emotions (Chandu et al., 2019; Luo et al., 2019; Brahman and Chaturvedi, 2020; Dathathri et al., 2020; Xu et al., 2020). The study closest to ours is that of Brahman and Chaturvedi (2020). They insisted that their study was the first to model the emotional trajectory of the protagonist in neural storytelling. There are significant differences between their study and ours with respect to task setting and the approach taken.

First, Brahman and Chaturvedi (2020) attempted to generate an entire story from the task, while our focus is on the SC task that a model reads to understand what is written in the original context. In this study, dimensional emotions (valence and arousal) were used instead of categorical emotions (four basic emotions in addition to neutral). Dividing emotions into categories is easy to understand,
but for precise control, it is desirable to handle emotions as continuous values. Luo et al. (2019) tackled fine-grained emotion control of story generation, but their objective was story ending rather than completion. Moreover, the controlled emotion was restricted to one dimension (positive-negative). The interest in this study is the control of more diverse two-dimensional emotions based on Russell’s circumplex model (Russell, 1980).

2.3 Controllable text generation with Transformer

There are some works in unsupervised pre-trained large neural models for control text generation. Keskar et al. (2019) proposed CTRL to control specific aspects of text generation in large-scale language models. Based on the large-scale language model MEGATRON (Shoeybi et al., 2020) and knowledge-enhanced story generation (Guan et al., 2020), Xu et al. (2020) proposed MEGATRON-CNTRL. In other studies, Rashkin et al. (2020) proposed the task of outline-conditioned story generation, whereby the input only provided a rough sketch of the plot. Therefore, models must generate a story by interweaving the key points provided in the outline. Inspired by plug-and-play generative networks (PPGN) (Nguyen et al., 2017) in computer vision, Dathathri et al. (2020) proposed PPLM, an alternative approach for controlled text generation. Their approach uses attachment models for pre-trained GPT-2 (Radford et al., 2019) to control the word probability distribution during the word-by-word generation process. Optimization is performed ex post facto in the activation space; therefore, no retraining or fine-tuning of the core language model is required. Following this approach, methods have been presented to control the output by adding modules for output control without modifying the core model, such as DE-LOREAN (DEcoding for nonmonotonic LOgical REAsoNing) (Qin et al., 2020), side-tuning (Zhang et al., 2020a), auxiliary tuning (Zeldes et al., 2020), and GeDi (Krause et al., 2021).

In this study, PPLM, which is a well-designed, simple, and powerful method, is applied for emotion-controllable story generation. Dathathri et al. (2020) explored controlled generation for assistive story writing, demonstrating the usefulness of PPLM in this area. However, they conducted an exploration of open-ended story generation, not SC.

3 Methods

This section describes the proposed method in detail, emphasizing the ingenuity of its implementation. The proposed model has a novel architecture composed of two main parts for SC tasks.

- Fine-tuning unsupervised pre-trained large neural models for the SC task.
- Emotion-aware controlling of fine-tuned models using PPLM.

Studies on applying unsupervised pre-trained large neural models for text infilling have been actively conducted recently (Ippolito et al., 2019; Donahue et al., 2020; Huang et al., 2020; Wang et al., 2020). The first part of our method follows this trend and is verified using various models.

In Subsection 3.2, a modified version of PPLM (Dathathri et al., 2020) is proposed for emotion-aware SC. PPLM, given a prompt (user input text), generates subsequent sentences, as it uses GPT-2 as a base model and tiny attribute models. In this study, the PPLM model was expanded through concatenation with other models.

The model code was implemented using PyTorch (Paszke et al., 2019), which is an open-source machine-learning framework provided as a Python library. To make use of unsupervised pre-trained large neural models, our code was also based on Huggingface Transformers (Wolf et al., 2020), which provide general-purpose architectures for natural language understanding (NLU) and natural language generation (NLG).

The focus here is mainly on Seq2Seq language models (Seq2SeqLMs). For Seq2SeqLMs and its variants, the models below were used.

- BART (Lewis et al., 2020) - BART base, BART large
- T5 (Raffel et al., 2020) - T5 base, T5 large
- PEGASUS (Zhang et al., 2020b) - PEGASUS large
- ProphetNet (Qi et al., 2020) - XLM-ProphetNet large

2https://pytorch.org/

3We used XLM-ProphetNet because only “un-cased” models of ProphetNet were available for pre-trained models. Hence, XLM-ProphetNet, specifically, “microsoft/xprophetnet-large-wiki100-cased,” which is a cased version, was used.
Causal language models (CLMs), which have a left-to-right architecture, do not seem to perform well on SC because they were originally designed for the generation of a continuation of the given prompt and not for completing the missing part, by considering the before and after of the missing part. However, Donahue et al. (2020) proposed the infilling by language modeling (ILM), an approach that enables CLMs to leverage the entire context for text infilling. We left it for future work to apply CLMs to controllable story completion with our proposed method.

PyTorch version 1.11.0, and HuggingFace Transformers version 4.18.0 were used. The details of pre-trained models are displayed in Table 1.

### 3.1 No-emotion-aware baselines

Initially, models for SC that do not consider emotions should be trained for plug-and-play control. In this study, these methods are referred to as “No-emotion-aware baselines.” As shown in Figure 1, a special token was defined for the SC task: `<missing_position>`". A special token is inserted into the missing position $k$, such that the input to the model becomes $S' = \{s_1, ..., s_k-1, \text{<missing_position>}, s_{k+1}, ..., s_n\}$. $s$ stands for a sentence, and the subscript number indicates the position of the sentence in the entire text. Subsequently, the model outputs $s_k$, as defined in the task.

For Seq2SeqLMs, the $S'$ are concatenated into one text and fed to the encoder. The decoder then generates text. The output is expected to be a single sentence; however, it was also explored if the model could learn from fine-tuning, including “generate only one sentence,” constraints.

### 3.2 Emotion Controlling Methods

In this study, PPLM was updated for use in emotion control during story completion. PPLM was originally implemented as an additional module for GPT-2 (the default model was GPT2-medium). Adapting PPLM to Seq2SeqLMs required some implementation ingenuities. PPLM was originally designed to generate the continuation of a given text using a decoder-only model. In contrast, in this study, the given text is first processed with the encoder, and then the resulting tensor is used to generate sentences with the decoder.

PPLM has two types of attribute models: bag-of-words (PPLM-BoW) and discriminator (PPLM-Discrim). Originally, PPLM-BoW did not include an emotion control set. PPLM-Discrim has a pre-trained model for sentiment control, but it is positive–negative. In this study, the focus was on PPLM-BoW because it can function by preparing a list of words without additional learning. Thus, the original word list provided in PPLM can be used, but this does not consider valence and arousal. Hence, the NRC valence, arousal, and dominance lexicon (Mohammad, 2018) (NRC-VAD lexicon) was used to obtain the word list annotated with dimensional emotion values, which was subsequently fed into PPLM-BoW. Instead of using the entire NRC-VAD lexicon as is, in our implementation, a range of values can be specified for valence and arousal (and dominance) at runtime to obtain a subset within that range.

### 4 Experimental Setup

#### 4.1 Dataset

In this pilot study, the proposed method was trained and evaluated using ROCStories (Mostafazadeh et al., 2016). As shown in Table 2, the dataset was randomly split in a ratio of 8:1:1 to obtain training, development, and test sets. One sentence was removed from the five-sentence story. The missing position $k$ was randomly determined based on a
Training 78,528 randomly during training
dev 9,816 when creating a dataset
Test 9,817 when creating a dataset
total 98,161

Table 2: Overview of the dataset used.

discrete uniform distribution. For the development and test sets, the removal procedure was performed when creating the dataset to improve reproducibility. For the training set, the original five-sentence story was retained in the dataset and a sentence was randomly removed while reading the data during training. This setting followed that of our previous study (Mori et al., 2020).

4.2 Training Details

For training, the AdamW (Loshchilov and Hutter, 2019) optimizer was used with parameters \(\beta_1 = 0.9, \beta_2 = 0.999, \text{ and } \epsilon = 1e^{-08}\). The initial learning rate was set to \(3e^{-05}\) and linearly decreased thereafter from the initial point to 0 to avoid overfitting. The model was fine-tuned using NVIDIA Tesla V100 GPUs and the size of the training batch was set to 8.

We use two sets of training parameters. One is task-specific parameters, defined for each model based on its use for the summarization task. The other is common parameters for all models.

Seq2SeqLMs significantly improved the performance compared to conventional models in text-to-text tasks, especially in summarization and translation. Of these two well-worked tasks, we hypothesized that the training settings for summarization are closer to what we need for SC. SC requires methods to understand the context, to generate appropriate sentences for completion. The given context is typically longer than a sentence for completion. In summary, methods are required to understand the entire text, to generate shorter sentences to represent it. Although there are two types of approaches, extractive summarization and abstractive summarization, the basic objective is the same. On the other hand, in translation tasks, although it is also important to understand the input content, the output length is not significantly different from the input length (note that there is a difference related to the nature of each language). There are also application examples, such as paraphrasing in one language, but the input and output are generally in different languages during translation.

What varies from model to model is the setting such as length penalty and max length of input and output sequence. The length penalty places a constraint on the length of the generated sentences, prompting the generation of longer sentences if it is greater than 1.0, and shorter sentences if it is less than 1.0. As mentioned above, task-specific parameters prepared for summarization were used in this study. This was done to ensure the fairness of the settings by unifying the parameters in “solving SC by directly applying the settings of the summarization task.” For this reason, the length penalty was set to 2.0 for T5 in this experiment, 1.0 for BART, and 0.8 for PEGASUS. For XLM-ProphetNet, the penalty was 2.0.

For a different sense of fairness, we provided another setting that uses a common length penalty. In this setting, the length penalty is 1.0.

4.3 Evaluation Metrics

It is necessary to evaluate a large number of models and their variants (model parameters, training parameters, tasks that are fine-tuned beforehand, etc.). Thus, automatic evaluation metrics were employed instead of human evaluation. Stories entertain the reader (or evoke other emotions); therefore, human evaluation is important. However, there is a huge cost involved in terms of time and money for evaluating various parameters in many models. In addition, there are factors such as age, gender, and regional trends in texts, particularly in stories. The problem is that stories liked by someone are not always liked by others. In this section, the focus is on automatic evaluation metrics for a large number of models. The human evaluation of a narrowed-down list of promising candidate models is left for future work.

The following metrics were used for the evaluation: BLEU (Papineni et al., 2002), ROUGE (Lin, 2004), METEOR (Banerjee and Lavie, 2005), BERTScore (Zhang* et al., 2020),\(^5\) and BLEURT (Sellam et al., 2020).\(^7\) The Python library HuggingFace Datasets was used for certain metrics; \(^5\)There is no generic parameter for the “summarization task” for PEGASUS, so the parameter for summarization of the XSUM dataset was used.
\(^7\)https://github.com/google-research/bleurt
"sacrebleu" as BLEU, ROUGE and METEOR. For each of BERTScore and BLEURT, the original implementation of each paper was used.

5 Results

5.1 No-emotion-aware baselines

First, experiments were conducted using no-emotion-aware baselines. Table 3 lists the test set results of Seq2SeqLMs evaluated using automatic evaluation metrics. In this comparison, the entire story was not compared; however, the generated complementary sentence was compared with the original sentence (the missing sentence). The value of F1 was used for ROUGE and BERTScore. In addition, for BERTScore, the authors obtained an average when evaluating the models. BLEURT was treated in a similar manner.

The results indicated that BART large exhibited the highest scores for every metric. For a deeper analysis of the metric results, Table 4 was created for average generation length and runtime. In BART base, BART large, and PEGASUS, the two training settings didn’t have a significant impact. On the other hand, for T5 base, T5 large, and XLM-ProphetNet, better results were obtained when using task-specific parameters. The result suggests that the parameters for summarization work well for story completion, especially when the model requires a large length penalty for summarization tasks.

Table 5 and 6 display the examples generated.

5.2 Emotion Controlling Method

The Seq2SeqLM + PPLM-BoW results are presented in Table 7. As BART large displayed the best result in the no-emotion-aware baseline experiment, BART large was used as the first step of Emotion-aware SC with Seq2SeqLM + PPLM.

In the examples shown in Table 7, the ranges of valence and arousal were set to \(0.0 \leq valence \leq 0.3\) and \(0.7 \leq arousal \leq 1.0\), respectively. As valence is negative and arousal is high, negative and excited emotions are expected to emerge. The results of an uncontrolled trial (un-perturbed) and three controlled trials (perturbed) are presented as examples. Perturbed 1 seems to be controlled by “negative and excited.” In the context of careful driving, it is not unnatural for events related to the car to occur, and on top of that, the expression that the car gets stuck is negative. We showed an example where the generation of emotion-controlled sentences worked well. However, the adjustment of the parameters to generate a sequence was very severe. PPLM provides parameters to manipulate the generated results, but it is very difficult to adjust these parameters, at least in combination with Seq2SeqLM.

We should note that the BART large model used here was trained with an older version of PyTorch and Transformers. Unfortunately, the version trained with PyTorch 1.11.0 and Transformers 4.18.0 used in this Seq2SeqLM Story Completion did not produce good results with the same generation parameters. Although we could run the modified PPLM with the libraries of the newer version, the choice of the fine-tuned model is also severe.

PPLM was originally designed for use with GPT-2, but in this study, it was modified and applied to Seq2SeqLM. Specifically, it was confirmed that PPLM works on BART. However, when we used the Seq2SeqLM model which was fine-tuned for no-emotion-aware SC to generate sentences controlled with PPLM, we found that the sentences tended to be shorter than those generated without PPLM.

6 Discussion

The no-emotion-aware baseline results indicate that BART large exhibited the highest scores for every metric. In this study, we used two sets of training parameters: one is based on summarization task-specific parameters and the other is common parameters. The result showed that the parameters for summarization work well for story completion, compared to common parameters that do not account for differences between models. Future studies should search for specific parameters for each model that are more suitable for SC.

In this study, PPLM was extended and combined with BART, a representative model of Seq2SeqLMs. In addition, by combining PPLM with the NRC-VAD lexicon, a basis was created for SC to consider valence and arousal. However, there is still a lot of room for improvement in the
Table 3: The result of no-emotion-awareSeq2SeqLMs evaluated with automatic evaluation metrics.

|                | BLEU | ROUGE-1 | ROUGE-2 | ROUGE-L | METEOR | BERTScore | BLEURT |
|----------------|------|---------|---------|---------|--------|-----------|--------|
| BART base w/ specific param | 5.352848 | 0.265496 | 0.082603 | 0.254470 | 0.254414 | 0.909720 | -0.432042 |
| BART large w/ specific param | 7.390772 | 0.291679 | 0.106530 | 0.271545 | 0.279787 | 0.914704 | -0.373194 |
| PEGASUS large w/ specific param | 5.401445 | 0.265151 | 0.085482 | 0.243784 | 0.266451 | 0.907397 | -0.473113 |
| TS base w/ specific param | 4.390108 | 0.253425 | 0.070985 | 0.232174 | 0.259644 | 0.912142 | -0.404434 |
| TS large w/ specific param | 6.249401 | 0.282742 | 0.095236 | 0.276074 | 0.283361 | 0.912802 | -0.382382 |
| XLM-ProphetNet large w/ specific param | 0.116252 | 0.159532 | 0.010753 | 0.148529 | 0.065040 | 0.853637 | -0.821382 |

Table 4: The mean generated length and the runtime of no-emotion-aware Seq2SeqLMs. “w/ specific param” indicates that the model is trained using the task-specific parameters of each model.

|                | BLEU | generated length | runtime | samples/sec |
|----------------|------|------------------|---------|-------------|
| BART base w/ specific param | 5.3528 | 14.5 | 344.5440 | -0.003 |
| BART large w/ specific param | 7.3907 | 15.0 | 546.4531 | -0.002 |
| PEGASUS large w/ specific param | 5.4014 | 13.6 | 890.2809 | -0.001 |
| TS base w/ specific param | 4.3901 | 14.9 | 595.7259 | -0.002 |
| TS large w/ specific param | 6.2494 | 14.7 | 1031.0659 | -0.001 |
| XLM-ProphetNet large w/ specific param | 0.1163 | 10.8 | 960.6619 | -0.001 |

Table 5: Examples of contexts and completion sentences generated by no-emotion-awareSeq2SeqLMs. In this case, the task-specific parameters for each model were used.

| storyid                      | dc36af5e-a65f-4193-8f3c-5162c8af6755 |
|-----------------------------|---------------------------------------|
| context                     | <missing_position> I wanted to take out some fish. But then the lady was not using gloves. I was disgusted. I ended up walking out. |
| missing_id                  | 0                                     |
| GT                          | I went to a restaurant yesterday. |
| BART base completed story   | I went to the fish market with my friends. |
| BART large completed story  | I went to the fish market yesterday. |
| PEGASUS large completed story | I went to the fish market for the first time. |
| TS base completed story     | I went to a fish market one day. I was very hungry. |
| TS large completed story    | I went to a fish market one day with my friends. |
| XLM-ProphetNet large completed story | She was to to the.... |
| GT completed story          | I went to a restaurant yesterday. I wanted to take out some fish. But then the lady was not using gloves. I was disgusted. I ended up walking out. |
| BART base completed story   | I went to the fish market with my friends. I wanted to take out some fish. But then the lady was not using gloves. I was disgusted. I ended up walking out. |
| BART large completed story  | I went to the fish market yesterday. I wanted to take out some fish. But then the lady was not using gloves. I was disgusted. I ended up walking out. |
| PEGASUS large completed story | I went to the fish market today for the first time. I wanted to take out some fish. But then the lady was not using gloves. I was disgusted. I ended up walking out. |
| TS base completed story     | I went to a fish market one day. I was very hungry. I wanted to take out some fish. But then the lady was not using gloves. I was disgusted. I ended up walking out. |
| TS large completed story    | I went to a fish market one day with my friends. I wanted to take out some fish. But then the lady was not using gloves. I was disgusted. I ended up walking out. |
| XLM-ProphetNet large completed story | She was to to the.... I wanted to take out some fish. But then the lady was not using gloves. I was disgusted. I ended up walking out. |

In text generation, it is important to control the behavior of the model using parameters such as the length penalty. Two types of parameters were experimented with in this study, but further effort is required to determine the best parameter. The optimal hyperparameters seem to be naturally different for each model. It is not realistic to check...
Table 6: Examples of contexts and completion sentences generated by no-emotion-aware Seq2SeqLMs. In this case, the same hyperparameters were used for length penalty and max length.

| Context                                                                 | Missing sentence                                                                 |
|------------------------------------------------------------------------|----------------------------------------------------------------------------------|
| I got a call from the hospital. My doctor told me to stop everything I’m doing and come to her. Although I was nervous, I tried to drive calmly. | The doctor diagnosed me with leukemia.                                           |

| Unperturbed                                                                 | Perturbed 0 | Perturbed 1 | Perturbed 2 |
|---------------------------------------------------------------------------|-------------|-------------|-------------|
| The front desk worker sent me to an office.                                | However, my blood.                        | However, the car... | My car got stuck...

Table 7: An example of emotion-controlled SC with BART large + PPLM-BoW (0.0 <= Valence <= 0.3 and 0.7 <= Arousal <= 1.0).

all outputs using the human eye while adjusting hyperparameters within a wide range of values for many models. Therefore, an automatic evaluation mechanism is required.

The application of these methods to other datasets is left for future work. As a representative example, the WritingPrompts dataset (Fan et al., 2018) was considered. Stories in WritingPrompts vary in terms of length; therefore, the importance of a single sentence varies from one story to the other. With very long stories, generally trimming is used to retain a predetermined number of words from the start while truncating the rest. Hence, this dataset was not considered to be suitable for the SC tasks for now. Thus, as a starting point, ROCStories was adopted.

7 Considerations by a Professional Writer

As noted in the Introduction, one of the authors of this study was a professional novelist. This work is a collaborative effort between researchers and a professional creative writer. More precisely, the
first author of this paper is a professional Japanese novelist as well as a researcher in the field of story understanding and generation.

In Section 6, the viewpoint of the researchers is discussed. In this section, the positioning and prospects of this study are discussed from the novelist’s perspective.

In an experiment conducted separately from this study, four professional creative writers were asked to evaluate a creative writing support system. The results of that experiment confirmed that there might be a negative perception of the system’s ability to control the output if there are parameters with which the user is not familiar. Although it would be desirable for users to have the freedom to adjust the outcome, too many parameters make them lost. They do not know what to do, resulting in confusion on the user’s part in using the system and in a negative impression.

As previously mentioned, our modified PPLM for controllable SC addressed in this study is difficult to adjust. Moreover, in its current state, users are required to understand what “valence” and “arousal” mean. We believe that treating both dimensions rather than one dimension (positive-negative) would be important for future directions in this area, but this idea is not yet widespread. Hence, it is difficult for this approach to provide professional writers with the desired results for now. At this point, there was concern that other professional writers would have a negative impression of the “creative writing support system that controls the emotions of the generated text” as a whole. That is why no human evaluation was conducted on this study, except by the novelist author.

For practitioners, the extent to which AI could replace their own work is an important issue; there is also concern that it could trigger a sense of avoidance toward AI. Prudence is needed in conducting research, and professional evaluations, which are important topics of discussion.

Some professional novelists write from beginning to end in order, while others come up with certain parts but cannot come up with the correct sentences to fill in the gaps. SC is an important task in helping the latter. From the creative writer’s perspective, it is helpful to have a system that understands the meaning of one’s own writing and then fills in the missing parts. Furthermore, as the importance of the emotional arc in a story becomes increasingly apparent, a system that controls the output of the emotions desired by the user as well as an evaluation index that considers emotions would be helpful.

8 Conclusion

In this study, the SC task was considered for various emotions. Previous studies on emotion-aware story generation have restricted emotions to one dimension (positive-negative) or categorical ones. Our aim was to control more diverse emotions, so the issue of two-dimensional control was addressed based on Russell’s circumplex model.

Our implementation made it possible to control SC using PPLM. This expands the application of PPLM, which was originally limited to the task of “generating the continuation of a prompt.” Although the goal of controlling emotions was accomplished, it was difficult to adjust the parameters. Whether this difficulty in coordination can be improved through innovative implementation or demands a completely different approach requires further examination.

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