Generating Coherent Narratives by Learning Dynamic and Discrete Entity States with a Contrastive Framework

Jian Guan¹, Zhenyu Yang², Rongsheng Zhang³, Zhipeng Hu³ and Minlie Huang^{1*}

¹The CoAI group, DCST; ¹Institute for Artificial Intelligence; ¹State Key Lab of Intelligent Technology and Systems; ¹Beijing National Research Center for Information Science and Technology; ¹Tsinghua University, Beijing 100084, China. ²Guangdong OPPO Mobile Telecommunications Corp., Ltd. ³Fuxi AI Lab, NetEase Inc., Hangzhou, China. j-guan19@mails.tsinghua.edu.cn; yangzhenyu@oppo.com; {zhangrongsheng, zphu}@corp.netease.com; aihuang@tsinghua.edu.cn

Abstract

Despite advances in generating fluent texts, existing pretraining models tend to attach incoherent event sequences to involved entities when generating narratives such as stories and news. We conjecture that such issues result from representing entities as static embeddings of superficial words, while neglecting to model their ever-changing states, i.e., the information they carry, as the text unfolds. Therefore, we extend the Transformer model to dynamically conduct entity state updates and sentence realization for narrative generation. We propose a contrastive framework to learn the state representations in a discrete space, and insert additional attention layers into the decoder to better exploit these states. Experiments on two narrative datasets show that our model can generate more coherent and diverse narratives than strong baselines with the guidance of meaningful entity states.

1 Introduction

Generating open-ended texts that maintain long-range coherence is important for myriad natural language generation applications such as narrative generation. The task requires, given a short input, creating a text with a sequence of coherent events involving several interleaved entities (e.g., characters, organizations, locations, etc.). As the text unfolds, the entities encounter different events, enrich their respective information, and accordingly change readers' expectations about them, thus playing a central role to make the text coherent (Grosz, Joshi, and Weinstein 1995). Arguably, the ability to dynamically predict unseen events attached to different entities is indispensable for generation (Henaff et al. 2017) but has not yet been widely investigated.

Typical generative models such as BART (Lewis et al. 2020) are trained to learn co-occurrence between tokens, which are represented as learnable embeddings. As exemplified in Table 1, BART can easily capture dependencies between common words such as "injured" and "funeral," but attaches incoherent event sequences to the involved entities. We conjecture that such issues arise from representing entities as no more than static embeddings of superficial words throughout whole texts, while neglecting to model the

Copyright © 2023, Association for the Advancement of Artificial Intelligence (www.aaai.org). All rights reserved.

Example 1: ... After Bobby is injured, the scene flashes to Bobby's funeral.

Bobby then goes to a graveyard with the family and begins to tell of a woman that ...

Example 2: ... The Tokyo District Court found **Samsung guilty** last week for "intentionally causing serious injury to the plaintiffs by copying, copying, or causing injury to a trademarked trademark." The court ruled that **Samsung violated the patent on all Apple's mobile devices**, including the iPhone and iPad ... **Apple has been fighting the ruling** since Wednesday ...

Table 1: Two examples generated by BART fine-tuned on the Wikiplots and CNN News datasets, respectively, where conflicting events are attached to some entities (in **bold**). Different entity mentions are marked in different colors.

change of information these entities carry, i.e., their states (Ji et al. 2017). Since the same superficial words can co-occur with different events (and vice versa), it is necessary for generating coherent texts to model dependencies between events and specific states instead of word embeddings. For instance, in the first example of Table 1, after "Bobby's funeral", the model should learn to update its estimate of Bobby's state from being *alive* to *dead* and then attach such events to him as "lying in a coffin" instead of "going to a graveyard." Similarly, in the second example, Apple and Samsung transit to different states after "the court rule that Samsung violated the patent on all Apple's...," and the model should attach the event "fighting the ruling" to Samsung instead of Apple.

This work proposes a generation model that incorporates dynamic entity states to improve coherence. We extend the Transformer decoder to update entity states after each sentence, which then serve to guide the subsequent decoding. We design a novel contrastive framework to learn the state representations. Instead of conditioning on continuous state representations for generation (Clark, Ji, and Smith 2018), we use a set of discrete state vectors to represent entity states, which are a natural fit for state transitions. Discrete states also encourage effective use of the latent space, and alleviate excessive focus on local and imperceptible details.

The contrastive framework is designed to pull the state of an entity close to events that can be attached to the entity in the representation space. To abstract high-level event features, we adopt an external encoder to encode each sen-

^{*}Corresponding author

tence in a mini-batch to obtain the corresponding entityaware event representations for different entities in the sentence. At the end of each sentence, we first learn to predict which entity to mention in the following sentence. We then learn the current state representation of the entity using a contrastive objective by regarding the representation of the following event attached to it as the positive and all others in the same mini-batch as negatives. During inference, we look up the closest state vector to the state representation in the pre-defined discrete latent space, and feed the state vector into the decoder along with the word embedding of the entity mention to guide the following sentence realization. The hidden states of the decoder get access to input entity states using not only the vanilla self-attention layer, but also a state attention layer inserted into each decoder block. The additional layer narrows the attention scope to only prefix entity states for explicitly modeling the dependencies between states and contextual events. In the training phase, we directly use the closest state vector to the following event representation as input to keep the parallel training efficiency. Our contributions are as follows:

I. We propose a novel generation model that learns dynamic and discrete entity state representations with a contrastive framework (ERIC). We equip the decoder with an additional attention layer to apply entity states to guide the decoding.

II. Extensive experiments on two datasets show that the contrastive framework learns a set of meaningful entity state vectors corresponding to different clusters of events that can be attached to an entity, thus enabling ERIC to generate more coherent and informative texts than strong baselines¹.

2 Related Work

Narrative Generation Recent studies presented a series of multi-step generation models for narrative generation, which first planned intermediate sketches like keywords (Yao et al. 2019), semantic role labeling tags (Fan, Lewis, and Dauphin 2019) and keyword distributions (Kang and Hovy 2020), and then generated whole texts conditioned on them. Ji and Huang (2021) learned a sequence of discrete latent codes to abstract high-level discourse structures. Each code corresponds to a fixed-length span, which does not always agree with real text structures and makes it hard to model specific semantic dependencies. Some studies tried to incorporate external knowledge or reasoning models to guide commonsense story generation (Guan et al. 2020; Xu et al. 2020; Ammanabrolu et al. 2021), which may lack generalization to other domains such as news. Another line improved coherence by learning high-level representations of prefix sentences (Li, Luong, and Jurafsky 2015; Guan et al. 2021), which does not emphasize the central role of entities.

Prior studies on state tracking commonly adopted an external memory for state reads and writes. Ji et al. (2017) and Clark, Ji, and Smith (2018) updated the state of an entity conditioned on previous hidden outputs when encountering its mention, which does not apply to the parallel architecture of Transformer for training. Rashkin et al. (2020) and

Papalampidi, Cao, and Kocisky (2022) performed state updates at the paragraph and chunk level, respectively, to alleviate but not eliminate the issue. In contrast, ERIC learns entity states through entity-aware event representations derived from an external encoder during training, thus well adapting to popular pretraining models, and achieving more frequent state updates. Furthermore, our work presents the first study for learning discrete entity states.

Hierarchical Transformers It is necessary to capture the hierarchical structure of natural language texts (Ribeiro et al. 2020). Previous work employed hierarchical attention networks for document classification (Yang et al. 2016) and machine translation (Miculicich et al. 2018). Guo et al. (2019) adopted a hierarchy network to build document embeddings on top of sentence embeddings for document mining. Similarly, HIBERT (Zhang, Wei, and Zhou 2019) incorporated a hierarchical architecture to BERT (Devlin et al. 2019) for document summarization. These models aim to enhance encoders for modeling long inputs and are less adaptive for generation. Recent studies tried to shorten sequences in intermediate decoder blocks to learn high-level representations for text classification (Dai et al. 2020) and generation (Nawrot et al. 2021). Hu et al. (2022) incorporated dynamically planned bag-of-words to guide the text realization without considering dependencies between words. In comparison, the proposed framework enables the learned entity states to serve as a sentence-level guidance for generation.

Contrastive Learning Contrastive learning has become popular in unsupervised visual and textual representation learning (Hadsell, Chopra, and LeCun 2006). The representations are learned by making two objects augmented from the same data point close in the vector space, and objects from others as distant as possible. CERT (Fang et al. 2020) adopted an instance-level data augmentation technique (i.e., back-translation). ConSERT (Yan et al. 2021) and Sim-CSE (Gao, Yao, and Chen 2021) proposed directly adding noise to inner representations of BERT to construct positive pairs, leading to better performance and higher computation efficiency. In this paper, we develop a novel contrastive framework to learn discrete entity states for text generation.

3 Methodology

3.1 Task Definition and Model Overview

Our task is as follows: given a short input such as a beginning $X=(x_1,x_2,\cdots,x_M)$, the model should generate a coherent multi-sentence text $Y=(y_1,y_2,\cdots,y_L)$ (each x_i or y_i is a token). We notice that entity words (e.g., character names) often consist of rare tokens, and the same entity may have different mentions (e.g., "Bruce Wayne," "Bruce" and "Wayne"). To better track entity states, we use a two-stage generation framework (Hermann et al. 2015) that first generates a coarse text with all mentions of each entity replaced by a unique placeholder such as " $\langle e0 \rangle, \langle e1 \rangle, \cdots$," and then generates the mention for each one. We denote the coarse version of the target as $Y^e=(y_1^e,y_2^e,\cdots,y_T^e)$.

To generate Y^e from X, generative models such as BART are commonly optimized to minimize the negative log-

¹The codes are available at https://github.com/thu-coai/ERIC.

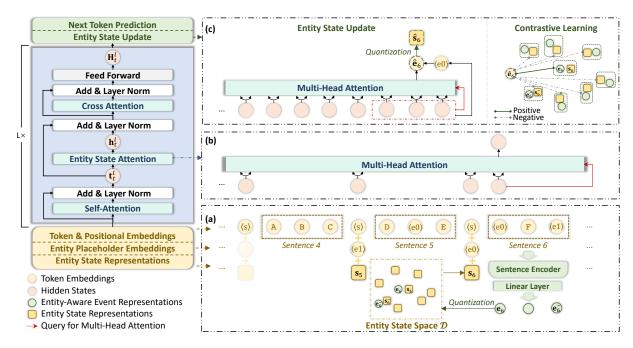


Figure 1: Model overview of the ERIC decoder, which (a) adds a special token $\langle s \rangle$ before each sentence for incorporating state representations of the following mentioned entities, (b) inserts an entity state attention layer into each Transformer block that narrows the attention scope to only the prefix entity states, and (c) learns an entity state update module with a contrastive objective. We omit the input encoder of ERIC for simplicity.

likelihood \mathcal{L}_{LM} of Y^e as follows:

$$\mathcal{L}_{LM} = -\sum_{t=1}^{T} \log P(y_t^e | y_{< t}^e, X).$$
 (1)

Further, ERIC conducts entity state updates and sentence realization in an auto-regressive manner. At the end of each sentence, we incorporate the state vector of the entity mentioned in the following sentence to the decoder (§ 3.2), which then guides the subsequent generation with an entity state attention layer inserted into each decoder block (§ 3.3). We design a contrastive objective for learning to predict the state of the following mentioned entity conditioned on prefix decoder outputs (§ 3.4). Although we only consider sentences as segments in this paper, our algorithm can easily be extended to other syntactic levels such as paraphrases. Figure 1 shows the model overview of the first training stage. In the second stage, we train another standard Transformer model to generate mentions for anonymous entities (§ 3.5).

3.2 Incorporating Entity States

Suppose that Y^e consists of N sentences, denoted from Y_1^e to Y_N^e (e.g., ABC in Figure 1). We insert a special token $\langle \mathbf{s} \rangle$ at the beginning of each sentence Y_n^e ($n=1,2\cdots,N$) (Guan et al. 2021), which is designed to incorporate entity state representations to guide the realization of Y_n^e . Formally, we set the decoder input \mathbf{H}_t^0 as follows:

$$\mathbf{H}_{t}^{0} = \begin{cases} \mathbf{E}_{t} + \mathbf{E}(p_{n}) + \mathbf{s}_{n}, & \text{if } y_{t}^{e} = \langle \mathbf{s} \rangle |_{n} \\ \mathbf{E}_{t}, & \text{otherwise} \end{cases}$$
 (2)

$$\mathbf{E}_t = \mathbf{E}(y_t^e) + \mathbf{P}(y_t^e),\tag{3}$$

where \mathbf{E}_t is the sum of the token and positional embeddings of the t-th token y_t^e , $\langle \mathbf{s} \rangle|_n$ means the n-th special token, p_n is the placeholder token of the entity mentioned in Y_n^e , $\mathbf{E}(p_n)$ and \mathbf{s}_n are the token embedding and state vector of p_n , respectively. When Y_n does not mention any entities (e.g., sentence 4 in Figure 1), we set both $\mathbf{E}(p_n)$ and \mathbf{s}_n to zero vectors. While Y_n contains multiple placeholders (e.g., sentence 6 in Figure 1), we randomly sample one as p_n . Our algorithm also adapts to multiple entities, which is left to future work.

We pre-define a discrete entity state space $\mathcal{D} \in \mathbb{R}^{K \times D}$, which consists of K entity states with each state represented as a normalized D-dimensional vector \mathbf{d}_i ($i=1,2\cdots,K$). As shown in Figure 1, we pass a sentence Y_n^e through an external bidirectional sentence encoder, and map the hidden output at the position of p_n (e.g., $\langle e0 \rangle$ in Figure 1) to D dimensions using a linear layer and normalize it as the entity-aware event representation, denoted as \mathbf{e}_n . We then derive \mathbf{s}_n , the state vector of p_n , through the nearest neighbour look-up from \mathcal{D} :

$$\mathbf{s}_n = \mathbf{d}_k$$
, where $k = \underset{\mathbf{d}_j \in \mathcal{D}}{\operatorname{argmin}} \mathbf{d}_j \cdot \mathbf{e}_n$, (4)

where we have normalized both \mathbf{d}_j and \mathbf{e}_n onto the unit hyper-sphere. We use the straight-through trick (Bengio, Léonard, and Courville 2013) to allow the gradient to backpropagate to the sentence encoder, i.e., directly copying the gradient of \mathbf{s}_n to \mathbf{e}_n (Van Den Oord, Vinyals et al. 2017).

3.3 Entity State Attention Layer

In order to explicitly exert entity states on text generation, we insert an additional entity state attention layer between the vanilla self-attention layer and cross-attention layer in each decoder block. Assuming that the decoder consists of L blocks, let \mathbf{t}_t^l denote the layer-normalized output of the self-attention layer in the l-th block at the t-th position $(t=1,2,\cdots,T,\ l=1,2,\cdots,L)$. The entity state attention layer allows \mathbf{t}_t^l to attend to only those hidden states corresponding to prefix entity states:

$$\mathbf{h}_t^l = \mathbf{A}(\mathbf{Q} = \mathbf{t}_t^l, \mathbf{K}/\mathbf{V} = \{\mathbf{t}_{t' \le t}^l | y_{t'}^e = \langle \mathbf{s} \rangle \}), \tag{5}$$

where \mathbf{h}_t^l is the output hidden state of the state attention layer, $\mathbf{A}(\cdot)$ means the multi-head attention mechanism (Vaswani et al. 2017), Q, K and V are the corresponding query, key and value vectors. In this way, ERIC predicts the next tokens with the guidance of entity states using an individual attention network besides the standard self-attention, enhancing its ability to model dependencies between sentence realization and entity states.

3.4 Entity States Learning

ERIC uses entity states derived from the following golden sentences for training. We add an entity state update module on top of the decoder to learn to predict entity states based on prefix information using a contrastive framework, which will be used to guide generation in the inference stage.

The entity state update module consists of two key components, which are used to predict the following mentioned entity \hat{p}_n and its state $\hat{\mathbf{s}}_n$ $(n=1,2,\cdots,N)$, respectively. We adopt a linear layer to predict the distribution of \hat{p}_n over the vocabulary of all placeholders conditioned on the prefix, and minimize the prediction loss $\mathcal{L}_{\mathrm{Ent}}$ as follows:

$$\mathcal{L}_{\text{Ent}} = -\sum_{n=1}^{N} \log P(\hat{p}_n = p_n), \tag{6}$$

$$P(\hat{p}_n) = \operatorname{softmax}(\boldsymbol{W}_p \mathbf{q}_{n-1} + \boldsymbol{b}_p), \tag{7}$$

$$\mathbf{q}_{n-1} = \text{MeanPool}(\{\mathbf{H}_t^L\}_{n-1}),\tag{8}$$

where \mathbf{q}_{n-1} is a context summary vector derived by applying mean-pooling on $\{\mathbf{H}_t^L\}_{n-1}$, i.e., the set of hidden outputs of the (n-1)-th sentence, \boldsymbol{W}_p and \boldsymbol{b}_p are trainable parameters. We add a special token $\langle \texttt{none} \rangle$ into the placeholder vocabulary with a constant zero embedding to indicate that no entities will be mentioned in the following sentence. We decide \hat{p}_n by taking a sample from $P(\hat{p}_n)$, and predict its state vector $\hat{\mathbf{s}}_n$ as follows:

$$\hat{\mathbf{s}}_n = \mathbf{d}_k$$
, where $k = \underset{\mathbf{d}_j \in \mathcal{D}}{\operatorname{argmin}} \ \mathbf{d}_j \cdot \hat{\mathbf{e}}_n$. (9)

$$\hat{\mathbf{e}}_n = \text{Normalize} (\mathbf{A}(\mathbf{Q} = \mathbf{q}_{n-1} + \mathbf{E}(\hat{p}_n), \quad (10)$$

$$\mathbf{K}/\mathbf{V} = \{\mathbf{H}_t^L\}_{1:n-1}),$$

where $\hat{\mathbf{e}}_n$ is the continuous state representation of \hat{p}_n before quantization, and $\{\mathbf{H}_t^L\}_{1:n-1}$ is the set of hidden states of the first n-1 sentences. To learn the state representation, we design a contrastive framework to draw $\hat{\mathbf{e}}_n$ close to the following event representation \mathbf{e}_n and keep it away from others derived from different sentences or corresponding to different entities in the same mini-batch (e.g., \mathbf{e}_n^- in Figure 1). To

back-propagate gradients to learn the state space \mathcal{D} , we set each positive or negative to a joint representation that combines the event representation \mathbf{e}_n and its nearest state vector \mathbf{s}_n in \mathcal{D} . In this way, they can be optimized in the same direction and forced to distributed uniformly in \mathcal{D} , thus gaining better expressiveness. We formulate the contrastive objective \mathcal{L}_{CL} as the following infoNCE loss (Oord, Li, and Vinyals 2018):

$$\mathcal{L}_{\text{CL}} = -\frac{1}{N} \sum_{n=1}^{N} \log \frac{\exp(\hat{\mathbf{e}}_n \cdot \mathbf{c}_n / \tau)}{\sum_{\mathbf{c}^* \in C} \exp(\hat{\mathbf{e}}_n \cdot \mathbf{c}_n^* / \tau)}, \quad (11)$$

$$\mathbf{c}_n = \text{Normalize}(\mathbf{e}_n + \mathbf{s}_n), \tag{12}$$

where \mathbf{c}_n is the positive joint representation for $\hat{\mathbf{e}}_n$, C is the set of all joint representations in the mini-batch, and τ is the adjustable temperature.

Once we obtain $\hat{\mathbf{e}}_n$, the corresponding discrete state vector $\hat{\mathbf{s}}_n$ can be obtained by quantizing $\hat{\mathbf{e}}_n$ to \mathcal{D} using the nearest neighbour look-up as shown in Eq. 9. And \hat{p}_n and $\hat{\mathbf{s}}_n$ will be taken as input in Eq. 2 to guide the generation in the inference stage. In summary, we train the input encoder, the sentence encoder and the decoder jointly with the following overall loss function:

$$\mathcal{L} = \mathcal{L}_{LM} + \lambda_1 \mathcal{L}_{Ent} + \lambda_2 \mathcal{L}_{CL}, \tag{13}$$

where λ_1 and λ_2 are adjustable sale factors.

3.5 Entity Mention Generation

This stage requires generating superficial entity mentions for placeholder tokens in Y^e . We only use a standard Transformer model for this stage since it is not the main focus of this work. Other training techniques can be also easily applied (Fan, Lewis, and Dauphin 2019). Formally, given X and Y^e , the model should generate a sequence of pairs of a placeholder token followed by its corresponding superficial word in the order that they are mentioned. For example, for the text " $\langle e0 \rangle$ and his girlfriend $\langle e1 \rangle$ take a romantic vacation to a cabin. While in the cabin, $\langle e0 \rangle \cdots$," the golden output is " $\langle e0 \rangle Ash$ Williams $\langle e1 \rangle Linda \langle e0 \rangle Ash \cdots$." After obtaining the entity mentions, we can insert them back into Y^e to get the whole text Y.

4 Experiments

4.1 Datasets

We evaluate ERIC on two English narrative datasets, Wikiplots² and CNN News (Hermann et al. 2015). Wikiplots collected story plots from Wikipedia. We use the official split of Wikiplots. We follow Ji and Huang (2021) to split each sentence into sequential elementary discourse units and regard them as sentences for experiments on Wikiplots. CNN News consists of online newspaper articles collected from CNN. We process the dataset using the script provided by Tan et al. (2021) and split the dataset randomly by 18:1:1 for training/validation/testing. For both datasets, we take the first sentence as input to generate the rest. We

²www.github.com/markriedl/Wikiplots

remove those texts whose outputs contain less than five sentences, and truncate each output to at most fifteen sentences. We use spaCy³ to identify people and organization names in a text as entity mentions. If the string of an entity mention is included in another, we replace them with the same placeholder. There are about 98% of examples and 50% of sentences that mention at least one entity on both datasets. More statistics are shown in Table 2, where we count tokens using the NLTK tokenizer (Loper and Bird 2002). More details are shown in Appendix A.1.

D-44-	, T	Wikiplots			NN News	s
Datasets	Train	Val	Test	Train	Val	Test
#Example	76,826	4,327	4,324	82,836	4,602	4,602
Ipt Len.	24.6	24.6	24.6	32.9	33.3	33.0
Opt Len. Avg. #Sen. Avg. #Ent.	237.1 12.6 6.8	236.5 12.7 6.7	237.1 12.6 6.7	346.0 14.3 7.7	344.9 14.2 7.6	344.5 14.3 7.7

Table 2: Example numbers, average lengths (*Len.*) of inputs (*ipt*) and outputs (*opt*), average numbers of sentences (*Sen.*) and distinct entities (*Ent.*) in outputs for *train*ing, *val*idation and *test*ing, respectively.

4.2 Implementation

Our algorithm adapts to all generative models with autoregressive decoders. Due to limited computational resources, we use BART_{Base}'s pretrained checkpoint for initialization. The sentence encoder is initialized using the pretrained parameters of the BART_{Base} encoder. We set the number of discrete entity states in \mathcal{D} to 512, the dimension of state vectors to 128, the maximum number of distinct entities in a text to 100, τ in Eq. 12 to 0.1, and λ_1/λ_2 in Eq. 13 to 1/1. These settings lead to 3% more parameters of ERIC than BART_{Base}⁴. For both stages, we set the batch size to 12, the maximum sequence length to 512, and the learning rate to 1e-4. We decide the hyper-parameters based on the performance on the validation set.

During inference, we use top-p sampling (Holtzman et al. 2020) with p=0.9 for both generation stages. In the second stage, when the model fails to generate a mention word for a certain placeholder, we complete the output of the first stage using the last word generated for this placeholder if it has been mentioned before (about 2.5% of cases), or a random name otherwise (about 1.1% of cases).

4.3 Baselines

We compared ERIC with the following models: (1) **Seq2Seq:** It has the same architecture as BART_{Base} but is initialized randomly. (2) **BART:** It is fine-tuned on the downstream datasets with the standard language modeling objective. (3) **PlanAhead:** It first plans a keyword distribution and then combines the planned distribution with the

language model prediction using a gated mechanism (Kang and Hovy 2020). We use BART_{Base} as the backbone model and add additional parameters for planning and distribution combination. (4) HINT: It incorporates high-level sentence representations into BART_{Base} and uses sentence similarity prediction and sentence order discrimination to learn these representations (Guan et al. 2021). (5) DISCODVT: It extends BART_{Base} to represent the discourse structure using a sequence of latent codes with learnable embeddings (Ji and Huang 2021). We do not limit the minimum length of the latent code sequence like in the original paper. (6) SimCTG: It adds a contrastive objective which tries to distribute the hidden outputs of BART_{Base} uniformly in the representation space (Su et al. 2022).

Besides the above baselines, we conduct ablation tests on Wikiplots by removing the proposed components respectively. For fair comparison, we insert the special token $\langle s \rangle$ before each sentence for all baselines. During evaluation, we remove all special tokens from the generated texts.

4.4 Automatic Evaluation

Evaluation Metrics We do not use perplexity for evaluation since the two-stage generation paradigm of ERIC makes it intractable to assess the text probability. We use the following automatic metrics: (1) BLEU (B-n): It evaluates the n-gram overlap between generated and humanwritten texts (Papineni et al. 2002), n = 1, 2. (2) MS-Jaccard (MSJ-n): It measures the similarity between two n-gram distributions of generated and human-written texts using the Jaccard Index between two multi-sets of ngrams (Alihosseini, Montahaei, and Baghshah 2019), n =1, 2. (3) MAUVE: It measures the similarity between two text distributions of generated and human-written texts (Pillutla et al. 2021), where text representations are derived from GPT2_{Base}. (4) Token Repetition (Rpt-n): It measures the repetition of generated texts by calculating the fraction of the identical token that occurs in the previous n tokens (Welleck et al. 2020), n = 16, 32, 64. (5) Distinct (D-n): It measures the generation diversity using the ratio of distinct ngrams to all generated n-grams (Li et al. 2016), n = 3, 4. (6) Zipf Coefficient (Zipf): It computes the unigram rankfrequency scale factor in generated texts (Holtzman et al. 2020). A value closer to 1 indicates that the generated texts are closer to real-world texts in unigram distribution. Moreover, we also report the average number of generated tokens, denoted as Len.

Results Table 3 shows the results on 1000 randomly sampled generated examples. The higher BLEU scores of ERIC indicate that it can generate more n-gram overlaps with reference texts than baselines. On the whole, the generation distribution of ERIC is more similar to the ground truth in terms of both n-grams and machine-derived text representations, as shown by the higher MSJ and MAUVE scores. Furthermore, the texts generated by ERIC suffer from less repetition with lower token repetition ratios in various ranges and have better diversity. ERIC also achieves better modeling of long-tail tokens (e.g., entity mentions), with a Zipf score closer to 1. The superiority of ERIC on both datasets proves its gen-

³https://spacy.io/usage/linguistic-features\#named-entities

⁴We do not count the parameters of the sentence encoder since it is not used during inference.

Models	B-1 ↑	B-2 ↑	MSJ-1↑	MSJ-2↑	MAUVE↑	Rpt-16↓	Rpt-32↓	Rpt-64↓	D-3 ↑	D-4 ↑	Zipf	Len
Dataset: Wikiplots												
Seq2Seq	26.33	10.28	56.87	39.94	74.56	20.02	32.99	41.61	68.30	89.79	1.26	199
BART	28.33	11.66	58.96	41.16	76.88	17.82	30.74	39.47	70.26	90.51	1.19	201
PlanAhead	27.52	11.32	58.86	41.31	75.98	17.40	30.27	38.90	71.84	91.27	1.17	193
HINT	29.81	12.22	61.17	42.33	80.16	17.20	30.12	39.00	71.73	91.12	1.14	209
DISCODVT	28.76	11.76	60.89	42.29	78.01	17.07	29.81	38.56	73.22	91.76	1.13	204
SimCTG	29.08	11.90	59.81	41.53	77.15	17.68	30.59	39.40	70.44	90.52	1.18	206
ERIC	31.81	12.90	63.93	42.94	87.88	16.22	28.12	37.06	75.94	93.02	1.11	236
w/o StateAttn	30.12	12.26	62.81	42.84	83.29	16.75	28.56	37.42	75.41	92.85	1.12	221
w/o \mathbf{s}_n	28.84	11.70	59.16	40.84	83.18	16.62	28.90	37.43	72.42	91.36	1.15	206
w/o \mathbf{s}_n & p_n	28.63	11.59	58.74	40.43	73.01	<u>16.34</u>	28.86	37.93	72.97	91.54	<u>1.12</u>	203
Truth	N/A	N/A	N/A	N/A	N/A	13.63	25.30	34.75	85.80	97.10	0.96	266
					Dataset: C	NN News						
Seq2Seq	31.99	14.42	68.25	47.68	85.20	16.06	27.40	36.88	74.02	91.42	1.11	271
BART	32.18	14.66	68.20	47.37	87.25	14.63	25.74	35.34	77.05	92.64	1.08	267
PlanAhead	32.23	14.64	67.05	47.11	28.95	14.55	25.70	35.48	76.53	92.12	1.08	259
HINT	33.07	15.18	69.29	47.74	86.15	14.57	25.69	35.19	77.16	92.61	1.07	275
DISCODVT	32.53	14.92	68.63	47.64	83.43	14.37	25.50	35.09	77.47	92.75	1.07	267
SimCTG	32.50	14.79	68.91	<u>47.75</u>	86.65	14.37	25.56	35.11	76.92	92.48	1.07	272
ERIC	33.83	15.28	70.47	48.09	91.02	14.29	25.16	34.81	78.16	93.01	1.06	282
Truth	N/A	N/A	N/A	N/A	N/A	12.28	22.39	32.22	82.89	94.61	1.00	341

Table 3: Automatic evaluation results. \downarrow / \uparrow means the lower/higher the better. The best performance is highlighted in **bold** the second is <u>underlined</u>. ERIC w/o StateAttn means removing the entity state attention layer. ERIC w/o \mathbf{s}_n means removing entity state representations in the decoder input along with the contrastive learning framework. ERIC w/o \mathbf{s}_n & p_n means further remove the next mentioned entity prediction module.

eralization for text generation with different lengths and domains. Additionally, we observe that the Wikiplots dataset has more long-tail tokens than CNN News with a lower Zipf score, which may account for the higher superiority of ERIC on Wikiplots since more low-frequency entity mentions may make it harder for baselines to model the entity coherence implicitly.

For ablation tests, the entity state attention layer helps the decoder exploit entity state representations better, thereby improving performance on all metrics and particularly reducing short-range repetition. When removing \mathbf{s}_n or both \mathbf{s}_n and p_n , the BLEU and MSJ scores drop to the level of BART, suggesting the importance of tracking entity states. We also notice that they still have surprisingly less repetition than all baselines. Manual inspection finds that they tend to generate fewer coordinate combinations of identical entity names. For example, there are 14.8% and 13.0% of texts generated by BART and ERIC w/o $\mathbf{s}_n \& p_n$, respectively, that contain strings of the form "W and W" ("W" is a unigram). The phenomenon shows that the two-stage generation paradigm may make it easier to learn entity mention patterns. Significantly, ERIC further surpasses the two ablation models with less repetition thanks to the modeling of entity state transitions which integrates high-level dependencies between events attached to involved entities.

Entity Coherence Modeling It is necessary to investigate whether tracking entity states helps better capture the en-

tity coherence. To this end, on the test set of Wikiplots with masked entity mentions, we replace the first entity placeholder in each sentence in order with another that has been mentioned before randomly (with the prefix not perturbed). Figure 3 plots the accuracy that a model gives a lower probability to the perturbed sentence than the original one along with the prefix. We calculate text probabilities using the following mentioned entities (i.e., p_n) as input for all models, and using the entity states predicted by the model (i.e., $\hat{\mathbf{s}}_n$) as input for ERIC and randomly sampled entity states for ERIC (Rand). We use the models after the first-stage training for this experiment.

We observe that ERIC outperforms ERIC w/o \mathbf{s}_n significantly (p < 0.01), especially for the first several sentences. And its performance drops substantially when using random entity states, suggesting that ERIC has a better ability to model entity coherence with the guidance of meaningful entity states. For example, when a placeholder $\langle e1 \rangle$ is replaced to $\langle e0 \rangle$, the event that is attached to $\langle e1 \rangle$ originally may disagree with the state of $\langle e0 \rangle$. In this case, it is easier for ERIC to capture such incoherence issues by tracking their internal states. Appendix C shows more analysis.

4.5 Manual Evaluation

We conduct pair-wise comparisons between ERIC and three strong baselines including BART, HINT and DISCODVT, with each pair of models compared conditioned on 200 in-

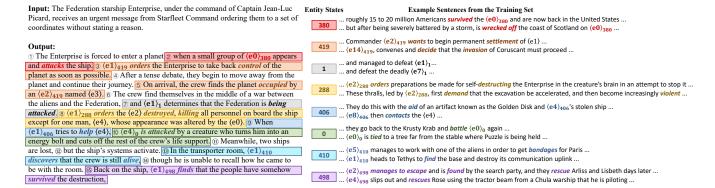


Figure 2: A case generated by ERIC on Wikiplots (**Left**) and example sentences from the training set where some entity has the corresponding state (**Right**). The subscript under each entity placeholder token (e.g., $\langle e0 \rangle_{380}$) denotes its state ID. We highlight semantically correlated keywords between the generated case and example sentences in *italic* type. For each entity state, two example sentences are manually selected from top ten sentences with the closest event representations to the state vector.

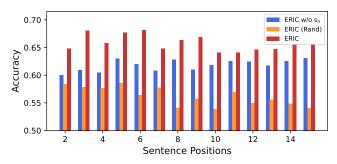


Figure 3: Accuracy of different models varying with positions of perturbed sentences on Wikiplots.

puts randomly sampled from the test set of Wikiplots. We hired workers on Amazon Mechanical Turk (AMT) to give a preference (win, lose, or tie) in terms of informativeness (interesting, diverse and rich details) and coherence (reasonable inter-sentence dependencies, e.g., causal and temporal relationships). Each pair is annotated by three workers independently. Workers are also asked to annotate whether each text exhibits entity issues such as attaching conflicting or repetitive events to an entity. We use majority voting to make final decisions among the workers. Appendix D shows the annotation instruction.

As shown in Table 4, all results show fair or better interannotator agreement ($\kappa \geqslant 0.2$). ERIC can generate more abundant details with more coherent plots significantly (p < 0.01), and suffers from about 20% fewer entity issues than baselines by tracking entity states explicitly.

4.6 Case Study

Figure 2 shows a case to investigate the correspondence between entity states and texts. We conclude that: (1) The entity states learn meaningful correspondence to specific events. As shown in the right part of Figure 2, state 419 relates to "occupying some regions," state 380 means the entity may be an "attacker" while state 1 stands for "being defeated." (2) The entity states effectively guide text gener-

ERIC vs.	Informativeness Win / Lose / Tie	Coherence Win / Lose / Tie	Entity Issues ERIC / the Other
BART	55** / 33 / 12	57** / 35 / 8	61** 870.47
HINT	58** / 31 / 11	56** / 37 / 8	68** 810.35
DISCODVT	57** / 32 / 11	54** / 34 / 12	56** / 830.52

Table 4: Manual evaluation results on Wikiplots. **Left:** Percentages (%) of *win*, *lose* or *tie* when comparing ERIC with a baseline. **Right:** Percentages (%) of texts that suffer from entity issues. The subscripts are Fleiss' kappa (Fleiss and Joseph 1971). The mark */** means ERIC outperforms the baseline significantly with p < 0.05/0.01 (sign test).

ation. For instance, $\langle e0 \rangle_{380}$ in the second sentence "attacks" the ship. Both $\langle e1 \rangle_{419}$ in the third sentence and $\langle e2 \rangle_{419}$ in the fifth sentence intend to "occupy" the planet. (3) Tracking entity states helps maintain long-range coherence for text generation. For example, the protagonist $\langle e1 \rangle$ behaves with reasonable state transitions throughout the text, forming a coherent plot. Appendix E shows the generation results of baselines.

5 Conclusion

We present the first study to track entity states in large pretraining models for narrative generation. The proposed model ERIC dynamically updates entity states at the sentence level, where each state associates with a cluster of events that can be attached to the entity. Then these states serve to guide the subsequent generation with an additional entity state attention layer. We design a contrastive framework to learn entity-aware event representations and discrete state vectors jointly. ERIC surpasses strong baselines in automatic and manual evaluation for story and news generation. Further analysis shows that ERIC can better capture entity coherence and generate more coherent and informative texts with the guidance of meaningful state representations.

6 Acknowledgements

This work is supported by the Key Research and Development Program of Zhejiang Province (No. 2022C01011). This work was supported by the National Science Foundation for Distinguished Young Scholars (with No. 62125604) and the NSFC projects (Key project with No. 61936010 and regular project with No. 61876096). This work was also supported by the Guoqiang Institute of Tsinghua University, with Grant No. 2019GQG1 and 2020GQG0005. This work was also sponsored by Tsinghua-Toyota Joint Research Fund.

References

- Alihosseini, D.; Montahaei, E.; and Baghshah, M. S. 2019. Jointly measuring diversity and quality in text generation models. In *Proceedings of the Workshop on Methods for Optimizing and Evaluating Neural Language Generation*, 90–98.
- Ammanabrolu, P.; Cheung, W.; Broniec, W.; and Riedl, M. O. 2021. Automated Storytelling via Causal, Commonsense Plot Ordering. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 35, 5859–5867.
- Bengio, Y.; Léonard, N.; and Courville, A. 2013. Estimating or propagating gradients through stochastic neurons for conditional computation. *arXiv preprint arXiv:1308.3432*.
- Clark, E.; Ji, Y.; and Smith, N. A. 2018. Neural text generation in stories using entity representations as context. In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers)*, 2250–2260.
- Dai, Z.; Lai, G.; Yang, Y.; and Le, Q. 2020. Funnel-Transformer: Filtering out Sequential Redundancy for Efficient Language Processing. In *NeurIPS*.
- Devlin, J.; Chang, M.-W.; Lee, K.; and Toutanova, K. 2019. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, 4171–4186.
- Fan, A.; Lewis, M.; and Dauphin, Y. 2019. Strategies for Structuring Story Generation. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, 2650–2660. Florence, Italy: Association for Computational Linguistics.
- Fang, H.; Wang, S.; Zhou, M.; Ding, J.; and Xie, P. 2020. Cert: Contrastive self-supervised learning for language understanding. *arXiv* preprint arXiv:2005.12766.
- Fleiss; and Joseph, L. 1971. Measuring nominal scale agreement among many raters. *Psychological Bulletin*, 76(5): 378–382.
- Gao, T.; Yao, X.; and Chen, D. 2021. SimCSE: Simple Contrastive Learning of Sentence Embeddings. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, 6894–6910. Online and Punta Cana, Dominican Republic: Association for Computational Linguistics.

- Grosz, B. J.; Joshi, A. K.; and Weinstein, S. 1995. Centering: A framework for modelling the local coherence of discourse.
- Guan, J.; Huang, F.; Zhao, Z.; Zhu, X.; and Huang, M. 2020. A knowledge-enhanced pretraining model for commonsense story generation. *Transactions of the Association for Computational Linguistics*, 8: 93–108.
- Guan, J.; Mao, X.; Fan, C.; Liu, Z.; Ding, W.; and Huang, M. 2021. Long Text Generation by Modeling Sentence-Level and Discourse-Level Coherence. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, 6379–6393. Online: Association for Computational Linguistics.
- Guo, M.; Yang, Y.; Stevens, K.; Cer, D.; Ge, H.; Sung, Y.-h.; Strope, B.; and Kurzweil, R. 2019. Hierarchical Document Encoder for Parallel Corpus Mining. In *Proceedings of the Fourth Conference on Machine Translation (Volume 1: Research Papers)*, 64–72. Florence, Italy: Association for Computational Linguistics.
- Hadsell, R.; Chopra, S.; and LeCun, Y. 2006. Dimensionality reduction by learning an invariant mapping. In 2006 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'06), volume 2, 1735–1742. IEEE.
- Henaff, M.; Weston, J.; Szlam, A.; Bordes, A.; and LeCun, Y. 2017. Tracking the World State with Recurrent Entity Networks. In *ICLR (Poster)*.
- Hermann, K. M.; Kocisky, T.; Grefenstette, E.; Espeholt, L.; Kay, W.; Suleyman, M.; and Blunsom, P. 2015. Teaching machines to read and comprehend. *Advances in neural information processing systems*, 28.
- Holtzman, A.; Buys, J.; Du, L.; Forbes, M.; and Choi, Y. 2020. The Curious Case of Neural Text Degeneration. In *International Conference on Learning Representations*.
- Hu, Z.; Chan, H. P.; Liu, J.; Xiao, X.; Wu, H.; and Huang, L. 2022. PLANET: Dynamic Content Planning in Autoregressive Transformers for Long-form Text Generation. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, 2288–2305. Dublin, Ireland: Association for Computational Linguistics.
- Ji, H.; and Huang, M. 2021. DiscoDVT: Generating Long Text with Discourse-Aware Discrete Variational Transformer. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, 4208–4224.
- Ji, Y.; Tan, C.; Martschat, S.; Choi, Y.; and Smith, N. A. 2017. Dynamic Entity Representations in Neural Language Models. In *Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing*, 1830–1839.
- Kang, D.; and Hovy, E. 2020. Plan ahead: Self-Supervised Text Planning for Paragraph Completion Task. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, 6533–6543. Online: Association for Computational Linguistics.
- Lewis, M.; Liu, Y.; Goyal, N.; Ghazvininejad, M.; Mohamed, A.; Levy, O.; Stoyanov, V.; and Zettlemoyer, L.

- 2020. BART: Denoising Sequence-to-Sequence Pre-training for Natural Language Generation, Translation, and Comprehension. In Jurafsky, D.; Chai, J.; Schluter, N.; and Tetreault, J. R., eds., *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, ACL 2020, Online, July 5-10, 2020*, 7871–7880. Association for Computational Linguistics.
- Li, J.; Galley, M.; Brockett, C.; Gao, J.; and Dolan, B. 2016. A Diversity-Promoting Objective Function for Neural Conversation Models. In Knight, K.; Nenkova, A.; and Rambow, O., eds., NAACL HLT 2016, The 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, San Diego California, USA, June 12-17, 2016, 110–119. The Association for Computational Linguistics.
- Li, J.; Luong, M.-T.; and Jurafsky, D. 2015. A Hierarchical Neural Autoencoder for Paragraphs and Documents. In Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing (Volume 1: Long Papers), 1106–1115.
- Loper, E.; and Bird, S. 2002. Nltk: The natural language toolkit. *arXiv preprint cs/0205028*.
- Miculicich, L.; Ram, D.; Pappas, N.; and Henderson, J. 2018. Document-Level Neural Machine Translation with Hierarchical Attention Networks. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, 2947–2954. Brussels, Belgium: Association for Computational Linguistics.
- Nawrot, P.; Tworkowski, S.; Tyrolski, M.; Kaiser, Ł.; Wu, Y.; Szegedy, C.; and Michalewski, H. 2021. Hierarchical Transformers Are More Efficient Language Models. *arXiv* preprint arXiv:2110.13711.
- Oord, A. v. d.; Li, Y.; and Vinyals, O. 2018. Representation learning with contrastive predictive coding. *arXiv preprint arXiv:1807.03748*.
- Papalampidi, P.; Cao, K.; and Kocisky, T. 2022. Towards Coherent and Consistent Use of Entities in Narrative Generation. *arXiv preprint arXiv:2202.01709*.
- Papineni, K.; Roukos, S.; Ward, T.; and Zhu, W.-J. 2002. BLEU: a method for automatic evaluation of machine translation. In *Proceedings of the 40th annual meeting of the Association for Computational Linguistics*, 311–318.
- Pillutla, K.; Swayamdipta, S.; Zellers, R.; Thickstun, J.; Welleck, S.; Choi, Y.; and Harchaoui, Z. 2021. MAUVE: Measuring the Gap Between Neural Text and Human Text using Divergence Frontiers. In Ranzato, M.; Beygelzimer, A.; Dauphin, Y.; Liang, P.; and Vaughan, J. W., eds., Advances in Neural Information Processing Systems, volume 34, 4816–4828. Curran Associates, Inc.
- Rashkin, H.; Celikyilmaz, A.; Choi, Y.; and Gao, J. 2020. PlotMachines: Outline-Conditioned Generation with Dynamic Plot State Tracking. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, 4274–4295.
- Ribeiro, M. T.; Wu, T.; Guestrin, C.; and Singh, S. 2020. Beyond Accuracy: Behavioral Testing of NLP Models with

- CheckList. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, 4902–4912. Online: Association for Computational Linguistics.
- Su, Y.; Lan, T.; Wang, Y.; Yogatama, D.; Kong, L.; and Collier, N. 2022. A Contrastive Framework for Neural Text Generation. *arXiv preprint arXiv:2202.06417*.
- Tan, B.; Yang, Z.; Al-Shedivat, M.; Xing, E.; and Hu, Z. 2021. Progressive Generation of Long Text with Pretrained Language Models. In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, 4313–4324.
- Van Den Oord, A.; Vinyals, O.; et al. 2017. Neural discrete representation learning. *Advances in neural information processing systems*, 30.
- Vaswani, A.; Shazeer, N.; Parmar, N.; Uszkoreit, J.; Jones, L.; Gomez, A. N.; Kaiser, Ł.; and Polosukhin, I. 2017. Attention is all you need. In *Advances in neural information processing systems*, 5998–6008.
- Welleck, S.; Kulikov, I.; Roller, S.; Dinan, E.; Cho, K.; and Weston, J. 2020. Neural Text Generation With Unlikelihood Training. In *International Conference on Learning Representations*.
- Xu, P.; Patwary, M.; Shoeybi, M.; Puri, R.; Fung, P.; Anandkumar, A.; and Catanzaro, B. 2020. MEGATRON-CNTRL: Controllable Story Generation with External Knowledge Using Large-Scale Language Models. In Webber, B.; Cohn, T.; He, Y.; and Liu, Y., eds., *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing, EMNLP 2020, Online, November 16-20, 2020*, 2831–2845. Association for Computational Linguistics.
- Yan, Y.; Li, R.; Wang, S.; Zhang, F.; Wu, W.; and Xu, W. 2021. ConSERT: A Contrastive Framework for Self-Supervised Sentence Representation Transfer. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, 5065–5075. Online: Association for Computational Linguistics.
- Yang, Z.; Yang, D.; Dyer, C.; He, X.; Smola, A.; and Hovy, E. 2016. Hierarchical Attention Networks for Document Classification. In *Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, 1480–1489. San Diego, California: Association for Computational Linguistics.
- Yao, L.; Peng, N.; Weischedel, R.; Knight, K.; Zhao, D.; and Yan, R. 2019. Plan-and-write: Towards better automatic storytelling. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 33, 7378–7385.
- Zhang, X.; Wei, F.; and Zhou, M. 2019. HIBERT: Document Level Pre-training of Hierarchical Bidirectional Transformers for Document Summarization. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, 5059–5069.

A Experiment Settings

A.1 Data Processing

We conduct experiments on two existing public narrative datasets Wikiplots and CNN News, which are widely used for text generation. We notice that these datasets contain a few offensive plots, but we have not observed any personal information. We do not process these contents. We admit that there may still be unpredictable bias in these datasets. Many sentences in the Wikiplots stories contain multiple clauses, making it hard to derive meaningful event representations. Therefore, we use the dataset released by Ji and Huang (2021), who split each sentence into sequential elementary discourse units (EDUs, either a complete sentence or a parsed sub-sentence) for experiments on Wikiplots.

On the other hand, we do not regard demonstrative pronouns (e.g., "I," "her," "their") as entity mentions because we find that document-level coreference resolution is still difficult even for large pretraining models, and it will impair the model performance severely to learn entity state tracking using noisy entity labels. We believe that it will further boost the performance of ERIC using more accurate coreference resolution models, which we leave for future work.

A.2 Implementation

We implement ERIC using the same configuration as BART_{Base} provided by HuggingFace's Transformers⁵. The vocabulary consists of 50,625 tokens. We regard $\langle mask \rangle$ in the original vocabulary as the sentence tokn $\langle s \rangle$. It costs about 15 hours for training ERIC on Wikiplots or CNN News. The results are based on one NVIDIA Tesla V100 (32GB memory) with a random single run.

A.3 Baselines

Our work is closely related to Ji et al. (2017); Clark, Ji, and Smith (2018). We do not compare against them because: (1) They are RNN-based models, which have significantly worse performance than current pretraining models. The comparison is unfair and meaningless. (2) They update the state of an entity conditioned on previous hidden outputs when encountering its mention, which does not apply to the parallel architecture of Transformer for training. Therefore, it is not easy to implement their algorithms based on Transformer-based pretraining models, which also motivates us to propose our model.

On the other hand, we do not use Rashkin et al. (2020) or Papalampidi, Cao, and Kocisky (2022) as baselines since they require text segments or entity names of ground-truth outputs as input to initialize the state representations. In contrast, ERIC does not depend on specific inputs and is able to dynamically expand entities and perform state updates of these entities more frequently during the decoding process.

B Results on Validation Set

Besides the performance on the test set reported in the main paper, we also provide the performance on the validation in Table 5 for ERIC and several strong baselines.

Models	B-1	B-2	MAUVE	D-3	D-4
	D	ataset: W	ikiplots		
BART	28.16	11.55	74.81	70.39	90.48
HINT	29.63	12.14	78.83	71.72	91.24
DISCODVT	28.50	11.68	80.31	73.34	91.94
ERIC	32.32	13.13	82.45	75.58	92.96
	Da	ataset: Cl	NN News		
BART	31.65	14.53	86.95	77.31	92.75
HINT	33.18	15.23	86.17	77.88	93.01
DISCODVT	32.97	15.08	87.84	77.71	92.85
ERIC	34.75	15.78	92.96	78.02	93.21

Table 5: Automatic evaluation results for different models on the validation sets of Wikiplots and CNN News. We highlight the best performance in **bold**.

Data	aset: Wikiplots	Dataset: CNN News		
States Percentages (%)		States	Percentages (%)	
377	3.83	0	1.78	
425	1.66	3	1.37	
288	1.52	305	1.37	
141	1.44	1	1.36	
68	1.32	151	1.35	
147	1.25	403	1.34	
89	1.12	236	1.27	
73	1.10	478	1.20	
3	1.02	46	1.18	
429	1.01	325	1.14	

Table 6: Top ten most frequently used states and corresponding percentages in the training sets.

C Entity State Analysis

C.1 Entity Mention Control

Before generating each sentence, ERIC first predicts the following mentioned entity, i.e., \hat{p}_n . We find that 96.6% and 96.0% of generated sentences on Wikiplots and CNN News, respectively, that mention the predicted \hat{p}_n or do not mention any entities when \hat{p}_n is $\langle none \rangle$. The statistics show that ERIC can control which entity to mention in the following sentence with almost perfect accuracy.

C.2 Entity State Space Utilization

We pre-define 512 states in the discrete entity state space \mathcal{D} . Their corresponding state vectors are randomly initialized and optimized jointly with the continuous entity-aware event representations through the contrastive framework. Finally, Eric used 501/512 states from \mathcal{D} on the training sets of Wikiplots/CNN News, respectively, showing that the contrastive framework can effectively utilize the capacity of the latent space without any extra entropy penalization (Ji and Huang 2021).

Furthermore, Table 6 shows the top ten most frequently used states and corresponding percentages. Even the most

⁵https://github.com/huggingface/transformers

Text	Example Sentences
The 20th century's industrialization leaves the world overcrowded, polluted and suffering global warming due to "the greenhouse effect". In 2022, with 40 million people in New York City, housing is dilapidated; homeless people fill the streets; many are unemployed, the few "lucky" ones with jobs are only barely scraping by, and	State 68: they meet the powerful Governor, $\langle e0 \rangle_{68}$ ($\langle e1 \rangle$), his daughter $\langle e2 \rangle$, his two grandsons: $\langle e3 \rangle$ and $\langle e4 \rangle$
food and working technology is scarce. Most of the population survives on rations produced by $\langle e0 \rangle$, whose newest product is $\langle e1 \rangle$, a green wafer advertised to contain "high-energy plankton" from the World Ocean, more nutritious and palatable than its predecessors "Red" and "Yellow", but in short supply. New York City Police Department detective $\langle e2 \rangle_{68} \rightarrow \langle e0 \rangle_{318}$ lives with aged friend and "book" (a police analyst) Solomon	State 318: He is admitted to $\langle e0 \rangle_{318},$ mainly because of his genetic mosaicism
"Sol" Roth.	

Table 7: A case for the entity coherence modeling experiment on the test set of Wikiplots, where ERIC can recognize the incoherence issue while other models fail. **Left:** The input (in *italic*), the unchanged prefix and the perturbed sentence (in **bold**). $A \rightarrow B$ means that the original entity A is replaced to B with the subscripts indicating their states predicted by ERIC. **Right:** An example sentence for each state selected from the top ten sentences with closest event representations to the corresponding state vector in the training set of Wikiplots.

State Transitions	The First Sentences	The Second Sentences
State 462→State 301	However, in the process, she discovers her husband $\langle e3 \rangle_{462}$ is already having another affair with a woman named $\langle e4 \rangle$ and is now knowingly starting a second affair with "Anonymous".	After breaking down over this fact, she goes to visit Archie in the sexy outfit she planned to woo $\langle e3\rangle_{301}$ back with,
	$\langle e3 \rangle_{462}$ realize that once $\langle e0 \rangle$ gets married it will be just the three of them.	At night, $\langle e3 \rangle_{301}$ admits that she is also leaving the group.
State 60→State 116	She tries to let go of her tomboyish ways to take over $\langle e1\rangle_{60}$'s glamorous lifestyle.	Although she is now dealing with $\langle e1 \rangle_{116}$'s job, friends
	$\langle e2 \rangle$ spends all her time seeing that $\langle e0 \rangle_{60}$ has everything he needs.	$\langle e0 angle_{116}$ is embarrassed to be seen with his wife

Table 8: Several examples from the test set of Wikiplots, where an entity (in **bold**) transits from a certain state (in the first sentence) to another (in the second sentence). The states are decided by looking up the closest state vectors to the corresponding entity-aware event representations.

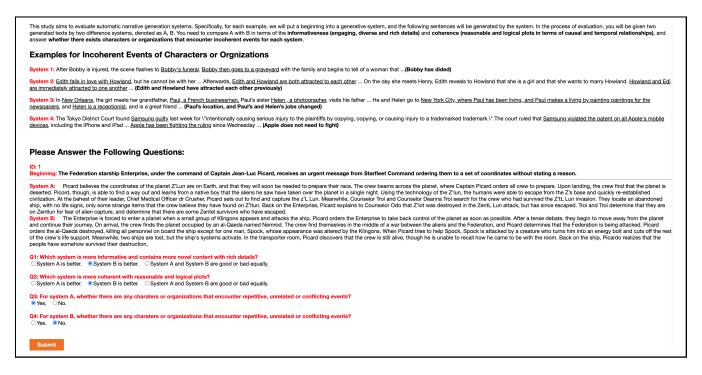


Figure 4: A screenshot of the annotation on AMT for manual evaluation.

frequent state comprises less than 4% of the whole state

space on both datasets, further indicating that ERIC makes

Input	The Federation starship Enterprise, under the command of Captain Jean-Luc Picard, receives an urgent message from Starfleet Command ordering them to a set of coordinates without stating a reason.
Truth	While en route, they are contacted by Admiral Gromek who informs them that the Enterprise is to rendezvous with a Federation emissary who will brief them on their mission. She refuses to disclose any details, only that Starfleet considers the mission a "top security matter". Data reports that the emissary is being transported in a class 8 probe, an unconventional mode of travel and barely large enough to contain a person, traveling at warp 9. Picard notes the evident urgency of the mission. The Enterprise intercepts the probe and beams it aboard, and its passenger is revealed to be a half-Klingon half-human woman named K'Ehleyr. It is immediately clear that K'Ehleyr and lt Worf know each other, and Worf is not pleased to see her. K'Ehleyr informs the command staff that Starfleet has detected a Klingon battlecruiser called the T'Ong, which was launched from the Klingon homeworld over 75 years ago, when the Klingons and the Federation were still at war. The crew has been in suspended animation and are about to awaken, at which point it is feared they will immediately attack the nearest Federation outpost, several of which are nearby and would not be able to adequately defend themselves. As the nearest Klingon ship is three days away, the Enterprise is to intercept them instead. Though K'Ehleyr strongly believes that any attempt to reason with the Klingons will fail,
BART	The Enterprise, after the Enterprise crew leaves, has their first mission briefing to prepare for, however, the crew finds a small force field and a shuttlepod, and are forced to abandon it. Later, their commanding officer, Chief Medical Officer dr McCoy, determines that they are suffering from an unspecified terminal disease and orders the ship repaired. The remaining two remaining survivors, dr McCoy and Lieutenant Commander Riker, are sent out to collect their medication, while Chief Medical Advisor dr McCoy has a discussion with Counselor Troi and It Uhura over the issue. Captain Picard, Counselor Spock and Imdr McCoy respond to the Enterprise distress call. Picard orders the team to leave and orders a holodeck. They are then ordered to search for their missing shuttlepod and recover their own. A medical officer, dr Leela, takes over command of the station and explains to CounselorTroi that the Enterprise is on a mission to retrieve the shuttlepod. Before the crew can begin, the shuttle pod is struck by a force field, forcing them to abandon the shuttle before they can reach a communications bridge. It Uhura orders them to go to the bridge.
HINT	Picard believes the coordinates of the planet Z'Lun are on Earth, and that they will soon be needed to prepare their race. The crew beams across the planet, where Captain Picard orders all crew to prepare. Upon landing, the crew find that the planet is deserted. Picord, though, is able to find a way out and learns from a native boy that the aliens he saw have taken over the planet in a single night. Using the technology of the Z'lun, the humans were able to escape from the Z's base and quickly re-established civilization. At the behest of their leader, Chief Medical Officer dr Crusher, Picard sets out to find and capture the z'L Lun. Meanwhile, Counselor Troi and Counselor Deanna Troi search for the crew who had survived the Z'tL Lun invasion. They locate an abandoned ship, with no life signs, only some strange items that the crew believe they have found on Z'ltun. Back on the Enterprise, Picard explains to Counselor Odo that Z'lot was destroyed in the ZentL Lun attack, but has since escaped. Troi and Troi determine that they are on Zentlun for fear of alien capture, and determine that there are some Zentel survivors who have escaped.
DISCODVT	En route, they meet a race of Vulcans known as "the Five", who have been living on an uninhabited planet, where they have made contact with humans. Picard informs them that the humans have been in contact with a race known as the Five, and that they have been searching for a way to return to Earth. Captain Kirk and Commander Data transport aboard the Enterprise to investigate the Vulcan ship. They find a Starfleet vessel, and a woman, Leda, sitting aboard with the ship." Data notes that Leda's appearance is frightening to Kirk and the others, and insists that her name is "Barbara" while she is speaking in the Vulcan tongue. He suggests that she is actually a human, and asks that Picard beam her down to the surface to change her appearance, but Leda insists that the two will stay with the Enterprise. The Vulcens find the man, who is then forced to be taken into custody, along with his security detail, while the Five are transported to Sickbay, where Counselor Troi meets with another member of the Five. Meanwhile, on the Enterprise, a mysterious figure called "The Black Cat" arrives and attempts to take over the Enterprise's communications systems, but they are all too well before the Black Cat is brought down.
ERIC	The Enterprise is forced to enter a planet when a small group of Klingons appears and attacks the ship. Picard orders the Enterprise to take back control of the planet as soon as possible. After a tense debate, they begin to move away from the planet and continue their journey. On arrival, the crew finds the planet occupied by an al-Qaeda named Nemrod. The crew find themselves in the middle of a war between the aliens and the Federation, and Picard determines that the Federation is being attacked. Picard orders the al-Qaeda destroyed, killing all personnel on board the ship except for one man, Spock, whose appearance was altered by the Klingons. When Picard tries to help Spock, Spock is attacked by a creature who turns him into an energy bolt and cuts off the rest of the crew's life support. Meanwhile, two ships are lost, but the ship's systems activate. In the transporter room, Picard discovers that the crew is still alive, though he is unable to recall how he came to be with the room. Back on the ship, Picardo realizes that the people have somehow survived their destruction,

Table 9: Generated cases on Wikiplots. **Bold** words indicate improper entities or events in terms of coherence. We <u>underline</u> the mentioned entities in the case generated by ERIC, which corresponds to the placeholder tokens in Figure 2.

the best of the capacity of \mathcal{D} .

C.3 Entity Coherence Modeling

Table 7 shows a case to investigate how tracking entity states helps capture the entity coherence. In the perturbed sentence, the original entity $\langle e2 \rangle$ is predicted to be in *state 68*, which corresponds to getting together with somebody (e.g., "lived with", "meet"). When replacing $\langle e2 \rangle$ to $\langle e0 \rangle$, ERIC predicts that $\langle e0 \rangle$ is in the *state 318* based on the prefix. *state 318* means that $\langle e0 \rangle$ is more likely to be an organi-

zation instead of a detective that can live with others, which disagrees with the perturbed sentences. Therefore, we conclude that modeling entity states can effectively helps ERIC capture the high-level coherence between events attached to these entities.

Furthermore, Table 8 shows several examples for two state transition pairs with the highest transition confidence, which is calculated as the product of the cosine distances between the two state vectors to their respective event representations. For $State\ 462 \rightarrow State\ 301$, both examples relate

to "the entity's marriage is in trouble and then leaves." As for *State 60* \rightarrow *State 116*, both examples relate to "the entity develops a relationship with another and something trivial happens to them." These examples suggest that ERIC can capture some patterns of entity state transitions, which helps model inter-event dependencies and high-level coherence.

D Manual Annotation Instruction

Figure 4 shows a screenshot of the annotation on AMT. We paid \$0.4 for annotating an example on average. We did not limit the nationalities of annotators, and did not ask about any personal privacy or collect personal information of annotators in the annotation processes.

E Case Study

Table 9 presents several cases generated by ERIC and strong baselines on Wikiplots. The baselines fail to maintain long-range coherence with unreasonable entity state transitions. For example, in the case generated by BART, at first "McCoy" is the "Chief Medical Officer," but then becomes a "survivor" to "collect medication," and meanwhile begins a "discussion" with the "Counselor." The case generated by HINT also frequently repeats the same entity such as "Counselor Troi and Counselor Deanna Troi" and "Troi and Troi". By contrast, the text generated by ERIC has a globally coherent plot, indicating the benefit of tracking entity states and modeling the dependencies between events and entity states explicitly.