Narrative Incoherence Detection

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Abstract

Motivated by the increasing popularity of intelligent editing assistant, we introduce and investigate the task of narrative incoherence detection: Given a (corrupted) long-form narrative, decide whether there exists some semantic discrepancy in the narrative flow. Specifically, we focus on the missing sentence and incoherent sentence detection. Despite its simple setup, this task is challenging as the model needs to understand and analyze a multi-sentence narrative text, and make decisions at the sentence level. As an initial step towards this task, we implement several baselines either directly analyzing the raw text (token-level) or analyzing learned sentence representations (sentence-level). We observe that while token-level modeling enjoys greater expressive power and hence better performance, sentence-level modeling possesses an advantage in efficiency and flexibility. With pre-training on large-scale data and cycle-consistent sentence embedding, our extended sentence-level model can achieve comparable detection accuracy to the token-level model. As a by-product, such a strategy enables simultaneous incoherence detection and infilling/modification suggestions.

1 Introduction

Long-form text understanding, reasoning, and generation are of great interest yet remain key challenges in natural language processing. Recent years have witnessed significant advances in natural language understanding and generation thanks to large-scale pre-trained language models, such as BERT (Devlin et al., 2019), GPT-2 (Radford et al., 2019), and GPT-3 (Brown et al., 2020). These models can produce individual sentences that are grammatical and fluent (Donahue et al., 2020). However, they are not designed to capture the long-term semantic flow among sentences and may have difficulty in processing or producing a coherent long-form narrative. For example, the output text often gets stuck in repetitions (Holtzman et al., 2020).

The aforementioned problem can be partially attributed to the lack of specific machinery to extract and characterize the inter-sentential semantic flow in long-form text (Ippolito et al., 2020; Kang and Hovy, 2020). Despite its importance, learning inter-sentential coherence remains an open challenge, as it requires (i) understanding, extracting, and representing the high-level semantic flow for a given text; (ii) at the discourse level, addressing logicalness, commonsense, and planning. In addition, evaluating the discourse-level understanding capability of a given model is also an open problem. Previous work has tackled specific aspects of this challenge such as causal reasoning for event series

Figure 1: Illustration of our Narrative Incoherence Detection (NID) tasks. Note that a narrative contains more sentences in real cases.
(Kang et al., 2017), abductive reasoning (Bhagavatula et al., 2020), sentence ordering (Barzilay and Lapata, 2008), narrative cloze test (Chambers and Jurafsky, 2008; Mostafazadeh et al., 2016), reading comprehension (Wang et al., 2019), and generation tasks: story generation (Fan et al., 2019), text infilling (Hua and Wang, 2019; Huang et al., 2020; Kang and Hovy, 2019), and counterfactual plot rewriting (Qin et al., 2019).

In this paper, we propose a new task called **Narrative Incoherence Detection** as a testbed for benchmarking a model’s ability to capture the discourse-level semantic flow of narratives. Specifically, as illustrated in Figure 1, we consider a multi-sentence passage. A certain amount of semantic discrepancies are introduced by removing or replacing a proportion of sentences. The task is to identify the positions of the missing/discordant sentences that introduce the semantic discrepancies if there are any. Compared with existing tasks, our task has the following merits: *(i)* it is conceptually simple; the required dataset can be created without human annotation or prior domain knowledge; *(ii)* it can be used to evaluate a broad range of phenomena in inter-sentential semantic understanding (e.g., logicalness, commonsense, causal reasoning, and temporal reasoning) as they are required for tackling different cases; *(iii)* the evaluation is straightforward; the results on our task can be easily and objectively assessed and thus fairly compared. Furthermore, the proposed task has independent merits in practice. Models developed for the task can be used to increase the functionality of intelligent writing assistants. For example, they can be used for document proofreading by *(i)* detecting missing sentences needed to bridge discontinuous context, and *(ii)* detecting problematic sentences that compromise the coherence of a narrative, especially when a document is written by multiple authors.

We also implement and investigate two baseline approaches as a first step towards solving the task. These include two popular modeling paradigms in the current literature: **token-level** and **sentence-level** approaches. The token-level approach directly operates on input tokens to find incoherent spots. It fine-tunes BERT (Devlin et al., 2019) with necessary modifications to the input format to accommodate our task. The input is an orderly concatenation of words in a (corrupted) narrative. In contrast, the sentence-level approach treats a multi-sentence narrative as a sequence of pre-trained sentence embeddings and processes them in a Transformer (Vaswani et al., 2017) with sentences as atomic units. The sentence-level approach is computationally more efficient than processing word embeddings, especially when the input narrative is long. To take advantage of the efficiency, we perform large-scale pre-training for the sentence-level model on massive data and observe significant performance improvement. Furthermore, the sentence-level approach opens up the possibility of joint incoherence detection and sentence infilling/modification suggestions with little extra architectural design and incremental computational overhead. Our experiments show that a joint model performs adequately well in both tasks.

The contributions of this paper are summarized as follows.\(^1\)

1. **We introduce the novel task of narrative incoherence detection, which can serve as a benchmark task for long-form text understanding and can facilitate applications such as intelligent writing assistance.**

2. **We establish two baseline approaches (token-level and sentence-level) and compare them in extensive experiments. The sentence-level approach is efficient which enables large-scale pretraining.**

3. **Our extended sentence-level approach can efficiently tackle the task of simultaneous incoherence detection and sentence infilling/modification.**

2 Related Work

**Inter-sentential Reasoning and Understanding**

Reasoning and understanding inter-sentential relationships have been studied in different forms, including classic discourse parsing tasks using human-annotated datasets such as the RST Discourse Treebank (RST-DT) (Carlson et al., 2001) and the Penn Discourse Treebank (PDTB) (Prasad et al., 2008). Narrative cloze tasks (Chambers and Jurafsky, 2008; Mostafazadeh et al., 2016) aim to find the right concluding sentence for an incomplete narrative. Chen et al. (2019) propose a suite of tasks including sentence position, binary sentence ordering, discourse coherence classification, and sentence section prediction. Bhagavatula et al.\(^2\) The source code, baseline models, and datasets will be released to facilitate future research.
(2020) formulate abductive commonsense reasoning in order to decide the most plausible hypothesis that could explain the transition between two observations. Our task makes a unique contribution to this area. Importantly, it enjoys the simplicity of data creation (free of annotation) yet potentially tests various long-range reasoning abilities.

Context-Aware Text Infilling and Modification

The problem of generating intermediate text in a context-aware manner has important implications for enabling intelligent writing assistants that can help humans edit or revise documents. A number of recent studies have explored this direction, but all have practical drawbacks. Most models (Fedus et al., 2018; Song et al., 2019; Liu et al., 2019; Joshi et al., 2020) can generate missing text in context, but require that the position and the length of the missing span be pre-specified. The generation of Zhu et al. (2019); Lewis et al. (2020); Shen et al. (2020b) can be of arbitrary length. However, all these previous approaches focus more on local appropriateness than inter-sentential semantic coherence. Recently, Huang et al. (2020); Wang and Wan (2019) explore the task of sentence infilling, where some intermediate sentences are removed from the narrative text, and the task is to generate the missing sentences. Some also explore context-aware text modification such as simplification (Biran et al., 2011) and style transfer (Cheng et al., 2020; Shih et al., 2019). Again, though, the input must specify the position to infill or modify. Kang and Hovy (2019) propose the bridging task to generate intermediate sentences between the first and last sentences. In summary, most previous work has focused solely on the problem of what to infill/modify and has not considered the problem of where to infill/modify. This is insufficient for practical applications, since we may not know the positions of missing spans or problematic sentences a priori (Mori et al., 2020). Our work bridges the gap between existing work on context-aware infilling/modification and real-world writing assistance.

3 Problem Statement

The task of Narrative Incoherence Detection is to take as input a multi-sentence text \( \tilde{x} \) containing one or more semantic discrepancies (a missing sentence or a discordant sentence), and return the positions of the discrepancies. Note that all sentences in the input prose are assumed to be grammatical and fluent. Formally, we lay out the mathematical notation as follows. Consider a dataset of \( T \) text paragraphs \( \{x^{(i)}_1, x^{(i)}_2, \ldots, x^{(i)}_{N_i}\} \) where each paragraph \( x^{(i)}_j \) is a contiguous sequence of \( N_i \) sentences. For brevity, we drop the index \( i \) in the following.

We consider two scenarios: missing sentence detection (MSD) and discordant sentence detection (DSD) as two subtasks of Narrative Incoherence Detection. These two scenarios cover the “insertion” and “replacement” needs for text editing.

Missing Sentence Detection (MSD) We first consider the case where some semantic gaps are caused by missing bridging sentences. For each paragraph \( x \), only a subsequence of sentences \( \tilde{x} = (\tilde{x}_1, \tilde{x}_2, \ldots, \tilde{x}_M) = (x_{n_1}, x_{n_2}, \ldots, x_{n_M}) \) is given where \( 1 = n_1 < n_2 < \ldots < n_M = N \) is a strictly increasing sequence of indices and \( M < N \). In other words, \( N - M \) intermediate sentences are selected and removed, and the remaining sentences are concatenated to form \( \tilde{x} \). Taking \( \tilde{x} \) as input, the goal is to predict whether there is a missing sentence (semantic gap) between \( \tilde{x}_{n_k} \) and \( \tilde{x}_{n_k+1} \) for all \( k \in [1, M] \).

Discordant Sentence Detection (DSD) Our second scenario is Discordant Sentence Detection, where some sentences in a paragraph are discordant to the surrounding context. For each paragraph \( x \), a subset \( I \subset \{1, 2, \ldots, N\} \) of indices is chosen. For each \( k \in I \), the sentence \( x_k \) is replaced with a “confounding sentence” \( x^*_k \). Thus, the input is \( \tilde{x} = (\tilde{x}_1, \tilde{x}_2, \ldots, \tilde{x}_N) \) where \( \tilde{x}_k = x_k \) if \( k \in I \) and \( \tilde{x}_k = x^*_k \) otherwise. Since this work focuses on inter-sentential semantic discrepancy rather than lexical or grammatical issues, the confounding sentence is grammatical and fluent, however semantically discordant in context (see more details in §5). The goal is to predict whether \( \tilde{x}_k \) is a replacement for all \( k \in [1, N, I] \).

Note that the paragraph \( x \) can be rather long, since each sentence \( x_k \) is itself a sequence of tokens \( x_k = (x_{k,1}, x_{k,2}, \ldots, x_{k,t_k}) \). After identifying the missing/discordant sentence positions, a natural and desirable next step would be to suggest appropriate sentences to fill such positions (Huang et al., 2020). While this paper focuses on the detection task, we also introduce an efficient method to tackle detection and appropriate sentence suggestions simultaneously (§4.2).
4 Baseline Methods

We consider two modeling paradigms as baseline approaches to tackle the Narrative Incoherence Detection task. First, we develop a token-level approach where the input text is directly processed as a sequence of individual tokens. Second, we explore several strategies of sentence-level approaches: The input text is first mapped to a sequence of sentence representations, and then a sentence-level model operates on the sentence representations for incoherence detection.

4.1 Token-Level Approach

The token-level model takes the sequence of tokens \( \tilde{x} \) as input. Suppose that the input text \( \tilde{x} \) has \( M \) sentences in total and the length of the \( k \)-th sentence is \( L_k \). The total number of tokens is \( \sum_{k=1}^{M} L_k \). We train our model by fine-tuning the pre-trained BERT. Figure 2 illustrates our proposed BERT architecture for Narrative Incoherence Detection.

Narrative Incoherence Detection can be formulated as the task of assigning a label \( \hat{y}_k \in \{0, 1\} \) to each slot (or sentence), indicating whether a missing sentence should be included in the slot (or whether an existing sentence is discordant with the context). However, BERT is pre-trained as a masked language model, and the output vectors are grounded to tokens rather than sentences. In order to represent the slots between sentences for MSD (or individual sentences for DSD), we insert \( M - 1 \) indicator symbols ([SEP]) between adjacent sentences. The resulting input sequence becomes \((\tilde{x}_{1,1}, \tilde{x}_{1,2}, \ldots, \tilde{x}_{1,L_1}, \text{[SEP]}, \ldots, \text{[SEP]}, \tilde{x}_{M,1}, \tilde{x}_{M,2}, \ldots, \tilde{x}_{M,L_M})\) of length \( \sum_{k=1}^{M} L_k + M - 1 \). In addition, BERT adds one [CLS] and one [SEP] to the beginning and end of the input sequence, respectively.

As shown in Figure 2(a), the input token sequence (with the special symbols [SEP]) is fed into the transformer layers in BERT to produce the contextualized vector representations for each token. The resultant vector \( s_k \) corresponding to the \( k \)-th [SEP] symbol is used as the representation of the slot between \( \tilde{x}_k \) and \( \tilde{x}_{k+1} \) for MSD, or the sentence representation of \( \tilde{x}_k \) for DSD.

The vectors \( \{s_k\}_{k=1}^{M} \) are then passed through a MLP layer (\( \text{MLP}_d \)) and a sigmoid layer to generate the normalized scores to predict the binary labels \( \hat{y} = \{y_1, \ldots, y_M\} \):

\[
y_k = \sigma(\text{MLP}_d(s_k)).
\]

The training loss is the binary classification entropy between the hypothesis \( \hat{y} \) and the ground truth, which is obtained when the data is created.

Note that for all predictions, the model has access to bi-directional context (i.e., all input sentences). Each prediction, however, is conditionally independent from the others.

4.2 Sentence-Level Approach

Despite its simplicity, the token-level approach is not efficient, as computation and memory scale
quadratically with the number of tokens in a vanilla transformer, rendering such an approach especially costly when processing long-form text. As an alternative, we also develop sentence-level models, which treat the input as a sequence of sentence embeddings. Incoherence detection then operates at the sentence level by considering each sentence as an atomic unit. This is more efficient than the token-level approach, as the sequence length becomes the number of sentences $M$.

**Model Architecture** Specifically, we take advantage of pre-computed sentence representations from existing representation learning models. In our experiments, we use the $[CLS]$ embedding of the last layer of a pre-trained bidirectional language model, BERT (Devlin et al., 2019). The architecture of our model is shown in Figure 2(b). The sentences in the input paragraph $(\tilde{x}_1, \tilde{x}_2, \ldots, \tilde{x}_M)$ are first transformed into vector representations $(h_1, h_2, \ldots, h_M)$ independently. Then, we use a sentence-level Transformer to exploit the associations among sentence embeddings.

In a similar manner to the token-level approach (Eq. 1), the final output vector $s_k$ corresponding to the $k$-th sentence is fed into a binary classifier in order to predict whether there is missing text between $\tilde{x}_k$ and $\tilde{x}_{k+1}$ in MSD, or whether $\tilde{x}_k$ is a discordant sentence in DSD.

Sentence-level models have three unique features compared with the token-level approach. (i) Sentence-level models concentrate on inter-sentence coherence and long-term semantic flow rather than word-level fluency and co-occurrence; (ii) Our sentence-level model takes as input fixed sentence embeddings, which can be pre-computed, saved, and reused; (iii) Sentence-level modeling decouples sentence representation learning and discourse-level understanding, and thus the two components can be separately optimized with additional training. The aforementioned features of sentence-level modeling allow three extensions as detailed below: *Semantic Matching as an Auxiliary Task, Generation as a Side Task, and Pre-training at Scale.*

**Semantic Matching as an Auxiliary Task** A follow-up task to the Narrative Incoherence Detection task is sentence infilling/modification (Huang et al., 2020), where the model generates an intermediate sentence from bi-directional context (or the current sentence, for DSD) given the position of the missing/discordant sentence. The generation task and our detection tasks are highly relevant and partially entail each other. For example, predicting whether a position requires an additional bridging sentence might requiring knowing, to some extent, what information is missing and what needs to be interpolated to complete the semantic flow. To take advantage of the information shared between these two tasks, we formulate the task of *sentence infilling/modification* as an auxiliary semantic matching objective in our sentence-level framework with minimal architectural changes.

Specifically, semantic matching can be performed by applying an additional MLP layer ($\text{MLP}_{sm}$) to the slot/sentence representation $s_k$:

$$\hat{h}_k = \text{MLP}_{sm}(s_k).$$  \hspace{1cm} (2)

The auxiliary training objective is defined as the cosine distance between the prediction $\hat{h}_k$ and the embedding of the ground truth sentence. Note that the semantic matching module receives the same hidden representations $s_k$ from the sentence-level transformer and runs in parallel with the detection classifier. The additional computational overhead of the semantic matching objective is negligible.

**Generation as a Side Task** The above observation further motivates us to explore the possibility of joint Narrative Incoherence Detection and Text Infilling/Modification. Our idea is to build a decoder that can faithfully reconstruct the original text given its corresponding sentence embedding. Consequently, the output of semantic matching (i.e., the predicted sentence embedding $\hat{h}_k$) can be passed to this decoder for generation.

Specifically, we initialize the decoder with a generative language model, GPT-2 (Radford et al., 2019). The sentence embedding from BERT is fed to GPT-2 as the embedding of the zeroth token. Then, we have the decoder generate a sequence of tokens in the hope that the sequence reconstructs the original sentence (padded with special tokens $[\text{BOS}]$ at the beginning and $[\text{EOS}]$ at the end). We fine-tune the parameters of GPT-2 to minimize the negative log-likelihood loss of reconstructing the original sentence. Note that the decoder is separately trained, and thus has no impact on the detection tasks. During training of the sentence-level transformer, we simply perform auxiliary se-
mantic matching in the latent space as previously described. The decoder is applied only at inference time to convert the predicted sentence representations $\hat{h}_k$ to text. The generation requires minimal computation as the sentence encoder and the sentence-level transformer are shared between detection and generation.

We note that the above generation approach is based on the following desirable properties of the latent sentence embedding: (i) cycle consistency (Zhu et al., 2017); the original sentence can be recovered from its latent representation. (ii) local smoothness; nearby latent vectors represent sentences with similar semantics. We suspect that the features learned by BERT may lose information required for sentence reconstruction since the masked language model objective does not enforce autoencoding. To remedy this problem, we further fine-tune the BERT encoder together with the GPT-2 decoder as an autoencoder aiming to construct a bijective mapping between natural language sentences and the latent semantic space. To improve the local smoothness of the latent space (Li et al., 2020; Shen et al., 2020a), we train the models using a denoising autoencoding (DAE) objective (Vincent et al., 2008) with a similar noising scheme as in Lewis et al. (2020) (permutation ratio 20%, mask ratio 20%, and random ratio 20%). The encoder from the fine-tuned DAE can replace the original BERT encoder for mapping sentences into latent representations.

Pre-training at Scale Sentence-level modeling requires much less computation and memory compared with token-level modeling. Specifically, suppose that a document contains $M$ sentences, each of which has $L$ tokens. The time complexity is reduced from $O(M^2L^2)$ (token-level) to $O(M^2 + ML^2)$. Moreover, sentence embeddings can be pre-computed and stored for later use. The resulting time complexity for the remaining sentence-level transformer is only $O(M^2)$. This is particularly useful in practice as we train models on the same dataset for many epochs or in various setups.

Due to the relatively cheap cost of sentence-level modeling, we pre-train our sentence-level model on large corpora such as STORIES (Trinh and Le, 2018) as detailed in the next section. Note that such a pre-training step for the token-level approach is prohibitively expensive.

### Table 1: Dataset statistics

| Dataset          | TripAdvisor | TimeTravel |
|------------------|-------------|------------|
| # Training Paragraph | 140,910     | 126,524    |
| # Dev Paragraph   | 17,613      | 7,484      |
| # Test Paragraph  | 17,613      | 7,484      |

5 Experimental Setup

**Datasets** We create benchmark datasets for our study from two public datasets: **TripAdvisor** (Wang et al., 2010) and **TimeTravel** (Qin et al., 2019). The TripAdvisor dataset is a collection of hotel reviews. We use the same preprocessing as in Huang et al. (2020), including removing duplicate reviews and discarding reviews containing non-English tokens or very long sentences (> 32 tokens). The TimeTravel dataset is an expansion of the ROC stories dataset (Mostafazadeh et al., 2016). It contains self-contained five-sentence stories focusing on commonsense and daily life. Both datasets consist of compact narratives that follow certain logic flow, and they vary in the number of sentences. Therefore, they provide ideal testbeds for evaluating the incoherence detection capability of different models over different text lengths. The corpus statistics are shown in Table 1.

**MSD datasets** For Missing Sentence Detection, we use the following strategy to create training, validation, and test instances. For the TripAdvisor dataset, for a review consisting of $N \geq 8$ sentences, we randomly sample a contiguous segment that has exactly 8 sentences. Then, we randomly remove 2 sentences out of the 8 sentences to create the altered data. Thus, the masking rate is 25%. For the TimeTravel dataset, we use all five sentences in each story and randomly remove one sentence. Thus, the masking rate of the TimeTravel dataset is 20%. It should be noted that, in all MSD instances, we do not remove the first or last sentence in the original paragraph, and the removed sentences are non-adjacent. To fully leverage the training set, training data instances are created dynamically and the same original paragraph may miss different sentences in different epochs. However, we use a fixed test set for all experiments by performing masking once during data preprocessing.

**DSD datasets** For Discordant Sentence Detection, we use the following strategy to create training, validation, and test instances. For the TripAdvisor dataset, for a review consisting of $N \geq 8$ sentences, we randomly sample a contiguous seg-
Table 2: Experimental results on Missing Sentence Detection. “+ SM” indicates joint detection and semantic matching training. “+ pre-train” indicates that the model is first pre-trained on the STORIES corpus. “P” and “R” stand for precision and recall scores, respectively.

| Model                      | TIME TRAVEL | TRIP ADVISOR |
|----------------------------|-------------|--------------|
|                            | Acc. | P    | R    | F1   | AUC | Acc. | P    | R    | F1   | AUC |
| **Token-level**            |      |      |      |      |     |      |      |      |      |     |
| 73.6                       | 61.6 | 55.2 | 58.2 | 77.3 |     | 66.5 | 60.1 | 48.4 | 53.6 | 69.9 |
| **Sentence-level**         |      |      |      |      |     |      |      |      |      |     |
| 71.2                       | 59.4 | 43.1 | 50.0 | 73.3 |     | 65.6 | 60.6 | 40.3 | 48.4 | 68.2 |
| + SM                       | 71.7 | 60.1 | 44.4 | 73.8 |     | 65.5 | 60.6 | 39.5 | 47.8 | 68.2 |
| + SM + pre-train           | 73.3 | **62.9** | 48.8 | 55.0 | 76.9 | 66.3 | 61.1 | 43.0 | 50.5 | 69.5 |
| + DAE                      | 69.3 | 55.1 | 42.9 | 48.2 | 70.4 | 64.7 | 58.5 | 40.1 | 47.6 | 66.8 |
| + DAE + SM                 | 70.1 | 57.5 | 39.2 | 46.6 | 71.0 | 65.2 | 59.7 | 40.0 | 47.9 | 67.4 |
| + DAE + SM + pre-train     | 73.2 | 62.2 | 50.3 | 55.6 | 76.5 | 66.5 | **61.2** | 44.4 | 51.5 | **70.0** |

Table 3: Experimental results on Discordant Sentence Detection. + SM indicates joint detection and semantic matching training.

| Model                      | TIME TRAVEL | TRIP ADVISOR |
|----------------------------|-------------|--------------|
|                            | Acc. | P    | R    | F1   | AUC | Acc. | P    | R    | F1   | AUC |
| **Token-level**            |      |      |      |      |     |      |      |      |      |     |
| 85.2                       | 63.2 | **62.4** | **62.8** | **87.3** |     | 75.4 | 52.3 | 18.1 | 26.8 | 68.9 |
| **Sentence-level**         |      |      |      |      |     |      |      |      |      |     |
| 83.5                       | 61.1 | 47.9 | 53.7 | 81.5 |     | 76.8 | 55.9 | **34.7** | **42.8** | 74.9 |
| + SM                       | 83.5 | 61.5 | 46.7 | 53.1 | 81.3 | 77.1 | 59.2 | 27.4 | 37.5 | 74.5 |
| + SM + pre-train           | 85.3 | 68.9 | 48.6 | 57.0 | 84.4 | **77.5** | **60.2** | 29.8 | 39.9 | 75.5 |
| + DAE                      | 82.1 | 55.8 | 49.9 | 52.7 | 80.6 | 76.6 | 55.4 | 32.0 | 40.6 | 74.1 |
| + DAE + SM                 | 82.1 | 56.1 | 49.2 | 52.4 | 80.5 | 76.8 | 56.6 | 30.7 | 39.8 | 74.1 |
| + DAE + SM + pre-train     | 84.6 | **65.0** | 50.4 | 56.7 | 83.9 | **77.5** | 59.0 | 32.9 | 42.2 | **75.8** |

Pre-training Corpus To pre-train the sentence-level transformer, we use the STORIES dataset (Trinh and Le, 2018), which is a subset of the CommonCrawl dataset. Most documents in STORIES are narratives with long chains of coherent events. We use the STORIES dataset for two purposes: (i) to fine-tune the sentence embeddings with the denoising autoencoder objective; (ii) to pre-train our sentence-level models. For the former purpose, we split the documents in STORIES into individual sentences. For the latter, we extract text segments of 16 contiguous sentences from the documents in STORIES and use a masking/replacing rate of 25%.

Evaluation Metrics We view incoherence detection as a series of binary classification problems for individual sentences or sentence boundaries. Following the common practice of reporting classification performance, we provide a set of quantitative evaluation results, including precision, recall, and F1 scores. We also draw Receiver Operating Characteristic (ROC) curves and report the Areas Under the Curves (AUC) (Fawcett, 2006).

Implementation Details Most components of our models are initialized with pre-trained BERT or GPT-2. They have the same size and configuration as the original BERT or GPT-2 from the HuggingFace Transformers library (Wolf et al., 2020) (“bert-base-cased” and “gpt2”). The only exception is the sentence-level transformer, which is learned from
Table 4: Generation evaluation. “Ent.” and “Len.” stand for Entropy and the average generation length, respectively. “REF” refers to the ground truth.

| Dataset          | Method | NIST N-2 | NIST N-4 | BLEU B-2 | BLEU B-4 | METEOR E-4 | Dist D-1 | Dist D-2 | Len. |
|------------------|--------|----------|----------|----------|----------|------------|----------|----------|------|
| **Missing Sentence Detection** |        |          |          |          |          |            |          |          |      |
| TimeTravel       | BERT   | 1.19     | 1.19     | 6.34     | 1.09     | **9.42**   | 2.94     | **12.51**| 14.92|
|                  | DAE    | **1.43** | **1.44** | **7.48** | **1.28** | 8.16       | 8.39     | 11.92    | 9.26 |
|                  | REF    | -        | -        | -        | -        | 10.44      | 11.00    | 43.12    | 9.50 |
| TripAdvisor      | BERT   | 0.96     | 0.97     | 5.65     | 0.89     | **8.41**   | 0.63     | **2.86** | 17.05|
|                  | DAE    | **1.27** | **1.29** | **7.23** | **1.24** | 7.43       | 6.85     | 0.69     | 2.82 |
|                  | REF    | -        | -        | -        | -        | 12.30      | 6.68     | 36.64    | 11.71|
| **Discordant Sentence Detection** |        |          |          |          |          |            |          |          |      |
| TimeTravel       | BERT   | 1.31     | 1.33     | 7.98     | 1.91     | 10.45      | 3.11     | 14.00    | 14.85|
|                  | DAE    | **2.59** | **2.68** | **18.48**| **6.84** | **13.66**  | 9.76     | **5.06** | **20.72**| 9.59 |
|                  | REF    | -        | -        | -        | -        | 10.45      | 12.08    | 47.45    | 8.90 |
| TripAdvisor      | BERT   | 1.44     | 1.47     | 9.49     | 2.37     | 11.05      | 10.22    | 1.12     | 5.90 |
|                  | DAE    | **2.71** | **2.83** | **19.43**| **6.92** | **13.69**  | **10.79**| **1.91** | **11.31**| 11.89|
|                  | REF    | -        | -        | -        | -        | 12.30      | 6.66     | 36.41    | 11.66|

Table: 4: Generation evaluation. “Ent.” and “Len.” stand for Entropy and the average generation length, respectively. “REF” refers to the ground truth.

scratches with random initialization. To make a fair comparison between sentence-level and token-level approaches, the sentence-level transformer has the same architecture as BERT.

6 Results and Discussions

Missing Sentence Detection Table 2 presents the results of our baseline approaches on the TimeTravel and TripAdvisor test sets. We observe the following.

- The performance of the token-level baseline is generally better than that of the sentence-level baselines. This is unsurprising as the sentence-level baselines compress sentences into vector representations, resulting in the loss of fine-grained inter-sentence token dependencies that the token-level baseline can capture.

- Joint training of Missing Sentence Detection and semantic matching slightly improves the detection performance, implying that they can work synergistically. This multi-task learning strategy leads to a performance boost as the detection and semantic matching tasks share the same underlying encoder and sentence-level transformer. Intuitively, understanding what is missing is important in helping determine whether a sentence is missing.

- Pre-training on a large corpus significantly improves the performance of the sentence-level baselines, leading to a prediction accuracy comparable to that of the token-level baseline, with much faster speed and much less computational cost at inference time.

- The original BERT embeddings perform slightly better than the DAE-fine-tuned embeddings. We speculate that the DAE fine-tuning alters the geometry of the latent embedding space for better reconstruction or generation capability while slightly sacrificing the discriminative features for the detection tasks. However, the large-scale pre-training diminishes the difference. With pre-training, the DAE embeddings even outperform the BERT embeddings on the TripAdvisor dataset.

Discordant Sentence Detection Table 3 presents the results for Discordant Sentence Detection, which are largely consistent with our findings in the Missing Sentence Detection experiments. Additionally, we observe the following.

- Joint training of Discordant Sentence Detection and semantic matching gives detection performance comparable to that of the detection-only models.

- The token-level baseline performs worse than sentence-level baselines on the TripAdvisor dataset. The reason might be that the relatively
Jill was in such a rush to catch the bus that she missed breakfast. In her first class of the day, her stomach kept growling. She wasn't sure she could make it until lunch. Between classes her friend Lou handed her a granola bar. Jill ate it and it kept her going until lunch. (DAE) Her stomach started to turn and she was hungry. (BERT) She was starving and couldn’t wait for the food to come out of her mouth.

Jen wanted all of her family to be together for Christmas. So she decided to fly out and visit them as a surprise. When she got there her family was gone. When she got home, she realized her cheese was gone. Jen was very sad. They had gone on a trip without her. (DAE) When she got home, she realized that her mother was gone. (BERT) When they arrived home, she was so upset that she had to take a nap.

Shay was meeting with a woman who wanted to hire a nanny. They met in a Starbucks and ordered some drinks. With their drinks, they sat down and got to know each other. Finally, the woman offered Shay the position. Shay was thrilled. (DAE) The girls had a great time and enjoyed it. (BERT) The woman convinced her to meet him at the bar and have a drink.

Marta needed to visit her son’s school award ceremony. Her toddler needed to go to the doctor. Marta roused her husband from his nap. Marta attended the ceremony. (DAE) She had to go to the hospital to get her doctor. (BERT) She was so excited that she had to go to the hospital to see her father.

| Discordant Sentence Detection | Long input sequences (8 sentences) are not handled well by the token-level model. |
|-------------------------------|---------------------------------------------------------------------------------|
| Jen wanted all of her family to be together for Christmas. So she decided to fly out and visit them as a surprise. When she got there her family was gone. When she got home, she realized her cheese was gone. Jen was very sad. They had gone on a trip without her. (DAE) When she got home, she realized that her mother was gone. (BERT) When they arrived home, she was so upset that she had to take a nap. | Marta needed to visit her son’s school award ceremony. Her toddler needed to go to the doctor. Marta roused her husband from his nap. Marta attended the ceremony. (DAE) She had to go to the hospital to get her doctor. (BERT) She was so excited that she had to go to the hospital to see her father. |

Table 5: Four generation examples. In each example, a sentence is removed (or replaced by a discordant sentence in italics) and the suggestions generated by our models are listed in the last two rows.

**Generation Quality** Following Galley et al. (2019); Huang et al. (2020), we perform automatic evaluation using standard reference-based metrics, including BLEU (Papineni et al., 2002), NIST (Doddington, 2002), and METEOR (Lavie and Agarwal, 2007). As a variant of BLEU, NIST weights n-gram matches by their information gain, and thus penalizes uninformative n-grams. We also use Entropy (Zhang et al., 2018) and Dist-n (Li et al., 2016) to evaluate lexical diversity. The results are shown in Table 4. For qualitative measure of the generation quality, we show some generation examples in Table 5. We observe the following.

- The DAE-fine-tuned embeddings outperform the original BERT embeddings in almost all relevance metrics on both datasets and both tasks. For the diversity scores, the DAE results are comparable to or even better than those from the BERT embeddings.
- The performance gap between the DAE-fine-tuned embeddings and original BERT embeddings is more obvious on the generation task corresponding to DSD than that to MSD.
- The average length of generation from DAE is closer to the ground truth than that from the BERT embeddings.

7 Conclusion

We introduced the task of narrative incoherence detection, where the goal is to identify any semantic discrepancy (missing sentence or incoherent sentence) in a narrative. Besides its practical value in writing assistance, this task can potentially be used in a pre-training then fine-tuning framework. For example, one could try to combine the MLM loss and the loss for missing/discordant sentence prediction when pre-training BERT. We hypothesize that this multi-task pre-training scheme may lead to performance improvements on downstream tasks that require capturing long-distance correlations between sentences.
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