INSET: Sentence Infilling with Inter-sentential Generative Pre-training

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Abstract

Missing sentence generation (or sentence infilling) fosters a wide range of applications in natural language generation, such as document auto-completion and meeting note expansion. Such a task asks the model to generate intermediate missing sentence that can semantically and syntactically bridge the surrounding context. Solving the sentence infilling task requires techniques in NLP ranging from natural language understanding, discourse-level planning and natural language generation. In this paper, we present a framework to decouple this challenge and address these three aspects respectively, leveraging the power of existing large-scale pre-trained models such as BERT and GPT-2. Our empirical results demonstrate the effectiveness of our proposed model in learning a sentence representation for generation, and further generating a missing sentence that bridges the context.

1 Introduction

Generating a span of missing tokens in a sentence or a longer text has recently attracted a lot research attention (Zhu et al., 2019; Song et al., 2019; Liu et al., 2019; Joshi et al., 2019). Here we study a related, but somewhat different task of sentence infilling. Specifically, as illustrated in Figure 1, intermediate sentences (or chunks of text) are removed from a long-form text (e.g. paragraphs, documents), and the task requires to generate the missing pieces that can smoothly blend into (and bridge between) the context. The generation can be either purely based on the context, or both context and side information such as keywords, knowledge graph or grounded text snippets. Developing models for such a task can facilitate many applications: e.g., document auto-completion by filling the missing bridging sentence with the surrounding context, collaborative document writing by unifying different writing styles from multiple authors, and meeting note expansion by stretching a note of discontinuous keywords to a natural sentence leveraging the context.

However, there are many challenges associated with the long-form text infilling task. This is typically a one-to-many problem where the possible outputs can be diverse. As the generated text is supposed to connect separate text pieces in a syntactically and semantically smooth manner, this task requires a wide range of understanding, planning and generation techniques. Large-scale pre-trained language models such as BERT (Devlin et al., 2019) and GPT-2 (Radford et al., 2019) have dramatically enhanced the understanding and
generation modules. However, how to integrate them in a holistic manner, and to analyze and establish the long-term dependency structure by high-level semantic planning is still challenging and yet to explore, as the semantic appropriateness is usually subtler than the syntactic appropriateness, which can be well characterized by autoregressive language models (Radford et al., 2019).

Few works have been done in this direction. Text infilling (Zhu et al., 2019) sequentially generates the missing text portion, starting from a mask token and until an end-of-blank token is generated. It allows arbitrary length for the generation. However, by design, such an approach focuses more on lexical appropriateness rather than global semantic aspects of the generated text. MASS (Song et al., 2019) proposed to obtain sentence representation by predicting the missing span in text. It can be applied to generate missing text, however, the missing span length needs to be pre-specified. Other related works (Liu et al., 2019; Joshi et al., 2019) also required the knowledge of the span length as an input to their models.

In this paper, we present a novel approach to generate the missing sentence in a multi-sentence paragraph, called INSET. Our model first produces sentence-level semantic features that encapsulate the missing high-level information. Then, grounded on these semantic features, the model generates the “syntactic” and “lexical” features to fill and fit the context. Specifically, the understanding, planning and generating aspects for this task are addressed by three modules in a synergistic manner: (i) a BERT-based encoder mapping each sentence in a paragraph into a latent semantic space $S$. (ii) a sentence-level planner to infer the missing information that can bridge the semantic meaning between the preceding and following text. (iii) a GPT-based generator to map the semantic meaning back to the text domain. These three components form a hierarchical generative structure.

We note that our framework has several advantages comparing to previous work. The main contributions of this work are summarized as follows: (i) We propose the task of sentence infilling which goes beyond the text infilling. Unlike text infilling which focuses on filling a span of missing tokens in order to deliver smooth text, in this task the interpolation is on a sentence-level granularity and focuses more on filling the missing semantic information. (ii) Our model decouples the understanding, planning and generation problems, allows leveraging pre-trained understanding and generation models (BERT, GPT-2). This scopes down the challenge of learning a single model, and each component can be separately examined and improved using additional unsupervised data. (iii) Our model interpolates a missing sentence feature within a latent semantic space at the sentence level and projects such a feature to text. Consequently, it focuses on completing the sentence infilling task in a semantically smooth way. (iv) Our model allows the generation to be in arbitrary length, as in (Zhu et al., 2019). (v) Comparing to directly process the text, our model reduces the demand of memory and computation by magnitudes, as the sentence feature can be pre-computed and the sequence length becomes the number of sentences (rather than the number of tokens).

2 Related Work

Natural Language Generation. The field of neural text generation has received considerable attention. Popular tasks include machine translation (Sutskever et al., 2014), text summarization (Paulus et al., 2018), and dialogue generation (Rajendran et al., 2018). Most of previous approaches use encoder-decoder architectures for sequence-to-sequence learning. To improve the quality of generated text, techniques like reinforcement learning (Ranzato et al., 2016), adversarial learning (Yu et al., 2017) and inverse reinforcement learning (Ho and Ermon, 2016) have also been applied.

Recent work has shown that language models pre-trained on large corpus play an important role in natural language generation and understanding through transferable contextualized word vectors (Devlin et al., 2019; Lample et al., 2019) and models (Howard and Ruder, 2018). Large transformer architectures (Vaswani et al., 2017) like GPT-2 (Radford et al., 2019), Megatron1 and T5 (Raffel

1https://github.com/NVIDIA/Megatron-LM
et al., 2019) can achieve state-of-the-art results without directly training for any particular language modeling benchmark. (Keskar et al., 2019) proposes a conditional generation model, trained to condition on control codes that govern style, content, and task-specific behavior. Different from them, our model builds sentence representation directly with BERT and fine-tunes it on a generation task.

**Context-aware Text Generation.** There are some related works for context-aware text generation (Mikolov and Zweig, 2012; Tang et al., 2016; Mangrulkar et al., 2018). Previous works for language modeling with context information (Wang and Cho, 2016; Wang et al., 2018) treat the preceding sentences as context. (Sordoni et al., 2015b; Wen et al., 2015) treat the dialogue history as context and generate response. (Vinyals and Le, 2015) proposes a model to predict the next sentence given the previous sentences in a dialogue session.

Comparing with these sequential generation tasks, our task is constrained by bidirectional context. It is more challenging because it requires a deeper understanding of the context. For instance, a generic sentence that is merely related to the topic is less likely to be good in our task than in the task of generating the last sentence.

Beyond dialogue generation, (Zang and Wan, 2017) proposes to generate long reviews from aspect-sentiment scores according to topic phrases. Text infilling (Zhu et al., 2019) aims at filling in the missing part of a sentence by making use of the information around the missing part. (Liu et al., 2019) introduces an iterative inference algorithm based on gradient search for text infilling. SpanBERT (Joshi et al., 2019) masks random contiguous spans and trains a language model to fill the entire masked span. Compared with them, we leverage pre-trained BERT and GPT-2 for the sentence infilling task.

More recently, (Kang and Hovy, 2019) models the logic connections between sentences and generates intermediate sentences by grounding on the inter-sentence flow. (Aakur and Sarkar, 2019) formulates abductive commonsense reasoning as a natural language inference task to decide the appropriate reason that can explain the observation in one sentence based on the background described in another sentence. These two works studied generation tasks that emphasize inter-sentence relationship and thus may be conceptually related to our motivation. However, our approach is clearly different from theirs in that we fully exploit large-scale pre-trained models to learn a smooth sentence embedding and then generate from the space of sentence embeddings.

**Hierarchical Text Generation.** Hierarchical text generation that leverages the high-level semantic planning has been explored by many previous works. (Sordoni et al., 2015a) presents a hierarchical recurrent encoder-decoder given encoded dialogue content. (Zhang et al., 2019a) proposes a framework to infer the semantic feature for response generation using self-supervised learning. Previous works have also used multi-level LSTM encoders (Yang et al., 2016; Hu et al., 2019) or hierarchical autoencoders (Li et al., 2015) to learn hierarchical representations for long text. (Shen et al., 2019) uses variational autoencoder to encode the entire paragraph into one single latent representation variable, where the paragraph can be hierarchically generated from. In contrast, our task focuses more on generating the intermediate sentence by leveraging surrounding context.

### 3 Method
#### 3.1 Task Definition
The task of sentence infilling is formally defined as follows. Consider a dataset with $N$ multi-sentence paragraphs $\{x^{(k)}\}_{k=1}^{N}$. Each paragraph $x^{(k)}$ has $M_k$ consecutive sentences $x^{(k)} = (s^{(k)}_{1}, s^{(k)}_{2}, \ldots, s^{(k)}_{M_k})$. For any $k$, we are given an integer $m_k \in [1, M_k]$ and the context $(s^{(k)}_{1}, s^{(k)}_{2}, \ldots, s^{(k)}_{m_k-1}, s^{(k)}_{m_k+1}, \ldots, s^{(k)}_{M_k})$, but $s^{(k)}_{m_k}$ is missing. We are asked to generate a sentence $\hat{s}^{(k)}_{m_k}$ at the missing place such that it fits the context. For simplicity and without any confusion, we drop the index $k$ from now on (please keep in mind that $M$ and $m$ may depend on $k$).

The criteria for successful sentence infilling
are: \(i\) The sentence \(\hat{s}_m\) represents fluent English. \(ii\) \((s_1, s_2, \ldots, s_{m-1}, s_m, s_{m+1}, \ldots, s_M)\) (the whole paragraph) obtained by combining the generated sentence with the context, is meaningful and semantically coherent. \(iii\) \(\hat{s}_m\) is written in the same style as the sentences in the context.

Since there could be multiple semantically different sentences that fit the same context well, it is not necessary for \(\hat{s}_m\) to be close to the ground truth \(s_m\). Rather, \(\hat{s}_m\) is considered a success as long as it satisfies the criteria above.

### 3.2 INSET: Inter-Sentential Transformer

**Model Overview.** At a high level, our model consists of two components: a (denoising) autoencoder and a sentence-level BERT-like transformer model. The former maps sentences to fixed-length sentence feature vectors in a latent semantic space, and reconstructs the sentence from the representation. The latter predicts the latent feature of the missing sentence based on the features of all other sentences in the context. We call our model as **INter-SEntenetial Transformer** (INSET).

To be more specific and formal, let \((\mathcal{E}, \mathcal{D})\) be the autoencoder, where \(\mathcal{E}\) (\(\mathcal{D}\)) is the encoder (decoder) such that \(\mathcal{E} \circ \mathcal{D}\) and \(\mathcal{D} \circ \mathcal{E}\) are supposed to be identity mappings. Let \(\mathcal{T}\) be the sentence-level transformer with positional embedding \(\mathcal{P}\). The transformer \(\mathcal{T}\) takes the contextual information as input and outputs a (hypothetical) representation of the missing sentence. We have

\[
\hat{s}_m = \mathcal{D}(\mathcal{T}(f_1 + \mathcal{P}(1), f_2 + \mathcal{P}(2), \ldots, f_{m-1} + \mathcal{P}(m-1), \bar{0} + \mathcal{P}(m), f_{m+1} + \mathcal{P}(m+1), \ldots, f_M + \mathcal{P}(M))[m]),
\]

where \(f_i = \mathcal{E}s_i\) is the encoding feature of the sentence \(s_i\), and \(\bar{0}\) is a zero vector representing the missing sentence. \(\mathcal{T}(\cdots)[m]\) denotes that we take the output of \(\mathcal{T}\) at the missing position \(m\).

**Sentence Representation Learning via Denoising Autoencoding.** Large-scale pre-training approaches (e.g., BERT) yield superior performance in many language modeling tasks related to sentence representation learning. However, the features learned (or fine-tuned by downstream tasks) from BERT cannot be directly used for generation tasks, as the masked language model (MLM) objective of BERT does not enforce the sentence feature to be able to reconstruct the original sentence. A similar point of view was made in a previous work (Reimers and Gurevych, 2019) based on extensive numerical experiments. Instead of directly applying BERT features, we learn the sentence representation via autoencoding, which naturally integrates BERT and GPT-2 and combines the learning of sentence representation and generation.

Specifically, we first pad a [CLS] token at the beginning of each sentence \(s_i\) and initialize \(\mathcal{E}\) using BERT. We extract the output feature corresponding to the [CLS] token as the sentence embedding (denoted by \(f_i = \mathcal{E}s_i\)) of the sentence \(s_i\).

For the decoder of the autoencoder, we initialize \(\mathcal{D}\) as GPT-2 and feed \(f_i\) as the embedding of the zeroth token. Then, we have \(\mathcal{D}\) generate a sequence of tokens in the hope that this sequence matches \(s_i\) (padded with the special token [SOS] at the beginning and [EOS] at the end).

To train the autoencoder, we use the teacher-forcing scheme and minimize the negative log-likelihood loss by jointly (fine-)tuning the parameters in \(\mathcal{E}\) and \(\mathcal{D}\).

An autoencoder embeds sentences into vectors in a latent space. We hope that the embedding is smooth in the sense that sentences with similar semantics are mapped to vectors that are close to each other. To this end, we use the following tricks: \(i\) We employ a denoising autoencoder, which has been reported to yield smoother embedding (Vincent et al., 2008). To inject noise, we randomly mask each token in \(s_i\) with a fixed probability \(p = 15\%\). This is achieved by replacing the masked tokens with the special token [MASK]. During training, we use the “noisy” \(s_i\) with masked tokens as the input to the encoder, and use the “clean” \(s_i\) without masked tokens to compute the loss function. \(ii\) We use early stopping. In our experiments, we observe that as training proceeds, the autoencoder validation error keeps decreasing. In the absence of masks, presumably it would eventually be
Figure 2: Model overview: Left panel: denoising autoencoder. The encoder $E$ takes a corrupted sentence (with each token masked randomly) and produce a representation of the sentence ($w_i$ for $i = 1, 2, \ldots, l$ are tokens of the sentence). The decoder is required to reconstruct the original sentence that is not corrupted. The weights in $E$ and $D$ are initialized as those in BERT and GPT-2, respectively. Right panel: Sentence-level BERT. Following the encoding step, we obtain the representation of each sentence in the context. All sentence representations are fed into a sentence-level transformer $T$, which aims to generate the missing sentence feature.

zero so that the autoencoder can exactly reproduce $s_i$. However, this does not imply that the latent-space embedding is simultaneously becoming smoother. On the contrary, an over-trained autoencoder often tries to remember every individual token and thus fails to achieve smoothness in the sentence representation space. Furthermore, it might also catastrophically forget some of the information in the initial pre-trained model (GPT-2) and loss the power of generating fluent sentences. In practice, we select a checkpoint by monitoring its validation performance on sentence interpolation. A few examples of sentence interpolation will be given in the experiment section.

**Missing-Sentence Feature Prediction.**

The above sentence feature encoding step is followed by a missing-sentence feature prediction step, which is conceptually similar to the masked language model objective in BERT (Devlin et al., 2019), but operates at a sentence-level.

Specifically, after encoding the sentences into feature vectors, we fix the encoder and train the sentence-level transformer $T$ with the loss function

$$L_{sentBERT} = 1 - \cos(T(\cdots)[m], f_m),$$

where $\cos(\cdot, \cdot)$ denotes the cosine similarity between the ground truth sentence feature vector $f_m$ and the hypothetical sentence feature vector $T(\cdots)[m]$ in Eq. (1). Note that $\cos(\cdot, \cdot)$ is a good similarity measure only when its arguments are unit vectors. This is guaranteed by the technical trick of fixing the parameters in the last LayerNorm of the transformers $E$ and $T$, i.e., no gradient for these parameters.

Regarding the implementation, we exactly follow that of BERT model. This sentence-level transformer takes sentence feature vectors as the token embedding in BERT, and takes sentence position ID as the position ID in BERT. Note that such a hierarchical model can analyze and process a document with hundreds of sentences at the discourse level with dramatically lower space and time complexity, comparing to the vanilla GPT-2 (as a language model). To be quantitative, suppose that a long-form text contains $N_s$ sentences, each of which has $N_t$ tokens. Then, the time complexity is reduced from $O(N_s^2N_t^2)$ to $O(N_s^2N_t + N_t^3)$.

Moreover, the sentence features can be pre-computed once and then reused for every epoch or even in other tasks on the same dataset. With the pre-computed sentence features at hand, the time complexity can be fur-
ther reduced to $O(N^2)$.

**Generating Sentence from the Sentence Feature.** At test time, we simply use the decoder of the autoencoder to generate the missing sentence by projecting the predicted feature obtained above to the text domain. Note that standard generation schemes such as top-$k$ sampling, beam search and nucleus sampling (Holtzman et al., 2019) can be applied without additional modeling efforts.

### 3.3 Sentence Infilling with Lexical Constraints

We further introduce a related task to the sentence infilling task, called “sentence infilling with lexical constraints,” which is the same as sentence infilling except that now we are given a few keywords of the masked sentence as additional input to hint the generation. The keywords are treated as “soft” constraints (a.k.a., priming): The generated sentences are not directly enforced to contain the exact keywords. The constraints may present as a synonym that shares similar semantic meaning as the constraints.

We hypothesize that the presence of keywords makes the task more difficult rather than easier, despite the fact that incorporating keyword constraints should significantly improve the BLEU score of the generation with respect to the ground truth. Intuitively, keywords force the model to speculate the exact meaning of the ground truth sentence, and significantly reduce the number of possible solutions. In the absence of keywords, the model has the freedom of completing the task based on its own way of thinking.

To handle keyword constraints, we introduce a new component called the *constraint feature encoder* to our architecture. This component is a transformer encoder $T'$ that maps a set of keywords to a numeric feature vector that lives in the same latent space of sentence embeddings.

To train such a constraint feature encoder, we leverage the strategy from knowledge distillation (Kim and Rush, 2016). The student model is the constraint feature encoder which takes a constraint as input to generate a constraint feature, while the teacher model is the sentence encoder $E$, which maps a sentence consistent with the constraint into a sentence feature. We use the cosine similarity loss between these two features to teach the student model.

For the implementation details, suppose we have 2 keywords $w_1, w_2$. Then, the input to $T'$ is three tokens ([CLS], $w_1$, $w_2$) and we replace the $\vec{0}$ vector in Eq. (1), which represents the missing sentence, by the output of $T'$ above the [CLS] token. We do not use positional embedding in $T'$ because keywords do not have ordering.

### 4 Experiments

#### 4.1 Experimental Setup

**Dataset and Pre-processing.** We use the TripAdvisor dataset of hotel reviews (Wang et al., 2010) and partially follows the pre-processing of (Cho et al., 2019). Our pre-processing includes but is not limited to: (i) discarding reviews in which at least one token is not in English; (ii) removing duplicate reviews so that only one copy is retained. We set the maximum number of tokens in a sentence to be 32 and the minimum number of sentences in a review to be 7 (so that the context is not too short). Any review with longer sentences or having a smaller number of sentences is discarded. After the pre-processing, the dataset (training, validation, and test combined) is about 102MB.

For simplicity, we use the following strategy to mask sentences. For a paragraph consisting of $M \geq 7$ sentences, we split it into $M-6$ data points, each of which has exactly 7 sentences. The $j$’th data point spans from the $j$’th to $(j+6)$’th sentence (inclusive) in the paragraph, for $j = 1, 2, \ldots, M - 6$. We always mask the middle (i.e., the 4th) sentence for each data point so that our masking rate is $1/7 \approx 14.3\%$, which is close to that (15%) in pre-training BERT.

We note that such a strategy always masks the middle sentence out of 7 sentences. This strategy is not only the simplest but also without loss of generality. Our model can be easily and readily applied to the situation where we randomly mask, e.g., 3 out of 20 sentences. However, the quality of human evaluation may be affected because the attention and patience of human evaluators might decrease when the
length of the contexts becomes longer. For simplicity and effectiveness of the evaluation, we use the simplest strategy to mask sentences in the experiments.

**Evaluation Metrics.** Following Refs. (Galley et al., 2019; Zhang et al., 2019b), we perform automatic evaluation using standard machine translation metrics, including BLEU (Papineni et al., 2002), METEOR (Lavie and Agarwal, 2007), and NIST (Doddington, 2002). NIST is a variant of BLEU that weights n-gram matches by their information gain, i.e., it indirectly penalizes uninformative n-grams. We also use Entropy (Zhang et al., 2018) and Dist-n (Li et al., 2016) to evaluate lexical diversity. More details are provided in (Galley et al., 2019).

BLEU, METEOR, and NIST measure the closeness between the generated sentences and the ground truth. We note that they might not be the ideal scores for our task because a sentence that is semantically very different from the ground truth can possibly fit the context perfectly well. Nevertheless, it may still be informative to roughly judge the quality of the generation using these automatic scores.

**Baseline** Our baseline is the self-attention model for text infilling (Zhu et al., 2019). It is essentially a transformer-based language model with novel positional embedding. The traditional approach of embedding the absolute position of each token is not directly applicable to our task simply because we do not know in advance the absolute positions of the contextual tokens following a missing sentence. To resolve this issue, (Zhu et al., 2019) divides the text into segments. In the case of only one masked sentence, the first (third) segment consists of contextual tokens before (after) the mask, and the second segment corresponds to the mask. Then, each token is indexed by its segment ID and its positional ID within the segment. The token-level positional embedding used by (Zhu et al., 2019) is generated from these two indices.

Training this baseline model on our dataset, we use the same set of hyper-parameters as in the original reference except that the batch size is set to be 250 (it was 400 in (Zhu et al., 2019)). We have to reduce the batch size because the original batch size leads to the out-of-memory error. Note that we are handling much longer sequences (usually > 100 tokens) than (Zhu et al., 2019), in which the maximum number of tokens in a sequence is only 16.

We train this baseline model for 35 epochs. During training, we monitor the training and test (negative log-likelihood) loss and perplexity. We observe that they saturate (up to small fluctuations) well before the 35th epoch. Here we report the results of the checkpoint after the 21st epoch, because this checkpoint has slightly smaller test loss and perplexity than others. Note that we have checked other adjacent checkpoints and did find that they behave very similarly on the test dataset.

**Extracting Keywords.** In the task of sentence infilling with lexical constraints, we need to extract keywords from the masked sentence and feed them into our model. Extracting keywords is a classical problem in information retrieval. Standard approaches include, but not limited to, the so-called tf-idf (term frequency-inverse document frequency) (Ramos, 2003).

We have tried tf-idf, which does not work well for our TripAdvisor dataset of hotel reviews. One reason is that this dataset has quite a bit of typos, and unfortunately tf-idf favors them because typos occur less frequently than normal words. This technical issue can be resolved by manually filtering out all typos. After this fix, however, we observe that the quality of extracted keywords remains unsatisfactory.

In the experiments we use the following strategy to extract keywords. We first define a list of stop words. To this end, we use the stopword list from the NLTK library and manually add a number of words (e.g., “hotel”), which are not very meaningful for the particular dataset of hotel reviews. For each sentence, we select the words that are not stop words but appear most frequently in the entire dataset. After this fix, however, we observe that the quality of extracted keywords remains unsatisfactory.

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The pool area was nice and sunbathing was great.
- The pool area was nice and sunbathing was great.
- The pool area was nice and sunbathing was great.
- The pool area was nice and staff was great.
- The pool area staff was nice and very helpful.
- Front desk staff were very nice and helpful.
- Front desk staff were very helpful and friendly.
- Front desk staff were very helpful and friendly.

Front desk staff were very nice and helpful.

The service was attentive and we had the best food in town.
- The service was attentive and we had the best food in town.
- The service was attentive and we had a great room with plenty of food.
- The room was spacious with good service and we had a queen bed.
- The room was spacious with 2 queen beds.
- The room was very spacious with queen beds.
- The room was very spacious with 2 queen beds.

The room was very spacious with 2 queen beds.

Table 1: Interpolations results from denoising autoencoder. “A” and “B” denote the two original sentences. The interpolated sentence generation is based on a epi-distance grid between A and B.

Table 2 compares the text infilling baseline (Zhu et al., 2019), our results (without keywords), and the ground truth. Our results perform better than the baseline on all scores. This suggests that our results are not only semantically closer to the ground truth, but also more diverse than the baseline. Also, the results on average length show that our results are more contentful than the baseline.

Table 2 also provides an ablation study on the usefulness of the context in the presence of keywords. We consider two models. The first model generates sentences based on the keywords only without looking at the context. This is achieved by directly decode the output of \( T' \) in Subsection 3.3 using our decoder \( D \). The second model relies on both the keywords and the context. We observe that the scores with context are slightly higher than those without context.

Human Evaluation. We also performed human evaluation to evaluate our methods. We asked crowd workers using a crowd evaluation platform to compare two systems and assess their fluency, informativeness and relevance to the surrounding context (coherence). We use 500 randomly sampled contexts from our test sets. Following recommended best practices, each context was judged by 5 judges, and we performed simple spam detection by excluding judges that were too fast or performed too low on a gold set. Additionally, we also randomized the position of each system to

Model Sizes and Hyper-parameter settings. Our architecture has several components. The encoder \( E \) and the sentence-level transformer \( T \) have the same size as BERT\_BASE. The decoder \( D \) has the same size as GPT-2 (117M). For sentence infilling with lexical constraints, the additional transformer \( T' \) also has the same size as BERT\_BASE. During decoding we use beam search with beam size 5.

4.2 Experimental Results

Sentence representation learning. We first qualitatively evaluate the smoothness of the latent-space sentence embedding learned from denoising autoencoding. The two chunks of sentences in Table 1 demonstrate our sentence interpolation examples. In each chunk, the first and last sentences are the inputs by hand and the 7 intermediate ones are interpolation generated by our (denoising) autoencoder. We see that the interpolation does not simply combine the words from both sentences, but attempts to generate readable, meaningful and semantically correct sentences that demonstrate a smooth transition from the first to the last sentence. We speculate that such a power for generating meaningful sentence interpolation might derive from the BERT and GPT-2 models. Inherited from these large-scale pre-trained models, the latent-space sentence embedding is reasonably smooth as reflected from the fluent sentences generated in our sentence interpolation experiments.

Automatic Evaluations. We compute the BLEU, METEOR, NIST, Entropy, and Dist-\( n \) scores as well as the average length, defined as the average number of words in the generated sentences. The results are summarized in Table 2.
### Table 2: Automatic evaluation results.

| Method | NIST (Zhu et al., 2019) | BLEU | METEOR | Entropy | Dist | Avg Len |
|--------|-------------------------|------|--------|---------|------|---------|
|       | 0.54 | 0.54 | 4.29%  | 0.54%   | 5.85%| 3.10 | 1.32%  | 2.23% | 6.97 |
| INSET (Ours) | 1.23 | 1.23 | 6.08%  | 0.96%   | 7.04%| 8.13 | 16.30% | 46.64% | 10.70 |

**Without keyword constraints:**

**With keyword constraints:**

INSET (Ours) w/o context: 3.00 3.04 19.47% 6.07% 16.00% 8.16 20.51% 57.41% 11.12

INSET (Ours) w/ context: 3.09 3.15 20.14% 6.57% 16.48% 8.34 22.61% 63.60% 11.23

ground truth (human): - - - - - 8.40 33.96% 79.84% 11.36

Table 2: Automatic evaluation results. “w/o context” refers to the results generated from the keywords only without relying on the context, while “w/ context” makes use of both the keywords and the context. Our results (without keywords) get significantly higher relevance scores (NIST, BLEU, and METEOR) and diversity scores (Entropy, Dist-n) comparing to text infilling baseline.

### Table 3: Human evaluation results.

| system A                  | system B                  | criterion          | prefer A (%) | same (%) | prefer B (%) |
|---------------------------|---------------------------|--------------------|--------------|----------|--------------|
| INSET (Ours) (Zhu et al., 2019) | coherence                | 54.16              | 13.76        | 32.07    |
|                           | fluency                   | 43.38              | 26.98        | 29.64    |
|                           | informativeness           | 53.48              | 18.79        | 27.72    |
| INSET (Ours) ground truth | coherence                | 27.87              | 15.69        | 56.44    |
|                           | fluency                   | 21.78              | 31.38        | 46.84    |
|                           | informativeness           | 27.49              | 21.92        | 50.59    |
| INSET w/ context & key    | coherence                | 34.97              | 17.06        | 47.97    |
|                           | fluency                   | 29.30              | 28.04        | 42.65    |
|                           | informativeness           | 31.73              | 23.24        | 45.03    |
| INSET w/ context & key    | coherence                | 18.50              | 23.45        | 58.04    |
|                           | fluency                   | 17.82              | 29.78        | 52.39    |
|                           | informativeness           | 20.54              | 26.13        | 53.33    |
| INSET w/ context & key    | coherence                | 37.71              | 37.62        | 24.68    |
|                           | fluency                   | 36.16              | 37.87        | 25.97    |
|                           | informativeness           | 35.93              | 39.86        | 24.21    |

Table 3: Human evaluation results. “INSET” denotes our method without keywords constraints. “INSET w/ context & key” denotes our results with keywords and context. “INSET w/ context w/o key” denotes our results with context but not keywords. “INSET w/ keyword w/o context” denotes our results with keywords only but not context. The numbers are in percentages.

Table 3 compares our results (without keywords) with the text infilling baseline (Zhu et al., 2019) and the ground truth. The human evaluators strongly favor our results over the baseline in all aspects: coherence, fluency, and informativeness. They also strongly favor the ground truth over our results in all aspects.

Table 3 also compares our results with keywords and context to three different systems: (1) the ground truth; (2) our results with context but no keywords; (3) our results with keywords but no context. The second comparison shows that adding keywords makes the performance of our model worse in all aspects, possibly because keywords introduce additional constraints that the model must take care of. Furthermore, the third comparison shows the usefulness of the context for improving all aspects of the generation in the presence of keywords.

**Generated Examples.** We present a few examples in Table 4 to qualitatively demonstrate the performance of our model. We see that the text infilling baseline (Zhu et al., 2019) tends to generate “generic” sentences, while our results (either with or without keywords) are more informative and can fit into the surrounding contexts well. In the presence of keywords, our model does not always generate the keyword. If not, then the generated
example of a positive review | example of a negative review
--- | ---
preceding context | It was such a pleasure to see something new every night. It was not very crowded so we were able to get great seats at either the pool or the beach. The VIP service was great for dinner reservations and pillow service. | The walls are very thin. Since this is a family vacation type of hotel, people are up at the pool/bbq area/hallways during all hours of the night. Do not stay here if you need a quiet night of sleep.

following context | Enjoyed the shrimp coctail and seafood salad delivered to us while enjoying the pool. All of us would not want to stay at another resort and are planning to go back again. Enjoy and Hola!Karen and Friends Milford, CT | You have to take multiple elevators to go all the way to the 5th floor. My other complaint is that the hotel staff seemed a bit unprofessional. Not what I’m used to when I stay at Marriot properties.

ground truth | We did bring a lot of $1 for tipping and of course the service stepped up a notch more. | Also, the elevator situation is weird.

baseline | The staff was friendly and helpful. | The rooms are very clean and well kept.

INSET(w/o keywords) | The buffet dinner was amazing and we had the best food in the resort. | There is only one elevator block in the hotel.

keywords | $, service | elevator, situation

INSET(w/ keywords) | Service fee for the buffet dinner was $5.00 and we paid $5.00 extra for food service. | The elevator problem is extremely frustrating.

Table 4: Generation examples from our system and baseline

sentence does carry the meaning of the keyword.

5 Conclusion and Discussion

We consider the sentence infilling task which resembles the masked language modeling task used to train BERT, but at the sentence level. It requires to understand high-level semantics and long-range correlation. It is complementary to the (token-level) masked language modeling task, which focuses more on syntactic correctness and short-range correlation. We propose a framework called INSET to decouple three aspects of this task, and address them in a unified manner. We demonstrate the effectiveness of our approach by comparing it to a baseline using automatic and human evaluations.

One possible scenario for future applications may be post editing in machine translation of long texts. It is often the case that the sentences in a paragraph are translated independently from each other. This sometimes leads to incoherence between translated sentences, which needs to be fixed. While this post editing task is not exactly the same as sentence infilling, it is certainly related. We speculate that sentence infilling or a variant of it can be a good pre-training task for downstream tasks like post editing in machine translation.

6 Acknowledgments

We thank Bill Dolan, Chris Quirk and Jingjing Liu for helpful discussions and suggestions.
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