E2S2: Encoding-Enhanced Sequence-to-Sequence Pretraining for Language Understanding and Generation

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Abstract—Sequence-to-sequence (seq2seq) learning is a popular fashion for large-scale pretraining language models. However, the previous seq2seq pretraining models generally focus on reconstructive objectives on the decoder side and neglect the effect of encoder-side supervision, which we argue may lead to sub-optimal performance. To verify our hypothesis, we first empirically study the functionalities of the encoder and decoder in seq2seq pretrained language models, and find that the encoder takes an important but under-exploitation role than the decoder regarding the downstream performance and neuron activation. Therefore, we propose an encoding-enhanced seq2seq pretraining strategy, namely E2S2, which improves the seq2seq models via integrating more efficient self-supervised information into the encoders. Specifically, E2S2 adopts two self-supervised objectives on the encoder side from two aspects: 1) locally denoising the corrupted sentence (denoising objective); and 2) globally learning better sentence representations (contrastive objective). With the help of both objectives, the encoder can effectively distinguish the noise tokens and capture high-level (i.e., syntactic and semantic) knowledge, thus strengthening the ability of seq2seq model to accurately achieve the conditional generation. On a large diversity of downstream natural language understanding and generation tasks, E2S2 dominantly improves the performance of its powerful backbone models, e.g., BART and T5. For example, upon BART backbone, we achieve +1.1% averaged gain on the general language understanding evaluation (GLUE) benchmark and +1.75% F1.0.5 score improvement on CoNLL2014 dataset. We also provide in-depth analyses to show the improvement stems from better linguistic representation. We hope that our work will foster future self-supervision research on seq2seq language model pretraining.

Index Terms—Language understanding and generation, pretraining, self-supervised learning, sequence-to-sequence learning.

I. INTRODUCTION

SEQUENCE-TO-SEQUENCE (seq2seq) pretrained language models (PLMs) [1], [2], [3], [4], [5] are widely used in the community of natural language processing and have achieved remarkable success in numerous downstream tasks of both natural language generation (NGL) and understanding (NLU), such as machine translation [2], [6], [7], text summarization [5], [8], grammatical error correction [9] and other discriminative tasks [3], [10], [11]. Specifically, seq2seq models are generally implemented with an encoder-decoder framework [12], where the encoder models the input sentence first and then the decoder generates the output tokens auto-regressively conditioned on the representation of encoder.

The large-scale seq2seq PLMs are basically trained with reconstructive self-supervisions. Concretely, the encoder receives the perturbed input with different token- and sentence-level noising functions [2], [3], [4], e.g., text infilling, token deletion, token masking, and sentence permutation. Then the decoder reconstructs the perturbed text. Such a self-supervised learning process is assumed to learn the knowledge contained in the large-scale text, thus providing better initialization for downstream tasks. For instance, MASS [2] takes the sentence with randomly masked fragment as input of encoder and makes the decoder predict this masked fragment. BART [3] improves the MASS via predicting the complete original sentence, instead of the missing tokens.

Although the remarkable progress of seq2seq pretraining has been witnessed, we find that most current seq2seq PLMs usually achieve suboptimal performance on downstream language understanding tasks. An obvious evidence is that the top-ranked systems of the General Language Understanding Evaluation (GLUE) leaderboard are almost (encoder-only) masked language models, i.e., BERT [13] and its variants [14], [15]. We attribute this phenomenon to the unsatisfactory capability of encoder in seq2seq PLMs, as most of them are trained via optimizing a reconstruction loss on the decoder side, but neglecting the impact of self-supervised information on the encoder side. To verify our hypothesis, we empirically study the functionalities of the encoder and decoder in the seq2seq PLM (i.e., BART [3]),
as shown the results in Fig. 1. Specifically, in Fig. 1 (Left), we remove the encoder and decoder layers of pretrained BART, respectively, and analyze the performance decrease. As seen, there is only a slight performance decrease when removing decoder layers. However, if we remove several encoder layers, the performance drops dramatically, which indicates that encoders have a greater influence on seq2seq models, which is similar to the findings of Kasai et al. [16] that confirm using deep encoders and shallow decoders is more effective in seq2seq scenarios. Additionally, results in Fig. 1 (Right) show that the encoder of seq2seq PLM is under-exploited, as the rate of activated neurons of encoder is much lower than those of decoder. In general, from these results, we can basically conclude that the encoder takes an important but under-exploitation role than the decoder in seq2seq PLMs.

To this end, we propose an encoding-enhanced seq2seq pertaining strategy, denoted as E2S2, to provide richer supervision for the seq2seq models via integrating two self-supervised objectives on the side of encoder. Specifically, we introduce the self-supervised information from two aspects: 1) locally denoising the corrupted sentence earlier (denoising objective); 2) globally learning better sentence representations (contrastive objective). First, given the input sentences corrupted with various noising functions, different from the vanilla seq2seq PLMs that only reconstruct the correct sentences on the decoder side, our motivation is to encourage the encoder to effectively distinguish the corrupted tokens earlier and then help the decoder better perform the reconstruction process. On the other hand, inspired by Li et al. [17] that find the encoder always induces a non-smooth anisotropic semantic space of sentences, which harms the performance of sentence representation, we further present a contrastive objective to globally improve the sentence representations learned by the encoder. In practice, for contrastive objective, we provide two solutions to obtain the sentence representations. The first is simply average pooling on all hidden representations of the last encoder layer. The second is to employ a more effective prompt-based sentence construction approach to acquire more reliable representations. In this way, the encoder is forced to learn better sentence representation, from which the decoder can acquire more knowledge and perform better on language understanding and generation.

Extensive experiments on several downstream tasks, including both NLU (i.e., GLUE benchmark [18]) and NLG (text summarization, grammatical error correction, and dialog generation), show that E2S2 consistently outperforms the vanilla seq2seq pretraining scheme. More specifically, using the typical seq2seq PLM (BART [3]) as the baseline model, E2S2 achieves +1.1% averaged performance improvement on test sets of GLUE benchmark, especially +2.3% improvement on the CoLA task that is highly related to the denoising objective. In addition to the positive effect on NLU tasks, we also observe consistent improvements on NLG tasks, e.g., +1.75% F0.5 score for grammatical error correction task. We also empirically prove that our E2S2 strategy is compatible with other seq2seq PLMs, e.g., T5 [4]. These results demonstrate the effectiveness and universality of our E2S2 strategy. Additionally, in-depth discussions in Section IV-F prove that E2S2 indeed enables the encoder to learn better linguistic representations.

Our main contributions can be summarized as follows:

- We explore the shortcomings (unsatisfactory capability of the encoder) of seq2seq pretraining and present an encoder-enhanced learning strategy (termed as E2S2) to recast the vanilla seq2seq pretraining scheme via integrating more self-supervised information on the side of encoder.
- We design two self-supervised pretraining objectives from two meaningful aspects, i.e., locally denoising the perturbed text earlier and globally learning better sentence representations, which are easy-to-implement and model-agnostic.
- Extensive experiments upon both NLU and NLG tasks validate the effectiveness and universality of E2S2. Quantitative analysis and in-depth discussion provide some insights into where the improvements come from.

The rest of this paper is organized as follows. In Section II, we briefly review the related works. In Section III, we introduce our proposed method in detail. Section IV reports and discusses our experimental results. Finally, we conclude our study in Section V.

II. RELATED WORKS

A. Pretrained Language Models

In recent years, we have witnessed numerous pretrained language models (PLMs) that achieved tremendous success in the community of NLP. Based on the model architectures, these PLMs can be classified into three main categories: decoder-only (auto-regressive) LMs, encoder-only (auto-encoding) LMs and encoder-decoder (sequence-to-sequence) LMs. Auto-regressive LMs aim to predict the future words towards a sequence of words, such as GPT [19] and its variants. Such auto-regressive models are well-suited for language generation, but they are unidirectional and usually fail short in the representation learning for understanding the sentence [20]. Thus, researchers turn to focus on auto-encoding LMs that introduce a bidirectional masked language modeling (MLM) objective to predict the masked text token based on the context. The most representative auto-encoding LMs are BERT [13] and its variants, e.g., RoBERTa [14] and DeBERTa [15].
In order to combine the advantages of auto-regressive LMs and auto-encoding LMs, seq2seq LMs are sequentially proposed, which first employ a separate encoder to model the source text and then use a left-to-right LM to decode the conditional target text. For example, as the typical seq2seq LMs, BART [3] and T5 [4] first corrupt the text with various noising functions on the encoder side and then train the models to reconstruct the original text in an auto-regressive manner. The encoder-decoder paradigm makes the seq2seq LMs not only generally suitable for text generation, but also well for text understanding tasks. In practice, for text understanding tasks, BART employs the final hidden state of the final decoder token as the sentence representation and introduces an additional MLP layer to output the prediction, while T5 converts the classification tasks as “text-to-text” generation tasks and directly generates the target texts, e.g., sentiment polarity for sentiment analysis task.

The above seq2seq PLMs have achieved remarkable progress in various NLP tasks, but there are still some limitations that need to be improved. In particular, when seq2seq PLMs are used to process language understanding tasks, their performance is usually worse than those of auto-encoding LMs. One possible reason is that the encoder of seq2seq LMs is not trained sufficiently and the representations given by the encoder are suboptimal. Intuitively, enhancing the encoder is beneficial for the pretraining of seq2seq LMs. To the best of our knowledge, our E2S2 is one of rare works that propose to integrate more self-supervised information into the encoder optimization in the encoder-decoder paradigm.

B. Self-Supervision Learning in PLMs

Self-supervised learning (SSL) is the de facto standard for large-scale pretraining in the NLP community [21], [22], [23], [24], [25], which helps model to learn universal knowledge based on the (pseudo) self-supervision provided by pretraining tasks. In general, self-supervised learning for PLMs can be classified into generative SSL, contrastive SSL and adversarial SSL. The generative SSL aims to train the models by decoding the encoded inputs. The most representative models are GPT [19] and BERT [13]. The former predicts the next tokens based on the previous tokens, while the later predicts random masked tokens based on the (bidirectional) unmasked tokens (token-level MLM). Motivated by GPT and BERT, more PLMs involving generative SSL are further proposed, e.g., SpanBERT [26] (span-level MLM), ERNIE [27] (entity-level MLM) and XLNet [28] (permutation language modeling).

Contrastive SSL refers to training the models by comparing, such as the next sentence prediction (NSP) objective in BERT that aims to distinguish whether the given sentence pair is consecutive. In addition to such a context-instance contrast, a breakthrough in contrastive SSL for PLMs has been recently achieved by instance-instance contrastive learning, e.g., SimCSE [29], ConSERT [30] and PromptBERT [31], which encourages the PLMs to “learn to compare” by a noise-contrastive estimation. For the adversarial SSL, the models are enforced to identify whether the input tokens are replaced or shuffled. The typical adversarial SSL includes the relaxed token detection [32], shuffled token detection [33], etc.

As aforementioned above, our work aims to integrate more self-supervised information into the encoder training. Specifically, in addition to the generative SSL (text infilling) on the decoder side, our approach involves enriching the semantic and linguistical knowledge of encoder by adding extra SSL supervision in a local-to-global manner, i.e., locally detecting the shuffle/random token (i.e., denoising objective) and globally learning better sentence representations (i.e., contrastive objective).

III. METHODOLOGY

In this section, we present the introduction of background, and then describe our proposed E2S2 strategy in detail.

A. Background

1) Sequence-to-Sequence Pretraining: Suppose we have a source sentence $s$, the goal of seq2seq pretraining is to train a seq2seq model by corrupting sentences and then optimizing the reconstruction loss. Specifically, we first apply noising schemes (e.g., token masking, text infilling, sentence permutation, etc.) to $s$ for obtaining the perturbed sentence $\tilde{s}$, which is then fed into the encoder to obtain the hidden representations $h$, and finally input $h$ into the decoder to auto-regressively reconstruct the original sentence $s$. Therefore, we can optimize the seq2seq model via maximizing the training objective, which is generally the log-likelihood of the sequence pairs $\{\tilde{x}, x\}$ and can be defined as follows:

$$
\mathcal{L}_{nll}(\theta_{alt}) = -\frac{1}{n} \sum_{i} \log P(x_i|x_i^\tau; \theta_{alt}),
$$

where the $\theta_{alt}$ denotes the parameters of full model, $n$ is the number of training samples in a mini-batch and $P(\cdot)$ is the predicted probability.

2) Contrastive Learning: Contrastive learning aims to obtain discriminative representations via mapping similar input sentences to nearby points in the output representation space, while mapping dissimilar input sentences to distant points [29]. Mathematically, given a set of paired samples $\{(x_i, x_j)\}_{i}^{n}$, where $\{x_i, x_j\}$ is a pair of semantically similar samples, we can obtain the corresponding hidden representations $\{(h_i, h_j)\}_{i}^{n}$. Notably, we follow the works [29], [30] and assume the samples from different pairs are negatives, i.e., $(x_i, x_j), (x_i, x_j^\tau)$ and $(x_i^\tau, x_j)$ are negative pairs, where $i$ is not equal to $j$. For a mini-batch with $n$ pairs of samples, the training objective of contrastive learning can be formulated as follows:

$$
\mathcal{L}_{ct} = -\frac{1}{n} \sum_{i} \log \frac{e^{\text{sim}(h_i, h_j^\tau)/\tau}}{\sum_{j=1}^{n} e^{\text{sim}(h_i, h_j^\tau)/\tau}},
$$

where $\text{sim}(\cdot)$ denotes the cosine similarity function, $\tau$ is the temperature factor and empirically set to 1 in this paper.

3) Prompt-Based Learning: Prompt-based learning attempts to integrate extra information by prepending textual prompts before the inputs and help the model to generate desired outputs.
of NLP tasks directly [34]. The critical problem in prompt-based learning is how to design the prompt template. In many previous works [35], [36], [37], the prompt is created based on human introspection and is normally a hard template, which is a textual string that has two main slots: one is the input slot \([X]\) for input \(x\) and the other is the representation slot \([Z]\) for \(z\) representation. Taking the sentiment analysis task as an example, we first fill the slot \([X]\) with the input sentence \(x\) and then obtain its corresponding representations, i.e., the output of \([Z]\), which can be further used to predict the target polarity. Such a simple prompt-based approach is easier to obtain the representations that contain richer linguistic knowledge from PLMs, as proven by the previous study [31].

### B. Encoding-Enhanced Sequence-to-Sequence Pretraining

As stated in Section I, we propose an encoding-enhanced strategy (E2S2) to improve the vanilla seq2seq pretrained models. To have a close look, we show a schematic comparison between the vanilla seq2seq pretraining scheme and our E2S2 scheme in Fig. 2. In particular, the major difference is the adding of several self-supervisions on the encoder side, which work from two aspects, i.e., locally denoising the perturbed sentences (denoising objective) and globally learning better sentence embeddings (contrastive objective). Taking the representative seq2seq model BART as our baseline, we sequentially introduce the processes of these two perspectives.

1) Locally Denoising the Perturbed Sentences: As mentioned above, the input sequence for training seq2seq PLMs is the perturbed sentence \(\tilde{x}\), which is corrupted by noising functions. Notably, we adopt text infilling, where a number of text spans are sampled and each span is replaced with a single masked token, as the basic noising function.\(^2\) Text infilling teaches the model to predict how many tokens are missing from a span. Besides, we introduce two additional linguistically motivated noising alternatives, i.e., Shuffle and Random,\(^3\) which have proved to be beneficial to language models [39], [40]. Shuffle refers to selecting some trigrams from unmasked tokens and then shuffling these tokens in each trigram, and Random refers to randomly replacing tokens with out-of-sequence tokens from the vocabulary. To distinguish different noising schemes, we denote the sequence corrupted by text infilling as \(\tilde{x}\) and that corrupted by the extended noising scheme (i.e., the combination of text infilling, Shuffle and Random) as \(\tilde{x}^*\).

Subsequently, we feed the corrupted sentence \(\tilde{x}^*\) into the encoder and obtain the hidden representations \(\tilde{h}^*\). Then, motivated by the success of ELECTRA [32], we employ a separate

\(^2\) Although Lewis et al. [3] designed five noising functions in their original paper, for simplification we only keep the most effective one – text infilling. In our preliminary experiments, we found that continuing pretraining the BART with the simplified objective achieved the comparable downstream performance (88.71 versus 88.75 average score on GLUE benchmark) against the counterpart pretraining with full objectives.

\(^3\) Notably, there are more sophisticated noising functions, such as adversarial attack [38]. However, our main focus is to incorporate more supervised signals into the encoder, instead of exploring more complex noising functions. Thus, we simply use the widely-used Shuffle and Random in this paper.
MLP classifier to detect whether each token of \( x \) is shuffled or replaced, instead of directly predicting the original tokens. Such a process has been demonstrated more computationally cheaper and more simple-efficient in previous works [39], [41]. The training objective is lastly built by minimizing the cross-entropy loss as formulated:

\[
\mathcal{L}_{de}(\theta_{enc}) = - \sum_{i} \sum_{j} \sum_{k} \hat{y}_{ij}^k \log \left( p_{ij}^k \right),
\]

where \( \hat{y} \) and \( p \) denote the ground-truths and predictions of the noise type (i.e., \( 1 \) for shuffle, \( 2 \) for randomly replacement and \( 0 \) for others, as shown in Fig. 2(c)). \( m \) and \( c \) are the length of the \( \hat{x}_i^* \) and the classes of noise type.

During training, the encoder is forced to acquire both syntactic and semantic knowledge by locally distinguishing between shuffled and replaced tokens in context. Therefore, the pretrained seq2seq model could effectively identify the noises from the input sentence, and perform better on downstream sequence rewriting tasks, e.g., grammatical error correction. This training objective performs in a denoising manner and enhances the encoder with more syntactic knowledge, thus we denote it as the denoising objective.

2) **Globally Learning Better Sentence Embeddings:** In addition to the objective of denoising the perturbed text, we also explore the poor performance of sentence embeddings on the encoder side. In particular, common wisdom in representation learning states that the contextualized language models, e.g., BERT, underperform in sentence embedding [17], due to the issue of representation collapse, i.e., anisotropy. In sequence-to-sequence learning, such poor sentence representations learned by the encoder and subsequently fed into the decoder, would greatly hinder the performance of various NLU and NLG tasks.

To address the problem, we design a contrastive pretraining objective, which globally improves sentence embeddings with contrastive learning. There are two keys to implement our contrastive objective: 1) how to construct positive instances; and 2) how to obtain sentence embeddings from the output of encoder. Regarding the former, we follow Yan et al. [30] and apply different noising functions on the input tokens to construct positive instances. In practice, given a sequence \( x \), we simply feed it into the encoder twice, where one sequence is augmented with the introduced noising functions (i.e., *Shuffle* and *Random*, obtaining \( \hat{x}^* \)), and the other is augmented with the original text infilling (denoted as \( \hat{\tilde{x}} \)), i.e., \( \{\hat{x}, \hat{\tilde{x}}\} \) is a pair of positive instances.

As for the latter, we provide two solutions to obtain sentence embeddings. The first is to simply use basic pooling operations, e.g., mean pooling, to process the hidden representations on the encoder side. The second is inspired by recent prompt-based studies, we introduce the prompt-based learning to acquire more reliable sentence representations. Specifically, we first create a manual prompt template, e.g., “[MASK]” is the representation of the sentence: \([X]\).”, where \([X]\) denotes the input slot. Then, we fill the slot \([X]\) with the input sentence \( \hat{x}^* \) and feed the filled template into the encoder. Note that the prompt templates are not included as the input in the decoder, i.e., the input of the decoder is still the original sentence. Lastly, the hidden vector of [MASK] token on the encoder side is used to represent the sentence embeddings. Notably, while the prompt-based learning is proved more efficient than the first solution, the performance of prompt-based method is unstable and depends on the quality of the manual prompt template. The in-depth discussions on the impact of prompt-based methods can be referred to Section IV-E3.

In this way, we can construct the positive pairs \( \{\hat{x}, \hat{\tilde{x}}\} \) and obtain the sentence representations of the encoder \( \{\hat{h}_i, \hat{h}_i^*\} \), respectively. Following (2), we can achieve the introduced contrastive objective.

3) **Overall Pretraining Objective:** Combining all training objectives, the overall pretraining objective function of our proposed E2S2 can be formulated as follows:

\[
\mathcal{L}_{all} = \mathcal{L}_{nll}(\theta_{all}) + \mathcal{L}_{nll}(\theta_{all}) + \lambda_{de}\mathcal{L}_{de}(\theta_{enc}) + \lambda_{cl}\mathcal{L}_{cl}(\theta_{enc}),
\]

where \( \mathcal{L}_{nll} \) and \( \mathcal{L}_{nll} \) are the vanilla reconstruct loss on the perturbed \( \hat{x}^* \) and \( \hat{\tilde{x}} \) respectively, and \( \theta_{enc} \) denotes the parameters of encoder. \( \lambda_{de} \) and \( \lambda_{cl} \) are hyper-parameters used to balance the weights of different objectives, and set to 0.05 and 0.1, respectively. The analysis of hyper-parameter can be seen in Section IV-E2.

To have a closer look, we illustrate the pretraining details, i.e., training loss curves and downstream performance across different pretraining steps, in Fig. 3. As seen, in the early stages of pretraining, the losses for each training objective were rapidly decreasing. Then, in the later stages of training, they gradually converged and reached stability in the final phase. Moreover, as training progresses, the performance of models on downstream tasks steadily improves, indicating the effectiveness of our E2S2 pretraining.
IV. EXPERIMENTS

In this section, we conduct extensive experiments to investigate the general language learning abilities of our proposed E2S2 strategy. Specifically, we evaluate the models trained with E2S2 on a diverse of downstream benchmarks, covering representative tasks from the fields of both language understanding and generation.

A. Tasks and Datasets

1) Discriminative Tasks: The discriminative tasks refer to making the corresponding predictions towards single-sentence or sentence-pair inputs. To provide a comprehensive comparison with the baselines, we report the results on the popular benchmark, i.e., General Language Understanding Evaluation (GLUE) [18], which consists of several language understanding tasks including sentiment analysis, question answering and textual entailment. The benchmark provides the resources of training and evaluating for each task, and a public leaderboard for analyzing the systems on the private test data. For fair comparison, we respectively report the results on the development and test sets of single-task, i.e., without multi-task or ensemble training. In practice, we evaluate the performance with Accuracy (“Acc”) metric for most tasks, except the F1 scores for QQP and MRPC, the Pearson-Spearman correlations (“Pcorr/Scorr”) for STS-B and the Matthew correlations (“Mcc”) for CoLA.

2) Abstractive Summarization: Given a long document, the abstractive summarization (AbsSum) aims to convert it into a short and adequate summary in the same language. For this task, we employ three widely-used summarization datasets, i.e., CNN/DM, XSum and SAMSum. The CNN/DM and XSum contain 287 K and 204 K document-summary pairs respectively, while the SAMSum consists of 14 K dialogue-summary pairs for training. We follow the prior studies to preprocess the data. During testing, for the CNN/DM, the minimum and maximum lengths were respectively set to 55 and 140, which were tuned on the development data. Similarly, we empirically set the minimum/maximum length of XSum and SAMSum as 10/60 and 5/100, respectively. Notably, the target summaries are closely related to source documents in CNN/DM, while the target summaries in XSum are more abstractive. Following the recent works, we report evaluation results in terms of the standard ROUGE metric, i.e., Rouge-1, Rouge-2 and Rouge-L, respectively.

3) Grammatical Error Correction: The grammatical error correction (EC) task aims to rewrite the input sentence with grammatical errors into the corresponding correct sentence, where the original and target sentences have the similar sentence lengths [48]. We conduct comparison experiments on the representative GEC benchmark, i.e., CoNLL2014, which contains 1.4 M, 5 K and 1 K training, validation and test samples, respectively. We closely follow Chollampatt et al. [49] to preprocess the data. The MaxMatch (M2) scores [50] are used for evaluation with Precision and F0.5 values.

4) Dialogue Generation: The dialogue generation (DiAGe) task refers to generating meaningful and coherent dialogue responses based on the dialogue history. We use four popular DiAGe public datasets as benchmarks, covering Person-alChat [51] (denoted as PChat), DailyDialog [52] (denoted as DADI), DSTC7 [53] and EmpatheticDialogues [54] (denoted as EChat). For this task, we report the PPL of validation test and use the BLEU [55] metric to evaluate the generated response for the test set. Specifically, BLEU metric is to compare n-grams of the candidate with the n-grams of the reference text and count the number of matches. The more the matches, the better the candidate responses are. In this paper, we follow the prior work [51] and report the 1-gram BLEU scores.

The statistics of all aforementioned datasets are listed in Table I.

| Task   | Dataset                | #Train | #Valid | #Test |
|--------|------------------------|--------|--------|-------|
| AbsSum | CNN/DM                 | 287,227| 13,368 | 11,490|
| GEC    | CoNLL2014              | 1,298,756| 5,448  | 1,312 |
| DiAGe  | PersonalChat           | 122,499| 14,602 | 14,056|
|        | DailyDialog            | 76,052 | 7,069  | 6,740 |
|        | DSTC7                  | 76,590 | 17,870 | 1,710 |
|        | EmpatheticDialogues    | 64,633 | 9,305  | 8,423 |

B. Implementation Details

As mentioned above, E2S2 is proposed for seq2seq transformer models. To validate the effectiveness of E2S2, we mainly implement it on a representative seq2seq model, i.e., BART [3]. For ease of illustration, we denote the BART trained with our E2S2 strategy as E2S2-BART. Sequentially, we describe details of the pretraining and fine-tuning of E2S2-BART, respectively.

1) Pretraining: In practice, our model is based on the BART-large [8] in the open-source toolkit fairseq [9] with 24 transformer layers, a hidden size of 1024, a maximum sequence length of 1024 and a learning rate of 1.5e-6. We initialize our E2S2-BART model with the corresponding pretrained BART model and continue pretraining the model for 50 K update steps with a batch size of 2000. Following BART, we employ the same corpora for pretraining, including 160 GB of BookCorpus, Wiki, Stories, OpenWebText and CC-News. During the data processing, we set

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5https://huggingface.co/datasets/cnn_dailymail
6https://github.com/Janpliu/ConDigSum
7https://www.comp.nus.edu.sg/~mlp/conll14st.html
8https://dl.fbaipublicfiles.com/fairseq/models/bart.large.tar.gz
9https://github.com/pytorch/fairseq
the proportions of text infilling, Shuffle and Random as {0.15, 0.05, 0.05}, respectively. The span length of Shuffling is set to 3. All models are trained on the NVIDIA DGX SuperPOD cluster, in which each machine contains 8 × 40 GB A100 GPUs.

2) Fine-Tuning: For the discriminative task, i.e., GLUE benchmark, we follow the original BART and employ the final hidden state of the last decoder token as the final sentence representation and feed the hidden state into a multi-class linear classifier to obtain the final predictions. For RTE, STS-B and MRPC of GLUE benchmark, following previous works [14], [15], we first fine-tune the pretrained E2S2-BART model on the MNLI dataset and then continue fine-tuning on their corresponding single-task corpus for better performance. As for ABSSUM, GEC and DialG tasks, we input the source sentence (long document or grammatical-error sentence) into the encoder and generate the corresponding outputs on the decoder side auto-regressively. The detailed hyper-parameters of fine-tuning is shown in Table II. To avoid stochasticity, we report the average results over 5 random seeds for NLU tasks, while for NLG tasks, we follow existing works [61], [62] and use the Bootstrap test [63] to calculate the statistical significance.

C. Compared Models

We compare our E2S2-BART with the following models:

- BART_Rc: Since the published paper of BART did not report the results on the GLUE leaderboard and GEC/DialG tasks, we reproduce the results of the original BART.

- BART_CONT: We initialize the model with the original BART and continually pretrain it with additional training steps, where the number of the additional training steps is equal to that of our E2S2-BART. This setting is to eliminate the doubt that the better performance of our E2S2 comes from more training steps.

- E2S2-BART_DeNO: One of E2S2-BART variant models trained with the proposed E2S2 strategy upon the single denoising objective. More specifically, we use the shuffle (denoted as Sf), random (denoted as Ra) replacement and their combination (denoted as SfRa) as extra noising functions, respectively.

- E2S2-BART_Joba: We simply combine the denoising and vanilla contrastive objectives, i.e., the first solution for the contrastive objective that performs basic pooling operations to obtain sentence representations, and apply it to pretrain the E2S2-BART models.

- E2S2-BART_JOp: The combination of denoising and prompt-based contrastive objectives is adopted to guide the pretraining of E2S2-BART. Notably, prompt-based contrastive objective refers to the second solution that uses prompts to obtain sentence representations.

Moreover, for evaluating the effectiveness of our proposed method, we also compare against other competitive pretrained models, including BERT [13], T5-large [4], UniLM [56], ERNIE2.0 [27], XLNet [28], SpanBERT [26], SemBERT [59], etc. Note that the models with larger capabilities could always achieve higher performance, and thus we only compare our E2S2-BART models with the pretrained models of comparable size for a fair comparison.

D. Main Results

We first present the detailed results of our E2S2-BART variant models and other cutting-edge pretrained models on the GLUE benchmarks, and then compare our models with the baselines on the generative summarization, GEC and dialogue generation tasks for further analysis.

1) GLUE Results: We follow the previous work [14] and report results on both dev and test sets of GLUE benchmark in Table III, where the results of test sets are obtained from the GLUE leaderboard. Compared with the powerful pretrained models and baseline models, our E2S2-BART models consistently achieve better performance on most tasks of GLUE benchmarks.
benchmark, indicating the effectiveness of our E2S2 method. In particular, when only using the denoising objective, it can be seen that Shuffle+Random (“w/ SFR”) objective generally performs better than the single Shuffle or Random objective, and achieves an average score of 89.2% and 87.0% on dev and test sets, respectively. More specifically, for the CoLA task, the Random objective significantly outperforms the shuffle objective, indicating that denoising the random replacement could be more beneficial to the correction of grammatical errors in CoLA dataset.

In addition, E2S2-BART_JoBa and E2S2-BART_JoPr outperform all compared models. Compared with the original BART, the averaged performance improvement on the test sets in improved by +1.1%. These results prove that more self-supervised information on the encoder side can improve the ability of language understanding, confirming our claim. To be more specific, from the test results of our E2S2 variants, we find that the models with contrastive learning can achieve higher performance on STS-B task, which is widely used to evaluate the performance of sentence representations [29], [30]. This result shows that contrastive learning could alleviate the problem of anisotropy and make the encoder output more efficient sentence representations, thus benefiting the understanding of sentences. Moreover, prompt-based contrastive learning can achieve further improvements, indicating that a prompt-based approach can indeed obtain more reliable and informative sentence representations.

2) Abstractive Summarization Results: Table IV reports the comparison results of CNN/DM, XSum and SAMSum datasets. Similar to the setting of Table III, we also divide the results into several groups. The first group lists the results of some powerful generative methods, and the second group reports the results of our E2S2-BART variants. Regarding the denoising objectives of E2S2-BART variants, we only present the results of “w/ SFR” setting for ease of illustration.

As shown in Table IV, with the help of our proposed pretraining strategy, E2S2-BART models are superior to other cutting-edge models, and substantially outperform the original BART model and its continual pretrained version on both abstractive summarization tasks. These results further prove that
TABLE IV

| Model               | CNN/DM | XSum | SAMSum | Score |
|---------------------|--------|------|--------|-------|
|                     | Rouge_1 | Rouge_2 | Rouge_L | Rouge_1 | Rouge_2 | Rouge_L | Rouge_1 | Rouge_2 | Rouge_L | Avg. | Δ     |
| Lead-3              | 40.42   | 17.62 | 36.67  | 16.30  | 1.60    | 11.95   | 31.40   | 8.70    | 29.40   | -     | -     |
| PTGEM [64]          | 36.44   | 15.66 | 33.42  | 29.70  | 9.21    | 23.24   | 40.40   | 15.30   | 36.60   | -     | -     |
| BERTSumAbs [65]     | 41.72   | 19.39 | 38.76  | 38.86  | 16.33   | 31.15   | -       | -       | -       | -     | -     |
| RoBERTaShare [46]   | 40.31   | 18.91 | 37.62  | 41.45  | 18.79   | 33.90   | -       | -       | -       | -     | -     |
| T5-large [4]        | 41.74   | 19.66 | 39.14  | -      | -       | -       | -       | -       | -       | -     | -     |
| MASS [2]            | 42.12   | 19.50 | 39.01  | 39.75  | 17.24   | 31.95   | -       | -       | -       | -     | -     |
| UniLMv2 [66]        | 43.16   | 20.42 | 40.14  | 44.00  | 21.11   | 36.08   | -       | -       | -       | -     | -     |

Notably, for ease of illustration, we only apply the Shuffle-Random (w/ SFTRA) noise as the denoising self-supervision on E2S2-based models. Best results are in bold. “*” indicates that E2S2-based models are significantly better than the baseline BART_CONT at significance level $p < 0.05$.

Fig. 4. Results on GEC task (CoNLL2014).

our E2S2 models can also perform better on the tasks of language generation. Notably, the improvement of E2S2 on abstractive summarization tasks is slightly smaller than that on the GLUE benchmark. One possible reason is that the text summarization task is not sensitive to the noise of input sentences, and more independent on the syntactic and semantic knowledge of pretrained models. As claimed in Krishna et al. [67], for text summarization task, the models pretrained with nonsense words can still achieve comparable performance with the carefully pretrained models.

3) GEC Results: We also compare E2S2-BART_Deno and E2S2-BART_JopR with the baselines, i.e., BART_RE and BART_CONT, and show the results in Fig. 4. Similarly, under the denoising self-supervision, our E2S2 method (Precision: 63.56%, $F_{0.5}$: 58.16%) achieves a significant performance improvement compared with BART_RE (Precision: 60.74%, $F_{0.5}$: 56.41%). This is because that the denoising pretraining objectives are strongly relative to the task of grammatical error correction. Interestingly, different from the other two tasks, i.e., GLUE benchmark and abstractive summarization, the prompt-based E2S2-BART_JopR (Precision: 64.09%, $F_{0.5}$: 57.66%) performs slightly worse on the GEC task. One possible reason is that the prompt template itself could introduce some noise and thus affect the ability of model on noise detection. Additionally, compared with the original BART, the continual pretrained BART achieves suboptimal performance on all metrics, which indicates that a longer pretraining could not always be better and continues proving the effectiveness of E2S2.

4) Dialogue Generation Results: Table V lists the results of our models and other baselines on several dialogue generation datasets. Obviously, our E2S2 models improve significant performance on these dialogue datasets. Specifically, compared with BART_RE, our E2S2-BART_JoBa decreases the validation PPL by 3.42 on PCHAT dataset, and our E2S2-BART_JopR brings 1.28 BLEU gains on ECHAT dataset.

The aforementioned results on both discriminative and generative tasks prove that the encoding-enhanced strategy not only improves the language understanding performance (more dependent on the abilities of the encoder), but also be helpful to the decoder-side language generation tasks via providing better sentence representation from the encoder.

E. Ablation Study

We conduct extensive ablation studies to investigate the effectiveness of multiple pretrained objectives in E2S2, the effect of coefficient $\lambda_{de}$ and $\lambda_{cl}$, and analyze the influence of different designed prompt templates used in prompt-based contrastive learning. Notably, some representative tasks of GLUE benchmark, e.g., CoLA, MRPC and STS-B, with their original training and dev sets are used for our analysis. We apply the Shuffle-Random noising function as the denoising self-supervision for all experiments.

1) Influence of the Pretraining Objectives: As (4), we optimize E2S2 with the combination of multiple training objectives, i.e., $\{L_{nll}^{de}, L_{nll}, L_{de}, L_{cl}\}$. To investigate their effectiveness, we report the results of different objective combinations in Table VI. Notably, to avoid the influence of prompt, we did not use the prompt-based approach in this study. For clarity, the models are denoted as M1 to M5 from top to bottom.

As shown in Table VI, the model with all pretraining objectives (i.e., M5) performs best and all objectives are beneficial to our E2S2 model consistently. Specifically, with the help of $L_{de}$, M2 greatly improves over the vanilla seq2seq model M1, especially on the CoLA task, with an improvement of +3.2%. Similarly, when using the full contrastive objective,
TABLE V
EXPERIMENTAL RESULTS ON DIALOGUE GENERATION TASK

| Model       | PCHAT (PPL, BLEU) | DADI (PPL, BLEU) | DSTC7 (PPL, BLEU) | ECHAT (PPL, BLEU) | Δ       |
|-------------|------------------|------------------|-------------------|------------------|---------|
| BART_Ri     | 18.90 28.12      | 17.88 27.10      | 8.81 39.37        | 26.36 19.84      | *       |
| BART_CONT   | 15.89 28.20      | 17.18 27.43      | 8.37 39.84        | 26.01 19.22      | 1.13 0.06 |
| E2S2-BART_DaNO | 15.72 22.26    | 16.60 27.58      | 8.17 39.95        | 25.58 20.37      | 1.47 0.56 |
| E2S2-BART_JoBA | 15.48 28.33      | 16.67 27.53      | 8.20 39.97        | 25.27 21.07      | 1.58 0.62 |
| E2S2-BART_JoPr | 15.52 28.32      | 16.60 27.48      | 8.09 39.90        | 25.23 21.12      | 1.63 0.59 |

The lower (‘‘’’) PPL and higher (‘‘’’) BLEU scores refer to better performance. ‘‘*’’ indicates that E2S2-based models are significantly better than the baseline BART_CONT at significance level p < 0.05.

The bold values indicate best results.

2) Parameter Analyses of λ_de and λ_cl: The factors λ_de and λ_cl in (4), which are used to balance different objectives, are two important hyper-parameters in our E2S2. Here, we analyze their influence by evaluating the performance of BART-large with different λ_de and λ_cl spanning {0.05, 0.1, 0.5}. Fig. 5 illustrates the average dev results of the GLUE benchmark.

As seen, compared with the baseline, i.e., BART_CONT with a 88.6 average score, our E2S2-BART models consistently achieve better performance across all ratios of λ_de and λ_cl, basically indicating that the performance of E2S2 is not sensitive to these factors. More specifically, the case of λ_de = 0.05 and λ_cl = 0.1 performs best, and we thereby use this setting in our experiments.

3) Effectiveness of Prompt Learning: As mentioned above, the design of prompt template is the key challenge of prompt-based learning [20]. To further analyze the influence of different prompts for our E2S2 models, we conduct comparative experiments on 6 manual templates. The prompt templates and their corresponding results are shown in Table VII.

Similar to the previous works [31, 68], different prompt templates achieve varied performance. In particular, the simple templates, e.g.“[MASK] means [X].”, perform worse than

TABLE VI
ANALYSIS OF DIFFERENT PRETRAINING OBJECTIVES USED IN E2S2 ((L_nll, L_nll, L_de, L_cl)), EVALUATED ON SOME REPRESENTATIVE TASKS

| L_nll | L_nll | L_de | L_cl | CoLA | MRPC | STS-B |
|-------|-------|------|------|------|------|-------|
| M1    | ✔     | ✔    | ✔    | 60.4 | 90/38.77 | 87.4/87.0 |
| M2    | ✔     | ✔    | ✔    | 63.6 | 91.9/89.1 | 88.8/88.8 |
| M3    | ✔     | ✔    | ✔    | 61.6 | 90.6/88.9 | 90.0/88.7 |
| M4    | ✔     | ✔    | ✔    | 61.1 | 91.1/88.5 | 89.5/89.9 |
| M5    | ✔     | ✔    | ✔    | 64.0 | 92.2/89.5 | 89.5/89.9 |

The bold values indicate best results.

Fig. 5. Parameter analyses of λ_de and λ_cl. We train the E2S2-BART_JoBA models with different coefficient combinations, and evaluate on the dev sets of GLUE benchmark.

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the other sophisticated templates, indicating the importance of manual template engineering. More specifically, the last prompt T6 performs best among all designed prompts, thus adopting it as the default setting. It is also noteworthy that manual template engineering is usually time-consuming and may fail to design optimal prompts, as the above prompts mostly fall short in the GEC task. The automated template learning, which can create the actual text prompts or continuous soft prompts automatically, could address the above problems efficiently [34], [68]. More potential prompt engineering will be explored in our future works.

F. Discussion and Analysis

1) Compatibility With Other seq2seq PLMs: As aforementioned, we show the effectiveness of our E2S2 strategy on BART model. To further prove the universality of our proposed strategy, we examine whether the strategy is compatible with other seq2seq PLMs. Specifically, we apply E2S2 strategy to another popular seq2seq PLM, i.e., T5-base [4]. Similar to the pretraining settings in E2S2-BART, we continue pretraining the original T5 model using E2S2-variant strategies and denote the obtained models as “E2S2-T5_*”. E2S2-based T5 models are evaluated on several GLUE sub-tasks and the results are listed in Table VIII.

Compared with the baselines T5_Rt and T5_CONT, our E2S2-T5 models achieve consistent performance improvements on these tasks, where the improvements on MRPC and STS-B tasks are +2.5% and +1.4%, respectively. These results demonstrate that our E2S2 is not only beneficial to BART model, but also works well on T5 model. Takeaway: Our proposed E2S2 strategy is universal and can be applied to more seq2seq PLMs.

2) is E2S2 Still Helpful When Training From Scratch?: In the above experiments, we trained the E2S2-BART/T5 models in the continual pretraining manner, i.e., based on a warm start from BART/T5. Some readers may concern that adding objectives in the E2S2 could affect the stability of regular pretraining and may wonder whether our E2S2 still be helpful when training from scratch. To address this concern, we further adopt our E2S2 into the regular pretraining phase (started from random weights) of BART-base[12], and report the contrastive results in Table IX. Notably, we do not adopt the E2S2-BART_JoBa here, as our focus is to investigate the influence of adding objectives (denoising and contrastive objectives), rather than the prompting method.

As seen, compared to the vanilla pretraining method, both of our E2S2 methods bring consistent and significant performance improvements, proving that adding our proposed objectives in the regular pretraining phase is still helpful. We attribute this to the complementarity between these adding objectives and original reconstruction objective in BART [3], as our E2S2 aims to encourage the encoder to learn better representations that are helpful for the decoder to reconstruct the sentences. Takeaway: Our E2S2 is still helpful when training the models from scratch.

3) Are the Encoder Indeed Enhanced?: As stated in Section I, the goal of E2S2 is to enhance the encoder of seq2seq PLMs, so that the encoder can provide more discriminative representations and be beneficial to the understanding and generation of natural language. To explore whether the goal is achieved, we conduct experiments on the encoder itself with the probing tasks [69] to evaluate the effect of learning representations of the encoder. The probing tasks aim to study the simple linguistic properties of sentences, which can be classified into three groups: a) “Surface”: used to evaluate the simple surface properties; b) “Syntactic”: used to quantify the syntactic reservation ability; c) “Semantic”: used to analyze the deeper semantic representation ability. Following Hao et al. [70], we introduce an MLP classifier on the encoder side and train the classifier on the train sets of probing tasks. For reference, we that consists of the dropped-out spans, delimited by the sentinel tokens used to replace them in the input. You can refer to the original paper [4] for more details.

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also compare our E2S2 method with the other two widely-used representation learning methods, i.e., SimCSE [29] and PromptBERT [31]. In practice, we basically follow the unsupervised training processes in the original papers to improve the encoder of BART, except that we use the average output of the last hidden layer as the sentence representation during the SimCSE training. The contrastive results on dev sets of these probing tasks are listed in Table X. As seen, compared with the vanilla seq2seq pretraining, our E2S2 method achieves better performance on all probing tasks, with an averaged gain of +1.25%. Moreover, we can see that our E2S2 achieves comparable or even better performance against the powerful SimCSE and PromptBERT methods that have been widely proved to effectively improve the sentence representations of encoder. These results can prove the superiority of our method. Takeaway: The proposed E2S2 strategy enables the encoder to learn better sentence representations that preserve more surface, syntactic and semantic knowledge.

V. CONCLUSION

In this paper, we propose an encoding-enhanced seq2seq pretraining strategy (E2S2) to improve the vanilla seq2seq pretrained models. Instead of only optimizing the text infilling objective on the decoder side, E2S2 presents two self-supervised pretraining objectives in a local-to-global manner, i.e., locally denoising the corrupted sentences and globally learning better sentence representations, on the encoder side to provide richer supervisions. With the help of these self-supervised information, the encoder is able to effectively distinguish the noise tokens and capture high-level (i.e., syntactic and semantic) knowledge, thus boosting the performance of the seq2seq model on both language understanding and generation tasks. Experiments show that E2S2 improves the seq2seq models on several tasks consistently, especially on the GLUE benchmarks and grammatical error correction. These results demonstrate the effectiveness and universality of our E2S2.

Future work includes validating the E2S2 on larger seq2seq PLMs, e.g., T5-11B [4], and integrating the automated prompt template [68] or soft prompt learning [34] to our E2S2 method. Additionally, it is also interesting to validate the effectiveness of E2S2 on more challenging downstream tasks, e.g., translation, in the future. Our work provides a new view of the seq2seq language model pretraining and we hope it can foster future self-supervision research in this field.

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13Considering that our E2S2 is a plug-and-play method, we believe that applying our method to larger cutting-edge models has the potential to achieve much better performance on the GLUE benchmark. However, due to the limited compute resources, we do not experiment on these large language models in this paper.

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