KnowDA: All-in-One Knowledge Mixture Model for Data Augmentation in Few-Shot NLP

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Abstract

This paper focuses on text data augmentation for few-shot NLP tasks. The existing data augmentation algorithms either leverage task-independent heuristic rules (e.g., Synonym Replacement) or fine-tune general-purpose pre-trained language models (e.g., GPT2) using a small training set to produce new synthetic data. Consequently, these methods have trivial task-specific knowledge and are limited to yielding low-quality synthetic data for weak baselines in simple tasks. To combat this issue, we propose Knowledge Mixture Data Augmentation Model (KnowDA): an encoder-decoder LM pretrained on a mixture of diverse NLP tasks using Knowledge Mixture Training (KoMT). KoMT is a training procedure that reformulates input examples from various heterogeneous NLP tasks into a unified text-to-text format, and employs denoising objectives in different granularity to learn to generate partial or complete samples. With the aid of KoMT, KnowDA could combine required task-specific knowledge implicitly from the learned mixture of tasks and quickly grasp the inherent synthesis law of the target task through a few given instances. To the best of our knowledge, we are the first attempt to scale the number of tasks to 100+ in multi-task co-training for data augmentation. Extensive experiments show that i) KnowDA successfully improves the performance of Albert and Deberta by a large margin on the FewGLUE benchmark, outperforming previous state-of-the-art data augmentation baselines; ii) KnowDA could also improve the model performance on the few-shot NER tasks, a held-out task type not included in KoMT.

1 Introduction

Neural NLP models require extensive supervised training data to achieve superior performance [1]. However, due to the enormous cost of annotating data, developers could only use limited labeled data for training in common real-world uses of neural NLP models. This problem has attracted considerable attention from the research community, formalized as few-shot learning. Many researchers [2–4] resort to data augmentation techniques to generate more synthetic samples to boost the learning of the target few-shot tasks.

The existing text data augmentation algorithms either leverage task-independent heuristic rules, such as Synonym Replacement [5] and Random Swap [6], or fine-tune general-purpose pre-trained language models, such as GPT2 [7] in LAMBADA [8] and T5 [9] in PromDA [3], using small training set to produce new synthetic data. Consequently, these data augmentation algorithms

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have trivial task-specific knowledge. They are limited to yielding low-quality synthetic data (e.g.,
either irrelevant or extremely similar to the training data) for simple tasks (e.g., single-sentence
classification), preventing them from practical usage for few-shot learning. Very recent work [4]
demonstrates the above methods perform even worse on tasks with complicated structures (e.g.,
SuperGLUE [10]).

The research community has accumulated a large amount of various human-annotated datasets.
Naturally, our idea is that by using these supervisions to teach an LM the synthesis patterns of various
tasks, the LM will learn to generate task-related data examples merely from a given few shots of the
target task. However, we have the following major obstacles to train such a unified data generator
across these datasets. The existing artificial NLP datasets have a variety of complex structures (e.g.,
sentence pairs classification, multiple-choice QA). There have been some successes [11, 12] in using
hard prompts for multi-task scaling to only improve the NLP task solving performance (i.e., only
generating correct output results). When adapting to the data augmentation scenarios, it becomes
increasingly difficult: producing a synthetic instance often requires generating multiple elements
in succession. For example, in the task of Machine Reading Comprehension (MRC), we need to
generate a document, question, and answer sequentially. More human-crafted prompts than the
aforementioned work are needed.

To overcome these challenges, we represent data examples from various heterogeneous NLP tasks
with a unified key-value list format where the key is typically a short phrase indicating the feature
function and the value is a string representation of the feature content. Unlike previous unified
multi-task learning works (e.g., CrossFit [13] and FLAN [11]) which only train the model to produce
output labels, we employ denoising objectives in different granularity to simulate the reconstruction
of any part of various NLP task instances. In this way, instead of relying on artificial natural language
instructions, we perform scaling of generative patterns by controlling the masking of different value
combinations in denoising objectives. For example, in the task of MRC, if we simultaneously mask
values of the document, question, and answer, it equals to the natural instruction "generate a whole
MRC example containing document, question, and answer." With the dynamic multi-granularity
masking mechanism and the unified format, we successfully scale Knowledge Mixture Training
(KoMT) of LM to about 100 NLP tasks without much human efforts. After the KoMT, our LM
Knowledge Mixture Data Augmentation Model (KnowDA) is capable of combing acquired knowledge
from the mixture of tasks and quickly adapting to generating synthetic examples from a few shots of
a new target NLP task. In data augmentation of complex tasks, compared to the prior state-of-the-art
approach FlipDA [4] that applies local phrase-level edits over the original training data, KnowDA can
generate brand new samples from scratch, providing more training signals to the downstream models.

For evaluation, we conduct experiments on the challenging SuperGLUE benchmark [14] with 32
training examples. We also verify the effectiveness of KnowDA on two Sequence Labeling tasks,
CoNLL’03 [15] and WikiAnn [16], whose task types are held-out during KoMT. KnowDA successfully
outperforms recently proposed state-of-the-art data augmentation algorithms such as FlipDA and
PromDA [3]. We further compare the quality of generated synthetic data from KnowDA and FlipDA,
confirming that KnowDA produces synthetic data with a higher level of diversity and better quality
verified by humans.

To summarize, contributes of this paper are following:(1) To the best of our knowledge, we are
the first work to scale the number of tasks to 100+ in multitask pretraining for data augmentation;
(2) We propose a novel multitask pre-training approach KoMT for data augmentation, resulting
in a new pre-trained model, KnowDA; and (3) Experiments demonstrate that KnowDA outperforms
state-of-the-art data augmentation methods on the few-shot setting of well-established benchmarks
SuperGLUE, CoNLL’03, and WikiAnn.

2 Method

2.1 Data Augmentation for Few-shot NLP

In the few-shot NLP tasks, only a small amount of labeled training data samples \( T = \{ (x_i, y_i) \}_{i=1}^n \)
are available where \( n \) is relatively small (i.e., less than a hundred). Data Augmentation generates
synthetic data \( T_{Syn} = \{ (\hat{x}_i, \hat{y}_i) \}_{i=1}^m \) from the original labeled training data \( T \) using language models,
where \( m \) is allowed to be much larger than \( n \). The goal is that few-shot NLP models trained using
\( T \cup T_{Syn} \) outperform the ones only trained using \( T \).
2.2 Overview of KnowDA

KnowDA is an encoder-decoder generative language model that generates task-relevant and diverse synthetic data from scratch. It is initialized from an existing pre-trained encoder-decoder language model checkpoint that is already trained on large unlabeled corpus utilizing self-supervised learning. We further apply Knowledge Mixture Training (Sec. 2.3) to inject diverse NLP task-specific knowledge into KnowDA. Finally, we either fine-tune KnowDA using few-shot training data or directly inference from KnowDA to produce synthetic data used to boost up the performance of strong NLP baseline models (Sec. 2.4).

2.3 Knowledge Mixture Training

To recap, previous data augmentation methods lack task-specific knowledge. Currently, the research community has accumulated a large amount of various human-generated datasets. Our idea is to use these supervisions to teach an LM the synthesis patterns of various tasks. The resulting LM should learn to generate task-related data examples merely from a given few shots of the target task. However, existing artificially generated NLP tasks have a variety of complex structures (e.g., sentence pairs classification, multiple-choice QA) that makes learning a unified data generator quite challenging. We convert the generation of data examples from various heterogeneous NLP tasks into a unified text-to-text format and employ denoising objectives in different granularity to simulate the reconstruction of partial or whole instances. We call this training paradigm Knowledge Mixture Training (KoMT). We will elaborate on KoMT in detail in this section from three aspects: task Collection, unified text-to-text format, and the denoising objectives.

Task Collection The success of KoMT is built upon a resource with a sufficient number of tasks, covering a diverse range of NLP applications. Similar to [17], we select English monolingual datasets with open access in the Huggingface Datasets [18]. The tasks in KoMT broadly belong to the following task families: Text Classification, Natural Language Inference, Reading comprehension, Question Answering, Summarization, and other NLP applications. When we random sample examples from the mixture of tasks, examples from each task are sampled proportionate to the individual dataset’s size. To balance tasks with various sizes, at most 300k instances are sampled from a single task during KoMT.

Figure 1: A running example of the masked training instances in the Knowledge Mixture Training. Keywords within the brackets are the task key.

Unified Text-to-Text Format Although there are many NLP tasks with various structures, all of these tasks include one or more input features and an output result. For example, we have an input sentence/paragraph/document and an output label in the sentence classification tasks. Each
feature, including the output result, could be described as a key-value pair. The key is typically a short phrase indicating the feature function, and the value is a string representation of the feature content. That is, given an instance \((x_i, y_i)\) from arbitrary NLP tasks, we could always represent it as a unified key-value list format (length \(n\)): \((x_i, y_i) = [(k^1_i, v^1_i), \ldots, (k^n_i, v^n_i)]\) where each \((k^j_i, v^j_i)\) either corresponds to an input feature or the output result \(y_i\). Unlike previous works \[11, 12\] requiring exhausting human-crafted prompts to perform multi-task scaling, our key-value design only needs the feature name in the original NLP dataset. Therefore, our proposed unified format could quickly extend KoMT to arbitrary tasks without much human effort. To further exploit the given few shots, we add a demonstration section in our text-to-text format like GPT-3. As shown in Figure 1, we add exemplars without any value masking in the demonstration section, which are randomly sampled from the identical tasks. This follow-up design has the following benefits: a) We hope demonstrations enable \(\text{KnowDA}\) to recover the semantics of the task in context at test time even when the target task shares less similarities with tasks trained during the KoMT stage. b) When \(\text{KnowDA}\) needs to produce a brand new training example from scratch, demonstrations could aid \(\text{KnowDA}\) in recognizing the target task’s distribution.

### Denoising Objectives

Based on the unified key-value list format, our denoising objective is defined as follows: given each instance \((x_i, y_i)\), we randomly mask K values in the key-value list, where number K is sampled from range [1 to \(n\)] with equal probability and \(n\) is the total number of key-value pairs. Then, \(\text{KnowDA}\) is trained with the objective to reconstruct those masked values using the remaining information. In addition, we will prepend \(L\) examples as demonstrations in the front of the input to \(\text{KnowDA}\) during KoMT, where \(L\) is sampled from the range [0 to \(m\)] with equal probability and \(m\) is the hyperparameter of how many demonstrations to put at most. Figure 1 shows two masked training instances from the CB task \[19\] where Premise and Hypothesis are input features and Tag is the output result. This unified format only requires simple cross-entropy loss, avoiding extra task-specific effort for losses design, loss scaling, or explicit gradient accumulation \[20\]. This strategy trains \(\text{KnowDA}\) to reconstruct NLP task instances from multiple granularities, potentially satisfying different needs in the data augmentation tasks. Our dynamic random masking mechanism also encourages \(\text{KnowDA}\) to fully use the task-specific keys and demonstration examples. When most of the values are masked for prediction, they are the only reliable information for \(\text{KnowDA}\) to generate meaningful synthetic data. For example, in Figure 1 when both “Premise” and “Hypothesis” are masked, \(\text{KnowDA}\) could only obtain task-relevant information from keys and demonstrations.

#### 2.4 Generating Synthetic Data Using \(\text{KnowDA}\)

After KoMT, \(\text{KnowDA}\) could be further adapted to generate synthetic data for specific NLP tasks. To create an instance \((x_i, y_i)\) from scratch, we first analyze its feature dependency, then deploy different generation strategies for input features \(x_i\) and output result \(y_i\).

### Feature Dependency in the NLP Tasks

Different NLP tasks have various dependencies for input features. For example, as shown in Figure 2 in the task of Adversarial QA \[21\], the question is conditioned on the context, and the answer is conditioned on the context and question. We follow a task-specific dependency structure and start with the beginning feature without any pre-requirements. We generate context, question and answer sequentially. Figure 2 also shows the input for each step. Similar to PromDA \[4\], we use separated copy of \(\text{KnowDA}\) to generate different features to ensure the synthetic data diversity in the few-shot setting. Detailed data augmentation process for each evaluation task used in this paper can be found in Appendix A.5

![Figure 2: Feature Dependency in the task of Adversarial QA.](image-url)
**Text Generator — Generating input text**  As discussed in Sec. 2.3, \( v_i \) in an NLP instance could correspond to a list of key-value pairs \([(k_1^i, v_1^i), \ldots, (k_n^i, v_n^i)]\). For short \( v_i^j \) (e.g., less than 250 tokens), directly fine-tuning KnowDA with the few-shot training data is a straightforward solution. However, it is very challenging to handle long \( v_i^j \). Previous work [22] finds that existing state-of-the-art pre-trained language models still struggle to produce coherent long sequence outputs. We also observe similar issues in the preliminary experiments: naively fine-tuning KnowDA with the few-shot training data often leads to low-quality outputs. Instead, we find it beneficial for KnowDA to generate long values in zero-shot learning. That is, without any further training KnowDA with the few-shot data, we directly use the KnowDA checkpoint to generate the long values. To control the output value content and style to be close to the few-shot data, we use relevant keys (e.g., using Premise for RTE) and the full demonstration examples from the few-shot data as the input to the KnowDA.

**Task Solver — Generating output label**  An excellent synthetic instance simultaneously requires high-quality input features and correct output labels. The denoising objectives with a mixture of granularities enable KnowDA to have the ability to *generate* any part of an example. We find that if we only mask the value of the output result at test time (i.e., the left-masked instance in Figure[1]), KnowDA could act as a well *task solver* and achieve substantial few-shot language understanding performance (details please refer to Sec. 3.5.1). To maintain balance between data generation and task solver performance, we adjust the random masking strategy in KoMT to provide an equal opportunity to train KnowDA as a task solver and input text generator over large NLP task knowledge. During data augmentation, after the texts of all input features are generated, we make use of KnowDA, as a *Task Solver*, to assign the output results to the synthetic data. Specifically, we fine-tune another copy of KnowDA using few-shot training data which only output values are masked to predict.

### 3 Experiments

We first show the effectiveness of KnowDA, as a *Data Generator*, in the following settings: FewGLUE and few-shot NER tasks in Sec 3.2 and 3.3. We also show the performance of KnowDA, as *Task Solver*, in Sec 3.4. Finally, we conduct an in-depth analysis of KnowDA in Sec 3.5.

#### 3.1 Experimental Setup

In this paper, we conduct experiments on the FewGLUE [14] (i.e., a few-shot version of SuperGLUE [23]), CoNLL’03 [15] and WikiAnn [16] benchmarks. When preparing training data for KoMT, to avoid any form of data leakage, we exclude all SuperGLUE tasks from KoMT. We further filter out any training instances containing SuperGLUE train/dev/test input features in KoMT. To verify KnowDA’s ability to handle tasks with novel types, KoMT does not include any sequence labelling tasks. Finally, 114 diverse NLP tasks (See Appendix A.2 for details) are selected for KoMT. KnowDA is initialized from the T5-Large model [9]. We train KnowDA for 100k steps with a maximum sequence length of 512 and batch size 2048 in a Linux environment with 16 × A100 GPU (32G). Fine-tuning KnowDA for NLU and data augmentation are carried out only using a single A100 GPU (32G). We use Adam as the optimizer to train KnowDA. More details see Appendix A.1.

#### 3.2 Data Augmentation On FewGLUE

We use FewGLUE to evaluate KnowDA’s ability on few-shot data augmentation. Each challenging FewGLUE task only has 32 labeled instances.

**Setting**  Following the settings in FlipDA [4], we take PET [14], which is the state-of-the-art prompt-based few-shot learning algorithm, as the Baseline. We compare KnowDA with SR [5], EDA [24], T5-MLM [4], and FlipDA [4]. The PET templates and random seeds are identical to FlipDA. For each FewGLUE task, given the few-shot training data, KnowDA first generates a set of synthetic data which is combined with the few-shot training data and further fed into the PET Baseline model.

**Result**  By adding KnowDA’s synthetic data, the PET baseline models are improved in 7 out of 8 FewGLUE tasks, with an averaged improvement being 5.28 and 4.14 in the ALBERT and DeBERTa
baseline models, respectively. On average, KnowDA outperforms previous state-of-the-art FlipDA by 1.75 and 1.25 on the PET ALBERT and DeBERTa models, respectively. KnowDA consistently exceeds FlipDA on 5 out of 8 tasks, which include QA (BoolQ, MultiRC), NLI (RTE, CB), and Word Sense Disambiguation (WiC). This shows that KoMT is capable of transferring prior task-specific knowledge to similar tasks (i.e., QA, NLI), as well as novel tasks (i.e., Word Sense Disambiguation). Finally, KnowDA performs worse than FlipDA in the task of COPA and ReCoRD. This could be because KnowDA is unable to produce sufficient correct output labels for these two tasks (See results in Table 3.5.1).

Table 1: Performance of Baseline and KnowDA on FewGLUE with ALBERT-xxlarge-v2 model.

| Method | BOOLQ Acc. | RTE Acc. | CB. Acc./F1 | WiC Acc. | WSC Acc. | MultiRC Acc. | EM/F1 | COPA Acc. | ReCoRD Acc. | ReCoRD Acc./F1 | avg |
|--------|------------|----------|-------------|----------|----------|--------------|-------|-----------|-------------|---------------|-----|
| Baseline | 72.47      | 61.40    | 82.74/74.84 | 51.27    | 77.03    | 33.04/74.64  | 88.33 | 86.19/86.75 | 71.20        |
| SR      | 74.98      | 59.24    | 83.33/78.12 | 51.25    | 78.74    | 34.09/75.55  | 87.50 | 85.63/86.12 | 71.64        |
| EDA     | 72.68      | 58.33    | 81.10/73.58 | 51.81    | 75.85    | 28.74/73.05  | 84.50 | 85.39/85.95 | 69.63        |
| T5-MLM  | 73.86      | 62.27    | 83.48/75.01 | 51.08    | 79.17    | 33.79/74.06  | 87.33 | 85.15/85.69 | 71.54        |
| FlipDA  | 76.98      | 70.67    | 86.31/82.45 | 54.08    | 79.17    | 33.79/74.06  | 87.33 | 85.15/85.69 | 71.54        |
| KnowDA  | 78.18      | 78.70    | 89.58/85.39 | 55.85    | 77.88    | 36.82/76.23  | 89.17 | 86.43/86.97 | 74.63        |

Table 2: Performance of Baseline and KnowDA on FewGLUE with DeBERTa-v2-xxlarge model.

| Method | BOOLQ Acc. | RTE Acc. | CB. Acc./F1 | WiC Acc. | WSC Acc. | MultiRC Acc. | EM/F1 | COPA Acc. | ReCoRD Acc. | ReCoRD Acc./F1 | avg |
|--------|------------|----------|-------------|----------|----------|--------------|-------|-----------|-------------|---------------|-----|
| Baseline | 78.30      | 81.95    | 85.42/79.31 | 58.74    | 80.13    | 40.40/78.14  | 87.67 | 90.24/90.77 | 77.37        |
| SR      | 77.37      | 76.29    | 87.20/80.28 | 58.88    | 80.88    | 35.70/76.25  | 87.00 | 89.06/89.55 | 76.18        |
| EDA     | 74.42      | 77.38    | 83.63/76.23 | 59.28    | 78.74    | 37.02/77.05  | 85.83 | 88.11/88.60 | 75.12        |
| T5-MLM  | 77.39      | 81.23    | 83.04/73.71 | 60.73    | 82.37    | 35.02/74.98  | 88.17 | 89.71/90.25 | 76.66        |
| FlipDA  | 81.8       | 83.75    | 88.24/87.54 | 65.13    | 78.85    | 44.18/80.00  | 90.83 | 91.02/91.56 | 80.26        |
| KnowDA  | 83.87      | 86.76    | 92.11/89.16 | 66.54    | 79.49    | 46.76/81.25  | 90.67 | 89.71/90.27 | 81.51        |

3.3 Data Augmentation For Sequence Labeling Tasks

In Sec. 3.2, KnowDA shows success in handling NLP tasks whose types are included in KoMT. We further verify its effectiveness in the Sequence Labelling Tasks which are excluded from KoMT.

Setting Following [3], we take BERT-base [25] as the few-shot baseline. We compare with several strong data augmentation models, including SDANER [26], LAMBADA [8], MetaST [27] and PromDA [28]. PromDA is the previous state-of-the-art model for sequence labelling tasks. We conduct the shot-10 setting where 40 samples for CoNLL’03 and 30 samples for WikiAnn. We run KnowDA 5 times with different random seeds and few-shot data splits and report the averaged results in Table 3.5. Given the few-shot training data, KnowDA first generates a set of synthetic data, which is combined with the few-shot training data and further fed into the BERT-base model. As discussed above, when conducting data augmentation, KnowDA generates input features and output results separately. Surprisingly, we find that feeding KnowDA’s synthetic data back to itself could further improve KnowDA’s labeling performance. We, thus, use this improved Task Solver to produce better synthetic data, iteratively. Table 4 shows the labeling performance of KnowDA (as Task Solver) and BERT at each iteration. We iterate this process 4 times in total. More details see Appendix A.4.

Result Table 3 illustrates BERT labeling performance on the CoNLL’03 and WikiAnn Benchmark after using synthetic data from various DA methods. Compared to the BERT baseline models, BERT with KnowDA’s synthetic data achieves 12.9 and 16.1 F1 score improvements. Compared to the state-of-the-art PromDA method, KnowDA’s synthetic data gains an improvements of 7.8 points and 8 points on CoNLL’03 and WikiAnn, respectively. Both PromDA and KnowDA are based on the T5-Large checkpoints. The major difference is that PromDA only receives task-agnostic pre-training on a sub-set of C4 corpus [9], while KnowDA receives KoMT. This implies the effectiveness of using NLP prior task knowledge for data augmentation. As for the iteration results in Table 4, adding
KnowDA’s synthetic data substantially improves the labeling performance of KnowDA (as Task Solver) and BERT (i.e., $T_0$ vs. $T_1$). Both models are further improved as the iteration continues. Noticeably, feeding KnowDA’s synthetic data to itself could further strengthen its labeling performance from 80.1 to 85.0 and 62.5 to 64.9 in the CoNLL’03 and WikiAnn benchmark, respectively. This indicates that we could potentially conduct complicated self-train to KnowDA in the future work.

Table 3: Performance of DA on the sequence labeling benchmarks.

| Method   | CoNLL’03 | WikiAnn |
|----------|----------|---------|
| BERT-base| 72.5     | 50.2    |
| SDANER   | 72.9     | 51.7    |
| LAMBADA  | 75.0     | 52.9    |
| MetaST   | 76.7     | 56.6    |
| PromDA   | 77.5     | 58.3    |
| KnowDA   | 85.4     | 66.3    |

Table 4: Iteration Labeling Performance for KnowDA and BERT.

| Iter. | CoNLL’03 | WikiAnn |
|-------|----------|---------|
| $T_0$ | 80.1     | 72.5    |
| $T_1$ | 83.0     | 84.0    |
| $T_2$ | 84.9     | 84.8    |
| $T_3$ | 84.9     | 85.1    |
| $T_4$ | 85.0     | 85.4    |

3.4 Few-shot Task Solver

As discussed in Section 2.4, KnowDA is capable to generate output results given all input information. In this section, we show the performance of KnowDA, as Task Solver, on FewGLUE. As every task in FewGLUE is NLU task, we refer the performance as “NLU performance” below.

Setting For each FewGLUE task, we train a separated copy of KnowDA on the few-shot 32 training instances. We fine-tune KnowDA for 20k steps with batch size 12. Table 5 shows the performance of KnowDA and other baselines, including original T5-Large, PET ALBERT and PET DeBERTa.

Table 5: Performance of KnowDA on FewGLUE NLU tasks. PET (D) is based on DeBERTa-v2-xxlarge and PET (A) is based on ALBERT-xxlarge-v2.

| Method   | BOOLQ Acc. | RTE Acc. | CB. Acc./F1 | WiC Acc. | WSC Acc. | MultiRC EM/F1a | COPA Acc. | ReCoRD Acc./F1 | avg     |
|----------|------------|----------|-------------|----------|----------|----------------|-----------|----------------|---------|
| T5-large | 74.43      | 64.26    | 94.63/93.02 | 56.27    | 73.08    | 24.34/70.77    | 76.00     | 77.51/78.22    | 71.14   |
| PET (A)  | 72.47      | 61.40    | 82.74/74.84 | 51.27    | 77.03    | 33.04/74.64    | 88.33     | 86.19/86.75    | 71.20   |
| PET (D)  | 78.30      | 81.95    | 85.42/79.31 | 58.74    | 80.13    | 40.40/78.14    | 87.67     | 90.24/90.77    | 77.37   |
| KnowDA   | **79.72**  | **88.45** | **96.43/94.30** | **60.34** | **80.77** | **43.55/81.51** | **84.00** | **74.63/75.17** | **78.08** |

Result The original T5-large model only achieves similar performance as PET (A) which is roughly three times smaller (~223M vs. ~770M) and under-performs PET (D) by more than 6 points on average. However, after KoMT, KnowDA outperforms PET (D) by 0.71 on average, indicating that KoMT successfully integrates diverse NLP task-specific knowledge into KnowDA. As for individual tasks, KnowDA has clear advantages in the QA (i.e., BoolQ, MultiRC) and NLI (i.e, RTE, CB) tasks because KoMT includes similar types of tasks. KnowDA also outperforms the original T5-Large model in WIC and WSC task by 4.07 and 7.69. WIC and WSC are word sense and co-reference tasks. However, they are not included in KoMT. This shows that KoMT not only transfers knowledge between similar tasks, but also enables KnowDA to handle new types of tasks. We notice that KnowDA only lags behind the PET and T5-Large models on the ReCoRD task by a large margin. As ReCoRD requires the models to fill placeholder using entity candidates, this task could largely rely on the massive self-supervision training (e.g., masked token restruction). After large-scale KoMT, KnowDA may lost partial fill-in-the-blank ability due to catastrophic forgetting.

3.5 Discussion

In this section, we conduct an in-depth analysis of KnowDA. We investigate the impact of key choices and demonstrations for KnowDA when acting as Data Generator and Task Solver in Sec. 3.5.1. We further compare the synthetic data generated by KnowDA with the one from FlipDA in Sec 3.5.2.
3.5.1 Task Knowledge Transfer

KoMT has two important components to transfer task knowledge: 1) Task-specific key list; 2) Full demonstration examples. In this section, we will verify the impact of key choices and demonstration in the context of data augmentation and NLU Task Solver.

Data Augmentation To show the importance of key choices and demonstrations, we choose the challenging RTE and CB tasks, which involve unsupervised long document generation steps. The best template for RTE and CB long document generation is “Premise <MASK>” and “Text <MASK>”, respectively. In the Replace T., we replace the key Premise with Context in RTE and replace the key Text with Document in CB. We generate separated sets of synthetic data under three settings (Replace T., w/o Demonstrations, and both). We follow the settings in Table 1 and feed these sets of synthetic data into the PET ALBERT model separately. Figure 3 shows that both key and demonstrations have a considerable impact on the generated synthetic data: RTE drops up to 6.1% accuracy, and CB F1 score drops up to 8.7. Notably, the impact of key is larger than the demonstrations in the RTE task, while this is opposite in the CB task. We hypothesize that this could be because keys and demonstrations activate different knowledge from KnowDA, which have different impacts on the downstream tasks. This is further confirmed by the fact that applying both changes would further negatively impact the PET ALBERT model performance.

Task Solver Next, we examine whether key choices and demonstrations have a similar impact on the KnowDA’s NLU performance on the RTE and CB tasks. When KnowDA acts as a Task Solver, the best template for both tasks is: “Answer: <MASK> Hypothesis: [hypothesis] Premise: [premise]”. In the Replace T., we replace Premise with Precondition in the RTE task and replace Premise with Suppose in the CB task. We follow the settings in Table 5 and directly fine-tune KnowDA using the few-shot RTE and CB training data. Figure 3 shows a similar trend as we have seen in the data augmentation experiments: the accuracy of KnowDA RTE model drops by 2.2 points and 5.1 points, respectively; the F1 score of KnowDA CB model drops by 6.5 points and 2.7 points, respectively.

In summary, keys and demonstrations have similar and positive impacts to KnowDA in both data augmentation and NLU tasks. They effectively transfer appropriate and different prior task-specific knowledge to the ongoing task.

3.5.2 Synthetic Data Quality Analysis

Table 1 and 2 have confirmed that the synthetic data from KnowDA can effectively improve few-shot baseline ALBERT and DeBERTa in FewGLUE. We further examine the quality of generated synthetic data from KnowDA and compare that with FlipDA, including diversity analysis and human evaluation.

Table 6: Diversity analysis on Synthetic Data.

| Model   | Self-BLEU | Novel Entity |
|---------|-----------|--------------|
| FlipDA  | 67.9      | 758.5        |
| KnowDA  | 44.0      | 1048.3       |

Figure 4: Human Evaluation Results.
Diversity Analysis We compare the diversity of the generated synthetic data from KnowDA and FlipDA. We sample 200 synthetic data from each FewGLUE task. Following [3], we calculate Novel Entity (i.e., number of entity mentions or keywords not appearing in the training data) and Self-BLEU score [29] for each FewBLUE task separately. We report the averaged score across all tasks to quantify the overall synthetic data diversity. As shown in Table 6, synthetic data from FlipDA is less diverse than the one from KnowDA. Its Self-BLEU score increases from 44.0 to 67.9, and Novel Entity score decreases from 1048.3 to 758.5. This could explain the advantages of KnowDA in the FewGLUE benchmark because it provides more training signals to the downstream models.

Human Evaluation We further conduct human evaluation to analyze the quality of the synthetic data. We sample 50 instances from ground-truth training data (GT), KnowDA’s synthetic data (KnowDA), and FlipDA’s synthetic data (FlipDA) in each FewGLUE task, resulting in 1200 samples in total. We mask the data source of these samples and assign them to three annotators who are only told that there are slightly more machine-generated samples than human-generated ones. They are asked to judge whether each sample is generated by humans. Figure 4 shows the human evaluation results. 85% of GT are correctly classified, which shows that it is relatively easy to identify the human-generated samples. 67.1% of KnowDA’s synthetic data are identified as human-generated samples, while this number decreases to 42.1% for FlipDA’s synthetic data. This clearly exhibits that, compared to FlipDA, the synthetic data from KnowDA are more similar to the human-crafted data.

4 Related Work

Data Augmentation for Few-Shot NLP We divided data augmentation methods for few-shot NLP into two categories according to the complexity of the tasks that need to be augmented. The works of the first category focus on simple tasks, e.g., single-sentence classification and sequence labeling task that only has one sentence as input, and one sequence as output. Early, researchers propose word substitution based methods such as KNN replacement [30,31], Synonym Replacement [5], TF-IDF replacement [32] and EDA [24] integrated with multiple base replacements. Later, large generative models have been used for data augmentation, such as back translation [33,34] utilizes machine translation models to synthesize new data samples, LAMBADA [8] finetunes a GPT-2 model to generate augmented data, GPT3Mix [35] uses GPT-3 along with hard prompting to yield augmented examples, PromDA [3] leverages soft prompting to perform efficient learning from few shots. The previous work [4] demonstrates that these methods are hard to generate proper synthetic data for tasks with more complicated structures (e.g., SuperGLUE). Another line of few-shot data augmentation is exploring augmentating tasks with complicated structures (i.e., long sequences or multiple sentences). FlipDA [4] has conducted preliminary attempts on these tasks by applying local phrase-level edits over the original training data. Our method also make efforts on this setting. The main difference between KnowDA and FlipDA lies in that our KnowDA could generate the whole augmented examples from scratch.

Multi-task Pre-training A series of recent works (e.g., T5 [9], MT-DNN [36], FLAN [37], T0 [12], Ext5 [38], and ZeroPrompt [39]) have demonstrated that adding a large amount of supervision to the pre-trained language models could further improve the performance. Our model is broadly inspired by this long line of prior work on multi-task co-training. However, there are the following main differences. First, we focus on utilizing more human-annotated training datasets to learn how to generate synthetic samples of a given task rather than just learning how to complete the task. Second, most of the prior works rely on the human-crafted task-specific hard prompt as the unified format to do a multi-task pre-training. Our unified format only uses the attribute names from original data samples, allowing the KoMT to scale to as many tasks as possible easily.

5 Conclusion and Future Work

This paper explores multi-task learning paradigms at a massive scale for data augmentation in few-shot language learning for the first time. We demonstrate that the proposed Knowledge Mixture training enables pre-trained language models the capability of generating proper synthetic instances from scratch for complicated tasks (i.e., the data sample has long sequences or multiple sentences). Experiments verified the effectiveness of our KnowDA, and KnowDA outperforms state-of-the-art data augmentation approaches on well-established benchmarks SuperGLUE, CoNLL’03, and WikiAnn.
in the few-shot setting. We also perform ablation studies indicating the importance of including demonstrations and the impact of different keys. Moreover, increasing the size of multi-task scaling and investigating more advanced training objectives for data augmentation is still a promising direction worthy of long-term exploration.
References

[1] Samuel R. Bowman, Gabor Angeli, Christopher Potts, and Christopher D. Manning. A large annotated corpus for learning natural language inference. In Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing, pages 632–642, Lisbon, Portugal, September 2015. Association for Computational Linguistics.

[2] Varun Kumar, Ashutosh Choudhary, and Eunah Cho. Data augmentation using pre-trained transformer models. arXiv preprint arXiv:2003.02245, 2020.

[3] Yufei Wang, Can Xu, Qingfeng Sun, Huang Hu, Chongyang Tao, Xiubo Geng, and Daxin Jiang. Promda: Prompt-based data augmentation for low-resource nlu tasks. arXiv preprint arXiv:2202.12499, 2022.

[4] Jing Zhou, Yanan Zheng, Jie Tang, Jian Li, and Zhilin Yang. Flipda: Effective and robust data augmentation for few-shot learning. arXiv preprint arXiv:2108.06332, 2021.

[5] Xiang Zhang, Junbo Zhao, and Yann LeCun. Character-level convolutional networks for text classification. In C. Cortes, N. Lawrence, D. Lee, M. Sugiyama, and R. Garnett, editors, Advances in Neural Information Processing Systems, volume 28. Curran Associates, Inc., 2015.

[6] Jason Wei and Kai Zou. EDA: Easy data augmentation techniques for boosting performance on text classification tasks. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 6382–6388, Hong Kong, China, November 2019. Association for Computational Linguistics.

[7] Alec Radford, Jeffrey Wu, Rewon Child, David Luan, Dario Amodei, Ilya Sutskever, et al. Language models are unsupervised multitask learners. OpenAI blog, 1(8):9, 2019.

[8] Ateret Anaby-Tavor, Boaz Carmeli, Esther Goldbraich, Amir Kantor, George Kour, Segev Shlomov, Naama Tepper, and Naama Zwerdling. Do not have enough data? deep learning to the rescue! Proceedings of the AAAI Conference on Artificial Intelligence, 34(05):7383–7390, Apr. 2020.

[9] Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J. Liu. Exploring the limits of transfer learning with a unified text-to-text transformer. Journal of Machine Learning Research, 21(140):1–67, 2020.

[10] Victor Sanh, Albert Raffel, Colin Raffel, Stephen Bach, Lintang Sutawika, Zaid Alyafeai, Antoine Chaffin, Arnaud Stiegler, Arun Raja, Manan Dey, M Saiful Bari, Canwen Xu, Urmish Thakker, Shanya Sharma Sharma, Eliza Szczechla, Taewoon Kim, Gunjan Chhablani, Nihal Nayak, Debajyoti Datta, Jonathan Chang, Mike Tian-Jian Jiang, Han Wang, Matteo Manica, Sheng Shen, Zheng Xin Yong, Harshit Pandey, Rachel Bawden, Thomas Wang, Trishala Neeraj, Jos Rozen, Abheesht Sharma, Andrea Santilli, Thibault Fevry, Jason Alan Fries, Ryan Teehan, Teven Le Scao, Stella Biderman, Leo Gao, Thomas Wolf, and Alexander M Rush. Multitask prompted training enables zero-shot task generalization. In International Conference on Learning Representations, 2022.

[11] Qinyuan Ye, Bill Yuchen Lin, and Xiang Ren. Crossfit: A few-shot learning challenge for cross-task generalization in nlp. arXiv preprint arXiv:2104.08835, 2021.

[12] Timo Schick and Hinrich Schütze. It’s not just size that matters: Small language models are also few-shot learners. arXiv preprint arXiv:2009.07118, 2020.

[13] Erik F Sang and Fien De Meulder. Introduction to the conll-2003 shared task: Language-independent named entity recognition. arXiv preprint cs/0306050, 2003.

[14] Xiaoman Pan, Boliang Zhang, Jonathan May, Joel Nothman, Kevin Knight, and Heng Ji. Cross-lingual name tagging and linking for 282 languages. In Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 1946–1958, 2017.
[17] Qinyuan Ye, Bill Yuchen Lin, and Xiang Ren. CrossFit: A few-shot learning challenge for cross-task generalization in NLP. In Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing, pages 7163–7189, Online and Punta Cana, Dominican Republic, November 2021. Association for Computational Linguistics.

[18] Quentin Lhoest, Albert Villanova del Moral, Yacine Jernite, Abhishek Thakur, Patrick von Platen, Suraj Patil, Julien Chaumond, Mariama Drame, Julien Plu, Lewis Tunstall, Joe Davison, Mario Šaško, Gunjan Chhablani, Bhavityya Malik, Simon Brandeis, Teven Le Scao, Victor Sanh, Canwen Xu, Nicolas Patry, Angelina McMillan-Major, Philipp Schmid, Sylvain Gugger, Clément Delangue, Théo Matussière, Lysandre Debut, Stas Bekman, Pierrick Cistac, Thibault Goehringer, Victor Mustar, François Lagunas, Alexander Rush, and Thomas Wolf. Datasets: A community library for natural language processing. In Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing: System Demonstrations, pages 175–184, Online and Punta Cana, Dominican Republic, November 2021. Association for Computational Linguistics.

[19] Marie-Catherine De Marneffe, Mandy Simons, and Judith Tonhauser. The commitmentbank: Investigating projection in naturally occurring discourse. In proceedings of Sinn und Bedeutung, volume 23, pages 107–124, 2019.

[20] Armen Aghajanyan, Anchit Gupta, Akshat Shrivastava, Xilun Chen, Luke Zettlemoyer, and Sonal Gupta. Muppet: Massive multi-task representations with pre-finetuning. In Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing, pages 5799–5811, Online and Punta Cana, Dominican Republic, November 2021. Association for Computational Linguistics.

[21] Max Bartolo, Alastair Roberts, Johannes Welbl, Sebastian Riedel, and Pontus Stenetorp. Beat the AI: Investigating adversarial human annotation for reading comprehension. Transactions of the Association for Computational Linguistics, 8:662–678, 2020.

[22] Jian Guan, Xiaoxi Mao, Changjie Fan, Zitao Liu, Wenbiao Ding, and Minlie Huang. Long text generation by modeling sentence-level and discourse-level coherence. In Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers), pages 6379–6393, Online, August 2021. Association for Computational Linguistics.

[23] Alex Wang, Yada Pruksachatkun, Nikita Nangia, Amanpreet Singh, Julian Michael, Felix Hill, Omer Levy, and Samuel Bowman. Superglue: A stickier benchmark for general-purpose language understanding systems. Advances in neural information processing systems, 32, 2019.

[24] Jason Wei and Kai Zou. Eda: Easy data augmentation techniques for boosting performance on text classification tasks. arXiv preprint arXiv:1901.11196, 2019.

[25] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. BERT: Pre-training of deep bidirectional transformers for language understanding. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pages 4171–4186, Minneapolis, Minnesota, June 2019. Association for Computational Linguistics.

[26] Xiang Dai and Heike Adel. An analysis of simple data augmentation for named entity recognition. arXiv preprint arXiv:2010.11683, 2020.

[27] Yaqing Wang, Subhabrata Mukherjee, Haoda Chu, Yuancheng Tu, Ming Wu, Jing Gao, and Ahmed Hassan Awadallah. Meta self-training for few-shot neural sequence labeling. In Proceedings of the 27th ACM SIGKDD Conference on Knowledge Discovery & Data Mining, pages 1737–1747, 2021.

[28] Yufei Wang, Can Xu, Qingfeng Sun, Huang Hu, Chongyang Tao, Xiubo Geng, and Daxin Jiang. PromDA: Prompt-based data augmentation for low-resource NLU tasks. In Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 4242–4255, Dublin, Ireland, May 2022. Association for Computational Linguistics.

[29] Yaoming Zhu, Sidi Lu, Lei Zheng, Jiaxian Guo, Weinan Zhang, Jun Wang, and Yong Yu. Texygen: A benchmarking platform for text generation models. In The 41st International ACM SIGIR Conference on Research & Development in Information Retrieval, pages 1097–1100, 2018.

[30] Prashanth Vijayaraghavan, Ivan Sysoev, Soroush Vosoughi, and Deb Roy. Deepstance at semeval-2016 task 6: Detecting stance in tweets using character and word-level cnns. arXiv preprint arXiv:1606.05694, 2016.
[31] William Yang Wang and Diyi Yang. That’s so annoying!!!: A lexical and frame-semantic embedding based data augmentation approach to automatic categorization of annoying behaviors using petpeeve tweets. In Proceedings of the 2015 conference on empirical methods in natural language processing, pages 2557–2563, 2015.

[32] Qizhe Xie, Zihang Dai, Eduard Hovy, Thang Luong, and Quoc Le. Unsupervised data augmentation for consistency training. Advances in Neural Information Processing Systems, 33:6256–6268, 2020.

[33] Marzieh Fadaee, Arianna Bisazza, and Christof Monz. Data augmentation for low-resource neural machine translation. arXiv preprint arXiv:1705.00440, 2017.

[34] Rico Sennrich, Barry Haddow, and Alexandra Birch. Improving neural machine translation models with monolingual data. arXiv preprint arXiv:1511.06709, 2015.

[35] Kang Min Yoo, Dongju Park, Jaewook Kang, Sang-Woo Lee, and Woomyeong Park. Gpt3mix: Leveraging large-scale language models for text augmentation. arXiv preprint arXiv:2104.08826, 2021.

[36] Xiaodong Liu, Pengcheng He, Weizhu Chen, and Jianfeng Gao. Multi-task deep neural networks for natural language understanding. arXiv preprint arXiv:1901.11504, 2019.

[37] Jason Wei, Maarten Bosma, Vincent Y Zhao, Kelvin Guu, Adams Wei Yu, Brian Lester, Nan Du, Andrew M Dai, and Quoc V Le. Finetuned language models are zero-shot learners. arXiv preprint arXiv:2109.01652, 2021.

[38] Vamsi Aribandi, Yi Tay, Tal Schuster, Jinfeng Rao, Huaixiu Steven Zheng, Sanket Vaibhav Mehta, Honglei Zhuang, Vinh Q. Tran, Dara Bahri, Jianmo Ni, Jai Gupta, Kai Hui, Sebastian Ruder, and Donald Metzler. Ext5: Towards extreme multi-task scaling for transfer learning. In International Conference on Learning Representations, 2022.

[39] Hanwei Xu, Yujun Chen, Yulun Du, Nan Shao, Yanggang Wang, Haiyu Li, and Zhihui Yang. Zeroprompt: Scaling prompt-based pretraining to 1,000 tasks improves zero-shot generalization. arXiv preprint arXiv:2201.06910, 2022.

[40] Harsha Gurulingappa, Abdul Mateen Raiput, Angus Roberts, Juliane Fluck, Martin Hofmann-Apitius, and Luca Toldo. Development of a benchmark corpus to support the automatic extraction of drug-related adverse effects from medical case reports. Journal of biomedical informatics, 45(5):885–892, 2012.

[41] Max Bartolo, Alastair Roberts, Johannes Welbl, Sebastian Riedel, and Pontus Stenetorp. Beat the ai: Investigating adversarial human annotation for reading comprehension. Transactions of the Association for Computational Linguistics, 8:662–678, 2020.

[42] Rui Zhang and Joel Tetreault. This email could save your life: Introducing the task of email subject line generation, 2019.

[43] Peter Clark, Isaac Cowhey, Oren Etzioni, Tushar Khot, Ashish Sabharwal, Carissa Schoenick, and Oyvind Tafjord. Think you have solved question answering? try arc, the ai2 reasoning challenge. arXiv:1803.05457v1, 2018.

[44] Yixin Nie, Adina Williams, Emily Dinan, Mohit Bansal, Jason Weston, and Douwe Kiela. Adversarial NLI: A new benchmark for natural language understanding. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 4885–4901, Online, July 2020. Association for Computational Linguistics.

[45] Giovanni Grano, Andrea Di Sorbo, Francesco Mercaudo, Corrado A Visaggio, Gerardo Canfora, and Sebastiano Panichella. Android apps and user feedback: a dataset for software evolution and quality improvement. In Proceedings of the 2nd ACM SIGSOFT international workshop on app market analytics, pages 8–11, 2017.

[46] Wang Ling, Dani Yogatama, Chris Dyer, and Phil Blunsom. Program induction by rationale generation: Learning to solve and explain algebraic word problems. ACL, 2017.

[47] Chandra Bhagavatula, Ronan Le Bras, Chaitanya Malaviya, Keisuke Sakaguchi, Ari Holtzman, Hannah Rashkin, Doug Downey, Scott Wen-tau Yih, and Yejin Choi. Abductive commonsense reasoning. arXiv preprint arXiv:1908.05739, 2019.

[48] Achraf Othman and Mohamed Jemni. English-asl gloss parallel corpus 2012: Aasl-pc12. In 5th Workshop on the Representation and Processing of Sign Languages: Interactions between Corpus and Lexicon LREC, 2012.
[49] Dimitris Pappas, Petros Stavropoulos, Ion Androutsopoulos, and Ryan McDonald. Biomrc: A dataset for biomedical machine reading comprehension. In Proceedings of the 19th SIGBioMed Workshop on Biomedical Language Processing, pages 140–149, 2020.

[50] Tomer Wolfson, Mor Geva, Ankit Gupta, Matt Gardner, Yoav Goldberg, Daniel Deutch, and Jonathan Berant. Break it down: A question understanding benchmark. Transactions of the Association for Computational Linguistics, 2020.

[51] Annie Louis, Dan Roth, and Filip Radlinski. "i’d rather just go to bed": Understanding indirect answers. arXiv preprint arXiv:2010.03450, 2020.

[52] Thomas Diggelmann, Jordan Boyd-Graber, Jannis Bulian, Massimiliano Ciaramita, and Markus Leippold. Climate-fever: A dataset for verification of real-world climate claims, 2020.

[53] Bill Yuchen Lin, Wangchunshu Zhou, Ming Shen, Pei Zhou, Chandra Bhagavatula, Yejin Choi, and Xiang Ren. Commongen: A constrained text generation challenge for generative commonsense reasoning. arXiv preprint arXiv:1911.03705, 2019.

[54] Alon Talmor, Jonathan Herzig, Nicholas Lourie, and Jonathan Berant. Commonsenseqa: A question answering challenge targeting commonsense knowledge. arXiv preprint arXiv:1811.00937, 2018.

[55] Nazneen Fatema Rajani, Bryan McCann, Caiming Xiong, and Richard Socher. Explain yourself! leveraging language models for commonsense reasoning. arXiv preprint arXiv:1906.02361, 2019.

[56] Lifu Huang, Ronan Le Bras, Chandra Bhagavatula, and Yejin Choi. Cosmos qa: Machine reading comprehension with contextual commonsense reasoning. In arXiv:1909.00277v2, 2019.

[57] Jens Lehmann, Robert Isele, Max Jakob, Anja Jentzsch, Dimitris Kontokostas, Pablo N Mendes, Sebastian Hellmann, Mohamed Morsey, Patrick Van Kleeft, Sören Auer, et al. Dbpedia—a large-scale, multilingual knowledge base extracted from wikipedia. Semantic web, 6(2):167–195, 2015.

[58] Altaf Rahman and Vincent Ng. Resolving complex cases of definite pronouns: the winograd schema challenge. In Proceedings of the 2012 Joint Conference on Empirical Methods in Natural Language Processing and Computational Natural Language Learning, pages 777–789. Association for Computational Linguistics, 2012.

[59] Damien Sileo, Tim Van-De-Cruys, Camille Pradel, and Philippe Muller. Mining discourse markers for unsupervised sentence representation learning. arXiv preprint arXiv:1903.11850, 2019.

[60] Amrita Saha, Rahul Aralikatte, Mitesh M. Khapra, and Karthik Sankaranarayanan. DuoRC: Towards Complex Language Understanding with Paraphrased Reading Comprehension. In Meeting of the Association for Computational Linguistics (ACL), 2018.

[61] Angela Fan, Yacine Jernite, Ethan Perez, David Grangier, Jason Weston, and Michael Auli. Eli5: Long form question answering. arXiv preprint arXiv:1907.09190, 2019.

[62] Ankush Chatterjee, Kedhar Nath Narahari, Meghana Joshi, and Puneet Agrawal. SemEval-2019 task 3: EmoContext contextual emotion detection in text. In Proceedings of the 13th International Workshop on Semantic Evaluation, pages 39–48, Minneapolis, Minnesota, USA, June 2019. Association for Computational Linguistics.

[63] Elvis Saravia, Hsien-Chi Toby Liu, Yen-Hao Huang, Junlin Wu, and Yi-Shin Chen. Carer: Contextualized affect representations for emotion recognition. In Proceedings of the 2018 conference on empirical methods in natural language processing, pages 3687–3697, 2018.

[64] Hannah Rashkin, Eric Michael Smith, Margaret Li, and Y-Lan Boureau. Towards empathetic open-domain conversation models: a new benchmark and dataset. In ACL, 2019.

[65] P. Malo, A. Sinha, P. Korhonen, J. Wallenius, and J Lan Boureau. Good debt or bad debt: Detecting semantic orientations in economic texts. Journal of the Association for Information Science and Technology, 65, 2014.

[66] Kelvin Jiang, Dekun Wu, and Hui Jiang. Freebaseqa: A new factoid qa data set matching trivia-style question-answer pairs with freebase. In NAACL-HLT (1), pages 318–323, 2019.
[86] Bill Yuchen Lin, Seyeon Lee, Rahul Khanna, and Xiang Ren. Birds have four legs?! numersense: Probing numerical commonsense knowledge of pre-trained language models. In Proceedings of EMNLP, 2020. to appear.

[87] Sowmya Vajjala and Ivana Lučić. Onestopenglish corpus: A new corpus for automatic readability assessment and text simplification. In Proceedings of the thirteenth workshop on innovative use of NLP for building educational applications, pages 297–304, 2018.

[88] Todor Mihaylov, Peter Clark, Tushar Khot, and Ashish Sabharwal. Can a suit of armor conduct electricity? a new dataset for open book question answering. arXiv preprint arXiv:1809.02789, 2018.

[89] Yuan Zhang, Jason Baldridge, and Luheng He. Paws: Paraphrase adversaries from word scrambling. arXiv preprint arXiv:1904.01130, 2019.

[90] Yonatan Bisk, Rowan Zellers, Jianfeng Gao, Yejin Choi, et al. Piqa: Reasoning about physical commonsense in natural language. In Proceedings of the AAAI conference on artificial intelligence, pages 7432–7439, 2020.

[91] Emily Sheng and David Uthus. Investigating societal biases in a poetry composition system. arXiv preprint arXiv:2011.02686, 2020.

[92] Luheng He, Mike Lewis, and Luke Zettlemoyer. Question-answer driven semantic role labeling: Using natural language to annotate natural language. In Proceedings of the 2015 conference on empirical methods in natural language processing, pages 643–653, 2015.

[93] Tushar Khot, Peter Clark, Michal Guerquin, Peter Jansen, and Ashish Sabharwal. Qasc: A dataset for question answering via sentence composition. In Proceedings of the AAAI Conference on Artificial Intelligence, pages 8082–8090, 2020.

[94] Anna Rogers, Olga Kovaleva, Matthew Downey, and Anna Rumshisky. Getting closer to ai complete question answering: A set of prerequisite real tasks. In Proceedings of the AAAI conference on artificial intelligence, pages 8722–8731, 2020.

[95] Oyvind Tafjord, Peter Clark, Matt Gardner, Wen-tau Yih, and Ashish Sabharwal. Quarel: A dataset and models for answering questions about qualitative relationships. In Proceedings of the AAAI Conference on Artificial Intelligence, pages 7063–7071, 2019.

[96] Oyvind Tafjord, Matt Gardner, Kevin Lin, and Peter Clark. Quartz: An open-domain dataset of qualitative relationship questions. arXiv preprint arXiv:1909.03553, 2019.

[97] Pradeep Dasigi, Nelson F Liu, Ana Marasović, Noah A Smith, and Matt Gardner. Quoref: A reading comprehension dataset with questions requiring coreferential reasoning. arXiv preprint arXiv:1908.05803, 2019.

[98] Guokun Lai, Qizhe Xie, Hanxiao Liu, Yiming Yang, and Eduard Hovy. RACE: Large-scale ReAding comprehension dataset from examinations. In Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing, pages 785–794, Copenhagen, Denmark, September 2017. Association for Computational Linguistics.

[99] Byeongchang Kim, Hyunwoo Kim, and Gunhee Kim. Abstractive summarization of reddit posts with multi-level memory networks. arXiv preprint arXiv:1811.00783, 2018.

[100] Kevin Lin, Oyvind Tafjord, Peter Clark, and Matt Gardner. Reasoning over paragraph effects in situations. arXiv preprint arXiv:1908.05852, 2019.

[101] Bo Pang and Lillian Lee. Seeing stars: Exploiting class relationships for sentiment categorization with respect to rating scales. arXiv preprint cs/0506075, 2005.

[102] Bogdan Gliwa, Iwona Mochol, Maciej Biesek, and Aleksander Wawer. SAMSum corpus: A human-annotated dialogue dataset for abstractive summarization. In Proceedings of the 2nd Workshop on New Frontiers in Summarization, pages 70–79, Hong Kong, China, November 2019. Association for Computational Linguistics.

[103] Alec Go, Richa Bhayani, and Lei Huang. Twitter sentiment classification using distant supervision. CS224N project report, Stanford, 1(12):2009, 2009.

[104] Arman Cohan, Waleed Ammar, Madeleine Van Zuylen, and Field Cady. Structural scaffolds for citation intent classification in scientific publications. arXiv preprint arXiv:1904.01608, 2019.
[105] Johannes Welbl, Nelson F Liu, and Matt Gardner. Crowdsourcing multiple choice science questions. arXiv preprint arXiv:1707.06209, 2017.

[106] Tushar Khot, Ashish Sabharwal, and Peter Clark. Scitail: A textual entailment dataset from science question answering. In Thirty-Second AAAI Conference on Artificial Intelligence, 2018.

[107] Matthew Dunn, Levent Sagun, Mike Higgins, V Uğur Guney, Volkan Cırık, and Kyunghyun Cho. Searchqa: A new q&a dataset augmented with context from a search engine. arXiv preprint arXiv:1704.05179, 2017.

[108] Marco Marelli, Stefano Menini, Marco Baroni, Luisa Bentivogli, Raffaella Bernardi, and Roberto Zamparelli. A sick cure for the evaluation of compositional distributional semantic models. In Proceedings of the Ninth International Conference on Language Resources and Evaluation (LREC’14), pages 216–223, 2014.

[109] Tiago A Almeida, José Maria G Hidalgo, and Akebo Yamakami. Contributions to the study of sms spam filtering: new collection and results. In Proceedings of the 11th ACM symposium on Document engineering, pages 259–262, 2011.

[110] Maarten Sap, Hannah Rashkin, Derek Chen, Ronan Le Bras, and Yejin Choi. Socialiqa: Commonsense reasoning about social interactions. arXiv preprint arXiv:1904.09728, 2019.

[111] Tao Yu, Rui Zhang, Kai Yang, Michihiro Yasunaga, Dongxu Wang, Zifan Li, James Ma, Irene Li, Qingning Yao, Shanelle Roman, et al. Spider: A large-scale human-labeled dataset for complex and cross-domain semantic parsing and text-to-sql task. arXiv preprint arXiv:1809.08887, 2018.

[112] Pranav Rajpurkar, Jian Zhang, Konstantin Lopyrev, and Percy Liang. SQuAD: 100,000+ questions for machine comprehension of text. In Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing, pages 2383–2392, Austin, Texas, November 2016. Association for Computational Linguistics.

[113] Rowan Zellers, Yonatan Bisk, Roy Schwartz, and Yejin Choi. Swag: A large-scale adversarial dataset for grounded commonsense inference. arXiv preprint arXiv:1808.05326, 2018.

[114] Wenhao Chen, Hongmin Wang, Jianshu Chen, Yunkai Zhang, Hong Wang, Shiyang Li, Xiyue Zhou, and William Yang Wang. Tabfact: A large-scale dataset for table-based fact verification. arXiv preprint arXiv:1909.02164, 2019.

[115] Xin Li and Dan Roth. Learning question classifiers. In COLING 2002: The 19th International Conference on Computational Linguistics, 2002.

[116] Saiíl Mohammad, Svetlana Kiritchenko, Parinaz Sobhani, Xiaodan Zhu, and Colin Cherry. Semeval-2016 task 6: Detecting stance in tweets. In Proceedings of the 10th International Workshop on Semantic Evaluation (SemEval-2016), pages 31–41, 2016.

[117] Wenhan Xiong, Jiawei Wu, Hong Wang, Vivek Kulkarni, Mo Yu, Xiaoxiao Guo, Shiyu Chang, and William Yang Wang. Tweetqa: A social media focused question answering dataset. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, 2019.

[118] Jonathan Berant, Andrew Chou, Roy Frostig, and Percy Liang. Semantic parsing on Freebase from question-answer pairs. In Proceedings of the 2013 Conference on Empirical Methods in Natural Language Processing, pages 1533–1544, Seattle, Washington, USA, October 2013. Association for Computational Linguistics.

[119] Niket Tandon, Bhavana Dalvi Mishra, Keisuke Sakaguchi, Antoine Bosselut, and Peter Clark. Wiqa: A dataset for" what if..." reasoning over procedural text. arXiv preprint arXiv:1909.04739, 2019.

[120] Rémi Lebret, David Grangier, and Michael Auli. Generating text from structured data with application to the biography domain. CoRR, abs/1603.07771, 2016.

[121] Yi Yang, Wen-tau Yih, and Christopher Meek. Wikiqa: A challenge dataset for open-domain question answering. In Proceedings of the 2015 conference on empirical methods in natural language processing, pages 2013–2018, 2015.

[122] Jan A Botha, Manaal Faruqui, John Alex, Jason Baldridge, and Dipanjan Das. Learning to split and rephrase from wikipedia edit history. arXiv preprint arXiv:1808.09468, 2018.

[123] Victor Zhong, Caiming Xiong, and Richard Socher. Seq2sql: Generating structured queries from natural language using reinforcement learning. CoRR, abs/1709.00103, 2017.
[124] Shashi Narayan, Shay B. Cohen, and Mirella Lapata. Don’t give me the details, just the summary! topic-aware convolutional neural networks for extreme summarization. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, pages 1797–1807, Brussels, Belgium, October-November 2018. Association for Computational Linguistics.
A Appendix

In this Appendix, we provide more experiment details about KnowDA in Sec. A.1. We introduce the diverse NLP tasks used in KoMT in Sec. A.2. We add additional experiment description about our data augmentation experiments in Sec. A.3 and A.4. We present the detailed data augmentation procedure in Sec. A.5. We present the detailed templates for the few-shot Task Solver in Sec. A.6. Finally, in Sec. A.7, we showcase representative FewGLUE examples generated by KnowDA.

A.1 Experiment Details

**Demonstration Selection in KoMT** As we discussed above, we use demonstration in KoMT to allow KnowDA to transfer task-specific knowledge. Given the training NLP instance $T$, we first conduct random masking to it and treat the resulting string as initial input string. We then select 16 instances from the same NLP task and check to see the maximum number of instances (i.e., $m$) can be inserted into the input string within the maximum input length. Lastly, we will randomly select $k$ instances as demonstration where $k$ is also a random number between 0 and $m$, which avoids KnowDA from relying on the demonstration too much. The only requirement for the demonstrations is that they should come from the same NLP task as the masked NLP task instance. In addition, even in KoMT, long NLP instance (i.e., input length close to maximum input length) may never be accompanied by any full demonstration examples.

**Soft Prompt for Data Generator & Task Solver** We observe that, when KnowDA acts as a Data Generator, it generates relatively long text (e.g., a document for QA); when KnowDA acts as a Task Solver, it normally generates relatively short text (e.g., label phrases). To disentangle the different skills required for different roles, during KoMT, we prepend two sets of Soft Prompt (i.e, randomly-initialized trainable vectors) at the beginning of each layer. One for the Data Generator and another one for the Task Solver. Different from the standard prompt tuning, we train the parameters of KnowDA and these Soft Prompt together. We add 5 vectors per layer, resulting $5 \times 24 \times 1024 \times 2 = 245,760$ additional parameters (only 0.003% of the original T5-Large model). When applying KnowDA to downstream tasks, we should use the appropriate Soft Prompt for unsupervised generation or fine-tuning. Our preliminary experiments show that using different Soft Prompt has a significant impact on the overall performance.

A.2 KoMT Task Details

Table 8 and 9 list all supervision NLP tasks in KoMT. They are all available from Huggingface Dataset [18]. Popular task types include QA, Multiple Choices, Text Classification, Text Summarization and Generation and Machine Reading comprehensive.

A.3 FewGLUE

In this section, we add more implementation details for the FewGLUE data augmentation experiments in Sec. 3.2, including the hyper-parameters used in the data generator and task solver.

**Raw T5 DA Results** In Table 1 and 2, we did not include DA results produced by the raw T5-Large checkpoints. This is because we find that raw T5-Large checkpoints cannot directly follow KnowDA and generate reasonable long text for the BoolQ, RTE, CB, MultiRC and ReCoRD task. Similar experiment findings have also been reported in FlipDA (See Appendix A.2 in their paper) [4]. However, both T5-MLM and FlipDA are based on the raw T5-Large checkpoints. They are representative DA results obtained by the raw T5 model. KnowDA successfully outperforms both models, indicating the effectiveness of using NLP prior task knowledge for data augmentation.

**Few-shot Data Generator** Appendix A.5 shows the details of data augmentation procedure for each FewGLUE task. In all FewGLUE tasks, when we need to update the parameters of KnowDA, we simply fine-tune KnowDA (i.e., updating all parameters) with batch size 12 with learning rate of $5 \times 10^{-6}$ for 500 steps. For fair comparison with FlipDA, we directly produce synthetic data and feed into the ALBERT and DeBERTa model for further training. Unlike FlipDA which creates synthetic instances from the few-shot instances, KnowDA produces synthetic instances from scratch. Consequently, there is no explicit linkage between the synthetic instances and the few-shot instances. We therefore use
the ALBERT and DeBERTa model for Consistency filtering, which only keeps synthetic instances that have the consistent output results from KnowDA and the ALBERT and DeBERTa model. We find such filtering policy works as well as the complicated label-based filtering strategies proposed in FlipDA [4].

**Few-shot Task Solver**  As described in Sec. 3.4, we train a separated copy of KnowDA on the few-shot 32 training instances of FewGLUE for each task. We performed a grid search of hyper-parameters and reported the best-performing hyper-parameters combination for each task. For all of the 8 tasks, total number of training steps is 20,000, training batch size is 12 and we evaluate model per 100 steps. We search learning rate (LR) from \{1e-5, 5e-6, 1e-6\} and number of demonstrations (ND) from \{0, 3, 5\}. Table 7 shows the best hyper-parameters for each FewGLUE task. We note that the task of BoolQ, MultiRC and ReCoRD do not use any demonstration in their Task Solver. This is because their input sequence is very long and closed to our max length (i.e., 512) and there is no spare room for additional demonstration.

| Task  | LR   | ND | Task  | LR   | ND |
|-------|------|----|-------|------|----|
| BoolQ | 1e−5 | 0  | WSC   | 1e−5 | 3  |
| RTE   | 1e−5 | 3  | WiC   | 1e−5 | 5  |
| CB    | 1e−5 | 3  | MultiRC | 1e−5 | 0  |
| COPA  | 1e−5 | 3  | ReCoRD | 5e−6 | 0  |

### A.4 Sequence Labeling Tasks

In this section, we add more implementation details for the sequence labeling data augmentation experiments in Sec. 3.3, including data augmentation procedure, training technologies and iteration-based training.

**Data Augmentation Procedure**  In this paper, we largely follow the settings in [3] which randomly samples 5 data splits and reports the averaged performance over 5 runs. KnowDA produces synthetic data via two steps:

1. Generating raw sentences (without any entity annotations) via the sequence of named entity tags. This is similar to the Output View described in [3].
2. Use KnowDA, as a Task Solver, to detect named entities for the generated raw sentences.

For example, given a training sequence labeling data instance:

\\textbf{[Org} All Fishermen ‘s Association\\textbf{]} secretary [\textbf{Per N.J. Bose}] said the strike would continue indefinitely.

where \textbf{Org} corresponds to the entity label \textit{Organization} and \textbf{Per} corresponds to the entity label \textit{Person}. In the \textbf{Step 1}, the format of a training instances is:

\begin{align*}
\text{Input: } & \text{[Output Tags]: Organization and Person [Sentence]: } <\text{mask}> \\
\text{Target: } & \text{All Fishermen ‘s Association secretary N.J. Bose said the strike would continue indefinitely.}
\end{align*}

As sequence labeling tasks mostly involves with short sentences, we train a copy of KnowDA to complete this step. In the \textbf{Step 2}, following [38], the format of a training instances is:

\begin{align*}
\text{Input: } & \text{[Output Tags]: } <\text{mask}> [\text{Sentence}: \text{All Fishermen ‘s Association secretary N.J. Bose said the strike would continue indefinitely.} \\
\text{Target: } & \text{Organization All Fishermen ‘s Association}; \text{Person N.J. Bose.}
\end{align*}

Given the target outputs, we can easily map the entity strings back to the raw sentences and obtain word-level BIO tags. Although this approach may fail when entity appears multiple times in the input sentence, we find such case rarely impact on the final labeling performance. We train a separated copy of KnowDA to complete this step.

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Table 8: All of the training NLP task datasets used in KoMT.

| Dataset(s)         | Description                        | No. Train Datasets | Citation |
|--------------------|------------------------------------|--------------------|----------|
| ADECorpusV2        | Text Classification                 | 3                  | 23,516 [40] |
| Adversarial-QA     | Natural Language QA                 | 1                  | 30,000 [41] |
| AESLC              | Email Summarization                 | 1                  | 14,436  [42] |
| AG-News            | Text Classification                 | 1                  | 120,000 [5]  |
| AI2-ARC            | Multiple Choice                     | 1                  | 1,119   [43] |
| ANLI               | Adverserial NLI                     | 1                  | 162,865 [44] |
| AppReviews         | Text Scoring                        | 1                  | 288,065 [45] |
| Aqua-RAT           | Multiple Choice                     | 1                  | 97,467  [46] |
| ART                | NLI                                | 1                  | 169,654 [47] |
| ASLG-PC12          | Text Generation                     | 1                  | 87,710  [48] |
| BioMRC             | Machine Reading Comprehension       | 1                  | 700,000 [49] |
| Break-Data         | Question Decomposition Meaning Representations | 2 | 61,824 [50] |
| Circa              | Text Classification                 | 1                  | 34,268  [51] |
| Climate-Fever      | Text Scoring                        | 1                  | 1,535   [52] |
| Codah              | Multiple Choice                     | 1                  | 1,665   [53] |
| Common-Gen         | Text Generation                     | 1                  | 67,389  [54] |
| Commonsense-QA     | Open Domain QA                      | 1                  | 9,741   [55] |
| COS-E              | Text Generation                     | 1                  | 9,741   [56] |
| Cosmos-QA          | Multiple Choice                     | 1                  | 25,262  [57] |
| DBpedia14          | Text Classification                 | 1                  | 560,000 [58] |
| Definite-Pronoun-Resolution | Pronoun resolution           | 1                  | 1,332   [59] |
| Discovery          | Text Classification                 | 1                  | 1,566,000 [59] |
| Dream              | Multiple Choice                     | 1                  | 6,116   [60] |
| Duorc              | Abstractive QA                      | 1                  | 60,721  [61] |
| E2E-NL-Cleaned     | Text Generation                     | 1                  | 33,525  [62] |
| ELI5               | Abstractive QA                      | 1                  | 302,937 [63] |
| EMO                | Text Classification                 | 1                  | 30,160  [64] |
| Emotion            | Text Classification                 | 1                  | 16,000  [65] |
| Empathetic-Discours | Open Domain QA                      | 1                  | 26,673  [66] |
| Financial-Phrasebank | Text Classification            | 1                  | 2264    [67] |
| FreebaseQA         | Open Domain QA                      | 1                  | 20,358  [68] |
| Gigaword           | Text Summarization                  | 1                  | 3,803,957 [69] |
| GLUE               | General Language Understanding      | 7                  | 949,101 [70] |
| GoogleWellformedQuery | Text Scoring                      | 1                  | 17,500  [71] |
| HateSpeech18       | Text Classification                 | 1                  | 10,944  [72] |
| HateSpeechOffensive | Text Classification                     | 1                  | 24,783  [73] |
| Hateexplain        | Text Classification                 | 1                  | 15,383  [74] |
| HealthFact         | Text Classification                 | 1                  | 9,832   [75] |
| Hellaswag          | Text Generation                     | 1                  | 39,905  [76] |
| HotpotQA           | QA                                 | 1                  | 90,447  [77] |
| IMDbReviews        | Text Classification                 | 1                  | 25,000  [78] |
| Jeopardy           | Natural language QA                | 1                  | 216,930 [79] |
| KILT               | Knowledge-Intensive Language Tasks  | 6                  | 2,731,679 [80] |
| Liar               | Fake News Detection, Text Classification | 1                        | 10,269  [81] |
| Limit              | Text classification                | 1                  | 23,559  [82] |
| MathQA             | QA                                 | 1                  | 29,837  [83] |
| MC-Taco            | Multiple Choice                     | 1                  | 9,442   [84] |
| Medical-Questions-Pairs | Text Classification            | 1                  | 3048    [85] |
| Mocha              | QA                                 | 1                  | 31,069  [86] |
| Multi-News         | Text Summarization                  | 1                  | 44,972  [87] |
| NumerSense         | Numerical commonsense reasoning probing | 1                        | 10,444  [88] |
| OneStopEnglish     | Text Classification                 | 1                  | 867     [89] |
| OpenBookQA         | Open Domain QA                      | 1                  | 4,957   [90] |
| PAWS               | Text Classification                 | 1                  | 49,401  [91] |
| PIQA               | Multiple Choice                     | 1                  | 16,000  [92] |
| Poem-Sentiment     | Text Classification                 | 1                  | 892     [93] |
| QA-SRL             | Multiple Choice                     | 1                  | 6,414   [94] |
| QASC               | Multiple Choice                     | 1                  | 8,134   [95] |
| QUIL               | Multiple Choice                     | 1                  | 10,246  [96] |
| QUAREL             | Multiple Choice                     | 1                  | 1,941   [97] |
| QUARTZ             | Multiple Choice                     | 1                  | 2,696   [98] |
| QUOREF             | QA                                 | 1                  | 19,399  [99] |
| RACE               | School QA (MCQ)                     | 2                  | 87,866  [100] |
| Reddit-Tifu        | Text Summarization                  | 1                  | 42,139  [101] |
| Ropes              | Extractive-QA                      | 1                  | 10,924  [102] |
| Rotten-Tomatoes    | Text Classification                 | 1                  | 8,350   [103] |
| SamSum             | Text Summarization                  | 1                  | 14,372  [104] |
| Sentiment140       | Text Classification                 | 1                  | 1,600,000 [105] |
| SCICite            | Text Classification                 | 1                  | 8,194   [106] |
| SCI2Q              | Multiple Choice                     | 1                  | 11,679  [107] |
| SCITail            | NLI                                | 1                  | 23,596  [108] |
| Search-QA          | QA                                 | 1                  | 151,295 [109] |
| Sick               | Text Classification                 | 1                  | 4,439   [110] |
Table 9: All of the training datasets used in KoMT Part II.

| Dataset(s)   | Description            | No. Train Datasets | Citation |
|--------------|------------------------|--------------------|----------|
| SMS-Spam     | Text Classification    | 1                  | 5,574    | 109      |
| Social-I-QA  | QA                     | 1                  | 33,410   | 110      |
| Spider       | Text Generation        | 1                  | 7,000    | 111      |
| SQuAD        | QA (context)           | 1                  | 87,599   | 112      |
| Swag         | Text Classification    | 1                  | 73,546   | 113      |
| Tab-Fact     | Text Classification    | 1                  | 92,283   | 114      |
| TREC         | Text Classification    | 1                  | 5,452    | 115      |
| TweetEval    | Text Classification    | 9                  | 120,104  | 116      |
| TweetQA      | Natural Language QA    | 1                  | 10,692   | 117      |
| WebQuestions | QA (open)              | 1                  | 3,778    | 118      |
| WIQA         | QA                     | 1                  | 29,808   | 119      |
| Wiki-Bio     | Text Generation        | 1                  | 582,659  | 120      |
| Wiki-QA      | QA                     | 1                  | 20,360   | 121      |
| Wiki-Split   | Text Split             | 1                  | 989,944  | 122      |
| WikiSQL      | NLI                    | 1                  | 56,355   | 123      |
| XSum         | Text Summarization     | 1                  | 203,577  | 124      |
| Yelp-Polarity| Text Classification    | 1                  | 560,000  | 5        |
| YelpReviewFull| Text Classification   | 1                  | 650,000  | 5        |

**Total** 114 -

**Training KnowDA for Data Augmentation**

Interestingly, similar to [3], we find it beneficial to add Soft Prompt (i.e., trainable vectors prepended to each layer of PLM) when train KnowDA as a Task Solver. In this paper, we directly use randomly-initialized Soft Prompt (rather than the pre-trained Soft Prompt in PromDA). When we train KnowDA as a Task Solver in Step 2, we frozen all parameters of KnowDA and only train the newly added Soft Prompt parameters with a learning rate of $10^{-3}$. When we train KnowDA as a Data Generator, we simply fine-tune all KnowDA parameters with a learning rate of $50e^{-6}$.

**Iteration-based Training**

As shown in Table 4, feeding the synthetic data back to KnowDA could improve the labeling performance of KnowDA (as a Task Solver). We then iterate this process 4 times to further improve the sequence labeling performance. Specifically, using the few-shot sequence labeling data, we first train KnowDA as a Data Generator to generate a set of synthetic raw sentences (without any entity annotations). We then train KnowDA as a Task Solver whose labeling performance is shown as $T_0$ in Table 4, using the few-shot sequence labeling data, to tag the synthetic raw sentences. We feed these full synthetic data, combined with few-shot training data, to train KnowDA as a Task Solver whose labeling performance is shown as $T_1$ in Table 4. In every iteration, the synthetic raw sentences are fixed and we only update the labels over these sentences. We repeat this iteration process 4 times. We find that such iteration beneficial to the final sequence labeling performance.

**A.5 FewGLUE Data Augmentation Procedure**

In the task of BoolQ, RTE, CB, MultiRC and ReCoRD, we use KnowDA to generate long text without any further fine-tuning (i.e., zero-shot). All of these zero-shot components are in Blue with the snow mark. All components with fine-tuning are in Orange with the fire mark.

**BoolQ** As shown in Figure 5, the data augmentation procedure for the task of BoolQ has three steps: i) generating article; ii) generating question and iii) generating the final answer (i.e., True or False). As article in BoolQ are often relatively long, we generate it directly from KnowDA without any fine-tuning (e.g., zero-shot). We further separately fine-tune KnowDA for the rest two steps.

**RTE** As shown in Figure 6, the data augmentation procedure for the task of RTE has three steps: i) generating premise; ii) generating hypothesis and iii) generating the final relation label (i.e., whether premise and hypothesis are entailment). As premise in RTE are often relatively long, we generate
it directly from KnowDA without any fine-tuning (e.g., zero-shot). We further separately fine-tune KnowDA for the rest two steps.

**CB** As shown in Figure 7, the data augmentation procedure for the task of CB has three steps: i) generating premise; ii) generating hypothesis and iii) generating the final relation label (i.e., whether premise and hypothesis are entailment). As premise in CB are often relatively long, we generate it directly from KnowDA without any fine-tuning (e.g., zero-shot). The premise text in CB are often dialogue-based, which is different from commonly seen premise in other NLI tasks. We therefore use the key “text” and full demonstrations to generate synthetic data for CB premise. We further separately fine-tune KnowDA for the rest two steps.

**MultiRC** As shown in Figure 8, the data augmentation procedure for the task of MultiRC has four steps: i) generating document; ii) generating question; iii) generating answer and iv) generating label (i.e., whether the article, question and answer are correct). As document in MultiRC are often relatively long, we generate it directly from KnowDA without any fine-tuning (e.g., zero-shot). We further separately fine-tune KnowDA for the rest three steps.
WiC As shown in Figure 9, the data augmentation procedure for the task of WiC has two steps: i) generating the disambiguation word as well as the sentence pair containing the above word for selection; ii) generating final result (i.e., whether the words in the sentence pair have the same meaning). We fine-tune KnowDA for both steps.

WSC As shown in Figure 10, the data augmentation procedure for the task of WSC has two steps: i) generating the sentences that include the noun (e.g., person name) and pronoun which refers to the previous noun; ii) generating final result (i.e., whether the noun and pronoun refer to the same entity, such as specific person). We fine-tune KnowDA for both steps.

COPA As shown in Figure 11, the data augmentation procedure for the task of COPA has two steps: i) generating new premise text given the options and questions. This is because given the premise and question, there could be many possible options to be generated. We find those generated synthetic data contributes little to the ALBERT and DeBERTa model performance in our preliminary experiments; ii) generating final answer (i.e., which option is correct given the premise and question). We fine-tune KnowDA for both steps.

ReCoRD As shown in Figure 12, the data augmentation procedure for the task of ReCoRD has four steps: i) generating document; ii) generating entity list; iii) generating query text and iv) verifying the answer by generating the entity. As document in ReCoRD are often relatively long, we generate it directly from KnowDA without any fine-tuning (e.g., zero-shot). We further separately fine-tune KnowDA for the rest three steps. When generating query, we generating full sentences without any
placeholder. We will create placeholder for the query text if there is an entity appearing in the query text and the entity list.

![Diagram of Document, Entities, Query, and Query with placeholders]

Figure 12: The Data Augmentation Procedure for the task of ReCoRD.

A.6 FewGLUE Task Solver Templates

In this section, we show the templates (i.e., task-specific keys), as well as samples, for the tasks in the FewGLUE benchmark.

A.6.1 BoolQ

Template:

Answer: <MASK> Questions: [question] Article: [passage]

Sample:

Answer: <MASK> Questions: has lebron james ever been in the dunk contest Article: Slam Dunk Contest – Historically, the dunk contest drew some mild criticisms. One is that players who often compete in these contests are seen as dunkers only (with the obvious exceptions of Michael Jordan, Kobe Bryant, and Julius Erving), which is why notable high flying athletes like Shawn Marion and LeBron James have sometimes refused to participate. High-profile players such as Dwyane Wade and Charles Barkley have also declined to participate citing it as an unnecessary risk to injury. In the 2000 NBA Slam Dunk Contest, Tracy McGrady injured his wrist while performing a dunk. Also in the 1995 NBA Slam Dunk Contest, Tony Dumas hurt his knee while performing his “Texas Twister” dunk. Although a longtime critic, LeBron James said he would perform in the 2010 Slam Dunk Contest. This decision was made after watching the 2009 dunk contest when Dwight Howard and Nate Robinson went at it. However, he withdrew his statement once the All-Star Weekend came around.

Target : False

A.6.2 RTE

Template:

Answer: <MASK> Hypothesis: [hypothesis] Premise: [premise]

Sample:

Answer: <MASK> Hypothesis: A tropical storm has caused loss of life. Premise: Tropical Storm Debby is blamed for several deaths across the Caribbean.

Target : entailment

A.6.3 CB

Template:

Answer: <MASK> Hypothesis: [hypothesis] Premise: [premise]

Sample:
**Answer:** <MASK> **Hypothesis:** Jed should ask. **Premise:** Jed wondered. He’d scarcely set eyes on him since the night they’d had dinner together at the house in Westwood. Nobody had mentioned him either and Jed didn’t feel he should ask.

**Target:** contradiction

### A.6.4 COPA

**Template:**

Answer: <MASK> Solution1: [choice1] Solution2: [choice2] Premise: [premise] Question: What is the [question] for this?

**Sample:**

Answer: <MASK> Solution1: His stubble grew. Solution2: His stubble disappeared. Premise: The man slid the razor across his chin. Question: What is the effect for this?

**Target:** 2

### A.6.5 WiC

**Template:**

Answer: <MASK> pos: [start1] sentence1: [sentence1] sentence2: [sentence2] word: [word]

**Sample:**

Answer: <MASK> pos: 0 sentence1: Catch fire. sentence2: Catch the mood. word: catch

**Target:** true

### A.6.6 WSC

**Template:**

Answer: <MASK> Premise: [market text]

**Sample:**

Answer: <MASK> Premise: Billy cried because *Toby* wouldn’t share *his* toy.

**Target:** Toby

Note that in the FewGLUE WSC task, the labels of all 32 training examples are True. Following the settings in [14], we train KnowDA in a generative manner which directly generates the noun to which the given pronoun refers.

### A.6.7 MultiRC

**Template:**

Label: <MASK> Question: [question] Answer: [answer] Article: [passage]

**Sample:**

Label: <MASK> Question: What did Carl need before going to the lab? Answer: Tire. Article: I’m here to tell you the story of a robot named Carl. He came from a far away land known as Factory. Carl was sad because he was missing a part called a tire. He also needed a sun gatherer. But, the tire was more important. Once Carl got all these parts he could travel to his new home in the nation of Lab and the city of Office. It was a tricky thing to get there with missing parts. Just as he had given up hope Carl got a message from Mr. X saying the new parts were ready to be delivered. This made the robot very happy. The parts arrived a few days later and Carl put them in with 2 days of work. After this Carl began to travel the last bit of his goal to get to his new job. After this Carl took 10 days to get to Lab.

**Target:** True

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A.6.8 ReCoRD

Template:

Answer: <MASK> Query: [query] Passage: [passage]

Sample:

Passage: By Lizzie Parry The Pope has today told Ukraine’s Prime Minister he will ‘do everything possible’ for peace in the country, amid the first invasion of Russian forces into the ex-Soviet country’s airspace. It comes as Ukraine’s acting defence minister said if Russia sends ‘peace-keeping forces’ into the country, Kiev’s military will fight them. Prime Minister Arseniy Yatsenyuk is cutting short his trip to Rome as tensions in the eastern part of the ex-Soviet country and Western nations threaten sanctions. Scroll down for video Pope Francis (right) today told Ukrainian Prime Minister Arseniy Yatsenyuk (left) he would ‘do everything possible’ for peace in the ex-Soviet country after Russian military aircraft invaded Ukrainian airspace overnight Ukrainian Prime Minister Arseniy Yatsenyuk cutting short Rome trip Country’s acting defence minster said if Russia send ‘peace-keeping’ forces into Ukraine, Kiev’s military will retaliate and fight back Yatsenyuk said Russian aircraft invaded Ukrainian airspace overnight U.S. sends troops to neighbouring Lithuania as part of NATO manoeuvre. Query: Let me make this clear: should Lithuania need NATO, I guarantee @placeholder will be there,’ he said. Answer: <MASK>

Target : NATO

We cast ReCoRD as a generative task. In the training stage, we directly train the model to generate the ground truth entities without considering other entities. When evaluating, for each question, we take all candidate entities one by one as the target input model and calculate loss. Then we sort the loss of all samples and select the entity corresponding to the sample with the smallest loss values.

A.7 Case Study

In this section, we select eight representative examples from KnowDA in the FewGLUE benchmark (i.e., one example for each task). In the task of BoolQ, RTE, CB, MultiRC and ReCoRD, we use KnowDA to generate long text without any further fine-tuning (i.e., zero-shot). We show that KnowDA could produce high-quality text with similar styles in this challenging setting. In the task of COPA, WSC and WiC, we find that after task-specific fine-tuning, KnowDA could also generate appropriate text.

BoolQ  In the original BoolQ training data, there are some instances about biography of famous athletes (See Sec. A.6.1). KnowDA successfully produce another detailed, coherent and long athlete biography from the keys and demonstration examples, showing the success of KoMT.

Article: Selena Grace Anderson (born December 9, 1987) is an American football wide receiver for the University of Alabama at Birmingham (UAB). She was drafted by the New Orleans Saints in the third round of the 2011 NFL Draft. She played college football at Syracuse. Questions: Is Selena Grace a basketball player? Answer: False

RTE  Similar to the BoolQ task, many instances in the RTE task have long value in Premise. KnowDA successfully produce long and high-quality text for Premise only using key and demonstrations.

Hypothesis: Fort Lauderdale is part of the United States. Premise: The Millennium State Highway (the New Millennium) is a west-bound U.S. highway that runs for 183 miles (195 km) between the cities of Fort Lauderdale and Fort Lauderdale-Davis, Florida. Developed by the Federal Highway Administration in 1956, it is one of the major arterial roads in the U.S. Answer: entailment

CB  In the CB task, unlike above Wikipedia-style text, some instances are drawn from special domains, such as fiction (i.e., from British National Corpus) and spoken dialogue (i.e., from Switchboard). KnowDA still generate long text following these special styles.
**Hypothesis:** Jools Holland was the director of the movies. **Premise:** And who is the director of the movies in England? said Jools Holland who said he hoped we’d get some film or television. **Answer:** contradiction

**COPA** In this example, the original premise in the training is “The customer filed a complaint with the store manager.”. Given options and question, KnowDA could generate different but coherent premise text.

**Premise:** The customer was upset. **Solution1:** The sales associate undercharged the customer. **Solution2:** The sales associate acted rude to the customer. **Question:** What is the cause for this? **Answer:** 2

**WSC** In the WSC task, KnowDA directly generates the whole Premise text with the noun and pronoun work marked with “*”. The generated text are coherent: the pronoun “he” clearly refers to “Toby”. This shows that KnowDA has strong few-shot ability because it could quickly learn this pattern from only 32 examples.

**Premise:** Stan’s son *Toby* was playing football with his friends when *he* was injured. **Answer:** True

**WiC** In the WiC task, KnowDA directly generates word and the two sentences. The generated results follow the WiC data format: the sentence pair needs to include the word *hand*. This shows that KnowDA has strong few-shot ability because it could quickly learn this pattern from only 32 examples.

**sentence1:** You look like someone hand you a book. **sentence2:** I pushed a hand against a table. **word:** hand **Answer:** False

**MultiRC** KnowDA further demonstrate its ability in generating long text. The style of the article is similar to the training data in MultiRC. KnowDA also generates high-quality questions given the long article. This shows that KnowDA could make use the same skills for different tasks (e.g., in BoolQ, KnowDA also generates good questions).

**Article:** The women and two men were abducted on Thursday by students on their way to class in the Cambridge St Andrews Catholic Primary School. The child had been released in April after getting school clothes, but police believe there was too much blood on her leg. The condition of the pupils is not known. The Catholic school, which opened in 1962, has a special focus on education. Sisters and brothers from the school remain trapped in the school, a service which has been called a miracle. It is the first such ever celebration of modern education. **Question:** What school opened in 1962? **Answer:** Cambridge St Andrews Catholic Primary School **Label:** True

**ReCoRD** In the ReCoRD task, there are a few instances talk about Ukraine (See Sec. A.6.8). Interestingly, through the demonstration, KnowDA successfully generates another high quality piece of text regarding this topic.

**Passage** Ukraine’s prime minister has said it is not encouraging tense talks between President Vladimir Putin and the opposition in order to expel the dissident republican leader. Ukraine’s chief prosecutor accused Mr Putin of refusing to cooperate with the independent opposition, alleging that he had been building a grudge against the republican group. He was confronted in Chechnya on Sunday, but was not allowed to hold talks with the opposition. Ukraine was moved to emergency status as a result of its violations of the ceasefire with Russia after protests in Kiev and Shenyang over the halt to other steps. President Vladimir Putin denies intelligence evidence that Kiev has been preparing a terror campaign to combat the rebel group. Ukraine said in the statement on Monday that it was preparing a prosecution, though there is no evidence linking the attacks to what is known as a parallel deal between the two main parties in the region. The two sides’ treatment of each other in Kiev is said to have been a hostile act, with officers accusing Putin of triggering a war, while the opposition, which is not a ally of the Russians, denies any involvement. **Query** Mr Putin is not allowed to hold talks with the opposition in @placeholder because it would violate the ceasefire, Yuriy Yatsenyuk said. **Answer** Chechnya