PromDA: Prompt-based Data Augmentation for Low-Resource NLU Tasks

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Paper https://arxiv.org/abs/2202.12499
Code https://github.com/GaryYufei/PromDA

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Data Augmentation (DA) aims to create more training data from the exsiting training data. There are two types of DA technologies:

- Continuous DA: Dropout, SeqMix. These methods often manipulate the continuous embeddings of the inputs.
- Discrete DA: EDA, LAMBADA. There methods directly produce discrete training instances (e.g., sentences and labels).

This paper focuses on the **Discrete DA**.

The settings in this paper

The low-resource NLU task only has a small set of labeled training data $\mathcal{T} = \{(x_1, y_1), \cdots, (x_n, y_n)\}$. The *Data Augmentation Algorithm* generates synthetic labeled training data $\mathcal{T}_{LM} = \{(\hat{x}_1, \hat{y}_1), \cdots, (\hat{x}_n, \hat{y}_n)\}$ from T using (Pre-trained) language models. The goal is that the NLU models trained using $\mathcal{T} \cup \mathcal{T}_{LM}$ outperform the NLU models only trained using $\mathcal{T}$.

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Existing Solution for Low-Resource NLU

Previous works often produce extra "labeled data" to boost the performance of the Low-Resource NLU models.

- [4] deploys the *self-training* framework to produce *pseudo labelled training data* from *unlabeled in-domain data* which could be expensive to obtain.
- [5, 1] expand the original small training data using automatic heuristic rules, which could distort the text.

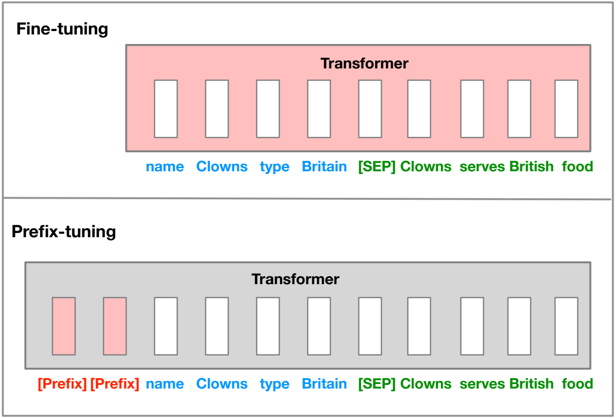
LM and PLM for DA

- To solve the above dilemma, Language Models (LMs) or Pre-trained Language Models (PLMs) are used for data augmentation.
- PLMs could be trained to generate synthetic training data.
- However, in the low-resource NLU tasks, directly fine-tuning PLMs could result in over-fitting. PLMs memorize the small training data.

Soft Prompt

Recent work [2, 3] propose prompt tuning, which only back-propagates the loss to the *Soft Prompts*, instead of the entire model. They show that prompt tuning is sufficient to be competitive with full model tuning while significantly reducing the amount of parameters to be tuned.

Soft Prompt



Fine-tuning
Transformer
name Clowns type Britain [SEP] Clowns serves British food
Prefix-tuning
Transformer
[Prefix] [Prefix] name Clowns type Britain [SEP] Clowns serves British food

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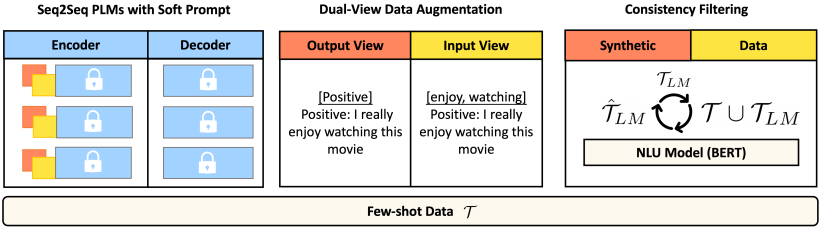
Overview of PromDA



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Seq2Seq PLMs with Soft Prompt

We prepend a sequence of trainable vectors at each transformer layer. We denote $P^j = \{\boldsymbol{p}_1^j, \cdots, \boldsymbol{p}_k^j\}$ as the *Soft Prompt* at the j^{th} layer. The i^{th} hidden states at the j^{th} layer $\boldsymbol{h}_i^j$ in the Transformer model is defined as follows:

$$\boldsymbol{h}_i^j = \begin{cases} \boldsymbol{p}_i^j & i \leq k \\ \boldsymbol{w}_i & i > k \wedge j = 0 \\ Trans(\boldsymbol{h}^{j-1})_i & \text{Otherwise} \end{cases} \tag{1}$$

where $Trans(\dot{)}$ is the forward function the Transformer layer and w_i is the fixed word embedding vector at the input layer.

Pre-training for Prompt Initialization

- The parameter initialization of the *Soft Prompt P* could be important.
- Given that data augmentation produces full syntactic data from partial information (e.g., output tags and keywords), we propose *Synonym Keywords to Sentence* pre-training task.
- We only use the task-agnostic general-purpose pre-training corpus.

Dual-View DA

	Sequence Labelling
GT:	**[Org All Fishermen 's Association]** secretary **[Per N.J. Bose]** said the strike would continue indefinitely.
IV:	All Fishermen 's Association and N.J. Bose and strike and indefinitely
OV:	Organization and Person
	Sentence Classification
GT:	The story has its redundancies, and the young actors, not very experienced, are sometimes inexpressive. **Negative**
IV:	redundancies and young actors and experienced and inexpressive
OV:	Negative

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Dual-View with Different Prompt

After prompt pre-training, we treat *Input View* and *Output View* as two independent models and use the *Soft Prompt* parameters P to initialize the parameters of P_{input} and P_{output} to ensure the diversity.

Consistency Filtering

Given synthetic data with generated labels produced by PromDA, we use the NLU models to label these data again and only keep the instances with *consistent* outputs from PromDA and the NLU models. We iterate this process N times to obtain stronger NLU models.

Final Algorithm of PromDA

Algorithm 1 Dual-View Data Augmentation: Given few-shot labeled dataset $\mathcal{T}$, the number of iteration N; return a trained NLU model M_{NLU}.

procedure $\textsc{DualViewDA}(\mathcal{D}, N)$

$\quad M_{LM} \leftarrow \textsc{Train}(LM, \mathcal{T})$

$\quad \mathcal{T}_I^1 \leftarrow \textsc{Gen}(M_{LM}, \mathcal{T}, \mathrm{I})$ ▷ Input

$\quad \mathcal{T}_O^1 \leftarrow \textsc{Gen}(M_{LM}, \mathcal{T}, \mathrm{O})$ ▷ Output

$\quad \mathcal{T}_I^2 \leftarrow \textsc{Gen}(M_{LM}, \mathcal{T}_O^1, \mathrm{I})$

$\quad \mathcal{T}_O^2 \leftarrow \textsc{Gen}(M_{LM}, \mathcal{T}_I^1, \mathrm{O})$

$\quad \hat{\mathcal{T}}_{LM} \leftarrow \mathcal{T}_I^1 \cup \mathcal{T}_I^2 \cup \mathcal{T}_O^1 \cup \mathcal{T}_O^2$

$\quad M_{NLU}^0 \leftarrow \textsc{Train}(NLU, \mathcal{T})$

$\quad$ **for** $r \in 1, \ldots, N$ **do**

$\quad\quad \mathcal{T}_{LM}^r \leftarrow \textsc{Consist}(M_{NLU}^{r-1}, \hat{\mathcal{T}}_{LM})$

$\quad\quad \mathcal{T}^r \leftarrow \mathcal{T}_{LM}^r \cup \mathcal{T}$

$\quad\quad M_{NLU}^r \leftarrow \textsc{Train}(NLU, \mathcal{T}^r)$

$\quad M_{NLU} \leftarrow M_{NLU}^N$

$\quad$ **return** M_{NLU}

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Experiments on Sequence Labelling

DataSet	C03		Wiki	
Shot	10	50	10	50
Baseline	72.7	82.9	50.8	65.4
SDANER♠	72.9	82.8	51.7	65.8
LAMBADA	75.0	83.7	52.9	66.4
MetaST♣	76.7	83.6	56.6	69.2
PromDA	77.5	84.1	58.3	70.1

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Experiments on Sentence Classification

DataSet	SST2		RT	
Shot	10	50	10	50
Baseline	66.1	81.5	57.8	72.0
EDA♠	66.7	80.4	58.5	73.9
Back T.	70.0	81.4	62.6	74.2
CBERT♣	67.8	83.4	61.5	75.3
LAMBADA	70.6	82.0	60.3	75.9
PromDA	<u>81.4</u>	<u>86.3</u>	<u>73.4</u>	<u>80.9</u>

Ablation Study

DataSet	C03	SST2	Ave.
Few-shot NLU Baseline	72.7	66.1	69.4
PromDA	77.5	81.4	79.5
Ablation for PT Pre-Training			
No PT	75.2	74.5	74.9
No PT Pre-Training	74.0	78.2	76.1
Full Pre-Training	75.0	72.0	73.5
LM Adaptation	75.4	73.3	74.4
Ablation for Dual-View DA			
Output Only	75.6	81.0	78.0
Input Only	74.4	70.6	72.5
Single Prompt	76.7	79.5	78.1

Ablation Study on Iteration

Setup	w/o Filtering	Iter-1	Iter-2	Iter-3
C03	72.0	76.7	77.6	77.5
SST2	69.2	77.5	79.7	81.4

Diversity Analysis

Model	NM↑	Self-B↓	F1↑
CoNLL03			
SDANER	141.4	0.770	72.9
LAMBADA	107.6	0.761	75.0
PromDA	**351**	**0.259**	**77.5**
SST2			
EDA	59.6	0.889	66.7
BackT.	101.8	0.826	70.0
CBERT	127	0.900	67.8
LAMBADA	51.8	0.926	70.6
PromDA	**276**	**0.578**	**81.4**

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Unlabelled Data

We design three settings: *Unlabeled In-domain Data* (**UID**), *Unlabeled Near-domain Data* (**UND**) and *Unlabeled General-domain Data* (**UGD**) where the unlabeled data come from *exactly same*, *similar* and *general-purpose* domains.

Dataset	C03	Wiki	SST2	RT	Δ
Baseline	72.7	50.8	66.1	57.8	-
w/ UID	76.2	55.2	70.2	59.7	+3.5
w/ UND	71.5	51.3	69.3	59.4	+1.0
w/ UGD	64.6	44.8	66.4	58.7	-3.2
PromDA	77.5	58.3	81.4	73.4	+10.8
w/ UID	80.0	61.7	83.0	73.9	+12.8

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Conclusion

In this paper, we present the first prompt-based pre-trained language model PromDA for low-resource NLU data augmentation. Experiments on four benchmarks show the effectiveness of our proposed PromDA method. In the future, we plan to expand PromDA to other NLP tasks, including question answering, machine reading comprehension and text generation tasks.

References

[1] Xiang Dai and Heike Adel. "An Analysis of Simple Data Augmentation for Named Entity Recognition". In: *Proceedings of the 28th International Conference on Computational Linguistics*. Barcelona, Spain (Online): International Committee on Computational Linguistics, Dec. 2020, pp. 3861–3867. DOI: 10.18653/v1/2020.coling-main.343. URL: https://aclanthology.org/2020.coling-main.343.

[2] Brian Lester, Rami Al-Rfou, and Noah Constant. "The Power of Scale for Parameter-Efficient Prompt Tuning". In: *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*. Online and Punta Cana, Dominican Republic: Association for Computational Linguistics, Nov. 2021, pp. 3045–3059. DOI: 10.18653/v1/2021.emnlp-main.243. URL: https://aclanthology.org/2021.emnlp-main.243.

[3] Xiang Lisa Li and Percy Liang. "Prefix-Tuning: Optimizing Continuous Prompts for Generation". 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)*. Online: Association for Computational Linguistics, Aug. 2021, pp. 4582–4597. DOI: 10.18653/v1/2021.acl-long.353. URL: https://aclanthology.org/2021.acl-long.353.

[4] Yaqing Wang et al. "Meta Self-training for Few-shot Neural Sequence Labeling". In: *SIGKDD 2021 (Research Track)*. Aug. 2021.

[5] 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)*. Hong Kong, China: Association for Computational Linguistics, Nov. 2019, pp. 6382–6388. DOI: 10.18653/v1/D19-1670. URL: https://aclanthology.org/D19-1670.