Related Work on Few-shot Method: A Review

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Abstract. As Natural Language Processing (NLP) technologies continue to expand into novel domains, few-shot learning emerges as a pivotal approach to addressing the challenge of data scarcity. Traditional neural networks, due to their strong reliance on abundant data, have posed limitations in their applicability to new domains. Consequently, there is a pressing need to introduce fresh research perspectives and solutions within this realm, aiming to propel its development towards greater practicality and efficiency. Firstly, solving the zero or few-shot Dialogue State Tracking problem has become necessary as the demand for deploying such systems in new domains continues to grow. This article explores the performance of D-REPTILE, a meta learner for Destination Address (DST) problems, in unknown domains. Then PET is extensively studied. Real-world tests on RAFT show cue-based learning works in low-sample settings, reinforcing the importance of instruction-based learning for human-like few-shot capabilities. Thirdly, to address the overfitting problem, this paper also explores the LA- UCL model, as well as its application, development, and challenges, which enables the LA-UCL model to enhance the Large Language Model data expansion effect through two modules. Finally, CausalCollab is introduced, which uses Incremental Stylistic Effects (ISE) as a guiding estimator for assessing the effectiveness of LM-human cooperation tactics through time.

Keywords: Few-shot, Meta-learning, Dialogue state tracking, Pattern-Exploiting Training, CausalCollab.

1. Introduction

With the widespread application of Natural language processing (NLP) technology in new fields, few-shot language learning has become the key to solving the problem of data scarcity. Traditional neural network models rely on a large amount of labeled data, which limits their rapid deployment in new fields. Although meta-learning algorithms can quickly adapt to new tasks with a small number of samples, they still face performance bottlenecks in complex tasks such as dialogue state tracking. At the same time,

DOI: 10.54254/2755-2721/96/20241299

the effectiveness of instruction-based learning methods in real few-shot settings has been questioned, and their performance is affected by instruction design. In addition, the lack of generalization ability of small-shot models also needs to be addressed. Given the limitations of the above research, this paper aims to explore more efficient and robust few-shot language learning methods. The paper pays special attention to the collaborative dynamics among language models (LM) and humans, and believe that by deeply studying how humans interact with models, the paper can reveal effective text interaction strategies, thereby improving the performance of models in few-shot scenarios. Through this perspective, the paper hopes to bring new research ideas and solutions to the field of few-shot language learning, and promote the development of this field in a more practical and efficient direction.

The first part of the paper analyzes and explores the application of the meta learning algorithm D-REPTILE in the field of dialogue state tracking (DST). Solving the zero/few sample DST problem has become necessary due to the increasing demand for deploying this problem in new fields[1]. Although traditional neural network models have good performance, they rely on a large amount of data, and applying these models to new unknown fields requires a large amount of domain specific labeled data, which limits their application. The meta learning methods MAML and REPTILE have been proven to be highly successful in efficiently and quickly adapting to new tasks with minimal labeled samples. These meta learning algorithms are independent of the underlying model and initialize their parameters. When fine-tuning with low resource target tasks, these parameters can achieve good performance. This article analyzes the advantages of the D-REPTILE meta learning algorithm in DST problems, and through experiments, analyzes its performance improvement compared to traditional methods in low resource target tasks.

As the scale of pre-trained LM expands, instruction-based learning methods, such as Pattern-Exploiting Training (PET) [2], attempt to guide the model to learn with a small number of samples by introducing manually designed instructions. This approach has great potential in theory. By revisiting PET (combining instructions with example fine-tuning) and verifying it on the RAFT [3] benchmark (enforced true few-shot setting), PET significantly outperforms the baseline and its performance is close to that of non-expert humans [4]. However, in actual evaluations, its performance is often affected by the quality of instruction design and the authenticity of the evaluation environment. Recent studies have questioned the effectiveness of such methods in truly few-shot scenarios.

In the few-shot learning task, the model is also required to have the ability to generalize from a few samples. Since the few-shot model lacks the cognitive ability, it cannot do to expand the sample space with limited samples. And there still exists the problem of overfitting, for this reason, Zhang Jing, Hui Gao, et al. proposed a framework LA-UCL: LLM-Augmented Unsupervised Contrastive Learning Framework for Few-Shot Text Classification[5]. LLM is the largest language module, which contains two algorithms 1) Self-augmented UCL, 2) External-augmented UCL. self -augmented UCL is designed to enable LLM to generate more distinguishable samples, which can expand the sample space and make the samples easier to recognize and compare with the original data set to conclude, thus improving the framework model's ability to discriminate and analyze the data. External-augmented UCL refers to the use of an external website to retrieve and find out unlabeled external knowledge information to construct a contextual model. external knowledge information, and constructing contexts to make the explanations generated by LLM richer and more accurate.

Finally, in a related paper that examines the collaborative dynamics among LM and humans, Bohan Zhang et al. recommend a fresh causal estimator - Incremental Stylistic Effect (ISE), describing the infinite the average impact of turning a text towards a particular style. On this basis, Bohan Zhang et al. developed the CausalCollab algorithm, which aims to evaluate the ISE of varieties of interaction tactics in dynamic LM and human cooperation. An empirical research of three different LM-human cooperation situations by BoanZhang et al. reveals that CausalCollab efficiently shortens confusion and observably builds up counterfactual estimates.

DOI: 10.54254/2755-2721/96/20241299

2. Research on Meta Learning Algorithms

Meta learning algorithm is a special type of machine learning algorithm that aims to quickly adapt to new tasks by utilizing the commonalities between different tasks under the condition of a small number of samples through the process of learning. In the field of dialogue state tracking (DST), meta learning has particular potential because there are often commonalities between dialogues in different domains, such as similar slots and dialogue processes. This article specifically analyses the meta learner D-REPTILE, which is mainly aimed at DST domain problems and has been experimentally proven to significantly improve baseline performance in different domains, base models, and datasets. Recent meta-learning techniques like MAML and REPTILE have shown great success in quickly adapting to new tasks with limited labelled data. These approaches are particularly effective in environments with numerous similar tasks but minimal data for each. They are designed to be model-agnostic and provide initial parameter settings, which, when fine-tuned on low-resource target tasks, can deliver strong performance. Following their success in few-shot image classification, many recent studies have explored their benefits in natural language processing (NLP) tasks. This article analyses D-REPTILE based on experimental results obtained from previous work[1], and illustrates how D-REPTILE can find initial points closer to similar fields (such as hotels and restaurants) through examples such as hotels, restaurants, and taxis, in order to achieve more effective fine-tuning in the target field (such as hotels).

Experimental setup: Two DST datasets, MultiWoz2.0 and DSTC8, were used in this experiment, and NFT (Naive pre training before Fine Tuning) baseline method was employed. This method initializes model parameters by minimizing the joint loss of all training domain data, and then fine tunes them on the target domain

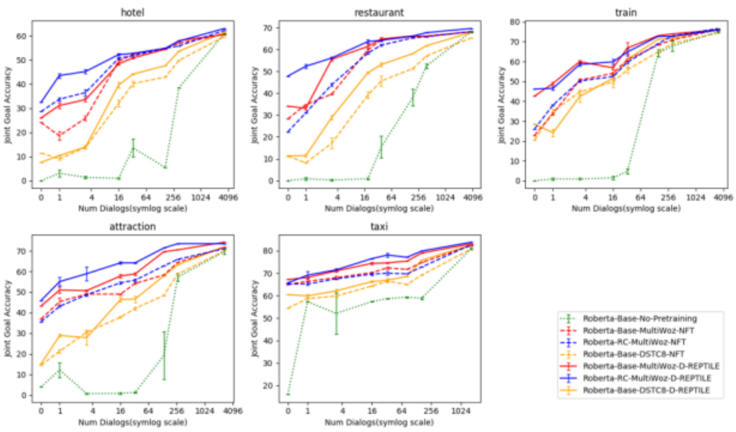

Figure 1. Accuracy of Joint Objectives in Different Fields with Different Data Volumes[1]

Figure 1 shows the performance comparison between the D-REPTILE meta learner and traditional NFT methods on different datasets. In the case of only a small amount of target domain data (such as 0, 1, 2 dialogues), D-REPTILE significantly outperforms NFT. This is because the initialization of D-REPTILE is closer to the optimal parameters of the target domain, which allows for more effective fine-tuning and preliminary analysis of experimental results. D-REPTILE uses meta learning algorithms to find an initialization point, from which it can reach the optimal parameters of the hotel domain with a small number of gradient descent steps. Due to the similarity between the restaurant and hotel domains, this initialization point may already be close to the optimal parameters for the hotel domain. NFT attempts to find an initialization point by minimizing the joint loss of all training domain data. However, this joint optimum may be far from the optimal parameters in the hotel domain, particularly as the number of training domains grows or the available data for each domain becomes more limited. Consequently, this led to a variation in the experimental outcomes between the two cases.

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3. Realistic Few-Shot Learning and Hints from a Real-World Perspective

PET[2] is a text classification approach that focuses on instruction-based operations. The key to PET is combining text instructions with regular fine-tuning on labelled examples. To achieve this, the user needs to design one or more patterns that transform the input samples into a cloze format that can be effectively processed by the Masked Language Model (MLM). These patterns can come in many different forms. In addition, the user needs to specify the specific meaning of all output categories. This is $y$done by a verbalizer that assigns a natural language expression to each output. The combination of a pattern and a verbalizer is called a pattern-verbalizer pair (PVP). Given a single PVP, let $p(y \mid x)$ be the probability that an MLM assigns to y's verbalization in the cloze question obtained by applying the pattern to x, normalized over all y. The MLM is finetuned on labeled examples (x, y) by minimizing the cross-entropy loss between $p(y \mid x)$ and a distribution that assigns a probability of 1.0 to y[4].If the user selects multiple PVPs, a separate model will be trained for each PVP. This approach is similar to knowledge distillation, and the models are then used to annotate unlabeled examples to train a final classifier with a regular sequence classification head. This approach is a weighted variant of PET that does not use auxiliary language modeling.

In terms of dataset selection, the experiment used three datasets: AG News, Yelp Reviews (full star rating), and Yahoo Questions. These datasets cover classification tasks in three different fields, similar to actual application scenarios. Detailed instructions were designed for each task in the experiment so that extensive testing can be performed using multiple modes.

To validate this finding in a real-world setting, researchers tested PET on RAFT[3], a benchmark of tasks drawn from real-world NLP applications for which no labeled development or test sets are available. PET achieves new state-of-the-art performance on RAFT and approaches non-expert human performance on 7 out of 11 tasks.

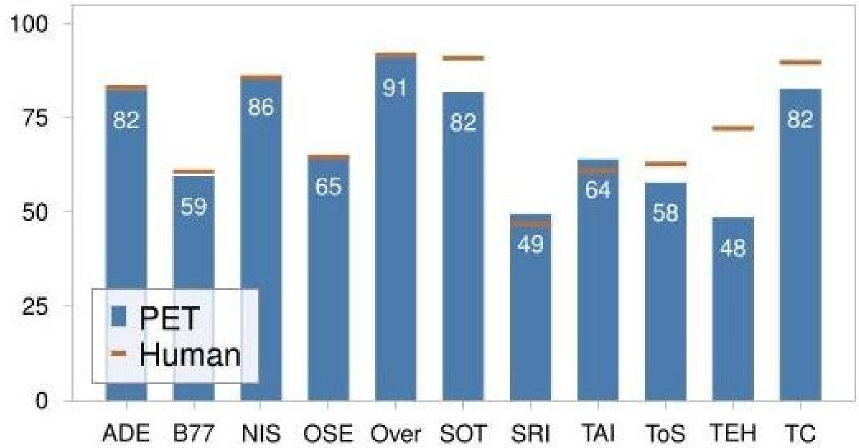

Figure 2. PET achieves near-human performance on 7 of the 11 tasks in the RAFT benchmark [4].

4. Experimental method of small sample model LA-UCL

In the LA-UCL paper, for a typical n-way k-shot text classification problem, three datasets are shown here: training set Ytrain, verification set Yval and testing set Ytest. To enhance the small-sample model's ability to discriminate data, the article also proposes an idea based on Mixup, the principle of the Mixup idea need to combine the positive and negative sample features to obtain new samples, which can increase the robustness of the model, so that the LLM can generate stronger samples, and thus enhance the unsupervised comparative learning. Includes “LLm data enhancement based on mixup strategy” “ Population-level contrast loss”.

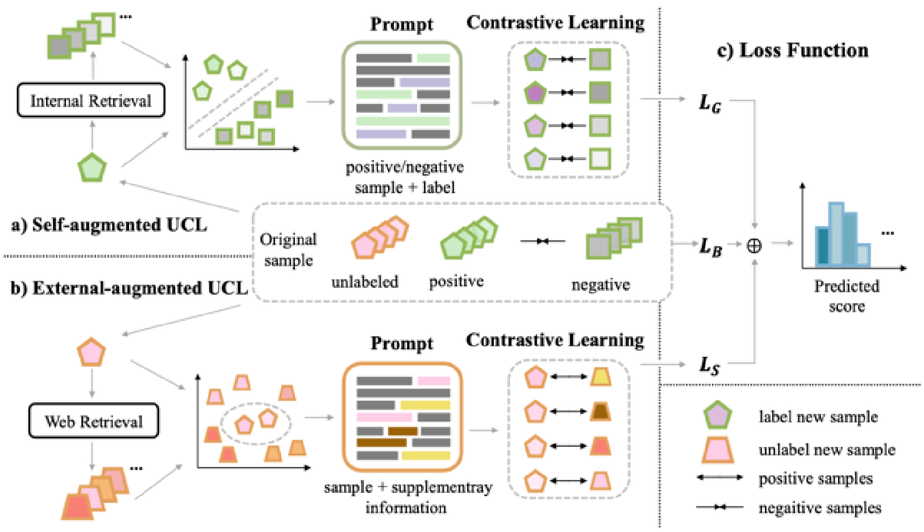

Figure 3. The overall of LA-UCL[5]

The researchers evaluate this problem on LA-UCL on 5-way 1-shot and 5-way 5-shot text cat settings. All experiments were run on NVIDIA Tesla V100 PCIe 32GB GPUs. Similarly, experiments were conducted on six text-based datasets in the article and eight different kinds of baseline comparisons were conducted. There are several key findings:

The LA- UCL model has superior performance on all baselines including meta-learning and contrast learning methods. These laboratory results afford powerful proof for the effectiveness of LA-UCL in solving small-sample studying challenges in short text categorization assignments. For the other new task, LA-UCL effectively improves the performance of modeling the shot-less problem. To validate the effectiveness of the model improvement mechanism, the following four experimental analyses were conducted, Ablation Study, Hyperparameter Analysis, Visual Analysis, Error Analysis, which demonstrate that LA- UCL effectively provides the model's performance for small number of samples through self-enhanced unsupervised comparison learning. classification ability.

5. Causal Reasoning for Machine Language Model-Human Cooperation

Allowing humans to learn from past human-machine interactions and thus improve machine-human cooperation is itself a causal problem.

The authors puts forward a new causal relationship estimation approach for collaborative LM-human, namely Incremental Stylistic Effects (ISE).

A "formalized" text's ISE will survey the accumulated incremental effect of increasing formality in a systematical way through every this kind of edit. The general applicability of these stylistic variations satisfies the positive situation when in causal inference, since to make every text to be more formal (in the author's stylistic example) is always possible.

Therefore, the authors next introduce an algorithm called CausalCollab, which uses the ISE as a guided estimation metric to assess the validity of LM-human cooperation tactics as time goes on. The algorithm operates by identifying and analyzing the stylistic variations that are prevalent in interactions of past machine-human. Then it assesses the influence of these variations in a variety of dynamic LM-human cooperation circumstances.

CausalCollab evaluation indexes: By assessing the capability of the middle underlying consequence assessments for $E\ [\ \{Y_i(\{\ f_t(\ a_t\ ,\ L_{it}\ )\}\ _{T_i=1}\ ]\ )$, the author can evaluate the quality of CausalCollab's ISE estimates.

Outcomes, confounders, observations, and counterfactual data: Both and counterfactual and observational data are necessary to efficiently test causal approaches [6,7].

Quantitative analysis of the consequences: The results of predicting these three different datasets(averaged on three seeds at random) using each approach are in Table 1 [8]. Because applying Mean Squared Error (MSE) performance is measured, the more inferior values is, the more superior capability is. In these three different datasets, intervention with g-estimation PCA or + CVAE obviously close the difference which is among the counterfactual and observed MSE. Compared to the unadjusted method, the proposed method obviously enhances the counterfactual capability while sustaining competing or capability better observed in these three different datasets.

Table 1. Performance (MSE) of different approaches on three datasets[8]

Dataset	DIALOCONAN		Baize		Coauthor	
Model	Counterfactual	Observational	Counterfactual	Observational	Counterfactual	Observational
No Adjustment	.489(.017)	.287(.018)	.351(.003)	.270(.011)	.353(.018)	.188(.004)
No Adjustment +CAVE	.357(.003)	.236(.004)	.276(.006)	.218(.004)	.407(.016)	.173(.003)
No Adjustment +PCA	.363(.003)	.227(.005)	.276(.005)	.215(.010)	.383(.015)	.163(.006)
GE	.488(.018)	.283(.106)	.346(.006)	.266(.009)	.252(.009)	.213(.010)
G-E+CAVE	.272(.002)	.227(.000)	.232(.001)	.202(.004)	.219(.004)	.216(.001)
G-E+PCA	.273(.004)	.222(.002)	.232(.003)	.199(.005)	.219(.004)	.201(.003)

Qualitative Analysis of consequences : Things about z arrests. Quantitative consequences of them display that the acquired processing embeddings triumphantly close the capability difference among counterfactual and observed data. However z arrests something which could help foretell consequences. The authors make the CVAE's words's definition that are semantically nearest to their acquired processing embeddings z_i in the human refinement A_i. Qualitative consequences display that the CVAE model can learn interpretable human policies based on the outcomes of the task.

The robustness of the proposed method to α~split, noisy and different dimensionality of CVAE 'latent space is evaluated by conducting empirical study on the CoAuthor dataset.

Figure 4[8], regardless of the strength of the promiscuous relationship, the authors' restructuring keeps the observational and counterfactual capabilities close (note that for lesser α , i.e., $\alpha < 0.5$, the confounding correlation is stronger.) The authors observe that their method significantly exceeds other methods in situations with elevated noise levels. In addition, it shows minimal performance change across distinct dimensions of z_i.

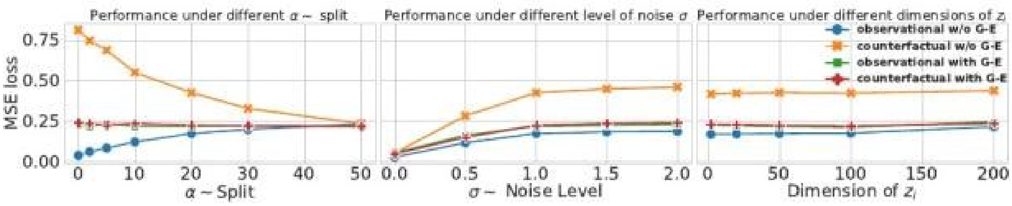

Figure 4. Bohan Zhang et al. 's method on the coauthor dataset has different α~split , noise level σ and dimension z values. [8]

6. Challenges and perspectives

For the first part of the meta learning D-REPTILE model, based on the analysis of existing experimental results, D-REPTILE performs outstandingly in conversation tracking, but faces challenges such as hyperparameter tuning, stability, experimental evaluation, and cross domain adaptation. Hyperparameters such as learning rate and gradient steps significantly affect performance, especially in limited data, and tuning to avoid overfitting/underfitting is particularly crucial. Transformer based

DOI: 10.54254/2755-2721/96/20241299

models may be unstable during fine-tuning, resulting in fluctuations in D-REPTILE performance, and stability and repeatability need to be improved. In addition, the experimental results are subject to random factors interference, and rigorous experiments need to be designed to accurately evaluate them. The slots between different domains are similar but the semantics are complex and varied, making it difficult for D-REPTILE to adapt during fine-tuning. Therefore, strategies need to be optimized to address semantic differences. The future development of D-REPTILE will focus on introducing more regularization and optimization techniques to stabilize model fine-tuning; Research precise domain migration methods to enhance cross domain adaptability; Explore combining traditional high data training methods to improve performance in a big data environment. These directions aim to comprehensively enhance the practicality and generalization ability of D-REPTILE.

There are still some limitations to the research on PET. First, a major challenge in practical applications is that it is impossible to predict the performance of PET on a specific task, so future research is needed to study how to evaluate performance without a large test set. In addition, the potential of PET has not been fully explored, for example, domain adaptive pre-training and auxiliary language modeling have not been explored, and these methods have been proven to be beneficial. At the same time, the impact of B77 decisions and monitoring effects have not been quantified, and the current research only involves English models and datasets. Finally, in addition to the comprehensive score, the performance of PET in other aspects has not been examined. Although there are difficulties in conducting such analysis on RAFT, similar studies on other datasets will help to more fully understand the actual capabilities of instruction-based methods.

Third, LA-UCL still has difficulty in handling some tasks with very long sequences. As well as, exploring the effect of data segmentation on few-shot learning. Then, it is still necessary to train the retrieval technique.

One limitation of the causal collaboration algorithm is that it totally assesses the availability of extant machine-human learning tactics rather than straightaway detecting optimalizing cooperation tactics, that can be a challenging pathway for tomorrow act. It is believed that the authors' approach has the potential to obviously enhance the dynamics of machine-human learning cooperation. Because language models proceed to develop and become increasingly an integration into a variety of fields, it will be critical to understand and optimize the interaction between humans and these models, and the authors inspire further exploration in the future.

7. Conclusion

This paper discusses four cutting-edge methods for solving few-shot and zero-shot learning in the field of natural language processing at this stage and analyzes their advantages: meta-learning algorithm D-REPTILE - combining meta-learning ideas, improving the model's initialization performance in new fields through cross-domain learning, accelerating adaptation to new tasks, and providing sufficient evidence for developers of automatic conversational systems in unknown fields; pattern utilization training PET model - combining text instructions and fine-tuning of labeled samples to achieve few-shot learning from a real-world perspective ; LA-UCL framework - improving the classification function of small samples through data enhancement and unsupervised contrastive learning to achieve efficient data expansion; causal reasoning of human-computer language model collaboration. The first three methods are currently the best methods to solve the few-shot and zero-shot problems in certain fields. However, through the research in this paper, it is found that the first three methods have limitations, including hyperparameter tuning of D-REPTILE, performance evaluation of PET on different tasks, and difficulty of LA-UCL in processing long sequence tasks. These issues provide important inspiration for future research directions, and also lead to a fourth method - causal reasoning of human-machine collaboration. This paper analyzes the causal estimation method Incremental Stylistic Effect (ISE), which provides new perspectives and tools for understanding and optimizing machine-human learning cooperation. At the same time, by analyzing three data sets of machine-human collaborative learning, it is verified that CausalCollab can precisely assess the causal influence of interaction tactics. By enhancing the model's ability to understand causal relationships through causal analysis, at this level, it

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is expected to solve the problem of few-sample learning, but there are still difficulties and challenges. Overall, this paper's work provides new ideas and methods for the application of small-sample learning in the area of DST, which has important theoretical and practical significance.

Authors Contribution

All the authors contributed equally and their names were listed in alphabetical order.

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