Multistage Collaborative Knowledge Distillation from Large Language Models

Jiachen Zhao[1], Wenlong Zhao[1*], Andrew Drozdov[1*], Benjamin Rozonoyer[1], Md Arafat Sultan[2], Jay-Yoon Lee[3], Mohit Iyyer[1], Andrew McCallum[1]

[1]University of Massachusetts Amherst, [2]IBM Research AI, [3]Seoul National University

jiachenzhao@umass.edu

Abstract

We study semi-supervised sequence prediction tasks where labeled data are too scarce to effectively finetune a model and at the same time few-shot prompting of a large language model (LLM) has suboptimal performance. This happens when a task, such as parsing, is expensive to annotate and also unfamiliar to a pretrained LLM. In this paper, we present a discovery that student models distilled from a prompted LLM can often generalize better than their teacher on such tasks. Leveraging this finding, we propose a new distillation method, multistage collaborative knowledge distillation from an LLM (MCKD), for such tasks. MCKD first prompts an LLM using few-shot in-context learning to produce pseudolabels for unlabeled data. Then, at each stage of distillation, a pair of students are trained on disjoint partitions of the pseudolabeled data. Each student subsequently produces new and improved pseudolabels for the unseen partition to supervise the next round of student(s) with. We show the benefit of multistage cross-partition labeling on two constituency parsing tasks. On CRAFT biomedical parsing, 3-stage MCKD with 50 labeled examples matches the performance of supervised finetuning with 500 examples and outperforms the prompted LLM and vanilla KD by 7.5% and 3.7% parsing F1, respectively.

1 Introduction

Low-resource tasks are common in real-life applications, including in specialized domains where data collection is expensive and requires expert knowledge (Verspoor et al., 2012). Semi-supervised learning has been proposed as a solution when abundant unlabeled data are available (McClosky et al., 2006; Blum and Mitchell, 1998; Han et al., 2018). In a typical application, a model is trained on limited labeled data and produces pseudolabels for unlabeled data (Amini et al., 2022; McClosky et al., 2008). The synthetic data are filtered according to some confidence threshold and used to train a new model. In more extreme few-shot cases, labeled data are too scarce to finetune a decent model to begin with. Since large language models (LLMs) can be prompted with a few demonstrations to perform a wide variety of sequence generation tasks, it has become popular to employ LLMs to synthesize pseudolabels (Wang et al., 2021b; Yoo et al., 2021; Ding et al., 2022). Fast and accurate domain-specific models can then be trained using knowledge distillation (KD) from LLMs.

In this paper, we study a challenging semi-supervised sequence prediction scenario where labeled data are too few to finetune a model and few-shot prompted LLMs also have suboptimal performance. This happens when the task is both expensive to annotate and unfamiliar to off-the-shelf LLMs. For example, it took 80 annotators around 2.5 years to parse the 20k sentences of biomedical text in the CRAFT corpus (Verspoor et al., 2012). An LLM pretrained on natural language data may not excel in parsing where the outputs are logical forms; in-context learning performance can also be mediocre now that input text is from a specialized scientific domain. Our overarching research question in this paper is whether in this scenario we can still leverage an LLM to develop a strong prediction model.

We examine vanilla KD using a few-shot prompted LLM as the teacher and find that the student model generally outperforms the LLM teacher on unseen evaluation data. This is not very surprising given the large distribution shift the teacher undergoes when applied to the task; at the same time, this result is encouraging as it opens up the possibility of leveraging the student as a teacher for further distillation. Motivated by this phenomenon, we propose a novel distillation method, multistage collaborative knowledge distillation from an LLM (MCKD), for semi-supervised

[*]Equal contribution

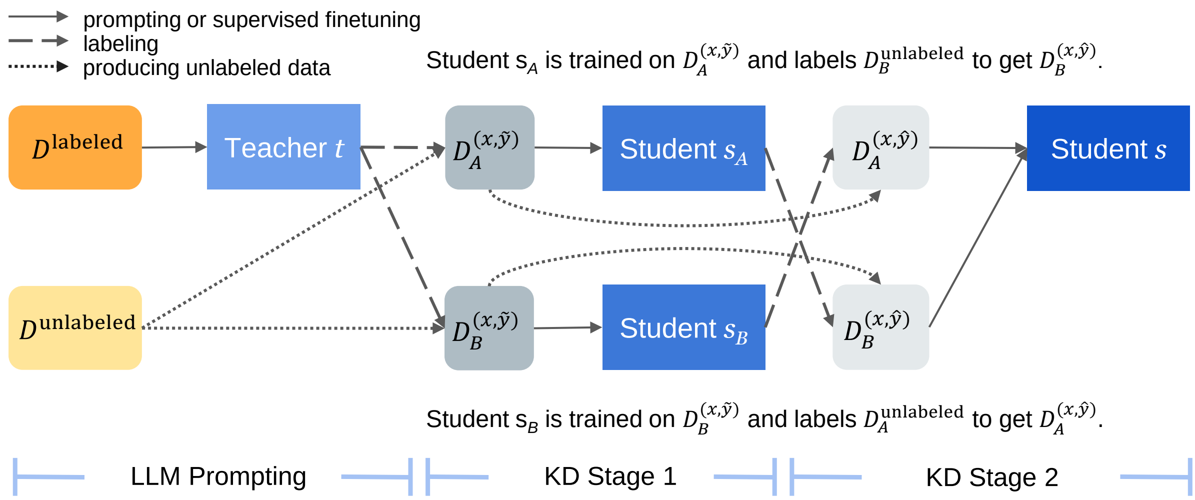


Figure 1: Overview of 2-stage multistage collaborative knowledge distillation from an LLM (MCKD). We prompt an LLM teacher t to produce pseudolabels for unlabeled data $\mathcal{D}^{\text{unlabeled}}$, using demonstrations from few-shot labeled data $\mathcal{D}^{\text{labeled}}$. We partition $\mathcal{D}^{\text{unlabeled}}$ into $\mathcal{D}_A^{\text{unlabeled}}$ and $\mathcal{D}_B^{\text{unlabeled}}$. Let $\mathcal{D}_A^{(x,\tilde{y})}$ and $\mathcal{D}_B^{(x,\tilde{y})}$ denote these data with teacher-generated pseudolabels. In KD stage 1, each of student s_A and s_B is trained on a partition and produces pseudolabels for the other partition. Let $\mathcal{D}_A^{(x,\hat{y})}$ and $\mathcal{D}_B^{(x,\hat{y})}$ denote unlabeled data with student-generated pseudolabels. In stage 2, the final student s is trained on both latest pseudolabeled partitions $\mathcal{D}_A^{(x,\hat{y})}$ and $\mathcal{D}_B^{(x,\hat{y})}$.

sequence prediction. We first collect pseudolabels for a large amount of unlabeled data from an LLM. Then we perform multistage knowledge distillation. We split the pseudolabeled data into two partitions and perform cross-partition labeling. At each stage, a pair of students are trained on distinct partitions of pseudolabeled data and produce improved pseudolabels for the data that they have not been trained on, taking advantage of the fact that the students generalize better than their teachers. In the final distillation stage, a single student is trained on all the latest pseudolabeled data.

Our main contributions are as follows:

- We study whether an LLM can be leveraged to train a strong student model for semi-supervised sequence prediction tasks on which the LLM itself performs suboptimally when prompted with in-context learning examples. We find that a student can often achieve better generalization than an LLM teacher when trained with vanilla KD.

- We propose a novel distillation method, multistage collaborative knowledge distillation from an LLM (MCKD), for semi-supervised sequence prediction. Data partitioning and cross-partition labeling enable us to gradually improve the quality of pseudolabels over multiple distillation stages, which in turn improves student performance.

- Given 50 to 250 gold labeled examples on two constituency parsing datasets, 2- and 3-stage MCKD consistently and significantly outperform few-shot prompted LLMs, direct supervised finetuning, and KD baselines. On CRAFT biomedical parsing, 3-stage MCKD with 50 labeled examples matches the performance of supervised finetuning with 500 examples and outperforms the LLM and vanilla KD with 50 labeled examples by 7.5% and 3.7% parsing F1, respectively.

- Further analyses show that (a) the student corrects many of the teacher's errors, and (b) a sufficiently large amount of unlabeled data is needed for the student to reach its peak performance.

2 MCKD: Multistage Collaborative Knowledge Distillation from an LLM

2.1 Problem setup

We study semi-supervised sequence prediction tasks where the training data consist of few labeled examples $\mathcal{D}^{\text{labeled}} = \{x_i, y_i\}_{i=1}^{N_{\text{labeled}}}$ and many unlabeled examples $\mathcal{D}^{\text{unlabeled}} = \{\bar{x}_i\}_{i=1}^{N_{\text{unlabeled}}}$. In each example, x and y are sequence data. We assume (1) $\mathcal{D}^{\text{labeled}}$ is not large enough for training a capable prediction network via direct supervised fine-tuning and (2) LLM few-shot prompting with demonstrations sampled from $\mathcal{D}^{\text{labeled}}$ has suboptimal performance. This is a challenging but prevalent scenario that happens when a task is both expensive to annotate and unfamiliar to off-the-shelf LLMs. Examples of these tasks include various parsing, domain-specific, and low-resource language applications.

2.2 Method

MCKD employs an LLM for synthetic data generation and multistage collaborative knowledge distillation to train a fast and accurate final prediction network. Figure 1 illustrates 2-stage MCKD; the KD Stage 1 of it can be repeated in MCKD with more stages.

LLM in-context learning. We sample examples from the labeled dataset $\mathcal{D}^{\text{labeled}}$ to prompt LLMs to produce pseudolabels for unlabeled data $\mathcal{D}^{\text{unlabeled}}$.

MCKD. We focus on tasks that are challenging for few-shot prompted LLMs and conjecture that training a specialized student model using a sufficient amount of pseudolabels from an LLM teacher can outperform the LLM teacher on held-out data. We confirm this speculation in Sec. 5.1, finding that when a student learns teacher pseudolabels well, its generalization performance can surpass the LLM in-context learning performance on the same held-out evaluation data.

Inspired by this finding, we propose a multistage knowledge distillation method with the hypothesis that a student distilled from an LLM teacher can produce better pseudolabels for training a next-stage student. Now that the student model well fits the teacher pseudolabels on its training data, using the student to label its training data will result in similar pseudolabels that it is trained on and no significant improvement. To leverage the better generalization performance of the student, we propose data partitioning and **cross-partition labeling**. We split unlabeled data $\mathcal{D}^{\text{unlabeled}}$ randomly and evenly into two distillation sets $\mathcal{D}_A^{\text{unlabeled}}$ and $\mathcal{D}_B^{\text{unlabeled}}$. At each intermediate distillation stage, we (1) train a pair of students using the distinct partitions with pseudolabeled data from the previous stage and (2) let each student predict pseudolabels for the partition that it has not been trained on, in order to gradually improve the overall quality of the latest pseudolabels for $\mathcal{D}^{\text{unlabeled}}$ over stages. In the final distillation stage, a student model is trained on the entire $\mathcal{D}^{\text{unlabeled}}$ with the latest pseudolabels.

Distillation mechanism. Throughout this work, we experiment with sequence-level knowledge distillation where a sequence prediction student is trained on hard labels generated by the teacher. This is an effective distillation method compared to token logit distillation for sequence generation tasks (Kim and Rush, 2016), commonly adopted in literature on distillation from LLMs (Wang et al., 2021b; Yoo et al., 2021; Ding et al., 2022; Li et al., 2023; Gilardi et al., 2023), and applicable given either open-source or closed-source LLM teachers.

3 Experimental Setup

3.1 Data and evaluation

Datasets. We perform experiments on two constituency parsing datasets where a general-purpose LLM pretrained to generate natural language text will undergo distribution shifts and produce suboptimal results. We use the Penn Treebank (PTB) dataset (Marcus et al., 1993) for news parsing and the Colorado Richly Annotated Full-Text (CRAFT) corpus for biomedical text parsing (Verspoor et al., 2012). PTB has standard training, validation, and testing splits. CRAFT contains 21121 sentences, but does not have standard splits; we randomly sample 50%/10%/40% of the sentences to form the training, validation, and testing sets. Semi-supervised learning for biomedical tasks is especially valuable since data annotation usually requires expertise and is formidably expensive. It took 80 annotators around 2.5 years to parse the 20k sentences in the CRAFT corpus.

Simulating low-resource scenarios. For each dataset, we sample 250 examples from the training set as labeled data and treat the remaining examples as unlabeled data. In different experiments, we randomly sample 50 or 250 of the 250 labeled data as the labeled set $\mathcal{D}^{\text{labeled}}$. For the main results (Table 1), We randomly sample 20k unlabeled data as $\mathcal{D}^{\text{unlabeled}}$ for PTB and all the available 9060 unlabeled data as $\mathcal{D}^{\text{unlabeled}}$ for CRAFT. We then randomly and evenly partition $\mathcal{D}^{\text{unlabeled}}$ into $\mathcal{D}_A^{\text{unlabeled}}$ and $\mathcal{D}_B^{\text{unlabeled}}$. We do not use the validation sets, assuming a low resource regime where the only available labeled data are $\mathcal{D}^{\text{labeled}}$. We use test sets for final evaluation.

Evaluation. We compute per-example parsing F1 and average over examples to measure model performance. We use bracketing in training and evaluation, but discard constituent tags (see Appendix B.1 for more details).

3.2 Model, learning, and prediction

LLM teacher. We use gpt-3.5-turbo, i.e., ChatGPT, to collect initial pseudolabels for $\mathcal{D}^{\text{unlabeled}}$. We access it through the OpenAI API. We randomly and uniformly sample 30 labeled parsing examples from $\mathcal{D}^{\text{labeled}}$ to include in the prompt for each unlabeled example in $\mathcal{D}^{\text{unlabeled}}$, since 50 or 250 examples will exceed the allowed maximum context length. More details about the prompt design are in Appendix C.

Student model. We use T5-Base as the student models (220M parameters). We use the same hyperparameters for training students in all experiments: learning rate 3×10^{-4}, batch size 32, and 21 maximum training epochs. We assume a low-data regime where no labeled validation dataset is available. We stop training runs when the difference in student's training performance among three epochs is within 0.1%. Student pseudolabels are predicted with greedy decoding.

3.3 Baselines

We compare MCKD with the LLM teacher, T5-Base finetuned using few-shot labeled data $\mathcal{D}^{\text{labeled}}$, and two knowledge distillation baselines described below.

Vanilla KD. We employ sequence-level knowledge distillation (Kim and Rush, 2016) where a student is trained on hard labels generated by gpt-3.5-turbo for the unlabeled dataset $\mathcal{D}^{\text{unlabeled}}$.

KD + SD w/ filtering. We train a student to match teacher pseudolabels on the entire unlabeled dataset $\mathcal{D}^{\text{unlabeled}}$ through vanilla KD. We then apply self-distillation (SD): letting the student predict pseudolabels for $\mathcal{D}^{\text{unlabeled}}$, filtering them by keeping half of the data where the student has the highest average token log-probabilities, and retraining a student on the filtered pseudolabeled data. Confidence-based filtering is a common method to optimize learning from pseudolables (Lang et al., 2022; Wang et al., 2021a; Mohananey et al., 2020; Vinyals et al., 2015; McClosky et al., 2006). KD + SD without filtering is similar to vanilla KD, since the student pseudolabels on $\mathcal{D}^{\text{unlabeled}}$ will be almost the same as teacher pseudolabels. Since we use a blackbox LLM teacher where logits are unavailable, we also do not use a baseline that filters LLM pseudolabels.

Method	PTB 50	PTB 250	CRAFT 50	CRAFT 250
ChatGPT	69.1	70.7	60.0	59.9
T5-Base	0	59.7	0	54.1
Vanilla KD	71.6	74.7	63.8	63.7
KD + SD w/ filter	72.4	74.6	64.3	64.9
2-stage MCKD	73.9	76.6	66.9	67.5
3-stage MCKD	**74.2**	**76.9**	**67.5**	**68.7**

Table 1: Parsing F1 on PTB and CRAFT test sets using 50 or 250 labeled training data. ChatGPT is few-shot prompted, while T5-Base is finetuned. MCKD outperforms baselines in all settings.

4 Main Results

Baseline performance. As shown in Table 1, ChatGPT's few-shot performance on constituency parsing is around 70% F1 for PTB and 60% for CRAFT. Sampling in-context demonstrations from a pool of 50 of 250 labeled data does not make a big difference, now that the number of samples that can fit in the ChatGPT input is the same. Vanilla KD can yield students that outperform the teacher. KD + SD w/ filtering performs similarly to or slightly better than vanilla KD. Direct supervised finetuning of T5-Base has the worst performance. On both datasets, 50 labeled data are too few to effectively finetune a T5-Base model.

MCKD performance. Our MCKD approach significantly outperforms the few-shot prompted ChatGPT and KD baselines in all setting. For example, on CRAFT with 50 gold labeled training examples, 2-stage MCKDperforms ChatGPT by 6.9% F1 and Vanilla KD by 3.1% F1. The 3-stage MCKDfurther improves the results, outperforming ChatGPT by 7.5% and Vanilla KD by 3.7%, but requires additional training time. Practitioners can choose the number of stages ad hoc.

Comparison with direct supervised finetuning. As shown in Figure 2, 3-stage MCKD using 50 labeled examples can match the performance of supervised finetuning of T5-Base using 500 labeled examples on PTB, and outperform SFT using 500 labeled examples on CRAFT. This demonstrates the label-efficiency of MCKD and its effective-

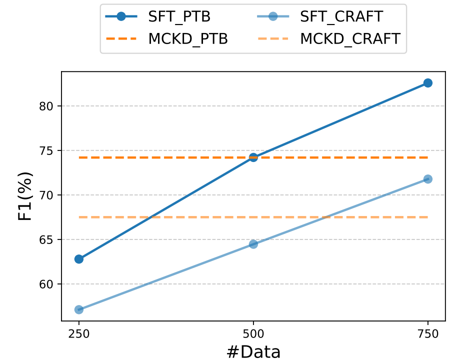


Figure 2: 3-stage MCKD with 50 labeled examples can match the performance of supervised finetuning (SFT) with 500 or more labeled examples on PTB and CRAFT.

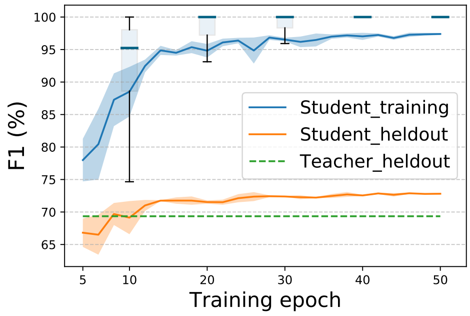


Figure 3: A student model is trained on 4k data $\mathcal{D}_A$ with LLM pseudolabels and evaluated on 4k held-out data $\mathcal{D}_B$. The student held-out performance (orange) increases as it better fits the teacher pseudolabels on the training data (blue) and outperforms the teacher performance on the held-out data.

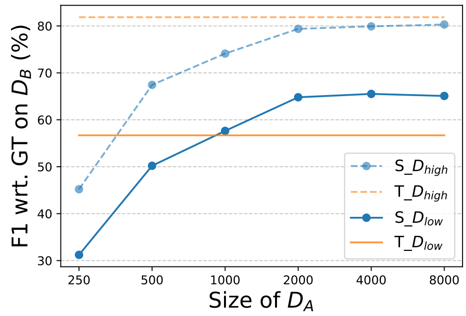


Figure 4: Further comparison between the performance on held-out data of student and teacher. We then compare the student and teacher on those two splits, as denoted by, e.g., S_$\mathcal{D}_{high}$ and T_$\mathcal{D}_{high}$. It is observed that the student and teacher have high agreement on $\mathcal{D}_{high}$, while the student can outperform the teacher on $\mathcal{D}_{low}$, i.e., where the teacher performs poorly.

ness in semi-supervised sequence generation tasks where annotation is expensive. When abundant labeled examples are available, practitioners can directly finetune a T5-base without needing to rely on LLM few-shot reasoning abilities.

5 Analysis

In this section, we perform analysis experiments using PTB data. We sample subset of $\mathcal{D}_A^{\text{unlabeled}}$ and $\mathcal{D}_B^{\text{unlabeled}}$ (Sec. 3.1), denoted as $\mathcal{D}_A$ and $\mathcal{D}_B$, of different sizes for various experiments. We train stage-1 students using $\mathcal{D}_A$ with pseudolabels from an LLM teacher, and evaluate them on $\mathcal{D}_B$ against ground truth labels. Then we train stage-2 students using $\mathcal{D}_B$ with pseudolabels from stage-1 students.

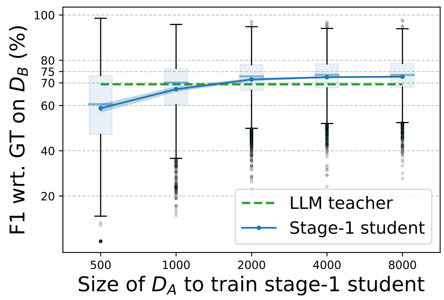
5.1 Student generalization correlates with training fidelity

When we train a stage-1 student on 4k data $\mathcal{D}_A$, we stop the runs when the student training F1 compared to the LLM teacher's pseudolabels converges. We find that as this training fidelity (Stanton et al., 2021) increases, the student performance on 4k held-out data $\mathcal{D}_B$ also increases (Figure 3). This trend similarly holds for other distillation set sizes (see Appendix A). When the average per-example F1 converges, the medium per-example F1 is close to 100%, indicating that the student has perfectly memorized many teacher pseudolabels. However, this does not affect the generalizable patterns learned by student model. The student generalization performance continues to increase and outperforms the few-shot prompted LLM teacher on $\mathcal{D}_B$. This suggests that in low-data regimes without a validation set, training the student toward high fidelity with teacher pseudolabels can be a viable strategy to pick checkpoints during the distillation process. We adopt this strategy in all distillation experiments.

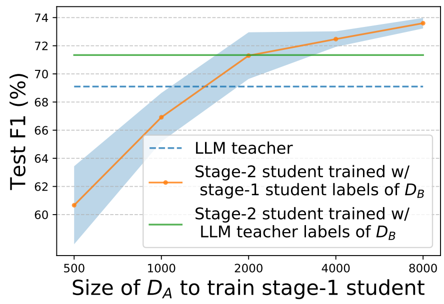
5.2 Student can correct teacher errors

We further look into how a student trained on various amounts of pseudolabeled data $\mathcal{D}_A$ may outperform an LLM teacher on 4k held-out data $\mathcal{D}_B$. We split $\mathcal{D}_B$ evenly into halves, $\mathcal{D}_{high}$ and $\mathcal{D}_{low}$, based on teacher performance. The teacher achieves high F1 on the former examples and low on the latter.

As shown in Figure 4, the student performance on both halves increase given more pseudolabeled training data $\mathcal{D}_A$. Give a large enough $\mathcal{D}_A$, the student approaches teacher performance on the examples that the teacher is good at, i.e. $\mathcal{D}_{high}$, and outperforms the teacher on examples where the teacher performs poorly, i.e., $\mathcal{D}_{low}$. The student can



(a)



(b)

Figure 5: (a) Stage-1 student performance on 4k held-out data D_B increases with more LLM pseudolabeled data D_A. (b) The test performance of stage-2 student trained by 4k D_B data with stage-1 student pseudolabels increases when the stage-1 student is trained on a larger teacher pseudolabeled D_A.

correct teacher mistakes especially on the examples that the teacher is bad at. This shows that the student is able to learn a generalizable distribution for the task by learning noisy teacher pseudolabels.

5.3 Larger distillation sets help student performance

Given the same amount of labeled data $\mathcal{D}^{\text{labeled}}$, we show that a larger amount of unlabeled data $\mathcal{D}^{\text{unlabeled}}$ can improve the performance of the final student. Figure 5a shows that as the training set $\mathcal{D}_A$ for the stage-1 student grows larger, the performance of the stage-1 student on the separate set of 4k data $\mathcal{D}_B$ increases. With 2k, 4k, and 8k data in $\mathcal{D}_A$, the stage-1 student outperforms the few-shot prompted LLM on the held-out set $\mathcal{D}_B$.

Then we use 4k $\mathcal{D}_B$ with pseudolabels from the stage-1 student to train a stage-2 student and evaluate it on the test set (Figure 5b). We observe that when the stage-1 student is trained on a sufficiently large $\mathcal{D}_A$, this outperforms the stage-2 student trained on 4k teacher pseudolabeled $\mathcal{D}_B$. Although using 2k, 4k, and 8k data to train the stage-1 student yields similar stage-1 student F1, we find that this F1 is not a good indicator for the supervision signals that a stage-1 student can provide for a stage-2 student. The stage-1 student trained with more data tends to have less variance in its per-sentence F1 and has less poor-performing examples. Accordingly, a better stage-2 student can be trained by using pseudolabels from a stage-1 student that is trained on more data. Overall, we find that an adequately large distillation set is necessary for the final student to achieve its peak performance. In MCKD, we partition the unlabeled dataset and use a pair of students at each stage to label all of them, so that the final student can take advantage of all the unlabeled data available.

6 Related Work

Knowledge Distillation. Knowledge distillation, apart from being used for model compression (Tang et al., 2019; Jiao et al., 2020; Bucila et al., 2006; Sun et al., 2020), is effective for semi-supervised learning (Iliopoulos et al., 2022), where a teacher model annotates unlabeled data to train a student model. In terms of KD for sequence-to-sequence tasks, it has been popular to use hard pseudolabels from teachers (Kim and Rush, 2016), including LLM teachers (Ding et al., 2022; Yoo et al., 2021; Wang et al., 2021b; Gilardi et al., 2023; Shridhar et al., 2022; Ho et al., 2022; Li et al., 2023). Self-distillation (SD) (Furlanello et al., 2018; Liu et al., 2021) through training the model with its self-generated labels on external unlabeled data is often valuable in enhancing generalization, but finding reliable confidence thresholds to filter the self-generated labels is often tricky.

Co-training. Co-training (Blum and Mitchell, 1998; Han et al., 2018; Lang et al., 2022) is relevant to our work as it involves using a separate model to generate improved pseudolables. Wei et al. (2021) provides theoretical explanation on why generated pseudolables can be more credible than original labels for training. Co-training employs two models that iteratively train each other, utilizing their own predictions and considering the newly generated confident pseudolables as more reliable. It can be seen as a form of KD with alternating roles of student and teacher. In contrast, our approach introduces a new compact student model instead of retraining the initial teacher model. This is more efficient than co-training and favorable when the teacher is an LLM (Lang et al., 2022).

7 Conclusion

We study semi-supervised sequence generation tasks where labeled data are too scarce to finetune a model and few-shot prompted LLMs have mediocre performance. We present the discovery that a student distilled from an LLM can often correct many teacher mistakes and generalize better than the LLM teacher on such tasks. We then propose multistage collaborative knowledge distillation (MCKD), a novel distillation method that significantly outperforms the LLM teacher and students trained by vanilla KD. Data partitioning and cross-partition labeling design enable us to leverage student generalization abilities to improve the quality of pseudolabels over stages, and thus obtain train student models. Extensive experiments demonstrate the label-efficiency of MCKD and its effectiveness for low-resource sequence prediction.

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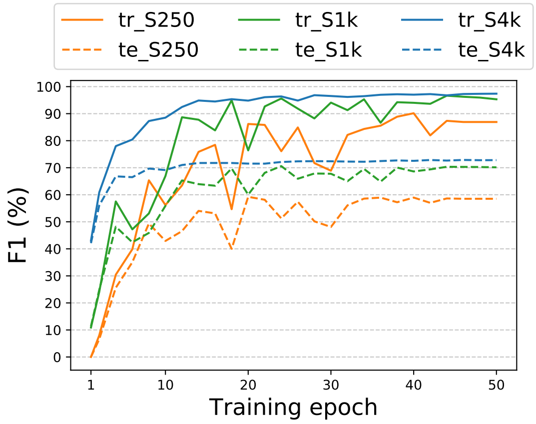

Figure 6: Training F1 of student wrt. teacher labels and according F1 wrt. ground truth on held-out data with different scales of distillation sets, e.g., "tr_S250" representing the training F1 of student trained with 250 teacher labels "te_S250" for performance on held-out data. Despite the reduced size of distillation set (4k, 1k, 250), the student will generally have higher test performance on held-out data rather than overfitting when the student memorizes more teacher labels during training.

A Effects of Training Fidelity in Distillation Sets of Different Sizes

As discussed in Section 5.1, we find high training fidelity, can generally lead to a better student's performance on held-out data, despite the unreliability of teacher labels. This section investigates whether the observation still holds with different scales of the distillation set, especially when the size is significantly smaller. Results are shown in Figure 6. Similar patterns across different scales of distillation sets can be observed. Even if the distillation set only contains 250 teacher labels, the student can still generally have better performance on held-out data rather when the student memorizes more teacher labels.

B Reproducibility Notes

B.1 Parsing F1

We use parsing F1 to measure model performance, and we remove punctuation before computing parsing F1.[1] Many constituency parsing models output binary trees which are partially flattened by using `-NONE-` tags, and sometimes no flattening is done which in turn limits the upperbound on parsing F1. The sequence-to-sequence approach we use has no such limitation. We minimally post-process model outputs, balancing brackets and fixing accidental word segmentation.[2]

...
Input:{input string of exemplar i}
Output:{output result of exemplar i}
...
Input:{input string of test data}
Output:

Table 2: The prompting format for LLM.

C Prompting LLM for Pseudolabel Generation

We employ the standard random selection approach (Brown et al., 2020) to choose in-context exemplars from available labeled data to prompt the LLM. The prompt is shown in Table 2.

[1] Ground truth parse tree decisions associated with punctuation are often arbitrary and deterministic, and are not informative for task performance.

[2] Our student and teacher generators are unconstrained — early in training T5 fails to consistently output well-formed parse trees but this is not an issue after the first few epochs.