

Meta-learning via Language Model In-context Tuning

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Abstract

The goal of meta-learning is to learn to adapt to a new task with only a few labeled examples. To tackle this problem in NLP, we propose *in-context tuning*, which recasts adaptation and prediction as a simple sequence prediction problem: to form the input sequence, we concatenate the task instruction, the labeled examples, and the target input to predict; to meta-train the model to learn from in-context examples, we fine-tune a pre-trained language model (LM) to predict the target label from the input sequences on a collection of tasks.

We benchmark our method on two collections of text classification tasks: LAMA and BinaryClfs. Compared to first-order MAML which adapts the model with gradient descent, our method better leverages the inductive bias of LMs to perform pattern matching, and outperforms MAML by an absolute 6% AUC ROC score on BinaryClfs, with increasing advantage w.r.t. model size. Compared to non-fine-tuned in-context learning (i.e. prompting a raw LM), in-context tuning directly learns to learn from in-context examples. On BinaryClfs, in-context tuning improves the average AUC-ROC score by an absolute 10%, and reduces the variance with respect to example ordering by 6x and example choices by 2x.

1 Introduction

Few-shot learning (FSL) refers to a system’s ability to quickly adapt to new tasks when very few labeled examples are available for training. FSL is a key feature of human learning and language understanding (Lake et al., 2016), but current machine learning systems are often data-hungry and rely on large amounts of labeled training data (Silver et al., 2016; He et al., 2016; Adiwardana et al., 2020). Building systems that are capable of FSL is important towards building human-like artificial

intelligence, and can also relieve the burden of collecting large-scale labeled data (Altae-Tran et al., 2016; Li et al., 2019).

Recent large pre-trained language models (LMs) show promising progress in FSL (Brown et al., 2020; Schick and Schütze, 2021a). To perform a new task, Brown et al. (2020) prompt a raw LM (i.e., a pre-trained LM that is not fine-tuned on any labeled data) with the task instruction, some input-output examples, and the input to be predicted on; then they extract the answer from the LM’s continuation. For example, to coax the model into performing sentiment classification on the target input “*This movie is a total waste of time*”, we can prompt the language model with the context “*I like the movie! Positive review? Yes. Horrible Movie! Positive review? No. This movie is a total waste of time. Positive review? ____*”, and check whether the next word is more likely to be “Yes” or “No”. LM prompting is highly effective for FSL and sometimes comparable to SOTA based on full-dataset fine-tuning (Brown et al., 2020).

However, raw LMs are not optimized for in-context FSL during pre-training, and exhibit undesirable properties when used for FSL prompting. For example, Zhao et al. (2021) observed that LMs suffer from the “recency bias”, where LMs tend to assign higher probability to labels that appear closer to the target input. As a result, the accuracy of GPT-3 becomes extremely sensitive to the ordering of the in-context examples. Previous work has also shown that prompting raw LMs is often oversensitive to example choices, example ordering, and instruction wording (Schick and Schütze, 2021a; Jiang et al., 2020; Zhao et al., 2021; Gao et al., 2021; Liu et al., 2021).

We address this weakness through a meta-learning lens and directly fine-tune the LM for FSL. Under the meta-learning framework, we meta-train a model to learn to adapt to new tasks from a few examples on a wide range of tasks, so that it better

* Work done during summer internship at AWS AI.

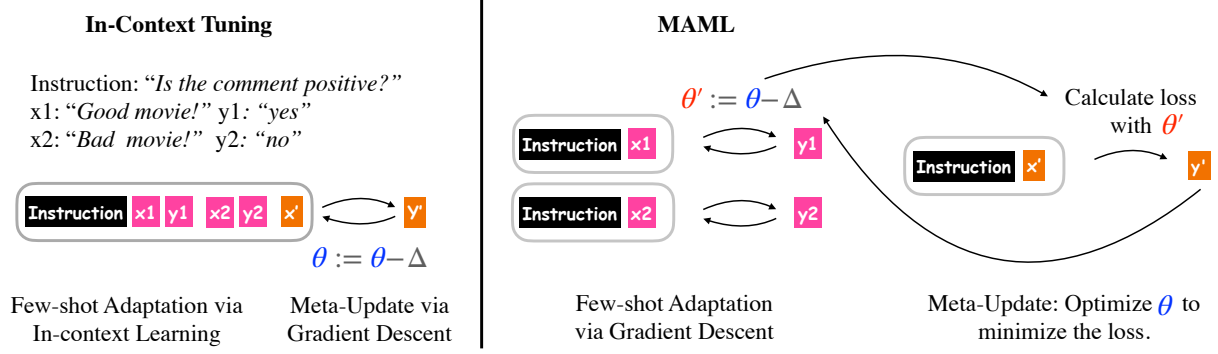


Figure 1: **MAML** (right): MAML aims to learn a task-agnostic model initialization θ that can adapt fast to new tasks. To adapt the model initialization to a new task \tilde{T} , a task-specific model θ' initialized with θ is updated with gradient descent using task examples from \tilde{T} . Meta-training of MAML involves bi-level optimization, where the inner optimization learns a task-specific model θ' using task examples from \tilde{T} , and the outer optimization learns a meta-initialization θ to minimize few-shot prediction loss of θ' on task \tilde{T} . **In-context Tuning** (left): our approach adapts to new tasks via in-context learning, and learns a single model θ shared across all tasks that is directly optimized with the FSL objective (Section 2.2). Because model parameters are frozen during task adaptation, our approach does not involve bi-level optimization during meta-training.

leverages the few-shot examples to adapt to new tasks at test time (Finn et al., 2017). Since the LM prompting framework has already reduced the “task learning and predict” process to a simple sequence prediction problem (Brown et al., 2020), we can meta-train the model by fine-tuning the language model to optimize for this sequence prediction problem on a wide range of tasks. Since we fine-tune our model to learn to learn from in-context examples, we call our approach *in-context tuning*. Our algorithm is illustrated in Figure 1 left.

We benchmark our algorithm on LAMA (Petroni et al., 2019), a dataset for testing models’ factual knowledge, and BinaryClfs (Zhong et al., 2021), which contains a wide range of binary classification tasks each annotated with a few language descriptions of the task. Compared to prompting raw LMs, in-context tuning improves performance by 7.2 points in Precision@1 on LAMA and 10.6% AUC ROC score on BinaryClfs. In addition, in-context tuning mitigates the over-sensitivity of raw LM prompting, significantly reducing the variance of the performance with respect to example ordering (by 68% on LAMA and 83% on BinaryClfs), example choices (by 56% on LAMA and 40% on BinaryClfs), and instruction wording (by 19% on LAMA).

Our approach also outperforms MAML, which adapts the model by gradient descent on a few examples and learns an initialization that can adapt to a new task through a few gradient steps (Finn et al., 2017; Nichol et al., 2018). Since our ap-

proach better takes advantage of the inductive bias of LMs to extrapolate from in-context examples, our approach outperforms first-order MAML by 2.8 points on LAMA and 5.1 points on BinaryClfs, with increasing advantage as models become larger.

Given the empirical effectiveness of in-context tuning (Section 4.1), we conjecture that the few-shot learning potential of large LMs (e.g., GPT-3) may be broadly underestimated if prompted without any direct optimization for FSL. We also conjecture that in-context tuning can mitigate various undesirable properties of LM prompting, such as over-sensitivity to example ordering, example choices, and instruction wording (Section 4.2).

2 Approach

We introduce the problem setup (Section 2.1), describe our in-context tuning algorithm (Section 2.2), compare our algorithm to gradient-based adaptation methods (Section 2.3), and other baselines (Section 2.4).

2.1 Problem Setup

We focus on the few-shot classification problem, where the model first learns from a set of training tasks $T \in T_{\text{Train}}$, each associated with its natural language instructions I_T and a large amount of task input-output examples $D_T = \{(x_T^i, y_T^i)\}$ (see Figure 1 left for examples). At test time, we ask the model to learn a new task \tilde{T} given its instruction and only a few (K) labeled examples, i.e. $S_{\tilde{T}} \subseteq D_{\tilde{T}}, |S_{\tilde{T}}| = K$. We denote the task input to be

predicted at test time as $x_{\tilde{T}}^{\text{target}}$.

Note that “task input” is different from “model input”. For example, on the left panel of Figure 1, the task input is “*Good movie!*” while the model input can be a concatenation of the instruction, task inputs and task outputs.

2.2 In-context Tuning Algorithm

In-context tuning directly optimizes pre-trained LMs with the few-shot in-context learning objective (Brown et al., 2020): task-agnostic LMs are meta-trained to perform few-shot in-context learning on a wide variety of training tasks. Similar to in-context learning, LMs trained with in-context tuning adapt to a new task by using few-shot training examples as the input prefix.

More formally, during meta-training, we build the model input by concatenating the task instruction I_T , task input-output pairs $S_T \subseteq D_T$, and the task input x_T^{target} to be classified. Then we fine-tune a pre-trained LM to predict y_T^{target} and we hope that the model learns to make use of the in-context examples S_T . Here is the few-shot in-context learning objective \mathcal{L} :

$$\mathcal{L}_T(\theta) := \sum_{(x_T^{\text{tgt}}, y_T^{\text{tgt}}) \in D_T} [-\log p_\theta(y_T^{\text{tgt}} | x_T^{\text{tgt}}, S_T, I_T)] \quad (1)$$

$$\mathcal{L}(\theta) := \sum_{T \in T_{\text{train}}} \mathcal{L}_T(\theta) \quad (2)$$

To adapt to a new task \tilde{T} at test time, we directly concatenate the few-shot examples $S_{\tilde{T}}$ with the instruction $I_{\tilde{T}}$ and the target task input $x_{\tilde{T}}^{\text{target}}$ to be classified to form the model input, and ask the model to predict its corresponding output. No gradient update is performed during adaptation.

2.3 Gradient-based Task Adaptation

We compare in-context tuning with two classical few-shot learning methods: multi-task fine-tuning (instruction tuning + fine-tuning) and MAML. Both methods adapt the model parameters to new tasks by gradient descent on few-shot examples.

Instruction Tuning + Fine-tuning We extend the recent work on zero-shot instruction tuning (Wei et al., 2021) to the FSL setting as a *multi-task fine-tuning* baseline. During meta-training, the model is optimized to predict the task output given

the task instruction and the task input on a wide range of tasks (Zhong et al., 2021). Formally, we train the model parameter θ to predict y_T^i given $I_T \circ x_T^i$, where θ is shared across all tasks and \circ represents the concatenation operation. During the few-shot adaptation phase, the model is presented with a new task \tilde{T} , its natural language instruction $I_{\tilde{T}}$ and a small set of (K) task input-output examples $S_{\tilde{T}} = \{(x_{\tilde{T}}^i, y_{\tilde{T}}^i) | i \in [K]\}$. We then fine-tune the model to predict the task output $y_{\tilde{T}}^i$ from the new task given $I_{\tilde{T}} \circ x_{\tilde{T}}^i$ and update θ with a few gradient steps to get $\theta_{\tilde{T}}$. Finally, we use the updated model $\theta_{\tilde{T}}$ to predict the output from the task input $x_{\tilde{T}}^{\text{target}}$ and the instruction $I_{\tilde{T}}$ under the test task \tilde{T} .

MAML The few-shot adaptation stage of MAML is the same as instruction tuning + fine-tuning, where we update the model parameters (initialized with θ) by gradient descent on K examples $S_{\tilde{T}}$. However, during meta-training, MAML aims to learn a task-agnostic model initialization θ such that, θ_T , which is to be found by initializing with θ and performing gradient descent on S_T , would lead to good performance (Finn et al., 2017).

Therefore, MAML involves two levels of optimization, an inner optimization to learn θ_T given θ and S_T , and an outer optimization to learn θ given θ_T . Due to the bi-level structure in this optimization problem, MAML has been found to be empirically unstable, sensitive to hyperparameters, and computationally expensive (Finn et al., 2017; Nikolaev et al., 2020). Even worse, few-shot task adaptation is known to be highly sensitive to optimization hyperparameters (Antoniou et al., 2019), while a large labeled validation set for hyperparameter tuning may not be available under a FSL setting (Perez et al., 2021).

In comparison, in-context tuning simplifies the two-stage process of (1) few-shot task adaptation and (2) task-specific prediction as one sequence prediction problem, where task-specific examples are concatenated to the model input to provide information about the task. Therefore, in-context tuning removes the bi-level optimization during meta-training, which is empirically unstable and expensive. Additionally, it is not sensitive to hyperparameters during task adaptation, since the model weights are frozen.

2.4 Other Baselines

We introduce two other baselines, and categorize all approaches in our paper based on their meta-

¹We sometimes abbreviate “target” as “tgt” to save space.

Method	Adaptation	Meta-train
In-context Tuning	In-context	Few-shot
MAML	Gradient	Few-shot
Ins-T	None	Zero-shot
Ins-T + fine-tuning	Gradient	Zero-shot
LM Prompting	In-context	LM

Table 1: We categorize our approach and the baselines according to 1) how the few-shot examples (if any) are used for adaptation, and 2) the meta-training objective. Ins-T refers to instruction tuning.

training objective and how they use task-specific examples in Table 1. In-context tuning is the only method that directly optimizes the FSL objective during meta-training without gradient-based adaptation.

Few-shot Raw LM Prompting We directly evaluate a raw LM on a new task using the same evaluation set-up for in-context tuning, without fine-tuning the LM on any labeled data.

Instruction Tuning The model learns to predict the target output only based on the instruction and the target input. Only the instruction is available during the adaptation phase, and this setup is also known as zero-shot learning.

3 Experimental Setup

Section 3.1 describes the datasets and metrics, and Section 3.2 describes implementation details.

3.1 Dataset and Metrics

We experiment with two datasets that contain a wide range of tasks, LAMA and BinaryClfs. Each task is associated with several different natural language descriptions, and we call them “instructions” for convenience, even though some of them are realized as questions.

LAMA LAnguage Model Analysis (Petroni et al., 2019) is a dataset that tests the factual and commonsense knowledge learned by LMs. In our experiments, we use the TReX-UHN portion of LAMA (Poerner et al., 2020), which consists of (subject, relation, object) triples from Wikidata. LAMA is an entity prediction task, where a model is asked to predict the object entity given the subject entity and the relation. In our experiments, we treat one relation as a task as in Perez et al. (2021).

Initial experiments on LAMA showed that LMs take significant advantage of “majority label bias”

(Zhao et al., 2021), where they assign higher probability to object entities that have appeared in the in-context examples, thus inflating the accuracy. To reflect the improvement due to few-shot learning rather than this simple heuristic to copy answers, for all tasks we prune the LAMA dataset so that all object entities appear less than 2.5% of times. Our final filtered LAMA dataset consists of 29 relations (tasks) and 12k (subject, relation, object) examples.

We use task instructions from two datasets: LAMA and LPAQA (Jiang et al., 2020). LAMA contains one task instruction for each task, and the auxiliary LPAQA dataset contains on average 10 additional instructions for each LAMA task.

We use the same evaluation protocol as in Petroni et al. (2019): 1) the object entity is predicted from a pre-defined vocabulary set of 21k words; 2) we compute mean precision at one (P@1) for each task, and report the average across tasks. We report the train-dev-test split in Appendix B.

BinaryClfs This dataset contains a wide range of **binary** classification tasks, and each task can be described by 1-4 “yes/no” questions, which we concatenate to the input context as instructions. There are in total 204 different tasks, and 73 of them are used for testing, which include sentiment classification, topic classification, definition detection, stance classification, etc. We use the same evaluation protocol as in Zhong et al. (2021): 1) we group the tasks by similarity and do not allow training tasks to be similar to testing tasks; 2) we treat “Yes” answer as the positive class and calculate the AUC-ROC score for each instruction of each task.

To fit model inputs (concatenation of in-context examples and task input to classify) within the maximum context length (1024) of our LMs, we leave out five evaluation tasks where the maximum task input length exceeds 230 BPE tokens. We also leave out the spam classification task due to its small test set. BinaryClfs does not come with an official validation set. To perform hyperparameter tuning, for each testing group, we randomly sample another testing group as its validation group.

3.2 Implementation Details

Architecture We use BERT models for LAMA (BERT-Base [110M parameters], BERT-Large [340M] and DeBERTa-V2-XLarge [900M]) and GPT2 models for BinaryClfs (GPT2-Medium [345M] and GPT2-Large [774M]). We use the Huggingface implementation (Wolf et al., 2020).

Hyperparameters We select hyperparameters based on few-shot classification accuracy on validation tasks. Our validation tasks and testing tasks are disjoint, so hyperparameter tuning on validation tasks does not use extra labeled examples on the testing tasks (Perez et al., 2021). See Appendix A for the hyperparameters we tuned.

Sampling Different instructions and few-shot example choices can lead to different predictions (Section 2.2). At training time, we expose the model to diverse task instructions and few-shot choices by randomly sampling task instructions and few-shot examples for each target example. Few-shot examples are randomly sampled from all labeled examples except the target example itself.

At test time, we report the average accuracy across task instructions and few-shot choices. Ideally we would report average of all few-shot choices; however, computing the average across all few-shot choices is intractable as there are combinatorically many distinct few-shot choices. We thus calculate the average accuracy of multiple random samplings of few-shot choices as approximation.

4 Results

In-context tuning out-performs MAML and a wide range of algorithmic variants (Section 4.1). It also significantly reduces sensitivity to instruction wording, example choices, and example ordering compared to prompting raw LMs without any fine-tuning (Section 4.2). Since we modify the LAMA dataset and BinaryClfs dataset (Section 3.1), the numbers reported in our work are not directly comparable to those reported by other work.

4.1 Accuracy

In-context tuning improves in-context learning accuracy over raw LMs. We compare in-context tuning with raw LM prompting in Table 2. In-context tuning consistently out-performs raw LM prompting by 7.2 points on LAMA and 10.6 points on BinaryClfs (averaged across model size and number of shots). Directly optimizing the few-shot in-context learning objective (Section 2.2) improves the few-shot in-context learning accuracy.

Few-shot examples lead to more effective adaptation. We compare in-context tuning with instruction tuning in Table 3. In-context tuning consistently out-performs instruction tuning on both LAMA and BinaryClfs with increasing per-

formance gains as the number of shots increases. Specifically, we observe that 5-shot in-context tuning out-performs instruction tuning by 5.6 points on LAMA and 4.0 points on BinaryClfs (averaged across model size). Results indicate that demonstration examples besides task instructions facilitate more effective task adaptation.

In-context tuning better leverages the inductive bias for pattern matching. By comparing MAML (the first row of Table 4) to instruction tuning (the first row of Table 3), we see that MAML out-performs instruction tuning in most evaluation settings, which indicates that MAML is indeed able to take advantage of the few-shot task examples for task adaptation. However, Table 4 shows that our approach of 5-shot in-context tuning out-performs 5-shot MAML consistently on both datasets with an accuracy gain of 2.8 points on LAMA and 5.1 points on BinaryClfs (averaged across model size). We argue that in-context tuning out-performs MAML because in-context tuning better leverages the existing inductive bias of pre-trained LMs to perform pattern matching and in-context learning.

We also compare in-context tuning to the pipeline of instruction tuning + task-specific fine-tuning (Table 5). Quite surprisingly, fine-tuning an instruction-tuned model on as few as one task-specific labeled examples can still significantly improve accuracy, without over-fitting to the few labeled examples. For example, Table 5 shows that instruction tuning + 1-shot fine-tuning out-performs instruction tuning by as many as 3.3 points on LAMA (averaged across model size). Our in-context tuning approach performs comparable or better than instruction tuning + fine-tuning, with increasing accuracy gains as models get bigger. For DeBERTa-XLarge-v2 (the largest models we use in this work), in-context tuning out-performs Ins-T+FT across all number of shots, achieving an accuracy gain of 1.7 points on LAMA (averaged across all number of shots). We conjecture that in-context tuning will be increasingly effective for bigger models that have a stronger inductive bias of pattern matching.

4.2 Sensitivity Analysis

We analyze the sensitivity of in-context tuning accuracy with respect to example ordering, example choices, and instruction wording, and compare it with prompting raw LMs. Let I denote a random selection of task instruction, S_T a random unordered

	LAMA						BinaryClfs	
	BERT-Base			BERT-Large			GPT2-Medium	GPT2-Large
	1-S	2-S	5-S	1-S	2-S	5-S	5-S	5-S
In-context Learning w/ Raw LM	8.5	10.8	14.1	12.1	15.4	18.7	57.8	58.3
In-context Tuning (Ours)	16.3	17.6	19.6	21.6	23.4	24.3	67.4	69.8

Table 2: Comparison of in-context tuning (ours) to in-context learning with raw LMs. K -S: K -shot learning. In-context tuning consistently out-performs few-shot raw LM prompting on both datasets and all model sizes.

	LAMA			BinaryClfs	
	BERT-Base	BERT-Large	DeBERTa-xl	GPT2-M	GPT2-L
Instruction Tuning (0-shot)	14.6	18.0	21.9	62.9	66.3
1-shot In-context Tuning	16.3	21.6	26.0	/	/
2-shot In-context Tuning	17.6	23.4	27.5	/	/
5-shot In-context Tuning	19.6	24.3	28.8	67.4	69.8

Table 3: Comparison of in-context tuning (ours) to instruction tuning. K -shot in-context tuning consistently out-performs instruction tuning, with increasing performance gains with respect to K .

	LAMA		BinaryClfs	
	BB	BL	GPT2-M	GPT2-L
MAML	16.9	21.4	63.3	63.9
ICT	19.6	24.3	67.4	69.8

Table 4: Comparison of in-context tuning (ours) to MAML under the 5-shot setting. BB: BERT-Base. BL: BERT-Large. GPT2-M: GPT2-Medium. GPT2-L: GPT2-Large. In-context tuning consistently out-performs MAML on both datasets and all model sizes.

set of few-shot training examples with size K , σ a random permutation of K examples. Therefore, the accuracy μ is a function of these three random variables, i.e. $\mu : (S_T, \sigma, I) \mapsto [0, 1]$. We can decompose the total variance of μ into its variance w.r.t. each of the three random variables, since they are independent:

$$\begin{aligned}
\text{Var}_{S_T, \sigma, I}[\mu] &= \underbrace{\text{Var}_I[\mathbb{E}_{S_T, \sigma}[\mu|I]]}_{\text{instruction wording variance}} \\
&+ \underbrace{\mathbb{E}_I[\text{Var}_{S_T}[\mathbb{E}_\sigma[\mu|I, S_T]]]}_{\text{example choice variance}} \\
&+ \underbrace{\mathbb{E}_{I, S_T}[\text{Var}_\sigma[\mu|I, S_T]]}_{\text{example order variance}}
\end{aligned}$$

We analyze each type of variance below.

In-context tuning is significantly less sensitive to example ordering. We approximate the vari-

ance with respect to example ordering with $\mathbb{E}_{S_T}[\text{Var}_\sigma[\mu(S_T, \sigma, I^*)]]$, where I^* denotes the single default prompt of LAMA and BinaryClfs. We compare this quantity (averaged across tasks) for in-context tuning and in-context prompting with raw LMs in Table 6. Results show that in-context tuning is significantly less sensitive to ordering of in-context examples compared to in-context prompting with raw LMs across both datasets and all model size, reducing the sensitivity by 68% on LAMA and 83% on BinaryClfs (averaged across model size).

In-context tuning is significantly less sensitive to example choices. We approximate the variance with respect to example choices with $\text{Var}_{S_T}[\mathbb{E}_\sigma[\mu(S_T, \sigma, I^*)]]$, where I^* is the single default prompt of LAMA and BinaryClfs. We compare this quantity for in-context tuning and in-context prompting with raw LMs in Table 7. Results show that in-context tuning is significantly less sensitive to selection of in-context examples compared to in-context prompting with raw LMs across both datasets and all model sizes, reducing the sensitivity by 56% on LAMA and 40% on BinaryClfs (averaged across model sizes). We conjecture that in-context tuning is significantly less sensitive to example ordering and selection because the model is exposed to a wide variety of example orderings and selections during in-context tuning.

	LAMA									BinaryClfs	
	BERT-Base			BERT-Large			DeBERTa-xlarge-v2			GPT2-M	GPT2-L
	1-S	2-S	5-S	1-S	2-S	5-S	1-S	2-S	5-S	5-S	5-S
Ins-T + FT	17.5	18.6	20.0	21.6	22.6	23.9	24.7	25.6	27.0	67.0	69.4
IC-T	16.3	17.6	19.6	21.6	23.4	24.3	26.0	27.5	28.8	67.4	69.8

Table 5: Comparison of in-context tuning (IC-T) to instruction tuning + task-specific fine-tuning (Ins-T+FT). K -S: K -shot learning. GPT2-M: GPT2-Medium. GPT2-L: GPT2-Large. In-context tuning has comparable or higher accuracy than Ins-T+FT, and on LAMA the advantage increases as models become larger.

	LAMA		BinaryClfs	
	BB	BL	GPT2-M	GPT2-L
Raw IC-L	1.82	2.14	9.26	8.84
IC-T	0.66	0.61	1.41	1.58

Table 6: Comparison of in-context tuning (IC-T) and in-context learning with raw LMs (Raw IC-L) in terms of their sensitivity to example ordering. In-context tuning is significantly less sensitive to example ordering compared to in-context learning with raw LMs.

	LAMA		BinaryClfs	
	BB	BL	GPT2-M	GPT2-L
Raw IC-L	3.74	6.30	18.52	20.33
IC-T	1.78	2.57	11.46	11.62

Table 7: Comparison of in-context tuning (IC-T) and in-context learning with raw LMs (Raw IC-L) in terms of their sensitivity to example choices. In-context tuning is significantly less sensitive to example choices compared to in-context learning with raw LMs.

In-context tuning is less sensitive to instruction wording. We report the variance with respect to instruction wording for in-context tuning and in-context prompting with raw LMs in Table 8. Results show that in-context tuning is less sensitive to the wording of task instructions compared to in-context prompting with raw LMs in five out of six evaluation settings, reducing the variance by 19% on LAMA (averaged across model size and number of shots). We conjecture that in-context tuning is much less sensitive to the wording of task instructions because the model is exposed to various task instructions during in-context tuning.

5 Related Work

LM Prompting for FSL Pre-trained LMs can be used to perform various FSL tasks when prompted with a natural language task instruction and several

	BERT-Base		BERT-Large	
	Raw IC-L	IC-T	Raw IC-L	IC-T
1-shot	35.38	26.31	34.03	28.78
2-shot	33.79	25.40	17.71	19.35
5-shot	24.90	15.64	6.36	5.16

Table 8: Comparison of in-context tuning (IC-T) and in-context learning with raw LMs (Raw IC-L) in terms of their sensitivity to task instruction wording. In-context tuning is much less sensitive to task instruction selection compared to in-context learning with raw LMs.

task examples (Radford et al., 2019; Brown et al., 2020; Gao et al., 2021). Recent work has revealed that small LMs can also perform FSL through self-training (Schick and Schütze, 2021b).

On the other hand, prompting raw pre-trained LMs for FSL is known to be sensitive to various artifacts, such as the wording of the task instruction and the selection and ordering of few-shot training examples (Schick and Schütze, 2021a; Jiang et al., 2020; Zhao et al., 2021; Gao et al., 2021; Liu et al., 2021). Our work is the first to show that meta-learning with an explicit FSL objective significantly reduces the sensitivity of LM prompting with respect to the choices and ordering of in-context examples.

Meta-learning for FSL Meta-learning is a widely used technique in NLP to improve cross-domain transfer (Yu et al., 2018; Geng et al., 2019; Holla et al., 2020; Deng et al., 2020) and cross-task transfer (Gu et al., 2018; Bansal et al., 2020; Dou et al., 2019). Optimization-based meta-learning methods (e.g., MAML) aim to learn a task-agnostic model initialization that can adapt to new tasks quickly (Finn et al., 2017; Jiang et al., 2019). Existing methods mostly perform task adaptation by fine-tuning a task-agnostic model on task-specific examples using gradient descent (Finn et al., 2017;

Jiang et al., 2019; Nichol et al., 2018). However, fine-tuning on few-shot task examples is sensitive to hyperparameters (Antoniou et al., 2019) and nested optimization during meta-training is often unstable (Nichol et al., 2018; Antoniou et al., 2019; Rajeswaran et al., 2019). In contrast, our approach performs few-shot task adaptation by using task-specific examples as part of the model input while keeping the model parameters frozen and task-agnostic during the adaptation stage.

Multi-task Learning In multi-task learning, a single model is trained on the union of training sets of multiple tasks to learn a shared representation (Liu et al., 2019). The multi-task model is then fine-tuned on task-specific examples to adapt to new tasks. Multi-task learning is shown to improve performance on various downstream tasks, especially tasks with small training sets (Khashabi et al., 2020; Ye et al., 2021; Aghajanyan et al., 2021). Compared to meta-learning, multi-task learning does not optimize task adaptation directly.

Fine-tuned LMs for Instruction Learning Recent work shows that fine-tuning LMs to learn task instructions on a wide variety of tasks can further leverage the inductive bias of LMs to perform instruction learning (Zhong et al., 2021; Mishra et al., 2021; Wei et al., 2021). Our work is partially inspired by this line of work, but we work under the more generic few-shot meta-learning setting, and show that our approach out-performs both instruction tuning and existing few-shot meta-learning methods (e.g., MAML). While previous work focuses on the accuracy improvement gained from instruction fine-tuning, our work also looks into the well-known over-sensitivity issue of FSL and shows that in-context tuning effectively reduces the sensitivity of FSL with respect to various factors.

6 Future Directions

Scaling Up and Broader Applications Our work only considered simple binary classification and knowledge retrieval tasks, at most 5 in-context examples, and models with fewer than 1 billion parameters. Nevertheless, it is straightforward to scale up our framework to a wider and more diverse range of general sequence-to-sequence tasks (Ye et al., 2021), more few-shot examples (which requires a longer context size (Dai et al., 2019; Child et al., 2019; Shen et al., 2021; Wang et al., 2020)), and larger models (Brown et al., 2020; Kaplan et al.,

2020). It is also straightforward to apply in-context tuning to a broader range of scenarios that require adapting to a new setup, e.g., adapting to a new label in classification tasks (Xia et al., 2021), an unseen database in semantic parsing tasks (Suhr et al., 2020; Lee et al., 2021), or a new language pair in machine translation tasks (Gu et al., 2018; Aharoni et al., 2019), etc.

Meta-learning for robustness Our work assumed that the few-shot training examples come from the same distribution as the test examples, but this assumption does not necessarily hold in practice. For example, the test distribution might constitute new input compositions (Lake and Baroni, 2018), rare subgroups (Sagawa et al., 2019), other types of distribution shifts (Hendrycks and Dietterich, 2019), or even adversarial examples (Kang et al., 2019). More effective meta-learning methods might learn a more robust learning mechanism and combat these generalization challenges.

Understanding In-context Learning Many properties of in-context learning are still unknown. For example, is in-context learning more robust towards distribution shift (Lester et al., 2021)? Can we combine in-context learning and gradient learning to get the benefit of both worlds (Wortsman et al., 2021)?

7 Conclusion

In this work, we propose meta-learning via in-context tuning, which recasts the few-shot learning process of task adaptation and task-specific prediction as a simple sequence prediction problem, where few-shot labeled examples are concatenated with the target example to form the model input. In-context tuning out-performs a wide variety of baselines in terms of accuracy, including raw LM prompting, MAML and instruction tuning. Compared to MAML which performs task adaptation with gradient descent, in-context tuning eliminates the need for bi-level optimization and the sensitivity to hyperparameters during task adaptation. Meanwhile, sensitivity study shows that our FSL approach of in-context tuning is significantly less sensitive to the few-shot examples and instruction wording compared to raw LM prompting.

Given the empirical effectiveness of in-context tuning, we conjecture that the few-shot learning potential of large LMs (e.g., GPT-3) might be broadly underestimated, and that in-context tuning can elim-

inate well-known artifacts of few-shot LM prompting such as over-sensitivity to example ordering, example selection and instruction wording.

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A Hyperparameters

In this section, we report the hyperparameters we tuned for our approach and each baseline.

In-Context Tuning (ours) We tune number of training epochs ([10, 15, 30] for LAMA and [1e-7, 3e-7, 1e-6, 3e-6] for BinaryClfs) and learning rate ([1e-7, 3e-7, 1e-6, 3e-6] for LAMA and [3e-6, 1e-5, 3e-5, 1e-4] for BinaryClfs).

MAML We assume that inner optimization and outer optimization use the same learning rate. We tuned number of adapt steps ([1, 2, 4] for both datasets) and learning rate ([3e-7, 1e-6, 3e-6, 1e-5, 3e-5, 1e-4, 3e-4, 1e-3] for LAMA and [3e-6, 1e-5, 3e-5, 1e-4, 3e-4, 1e-3] for BinaryClfs).

Instruction-Tuning + Fine-tuning For instruction tuning we tuned the same set of hyperparameters as in in-context tuning. The instruction tuning model with the highest validation performance are used for downstream task fine-tuning. For task fine-tuning, we tuned number of training epochs ([5, 10, 15, 30, 40] for LAMA and [5, 10, 15, 30, 40] for BinaryClfs) and learning rate ([1e-7, 3e-7, 1e-6, 3e-6, 1e-5, 3e-5] for LAMA and [3e-6, 1e-5, 3e-5, 1e-4, 3e-4, 1e-3] for BinaryClfs).

B Dataset Split of LAMA

Because LAMA does not have an official train-validation-test split, we use 8-fold cross-validation in our experiments. We randomly partition the 29 tasks into 8 groups of similar sizes. For each cross-validation split, we use six groups for training, one group for validation, and one group for testing. The test sets of the eight folds are disjoint and their union is the set of all tasks.