# CLAfICLe: Cross Lingual Adaptation for In-Context Learning

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## Abstract

As the field of NLP becomes enveloped with pre-trained large language models (LLMs), it becomes more and more dependent on data and compute. In parallel, fine-tuning paradigms such as in-context learning (ICL) have emerged to address these requirements. Unfortunately, most of this research has only been conducted in English and is either prohibitively expensive or impossible to repeat in other languages. Multilingual LLMs have been proposed to address this issue, but have been shown to be outperformed by their monolingual counterparts. While research on the language adaptation of monolingual models shows promising results, this typically focuses on encoder-only transformers and in the decoder-only setting limit themselves to intrinsic evaluation. In this work, we tackle the problem of the cross-lingual adaptation of monolingual models fine-tuned to perform ICL. We combine state of the art language and task adaptation techniques and show that it is still difficult to outperform a simple baseline consisting of sandwhiching the model between translation API calls. Finally, we introduce a novel technique for post-hoc disentanglement, PHoDiVA, and propose directions for future research.

## 1 Introduction

Pre-trained large language models (LLMs) are dominating natural language processing (NLP) research for tackling downstream tasks (Devlin et al., 2019; Raffel et al., 2020; Brown et al., 2020). These models rely on the availability of vast amounts of unsupervised training data and the high usage computing resources that can be leveraged by variants of the transformer architecture (Vaswani et al., 2017). Because access to such data and compute is limited, and due to the anglocentric nature of the field, the majority LLM research and application prioritises the English language. This leads to a large gap between what can be achieved in English and other languages. Research in multilingual LLMs attempts to address this issue, with encouraging results in many aspects (Conneau et al., 2020; BigScience Workshop, 2022). These multilingual models however have been shown to underperform against monolingual counterparts (Wu and Dredze, 2020), and datasets for more niche applications such as fine-tuning for zero-shot and in-context prompted generalisation remain almost exclusively in English (Bach et al., 2022; Mishra et al., 2022). One approach to address this issue is developing techniques for adapting existing English models to work in other languages. Recent research in model adaptation has shown promising results (Houlsby et al., 2019; Ainsworth et al., 2022), and there already exist some works applying these techniques directly to the problem of cross-lingual transfer (Artetxe et al., 2020). These works however mainly focus either on encoder-only transformer (EOT) variants or on performance on a few downstream tasks, through the use of additional language- and/or task-specific fine-tuning (de Vries et al., 2021; Gogoulou et al., 2022). Works that consider decoder-only transformer (DOT) variants on the other hand (de Vries and Nissim, 2021; Minixhofer et al., 2022) limit the scope to pretrained variants and intrinsic evaluation, with little focus on how their techniques interact with *fine-tuned* models and their performance on downstream tasks.

This work instead considers techniques for the efficient cross-lingual transfer of models fine-tuned on *in-context learning* (ICL). Here, the models are fine-tuned to leverage information presented in the context window to address some downstream task, demonstrating improved performance and generalisation (Wei et al., 2021; Sanh et al., 2022; Wang et al., 2022), enabling multi-task learning and eliminating the need for task-specific fine-tuning. Scaled versions of these models (Chung et al., 2022) are now on par with the best models from the similarly emerging paradigm of LLM training with rein-

forcement learning from human feedback (RLHF) (Ouyang et al., 2022). Lamentably, just like their training, the evaluation of these ICL fine-tuned models relies on instruction and prompt templates, which are mainly available only in English. This renders any cross-lingual adaptation of these models futile, as there is no way to extrinsically evaluate them in the target language. Recent work from Min et al. (2022) circumvents this requirement by directly fine-tuning a model on chains of input-output pairs from a suite of tasks, matching the performance of instruction-based ICL. We therefore focus on adapting models trained under this particular framework, and contribute the following:

1. We show that Minixhofer et al. (2022)'s WECHSEL language-adaptation technique scales, successfully adapting the large variant of GPT2 (774M) to French and German. We release the our checkpoints, which previously did not exist at this parameter scale for these languages.

2. We continue the evaluation of WECHSEL by assessing its robustness, applying it to a fine-tuned variant of GPT2 and measuring its performance on a number of downstream tasks, rather than just examining perplexity.

3. We share our methods and results for adapting fine-tuned models capable of ICL from English to French and German.

4. We introduce the notion of "targeted distillation", a form of post-hoc disentanglement leveraging adapters (Houlsby et al., 2019) to extract only the fine-tuned information from a fine-tuned model. We refer to our technique as PHODIVA (Post Hoc Disentanglement via Vessel Adapters).

Surprisingly, we fail to match the performance a simple baseline consisting of sandwhiching the model between translation API calls, which performs almost on par with the original model. We hypothesize this may be due to under-trained models, and propose directions for future research.

## 2   Related Work

### 2.1   In-context learning

ICL in NLP is a paradigm most famously popularized by Brown et al. (2020), where the input in a transformer's context window is augmented with some additional information useful for some downstream task. The model is said to "learn" from (*sc.* leverage) this information, without the need for any parameter updates. A very basic example of ICL is "prompting" the model by prefixing the input with task-specific instructions. ICL provides a number of advantages. Because the input is entirely in natural language, it acts an interpretable interface for human-model interaction. As mentioned, ICL does not require any parameter updates, greatly reducing the computational costs necessary and enabling the multi-task generalisation necessary for language-model-as-a-service applications (Sun et al., 2022). Considerable research attention has been devoted to the paradigm (Liu et al., 2022; Lu et al., 2022; Wu et al., 2022), with many contributions focusing on informal reasoning performance through scratchpads (Nye et al., 2021), bootstrapping (Zelikman et al., 2022), chain-of-thought prompting (Wei et al., 2022; Wang et al., 2023), learned verifiers (Cobbe et al., 2021) and selection-inference (Creswell et al., 2023) techniques among others. Dohan et al. (2022) propose a framework for formalizing these techniques while Zhao et al. (2021) propose solutions to the performance sensitivity to prompt choice and ordering. Unsurprisingly, some studies find a performance boost can be achieved by fine-tuning the models directly on ICL examples (Sanh et al., 2022; Wang et al., 2022) and develop template-based datasets for this purpose (Bach et al., 2022; Mishra et al., 2022). To circumvent the variability or need for templates, Lester et al. (2021) fine-tune a "soft" prompt instead of the task, while Min et al. (2022) directly use chains of input-output pairs for fine-tuning rather than templates. All of these approaches limit themselves to English, leaving a large gap in multilingual NLP. Our work attempts to partly address this gap by exploring ways of adapting ICL-fine-tuned English models to other languages.

### 2.2   Multilingual NLP

- multilingual nlp (XLM-r)

- monolingual non-english models

- wechsel, devries, artexte, etc.

### 2.3   Adaptation

- adapters

- meta-learning

- minimodel

## 2.4 Other related work

- distillation

- disentanglement

## 3 Method

### 3.1 MetaICL

Due to the complete lack of prompting/instruction templates in non-English languages, we rely on MetaICL (Min et al., 2022), which circumvents the need for prompt/instruction templates at train-time and test-time. With MetaICL, a pretrained DOT is fine-tuned by concatenating $k$ examples of input-output pairs ("shots") from a variety of tasks and feeding this as input to the model. The final input-output pair is truncated such that only the input is shown, and the model is trained to predict the output using a negative log-likelihood objective from a number of possible options. The trained model is then generalises to unseen tasks presented in the same way by utilizing the $k$ shots provided in the context. We refer to this model as *MetaICL*.

### 3.2 Sandwich

As a baseline, we consider the obvious solution of simply translating input in the target language to English, feeding the translation to MetaICL, and translating the output back to the target language. We refer to this model as *Sandwich*. We make use of Google's Cloud Translation AI API[1].

### 3.3 WECHSEL

Aside from translation API calls, to adapt a monolingual DOT from a source language to a target language we employ WECHSEL (Minixhofer et al., 2022), which has shown success in adapting the small variant of GPT2 (117M parameters) to a number of target languages. WECHSEL works by retraining the tokenizer into the target language and re-initializing the transformer embedding layers such that the target embeddings are semantically similar to the source embeddings. This is done by leveraging existing parallel multilingual static word embeddings. As done by de Vries et al. (2021), after re-initialization, additional causal language modeling (CLM) is performed in the target language to account for syntactical differences. Applying WECHSEL to MetaICL, we obtain what we refer to as *MetaICL-geWECHSELt*.

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[1]https://cloud.google.com/translate

### 3.4 Adapters

Because we are interested in adapting a fine-tuned DOT (MetaICL), we hypothesize that the additional CLM at the end of WECHSEL can lead to catastrophic forgetting of the fine-tuning. Furthermore, we hypothesize that the fine-tuning may contain language-specific information, entangled with the task information relevant to the fine-tuning objective. To address this issue, inspired by MAD-X (Pfeiffer et al., 2020b) we train a "task adapter" on the same ICL objective and data as MetaICL with a GPT2 base, obtaining an "ICL-adapter", which we refer to as *MetaICLA*. Adapters introduce "bottleneck" dense layers at each transformer layer of their base. The adapter is trained on a particular objective while the base is kept frozen, allowing for parameter-efficient and modular fine-tuning. These dense layers consist in a down matrix $\mathbf{W}_{down}$, projecting the hidden states into a lower dimension $d_{bottleneck}$, a non-linearity $f$, which is applied to this projection and an up matrix $\mathbf{W}_{up}$ that projects back to the original dimension:

$$\mathbf{h} \leftarrow \mathbf{W}_{up}f(\mathbf{W}_{down}\mathbf{h}) + \mathbf{r}, \qquad (1)$$

where $r$ is a residual connection. Having separated the task-specific information, we apply WECHSEL to the GPT2 base, obtaining what we refer to as *GPT2-geWECHSELt*. Adding MetaICLA to GPT2-geWECHSELt, we obtain a model theoretically capable of ICL in the target language, *GPT2-geWECHSELt+MetaICLA*.

### 3.5 PHoDIVA

To address situations where repeating fine-tuning is not permissible, either because the data is not released, the process too complicated or the compute simply not available, we propose PHoDIVA. Here, instead of repeating ICL fine-tuning, we leverage the fine-tuned MetaICL checkpoint, using it as a teacher in a modified student-teacher offline distillation (Hinton et al., 2015) setup. More specifically, before WECHSEL adaptation, we add a "vessel" adapter to a (frozen) GPT2 base, and then perform CLM in the source language (English). Vessel adapters are exactly the same as task adapters, except that they act as a "vessel" for distilled capabilities rather than as additional parameters for fine-tuning. Rather than predicting the actual next word, the adapter is trained to predict the next word greedily sampled from the teacher. The idea is to overfit the adapter to the teacher outputs (hence the
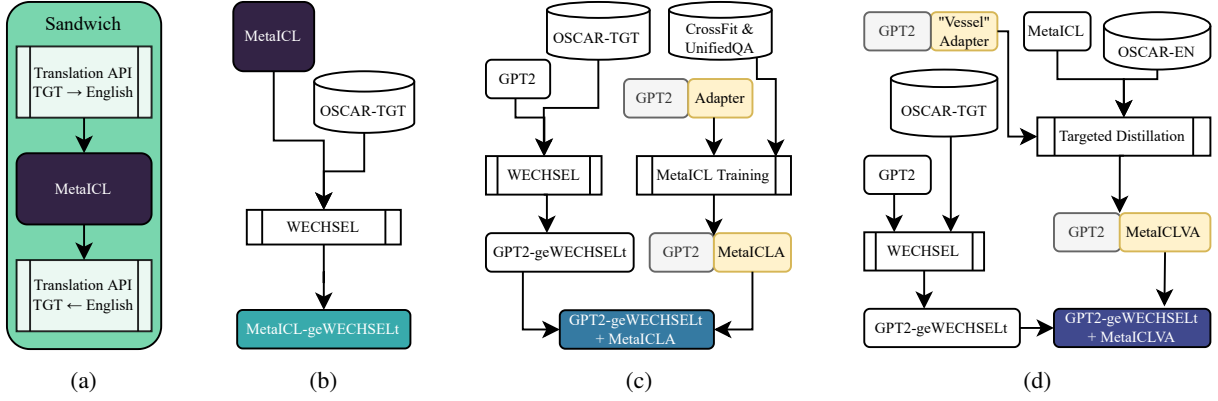
Figure 1: Overview of each of the models evaluated in one of the two TGT languages (French or German). The baseline Sandwich model (a) sandwiches MetaICL (Min et al., 2022) (which we separately evaluate only in English) between two complementary translation API calls. MetaICL-geWECHSELt (b) is the result of applying WECHSEL (Minixhofer et al., 2022) to MetaICL. GPT2-geWECHSELt+MetaICLA combines MetaICLA, an adapter trained on the MetaICL dataset and objective, with a TGT-language GPT2 base obtained via WECHSEL. GPT2-geWECHSELt+MetaICLVA does the same, except MetaICLVA is trained via targeted distillation with supervision provided by MetaICL. For more details, refer to section 3.

greedy sampling). Because the GPT2 base is frozen and theoretically shares the original language modeling capabilities of the teacher, we hypothesize that this "targeted distillation" can disentangle the fine-tuned capabilities into the vessel adapter. We use the CLM objective because of the constraint to keep the distillation process as simple as possible, so to make it advantageous over repeating a potentially complex fine-tuning process. The only constraint of this method is that the adapter base is the same pretrained base that was fine-tuned into the teacher. When using MetaICL as the teacher, we refer to the resulting vessel adapter as *MetaICLVA*. Like in section 3.4, after applying WECHSEL to a GPT2 base, we can then combine the language-adapted base and MetaICLVA to obtain *GPT2-geWECHSELt+MetaICLVA*, another model theoretically capable of ICL in the target language.

## 4 Experimental Setup

We use the PyTorch Lightning Python framework (Falcon and The PyTorch Lightning team, 2019) to implement our work. Because we envision the direct application of this work to be most useful to smaller companies and start-ups, we limit our compute to a single 40GB NVIDIA A100 GPU and run jobs for a maximum of 24 hours. Our code is available on GitHub[2].

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[2] https://github.com/thesofakillers/CLAfICLe

### 4.1 Models

There exist various possible adapter setups, specifying different configurations of the up and down weight matrices, non-linearity and residual connection, among other settings. For our work, we use the `pfeiffer` configuration from AdapterHub (Pfeiffer et al., 2020a).

Regarding MetaICL, Min et al. (2022) train a number of variants, releasing checkpoints however only for variants fine tuning the large version of GPT2 (774M parameters). We base the rest of our models on the same GPT2 version and use the "high resource to low resource" direct MetaICL checkpoint as we consider this to be the most realistic. We make use of the HuggingFace Transformers (Wolf et al., 2020) implementation of GPT2 throughout.

### 4.2 Evaluation

For assessing ICL, we reimplement the same evaluation setup as Min et al. (2022), evaluating a given model on a suite of tasks, prepending the input with $k = 16$ training examples sampled randomly for each task. For our evaluation metrics, like Min et al. (2022), we use F1 for tasks where the label options change across examples, and accuracy for tasks where the label options are always the same. Because the evaluation benchmark used by Min et al. (2022) is limited to English, we develop our own multilingual multi-task benchmark spanning 9 different tasks across 3 languages (English, German, and French). Our benchmark design is re-

Table 1: The datasets constituting our ICL benchmark. Most originate from pre-existing benchmarks, namely XGLUE (Liang et al., 2020) and (Lin et al., 2021).

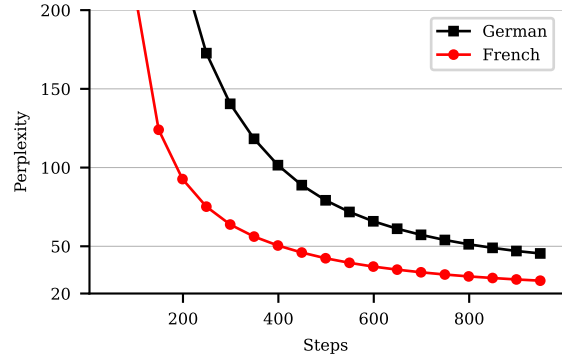| Dataset | (Origin) | Collection |
|---|---|---|
| HateCheck | (Röttger et al., 2021) | - |
| XNLI | (Conneau et al., 2018) | XGLUE |
| QAM | (Liang et al., 2020) | XGLUE |
| QADSM | (Liang et al., 2020) | XGLUE |
| PAWS-X | (Yang et al., 2019) | XGLUE |
| MARC | (Keung et al., 2020) | - |
| X-CODAH | (Lin et al., 2021) | XCSR |
| X-CSQA | (Lin et al., 2021) | XCSR |
| Wino-X | (Emelin and Sennrich, 2021) | - |



Figure 2: Perplexity on the held out set when performing the recommended CLM training after WECHSEL language-adaptation of GPT2. A step corresponds to an optimizer update. We evaluate every 50 steps.

stricted to tasks that can be handled by the MetaICL framework, namely multi-class, single-label tasks. To enable complete comparisons across languages, we also restrict our benchmark to only contain language-parallel datasets. Correspondingly, we list the ICL benchmark datasets in Table 1.

To evaluate the successful application of WECHSEL to GPT2, we use the same process as Minixhofer et al. (2022), namely measuring perplexity on a held out test set. For all language modeling, we use the original release of the OSCAR corpus (Ortiz Suárez et al., 2020).

### 4.3 Training

When performing CLM training, due to our limited compute, we heed the advice of Geiping and Goldstein (2022) and pack as samples into 1024-token sequences (the maximum length possible) by separating them with EOS tokens, so to minimize the number of padding tokens and maximize GPU utilisation. With this we are able to fit a batch size of 2 into memory, while actually presenting the model with more than two examples per batch in most cases[3]. We achieve a virtual batch size of 512 by accumulating gradients over 256 steps. We employ single-epoch training (Komatsuzaki, 2019) on a total of 600M tokens, which we estimate to be the number of tokens consumed by our model in a single epoch by running a profiling run on a smaller download. Based on the information in Geiping and Goldstein (2022) and Minixhofer et al. (2022), we decide to use Adam (Kingma and Ba, 2015) with a linear warmup for the first half of training to a peak learning rate of 5e-4, followed by

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[3]This technique is also suggested by HuggingFace in their CLM tutorial: https://huggingface.co/course/chapter7/6.

cosine annealing to 0 by the end of training. When performing targeted distillation for MetaICLVA, we reduce the linear warmup to the first 10% of training to help with our voluntary overfitting. As suggested by Izsak et al. (2021), to maximize training time, we evaluate on only 0.5% of the data, logging every 50 steps.

For the ICL training necessary for MetaICLA, we modify Min et al. (2022)'s implementation so to work with adapters. In particular, we use their HR→LR training mixture, which consists of 61 tasks sourced from the CROSSFIT (Ye et al., 2021) and UNIFIEDQA (Khashabi et al., 2020) benchmarks.

## 5 Results and Discussion

Fig. 2 shows the performance of GPT2 after around 1k steps of training, evaluated intrinsically in terms of perplexity. For both French and German, we see perplexity decrease to sub-50 values, with the French model reaching a perplexity of ≈ 28. Both models are clearly underfit, still monotonically decreasing by the end of the training. These observations are roughly in-line with Minixhofer et al. (2022)'s findings for smaller variants of GPT2, although we train for much less time and hence are left with higher perplexities. While we believe our preliminary results suggest WECHSEL scales well to larger models in terms of intrinsic evaluation, future work may wish to investigate whether this holds for longer training times. The rest of our work considers, among other questions, the robustness of WECHSEL via extrinsic evaluation on downstream tasks performed by MetaICL.

Fig. 3 shows the performance on each dataset of our benchmark for the two baseline models, MetaICL and Sandwich. As summarized in Table 2,
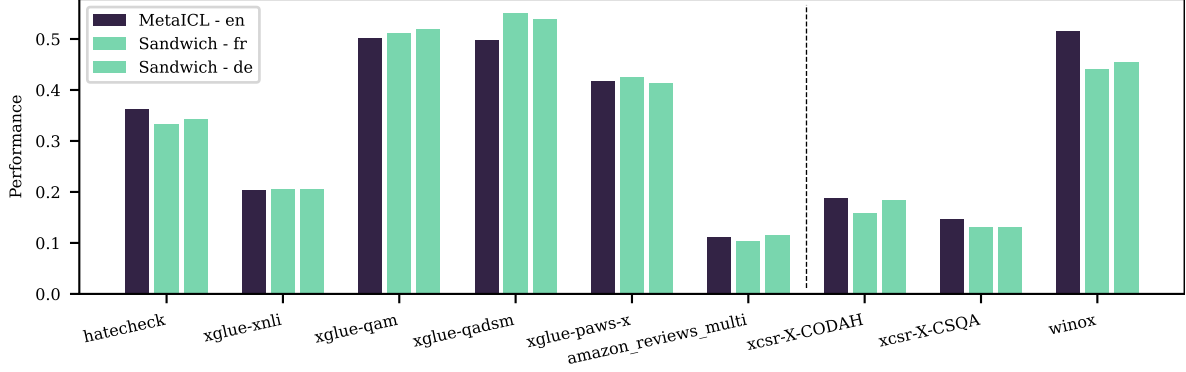
Figure 3: Performance (max is 1) on a particular language dimension of our multi-task benchmark of our two baseline models, MetaICL and Sandwich. The dashed line separates whether a given task uses accuracy (left) or F1-score (right) as the performance metric.

Sandwich performs roughly on par with MetaICL on both target languages, respectively with scores of 0.317 and 0.322 in French and German compared to MetaICL's score of 0.327 in English. We note generally low scores across all tasks. This is particularly perplexing in the case of MetaICL, scoring around 0.1 points less than with the evaluation ensemble used by Min et al. (2022), where the same checkpoint was reported scoring 0.417 in the worst case (a 25 % decrease). While similar values are reached in certain tasks in our benchmark (e.g. most of XGLUE and WINO-X), it is unclear what the origin of this discrepancy is, whether due to differences in evaluation implementation or difficulty of the tasks. Given that Min et al. (2022) simply report macro-averaged scores, it is impossible to verify the latter. Nevertheless, our results suggest that Sandwich-like solutions may be satisfactory for transferring performance from English to other languages given the surprisingly closeness of the scores. The decision between using Sandwich or "properly" adapted models with the same capabilities then becomes an economic one in terms of the cost of API calls (for the former) versus the cost of inference plus training (for the latter).

Fig. 4 shows the difference in performance on each dataset of our benchmark between the proposed models and Sandwich. In general, we observe that the proposed models underperform across almost all tasks in both French and German, with the trends aligning at a task-level (e.g. all models underperform on QAM, by roughly the same amount). As reported in Table 2, the best of our proposed models is MetaICL-geWECHSELt, which underperformed Sandwich by roughly 0.02-0.03 points. This undermines the motivation for the

other two models, which were designed to avoid catastrophic forgetting by separating language and ICL capabilities via adapters. The results suggest that the tradeoff between catastrophic forgetting and needing to train ICL-adapters leans in favour of the former in this compute regime. In this sense, we can conclude that WECHSEL does not suffer tremendously due to catastrophic forgetting when adapting fine-tuned DOTs such as the MetaICL variant of GPT2.

Table 2: Average performance (max is 1) across the datasets from our multi-task benchmark for the models considered in this work. We use "W" as a shorthand for "geWECHSELt". We report average difference in performance for each proposed alternative to Sandwich. Negative values indicate underperformance compared to Sandwich.

|  | en | fr | de |
|---|---|---|---|
| MetaICL | 0.327 | - | - |
| Sandwich | - | 0.317 | 0.322 |
| *Difference in Performance w.r.t. Sandwich* | | | |
| MetaICL-W | - | -0.020 | -0.026 |
| GPT2-W+MetaICLA | - | -0.041 | -0.042 |
| GPT2-W+MetaICLVA | - | -0.036 | -0.045 |

Our work is mainly limited by its preliminary nature. Apart for considering more appropriate (*sc.* larger) compute scales, future work could investigate training ICL-adapters more thoroughly, for example by performing hyperparameter optimization or incorporating more recent adapter research such as AdapterDrop (Rücklé et al., 2021), Adapter-Fusion (Pfeiffer et al., 2021) or Hyper-X (Üstün et al., 2022).

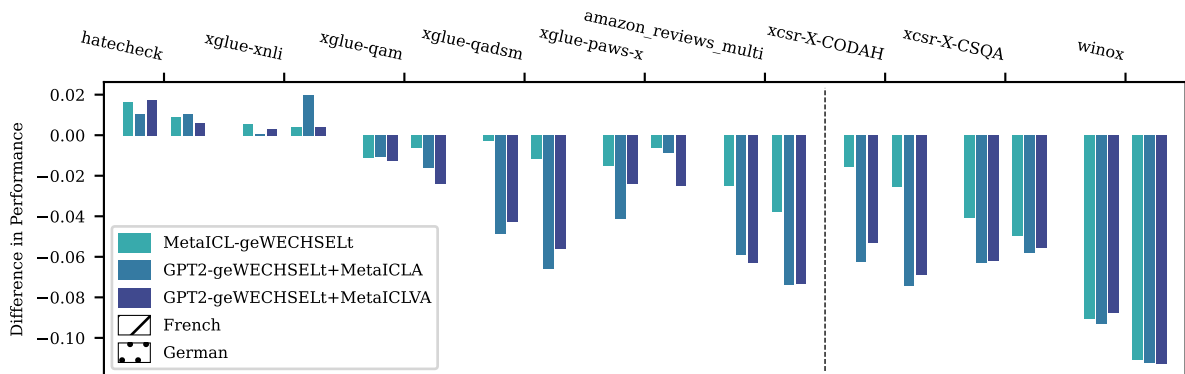Similarly, we note that the despite our best ef-

Figure 4: Performance gap on our multi-task benchmark between each of the language-adapted models and the "Sandwich" baseline. Positive values indicate that the adapted models are outperforming the baseline, while negative values indicate the reverse. The dashed line separates whether a given task uses accuracy (left) or F1-score (right) as the performance metric.

forts our ICL evaluation benchmark faces some limitations. Due to the design restrictions mentioned in Section 4.2 and the lack of non-English datasets we only evaluate on 9 tasks, despite focusing on high-resource languages like German and French. This is a small number of tasks compared to what is done in English, where 10s and 100s of tasks can comprise a multi-task benchmark. Furthermore, many of our datasets are either human or machine translated versions of English, which can lead to noise (Koppel and Ordan, 2011). We hope to raise awareness of the complete English dominance of the NLP data landscape.

We are also interested in a more complete treatment of PHODIVA. For instance, future work could explore different forms of student-teacher distillation, consider other forms of loss criterions, use beam search rather than greedy sampling and/or take inspiration from similar solutions such as Khrulkov et al. (2021)'s work on generative models. We believe work in this direction could benefit from simplifying the problem setting first, by considering a smaller, encoder-only transformer fine-tuned on a single downstream task on a single-language.

Other future work may consider different adaptation approaches that have recently emerged. For example, Marchisio et al. (2022)'s Mini-Model adaptation has yet to be tested on decoder-only transformers, and it would be interesting to see how it compares to WECHSEL in this regard. Other, slightly more distant approaches such as meta-learning a-la X-MAML (Nooralahzadeh et al., 2020) may provide different results.

Perhaps a clear limitation of this direction of

research is that the setting remains monolingual. Future work could explore whether it is possible to adapt a monolingual model to multiple languages simultaneously, and how such adaptations would compare to monolingual-to-monolingual adaptation in terms of resources and performance. Finally, undermining all of this work is our restriction to results on a single random seed. Future work with more seeds and more compute would be necessary to draw more definitive conclusions.

## 6 Conclusion

We explore the problem of language-adapting a monolingual DOT previously fine-tuned to perform in-context learning. To this end, we stress test the current SoTA adaptation method, WECHSEL, scaling to previously untested model sizes, applying it a fine-tuned variant of GPT2 (MetaICL) and evaluating extrinsically on a multi-task benchmark. While we find that WECHSEL successfully scales to larger model sizes, we find that at our compute regime, WECHSEL-adapted MetaICL underperforms compared to simply sandwiching the English model between translation API calls. We experiment with separating ICL fine-tuning and language adaptation to address potential catastrophic forgetting through the use of Adapters, but find these approaches unsuccessful. In doing so, we propose PHODIVA, a novel method for post-hoc disentanglement through vessel adapters. We share PHODIVA in this rudimentary form as a starting point for future work in this direction.

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