### Neural Machine Translation Models Can Learn to be Few-shot Learners

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#### Abstract

The emergent ability of Large Language Models to use a small number of examples to learn to perform in novel domains and tasks, also called in-context learning (ICL). In this work, we show that a much smaller model can be trained to perform ICL by fine-tuning towards a specialized training objective, exemplified on the task of domain adaptation for neural machine translation. With this capacity for ICL, the model can take advantage of relevant fewshot examples to adapt its output towards the domain. We compare the quality of this domain adaptation to traditional supervised techniques and ICL with a 40B-parameter Large Language Model. Our approach allows efficient batch inference on a mix of domains and outperforms state-of-the-art baselines in terms of both translation quality and immediate adaptation rate, i.e. the ability to reproduce a specific term after being shown a single example.

#### 1 Introduction

Large Language Models (LLMs) have demonstrated few-shot learning capabilities on various natural language processing tasks, as highlighted by Brown et al. (2020) or Garcia et al. (2023). When prompted with suitable example translations, they can compete with neural machine translation (NMT) models, built and trained specifically for translating between languages (Vilar et al., 2023). Interestingly, one can adapt LLMs to specific domains merely by adding example translations to their prompt at inference time (Moslem et al., 2023). This ability to adapt to specific tasks and domains is known as *in-context learning* (ICL). In contrast to traditional fine-tuning methods, ICL does not require a separate set of customized parameters for each domain, which implies major efficiency gains through batched inference.

In this paper, we integrate ICL for domain adaptation into NMT systems in multiple steps. We compare our method for adapting NMT systems to traditional fine-tuning approaches, as well as to the domain adaptation abilities of an open-source LLM. Specifically, our main contributions are the following:

- 1. We evaluate an unmodified NMT system's ICL capacity for domain adaptation and demonstrate its limitations.
- 2. We propose a training scheme to improve an NMT model's ICL capability.
- 3. We show that ICL can be combined with more traditional adaptation methods to further improve domain adaptation performance.
- 4. We compare our method to the performance of the open-source LLM FALCON-40B (Penedo et al., 2023) on a machine translation task with ICL for domain adaptation.

#### 2 Related Work

Bulte and Tezcan (2019) improve the translation performance of an NMT model by integrating translation fuzzy-matched pairs from a translation memory as input to an NMT model. This idea was further expanded by Pham et al. (2020) and Xu et al. (2020), who for a given source segment use sentence embeddings to retrieve similar examples and compared different schemes for integrating those as cues into the NMT network.

Our approach differs in that we only train on the tokens belonging to the translation and not on the tokens provided as context, which we show to work better. In addition, Pham et al. (2020)'s training procedure differs, as they train their model from scratch, using training data from multiple domains and evaluate on those same domains, while we train on general domain data and evaluate on a new domain that is not in the training data. Furthermore,

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we focus on the multi-domain adaptation task using light-weight adapters. This approach not only allows us to extend to new domains without retraining the full model, but also offers a more practical and efficient strategy for real-world applications.

The authors of (Moslem et al., 2023) investigated the capabilities of a proprietary LLM, specifically GPT-3.5, for adaptive machine translation using ICL. Their extensive experiments showed that GPT-3.5 can adapt well to in-domain sentence pairs and/or terminology.

#### **3** Experiments

We conduct a series of experiments to develop NMT systems that exceed at few-shot ICL domain adaptation. Here we present the experiments in a logical order, where we start with the baseline models described in Section 3.1 and subsequently introduce several stages of development. In stages 0 and 1 we attempt ICL with the unmodified and domain-fine-tuned baseline models, respectively. Then, in STAGE 2, we fine-tune the baseline model to the *task* of domain ICL, instead of a particular domain. Finally, we combine ICL and domain adaptation through fine-tuning in STAGE 3. Our experimental progression was guided by the metrics and datasets that we introduce in Sections 3.5 and 3.6, respectively.

#### 3.1 Models

Throughout this paper, we work with an NMT system and the FALCON-40B LLM, which we both describe here.

#### 3.1.1 FALCON LLM

To provide a direct comparison with LLMs and their capacity for ICL, we conduct experiments with the decoder-only Transformer language model FALCON-40B (Penedo et al., 2023), specifically the non-instruction-tuned variant<sup>1</sup>. Inference is done with greedy decoding. Following previous work (Bawden and Yvon, 2023; Garcia et al., 2023; Hendy et al., 2023) (*inter-alia*) the model is prompted to perform translation without specific fine-tuning towards the machine translation task.

A simple prompt template is used for all k-shot experiments with FALCON-40B, see Figure 1.

In preliminary experiments we found that k = 0

English: <source sentence>\n
German: <target sentence>\n
English: [...]

Figure 1: Prompt template for LLM.

does not work well with this specific  $model^2$  – the outputs tend to be entirely hallucinated.

#### 3.1.2 NMT Systems

The baseline model that we use as the starting point for all further experiments is a Transformer (Vaswani et al., 2017) model with 12 encoder layers and two decoder layers, implemented with the NVIDIA NeMo toolkit (Kuchaiev et al., 2019). The embedding size is 1,024 with a feed-forward network dimension of 4,096. The model has a joint vocabulary of 32,768 tokens, while embedding matrices are specific to the encoder, decoder, and output projection modules, i.e. parameters are not shared between them. The model was trained to support a maximum input size of 1,536 tokens by augmenting the training data with random concatenations of parallel sentences. We evaluate the model using greedy decoding.

For the experiments presented here, the baseline model is either fine-tuned in full (STAGE 2A and STAGE 2B), or light-weight adapters (Bapna and Firat, 2019) are added to the model (STAGE 1 and STAGE 3). We choose full-model fine-tuning on out-of-domain data to adapt the NMT model to a new task – translating with an increased context of related examples – and adapter layers for learning from in-domain data.

The adapters we use follow Bapna et al. (2019)'s formulation, but with layer normalization applied after the bottleneck rather than before it. We use a bottleneck width of 256 and insert adapters in every layer of the decoder and every other layer of the encoder.

We always fine-tune with the ADAM optimizer (Kingma and Ba, 2014) and early stopping based on validation loss.

### **3.2** STAGE 0 & STAGE 1: ICL with a Standard NMT Model

Motivated by the few-shot learning capabilities of LLMs, we examine the ability of a standard English-to-German NMT model to adapt to a domain given only similar and relevant translation

<sup>&</sup>lt;sup>1</sup>The model is available from the *huggingface* platform: https://huggingface.co/tiiuae/falcon-40b

<sup>&</sup>lt;sup>2</sup>For k = 0 the prompt contains only the single source sentence as input and the target language followed by a colon.

pairs as additional context, i.e., without changing the model's parameters.

To find similar source segments in the translation memory, we search for nearest neighbours in an embedding space. We use the multi-lingual sentence embedding model<sup>3</sup> from the sentence transformer library (Reimers and Gurevych, 2020) to embed the source sides of all segment pairs. Then we employ hnswlib (Malkov and Yashunin, 2020) to find the approximate nearest neighbours: Each source sentence in the domain-specific datasets is first encoded with the sentence-embedding model and then added to an index. For the sake of simplicity in this paper, we will refer to the approximate nearest neighbors simply as nearest neighbors. To measure the similarity between a pair of segments s and s', we use the cosine distance of the corresponding embedding vectors  $v_s$  and  $v_{s'}$ , i.e.,

$$\mathrm{d}(\mathbf{s},\mathbf{s}') := 1 - \frac{\mathbf{v}_{\mathbf{s}} \cdot \mathbf{v}_{\mathbf{s}'}}{\|\mathbf{v}_{\mathbf{s}}\|_2 \cdot \|\mathbf{v}_{\mathbf{s}'}\|_2}.$$

For a given source s and target segment t, we identify its nearest neighbours  $s_1, s_2, ..., s_k$ , using the the cosine distance above. Each source sentence  $s_i$  is paired with a reference translation  $t_i$  for i = 1, ..., k. We sort the pairs by their distance to s in the embedding space, i.e.,

$$d(\mathbf{s}, \mathbf{s}_1) \le d(\mathbf{s}, \mathbf{s}_2) \le \dots \le d(\mathbf{s}, \mathbf{s}_k) .$$

Our assumption is that similar segments should have similar translations. For STAGE 0 of the experiments, we treat the context sentences and actual source text as one body of text, separated only by a single space, ordering the segments from least similar to most similar, with the current source segment s at the end. As a result, the input of the encoder is

 s
$$_k$$
 s $_{k-1}$  ... s $_1$  s 

while for the decoder, we use the prefix:

 
$$t_k$$
  $t_{k-1}$  ...  $t_k$ 

where <bos> and <eos> represent the beginning-ofsentence and end-of-sentence tokens, respectively. The model's task is then to continue from the target prefix by generating a translation of the source segment s.

In our experiments, we evaluated the translation performance using a varying number k of nearest neighbors, specifically  $k \in \{1, 2, 5\}$ .

In STAGE 1 we run additional experiments where we fine-tune the model for each domain, using the in-domain training data in the original format. This domain-specific fine-tuning is performed by injecting adapter layers (Bapna and Firat, 2019) into the network while freezing the rest of the model, and leveraging a standard negative log-likelihood (NLL) loss for training. For each domain, we then test the fine-tuned model directly (0-shot in Tables 3 and 4) as well as with ICL (k-shot with  $k \neq 0$ ).

Adapters are trained towards convergence, i.e. until there is no further improvement in terms of validation loss.

### 3.3 STAGE 2A & STAGE 2B: Fine-Tuning towards ICL

To improve the model's capability to use nearest neighbor examples in the context, we further finetune the full model on out-of-domain data, namely *News-Commentary*<sup>4</sup> (Kocmi et al., 2022), which contains roughly 450K parallel segments. For validation we use a sample of 2K parallel segments from *EuroParl*<sup>5</sup> (Koehn, 2005). For this full model fine-tuning we do not train until convergence, but apply aggressive early stopping: Training is stopped when the validation loss does not decrease by at least 0.1 twice in a row, validating for every 1% of an epoch. This is to encourage the model to only learn the new task and data format, but not adapt to a new data distribution.

Instead of directly concatenating the nearest neighbors to the training examples, we add a special separation token  $-\langle sep \rangle -$  to separate the source and target segments. We then construct the training instances for the encoder as:

<br/> <br/> s\_k <sep> s\_{k-1} <sep> ... <sep> s\_1 <sep> s <eos>

and for the decoder as:

  
   
 
$$t_k$$
   $t_{k-1}$   ...   $t_1$   t  (1)

and compute the NLL loss on all tokens of (1). This training loss is identical to the one used in Pham et al. (2020). We denote this procedure as STAGE 2A.

For STAGE 2B the idea is that the model should learn to predict the target segment from the source

<sup>&</sup>lt;sup>3</sup>Model name on https://www.sbert.net/: all-MiniLM-L6-v2

<sup>&</sup>lt;sup>4</sup>From the WMT'23 evaluation campaign: https://data. statmt.org/news-commentary/v18.1/

<sup>&</sup>lt;sup>5</sup>Also from the WMT'23 evaluation campaign: https: //www.statmt.org/europarl/v10/

segment using the nearest neighbor translations but not learn to predict  $t_k, ..., t_1$  as in (Pham et al., 2020). Hence we mask the NLL training loss such that it is computed only on the tokens that belong to the target segment t, excluding all context tokens, thus fully focusing the training signal on translating t in the context of its k nearest neighbors.

We then use the same format as in STAGE 2A for training, while at inference time we provide the decoder with a prefix containing the ICL examples:

<br/> <br/> t\_k <sep> t\_{k-1} <sep> ... <sep> t\_1 <sep>

Finally, we measure quality of the predicted translation  $\hat{t}$  by computing BLEU and COMET scores with the target segment t as reference.

For both STAGE 2A and STAGE 2B, the *k*-nearest neighbors for each segment in the training data and validation data are extracted from the entire *News*-*Commentary* dataset as described in Section 3.2.

# **3.4** STAGE **3:** Combining ICL and Domain Adaptation

To combine STAGE 2B's ICL capacity with adapterbased domain adaptation, we add adapters to the model from STAGE 2B using the same configuration as for the STAGE 1 experiments. Again, we train separate adapter layers for each domain.

Each example from the training set is annotated with its nearest neighbors from the same training set, excluding itself.

#### 3.5 Metrics

For evaluating translation quality, we used the SacreBLEU framework (Post, 2018) that implements the BLEU metric (Papineni et al., 2002). We also evaluate with reference-based COMET (Rei et al., 2022) to compare the model outputs to the reference translations in the test data.

#### 3.6 Datasets

We run our experiments with the English-German language pair on 8 domains from the ACED- and MDNS corpus collections, which we describe in this section. Statistics for all datasets are provided in Table 1.

#### 3.6.1 ACED corpus

The ACED corpus (Lin et al., 2022) is comprised of three distinct datasets, namely Asics, Emerson, and Digitalocean, each consisting of English-German sentences extracted from various domains. ACED is a real-world benchmark containing data derived from translations performed by humans.

	Training	Validation	Test
Asics	1.4	0.5	0.6
Digitalocean	11.8	2.0	7.6
Emerson	4.3	1.3	1.7
IT	223	2.0	2.0
Koran	17.9	2.0	2.0
Law	467	2.0	2.0
Medical	248	2.0	2.0
Subtitles	500	2.0	2.0

Table 1: Segment counts for the domain-specific dataset splits used for experimentation, in thousands.

#### 3.6.2 MDNS corpus

The MDNS corpus (Aharoni and Goldberg, 2020) is a multi-domain corpus containing English-German parallel text from five diverse domains (IT, Koran, Law, Medical, Subtitles). It was specifically created for evaluating domain-adaptation.

#### 4 Results

Here we discuss the experimental results, progressing from STAGE 0 to STAGE 3. All results are depicted separately for ACED- and MDNS corpora in Tables 3 and 4 respectively.

#### 4.1 STAGE 0: ICL with Baseline NMT Model

When we add nearest neighbors to the inputs and target prefixes we first observe that the automated metrics are mostly improved across all datasets. Notably, the result with 1-shot nearest neighbors is the best in this group of experiments. Additionally we find that the 5-shot result often degrades below the baseline.

Specifically for the Medical and Subtitles corpora of MDNS, we find that the model fails to improve over the baseline for all k.

The cosine distance of the nearest neighbors seems to be a viable indicator of performance in this set of experiments, e.g. when comparing the results for ACED Emerson & Digitalocean, where the average cosine distance (see Table 2) for k = 1 is much lower for Emerson at 0.13, versus 0.3 for Digitalocean. We find a moderate, statistically insignificant, negative Pearson correlation (r = -0.43) between the average cosine distances for k = 1and the difference in BLEU scores between the STAGE 0 1-shot experiment and the baseline.

ACED					MDNS				
		Asics	Digitalocean	Emerson	IT	Koran	Law	Medical	Subtitles
	k = 1	0.19	0.30	0.13	0.15	0.18	0.13	0.12	0.24
	k = 2	0.21	0.31	0.14	0.17	0.20	0.15	0.14	0.25
	k = 5	0.23	0.34	0.16	0.21	0.24	0.17	0.17	0.27

Table 2: Average cosine distance in embedding space of test set sources to k-nearest neighbors from train, for  $k \in \{1, 2, 5\}$ .

		A	sics	Digit	alocean	Emerson		Av	erage
		BLEU	COMET	BLEU	COMET	BLEU	COMET	BLEU	COMET
	Baseline	34.5	0.8624	53.3	0.9043	44.9	0.9108	44.2	0.8925
0	1-shot	43.7	0.8578	54.4	0.8982	72.1	0.9213	56.7	0.8924
AGE	2-shot	44.5	0.8525	54.5	0.8967	67.2	0.9137	55.4	0.8876
$\mathbf{S}_{\mathrm{T}}$	5-shot	41.0	0.8420	53.9	0.8955	28.7	0.8705	41.2	0.8693
	0-shot	41.2	0.8780	60.1	0.9152	79.2	0.944	60.2	0.9124
GE ]	1-shot	46.4	0.8657	59.6	0.9099	78.1	0.9378	61.4	0.9045
STA(	2-shot	46.2	0.8628	59.0	0.9090	66.3	0.9275	57.2	0.8998
01	5-shot	44.2	0.8500	57.3	0.9038	32.2	0.893	44.6	0.8823
2A	1-shot	43.0	0.8765	55.0	0.9073	73.1	0.9382	57.0	0.9073
AGE	2-shot	43.5	0.8785	54.4	0.9072	71.6	0.9392	56.5	0.9083
ST/	5-shot	42.3	0.8662	54.4	0.9066	73.4	0.9347	56.7	0.9025
$2^{\mathrm{B}}$	1-shot	44.5	0.8766	54.9	0.9046	73.1	0.9391	57.5	0.9068
AGE	2-shot	44.5	0.8777	55.4	0.9080	74.3	0.939	58.1	0.9082
ST/	5-shot	44.7	0.8734	55.0	0.9072	70.0	0.9363	56.6	0.9056
33	1-shot	48.8	0.8896	60.5	0.9141	78.9	0.9480	62.7	0.9172
AGE	2-shot	48.5	0.8914	60.1	0.9132	80.7	0.9456	63.1	0.9167
$\mathbf{S}_{\mathrm{T}}$	5-shot	47.6	0.8837	59.0	0.9095	80.2	0.9437	62.3	0.9123
ц	1-shot	31.8	0.8588	40.0	0.8677	71.6	0.9380	47.8	0.8882
alco	2-shot	34.5	0.8671	44.8	0.8876	76.9	0.9416	52.1	0.8988
Ľ,	5-shot	40.8	0.8789	Х	Х	78.5	0.9434	X	Х

Table 3: Results for the ACED corpus of the multi-stage evaluation for various numbers of k-nearest-neighbors, using BLEU and COMET metrics. The "Baseline" scores are for the English-to-German NMT system described in Section 3.1. We omit the Digitalocean dataset for the FALCON-40B 5-shot evaluation.

While BLEU indicates improvement (COMET reduces only for k > 1), we find that the model's behavior is in fact degenerate. Specifically, the model often fails to produce any output after the given prefix and instead predicts <eos> immediately, which leads to empty translations. We find that the rates of empty translations are 8.5%, 8.1%, and 9.1% for k = 1, 2, and 5 respectively. In contrast, the baseline system has a 0% rate of empty outputs. This is despite the model being specifically trained to support inputs covering the full context-width in pre-training.

#### 4.2 STAGE 1: Combining ICL with Domain Fine-Tuning

For STAGE 1 we first observe that the model can be effectively adapted to each domain by training adapters (see the STAGE 1, 0-shot results in Tables 3 and 4). A notable exception is MDNS Subtitles, where adaptation only slightly improves over the baseline. This result is, however, consistent with other work (Aharoni and Goldberg, 2020).

When we combine the trained adapters with ICL, we find no improvements over STAGE 1's 0-shot results, with the exception of ACED Asics.

Performance drops catastrophically for the MDNS Medical & Subtitles corpora. The rate

			IT	K	loran		Law	Μ	edical	Su	btitles	Av	/erage
		BLEU	COMET	BLEU	COMET	BLEU	U COMET	BLEU	COMET	BLEU	COMET	BLEU	COMET
	Baseline	34.3	0.8153	14.7	0.7229	44.7	0.8696	43.5	0.8406	27.7	0.7891	33.0	0.8075
0	1-shot	35.9	0.7698	17.2	0.6580	51.6	0.853	42.3	0.7964	17.5	0.6358	32.9	0.7426
AGE	2-shot	35.9	0.7433	17.2	0.6346	49.9	0.8467	38.2	0.7810	22.4	0.7024	32.7	0.7416
$\mathbf{S}_{\mathrm{T}}$	5-shot	31.9	0.7196	14.5	0.6000	42.3	0.8287	30.5	0.7505	24.4	0.7400	28.7	0.7278
	0-shot	39.6	0.8403	22.6	0.7274	50.7	0.8824	47.8	0.8429	28.1	0.7879	37.8	0.8162
GE ]	1-shot	36.7	0.7620	21.1	0.6434	51.1	0.8228	7.1	0.5078	0.0	0.4306	23.2	0.6333
TAG	2-shot	35.6	0.7436	20.5	0.6152	48.9	0.8019	15.9	0.5441	0.0	0.4208	24.2	0.6251
01	5-shot	32.8	0.7296	18.4	0.5980	44.9	0.7940	23.4	0.5854	16.8	0.6388	27.3	0.6692
2A	1-shot	34.3	0.8277	15.5	0.7222	49.5	0.8739	43.6	0.8380	25.7	0.7838	33.7	0.8091
AGE	2-shot	35.8	0.8244	16.4	0.7154	49.6	0.8739	44.6	0.8362	24.1	0.7810	34.1	0.8062
ST/	5-shot	34.3	0.8203	15.9	0.7083	48.1	0.8659	40.7	0.8220	24.0	0.7712	32.6	0.7975
2B	1-shot	34.6	0.8269	16.0	0.7217	50.4	0.8752	44.2	0.8405	25.9	0.7830	34.2	0.8095
AGE	2-shot	35.5	0.8182	16.5	0.7150	49.9	0.8747	43.4	0.8349	24.5	0.7774	34.0	0.8040
$S_{T/}$	5-shot	33.5	0.8103	16.6	0.7070	48.2	0.8696	37.5	0.8274	25.2	0.7782	32.2	0.7985
33	1-shot	41.4	0.8423	28.8	0.7235	58.1	0.8862	52.9	0.8488	27.0	0.7846	41.6	0.8171
AGE	2-shot	41.7	0.8401	29.6	0.7225	57.3	0.8850	51.2	0.8480	27.6	0.7850	41.5	0.8161
$\mathbf{S}_{\mathbf{T}}$	5-shot	40.9	0.8296	29.2	0.7249	55.8	0.8804	48.7	0.8413	27.5	0.7876	40.4	0.8128
u	1-shot	31.5	0.7985	17.9	0.7081	45.4	0.8538	42.4	0.8035	21.7	0.7586	31.8	0.7845
alco	2-shot	35.5	0.8202	22.4	0.7263	49.5	0.8680	47.5	0.8288	21.4	0.7605	35.3	0.8008
Ĺ	5-shot	40.1	0.8377	24.5	0.7358	50.5	0.8749	50.1	0.8401	22.6	0.7776	37.6	0.8132

Table 4: Results for the MDNS corpus of the multi-stage evaluation for various numbers of k-nearest-neighbors using BLEU and COMET metrics. The "Baseline" scores are for the English-to-German NMT system described in Section 3.1.

of empty translations also increases dramatically<sup>6</sup>, with a rate of up to 63.1% for the 1-shot result on MDNS Medical (up from 8.0% at STAGE 0).

### 4.3 STAGE 2A & STAGE 2B: Fine-Tuning towards ICL

When we compare the STAGE 2B (fine-tuning with the masked loss as described in Section 3.3) to the STAGE 0 results, we find that adding the separator and fine-tuning the model leads to generally improved scores on the ACED corpora for all k.

BLEU Results on MDNS corpora show slightly worse performance compared to the STAGE 0 results in 3 out of 5 corpora for k = 1, but the averages are still improved. COMET scores are however consistently improved for this comparison. We also find that the scores for k = 2 and k = 1 are very close, with 2-shot being ahead of 1-shot by 0.6% BLEU points on average on ACED data, and 1-shot being ahead of 2-shot by 0.2 BLEU points on MDNS. Which is in contrast to what we have observed in STAGE 0. k = 5 still performs worse, but we observe high relative gains compared to the 5-shot STAGE 0 result.

When comparing STAGE 2A and STAGE 2B, i.e. the masked loss and the standard NLL loss the results are inconclusive.

We further observe that STAGE 2B exhibits almost negligible rates of producing empty translations, at 0.3%, 0.8%, and 1.2% for k = 1, 2, 5 respectively.

# 4.4 STAGE 3: Combining ICL and Domain Adaptation

When combining ICL with adapters trained with nearest neighbor annotated data, we observe the globally best results for the NMT models. Compared to STAGE 1, which is also fine-tuned towards each domain, we observe greatly improved results on all automatic metrics. STAGE 3 2-shot delivers the best result on ACED, with an improvement of 2.5 BLEU points compared to the runner-up in terms of average BLEU STAGE 1 1-shot. On MDNS, STAGE 3 1-shot improves over the runnerup STAGE 1 0-shot by 3.8 points.

Especially the scores for MDNS Koran improve

<sup>&</sup>lt;sup>6</sup>Empty translation rates of STAGE 1 for each k over all corpora: 1-shot: 20.0%, 2-shot: 20.6%, 5-shot: 13.6%.

well above all previous models, with a relative improvement of 101% compared to the baseline. The models seem to be able to make better use of close nearest neighbors in this dataset, which are often substrings of one another. See Section 4.6 for a detailed analysis of the copying behavior on the ACED Asics dataset.

The rate of empty translations is reduced to 0.0% for all k.

We further notice that the results for 1- and 2shot ICL are very similar, and that the scores for 5-shot are also improved.

## 4.5 FALCON: Adapting Both to a Task and a Domain at the Same Time

The FALCON-40B LLM proves to excel at ICL, learning a task and adapting to a domain at the same time. Notably, scores improve with higher values of k, which is the opposite behavior to what we have observed with NMT models. When nearest neighbors are close to the test data, as they are for the ACED Emerson and MDNS IT datasets, we find results that are close to the best STAGE 3 results.

FALCON-40B's generation speed is however very slow at an average of 2.6 tokens per second in the 1-shot setting.

Also note that we have no means at this time to check whether parts of the test data are contained in FALCON's training data.

#### 4.6 Qualitative Analysis

Maintaining consistency in translations is an important quality criterion in the localization industry, and is a major motivator in the use of translation memories, which help ensure that marketing materials, for example, are uniform in the promised features and functions of the products being advertised (Emery et al., 2011). In NMT models, this consistency is traditionally increased by fine-tuning a translation model for a specific domain, which we denote by "STAGE 1 with 0-shot". In this section, we compare the fine-tuning approach with our ICL, specifically "STAGE 3 with 1-shot". We evaluate translation consistency on the Asics dataset. For that purpose we select segments s in the test data for which the source nearest neighbor s' in the Asics train data differs by exactly one word. These segments s are denoted as word-substitution segments. For each pair (s, s'), we then use two sources and one target t' in the ICL prompt and the other target t as reference to compare the generated

translation to. We define the fraction of pairs for which the generated translation exactly matches the reference as the word substitution accuracy (WSA). The results are in Table 6.

The translation for STAGE 3 1-shot achieves a WSA score of 74.6%, compared to 57.14% for the fine-tuning approach (STAGE 1 0-shot), whereas the non-adapted model only produces the exact reference translation in 1.7% of cases.

#### **5** Conclusions

We have shown that a standard NMT system can be trained to be an effective in-context learner in domain adaptation tasks. We find that this is most effective when we combine generic fine-tuning towards the ICL task and training adapter layers for a specific domain with nearest neighbor annotated data.

When the model is not fine-tuned towards the task, we find that ICL works to some extent, but shows degenerate behavior.

While LLMs like FALCON-40B can adapt to the MT task with ICL, this comes at the cost of increased compute. Generally, the results with the LLM still underperform our dedicated MT models.

#### References

- Roee Aharoni and Yoav Goldberg. 2020. Unsupervised domain clusters in pretrained language models. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*. Association for Computational Linguistics.
- Ankur Bapna, Naveen Arivazhagan, and Orhan Firat. 2019. Simple, scalable adaptation for neural machine translation. *CoRR*, abs/1909.08478.
- Ankur Bapna and Orhan Firat. 2019. Simple, scalable adaptation for neural machine translation. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 1538– 1548, Hong Kong, China. Association for Computational Linguistics.
- Rachel Bawden and François Yvon. 2023. Investigating the translation performance of a large multilingual language model: the case of BLOOM. In *Proceedings of the 24th Annual Conference of the European Association for Machine Translation*, pages 157–170, Tampere, Finland. European Association for Machine Translation.
- Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind

Source	Strive for every point in the women's GEL-						
	DEDICATE TM 6 CLAY tennis shoe by ASICS.						
Reference Translation	Strebe nach jedem Punkt in dem GEL-DEDICATE						
	<sup>TM</sup> 6 CLAY Tennisschuh für Damen von ASICS.						
BASELINE	Mit dem GEL-DEDICATE TM 6 CLAY						
	Damen-Tennisschuh von ASICS kannst du jeden						
	Punkt erreichen.						
STAGE 1 with 0-shot	Mit dem ASICS GEL-DEDICATE						
	TM 6 CLAY Tennisschuh für Damen						
	kannst du jeden Punkt erreichen.						
STAGE 3 with 1-shot	Strebe nach jedem Punkt in dem GEL-DEDICATE						
	<sup>TM</sup> 6 CLAY Tennisschuh für Damen von ASICS.						

Table 5: Comparison of example translation outputs from different models and the reference translation. Words that differ from the reference translation are highlighted in **blue**. The nearest source neighbor is "Strive for every point in the men's GEL-DEDICATE <sup>TM</sup> 6 CLAY tennis shoe by ASICS." with the reference translation "Strebe nach jedem Punkt in dem GEL-DEDICATE <sup>TM</sup> 6 CLAY Tennisschuh für Herren von ASICS.". Notice that the nearest neighbor only differs by one word in each language.

	STAGE 3 with 1-shot	STAGE 1 with 0-shot	Non-Adapted Model
Word-substitution segments	74.60%	57.14%	1.7%

Table 6: Results for word substitution accuracy (WSA, cf. subsection 4.6) for various adapted and non-adapted models for word-substitution segments.

Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, et al. 2020. Language models are few-shot learners. *Advances in Neural Information Processing Systems*, 33:1877–1901.

- Bram Bulte and Arda Tezcan. 2019. Neural fuzzy repair: Integrating fuzzy matches into neural machine translation. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 1800–1809, Florence, Italy. Association for Computational Linguistics.
- Vince Emery, Karl Kadie, and Mary Laplante. 2011. Multilingual Marketing Content: Growing International Business with Global Content Value Chains. Outsell.
- Xavier Garcia, Yamini Bansal, Colin Cherry, George Foster, Maxim Krikun, Melvin Johnson, and Orhan Firat. 2023. The unreasonable effectiveness of fewshot learning for machine translation. In *Proceedings* of the 40th International Conference on Machine Learning, volume 202 of Proceedings of Machine Learning Research, pages 10867–10878. PMLR.
- Amr Hendy, Mohamed Abdelrehim, Amr Sharaf, Vikas Raunak, Mohamed Gabr, Hitokazu Matsushita, Young Jin Kim, Mohamed Afify, and Hany Hassan Awadalla. 2023. How good are GPT models at machine translation? A comprehensive evaluation. *arXiv preprint arXiv:2302.09210*.
- Diederik Kingma and Jimmy Ba. 2014. Adam: A method for stochastic optimization. *International Conference on Learning Representations*.

- Tom Kocmi, Rachel Bawden, Ondřej Bojar, Anton Dvorkovich, Christian Federmann, Mark Fishel, Thamme Gowda, Yvette Graham, Roman Grundkiewicz, Barry Haddow, Rebecca Knowles, Philipp Koehn, Christof Monz, Makoto Morishita, Masaaki Nagata, Toshiaki Nakazawa, Michal Novák, Martin Popel, and Maja Popović. 2022. Findings of the 2022 conference on machine translation (WMT22). In Proceedings of the Seventh Conference on Machine Translation (WMT), pages 1–45, Abu Dhabi, United Arab Emirates (Hybrid). Association for Computational Linguistics.
- Philipp Koehn. 2005. Europarl: A parallel corpus for statistical machine translation. In *Proceedings of machine translation summit x: papers*, pages 79–86.
- Oleksii Kuchaiev, Jason Li, Huyen Nguyen, Oleksii Hrinchuk, Ryan Leary, Boris Ginsburg, Samuel Kriman, Stanislav Beliaev, Vitaly Lavrukhin, Jack Cook, Patrice Castonguay, Mariya Popova, Jocelyn Huang, and Jonathan M. Cohen. 2019. Nemo: a toolkit for building ai applications using neural modules.
- Jessy Lin, Geza Kovacs, Aditya Shastry, Joern Wuebker, and John DeNero. 2022. Automatic correction of human translations. In Proceedings of the 2022 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 494–507, Seattle, United States. Association for Computational Linguistics.
- Yu A Malkov and Dmitry A Yashunin. 2020. Efficient and robust approximate nearest neighbor search us-

ing hierarchical navigable small world graphs. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 42(4):824–836.

- Yasmin Moslem, Rejwanul Haque, John D. Kelleher, and Andy Way. 2023. Adaptive machine translation with large language models. In *Proceedings of the* 24th Annual Conference of the European Association for Machine Translation, pages 227–237, Tampere, Finland. European Association for Machine Translation.
- Kishore Papineni, Salim Roukos, Todd Ward, and Wei-Jing Zhu. 2002. BLEU: A method for automatic evaluation of machine translation. In *Proceedings of the 40th Annual Meeting of the Association for Computational Linguistics*, pages 311–318, Philadelphia, Pennsylvania, USA. Association for Computational Linguistics.
- Guilherme Penedo, Quentin Malartic, Daniel Hesslow, Ruxandra Cojocaru, Alessandro Cappelli, Hamza Alobeidli, Baptiste Pannier, Ebtesam Almazrouei, and Julien Launay. 2023. The RefinedWeb dataset for Falcon LLM: Outperforming curated corpora with web data, and web data only.
- M. Pham, Jitao Xu, Josep Maria Crego, François Yvon, and Jean Senellart. 2020. Priming neural machine translation. In *Conference on Machine Translation*.
- Matt Post. 2018. A call for clarity in reporting BLEU scores. In *Proceedings of the Third Conference on Machine Translation: Research Papers*, pages 186–191, Brussels, Belgium. Association for Computational Linguistics.
- Ricardo Rei, José G. C. de Souza, Duarte Alves, Chrysoula Zerva, Ana C Farinha, Taisiya Glushkova, Alon Lavie, Luisa Coheur, and André F. T. Martins. 2022. COMET-22: Unbabel-IST 2022 submission for the metrics shared task. In *Proceedings of the Seventh Conference on Machine Translation (WMT)*, pages 578–585, Abu Dhabi, United Arab Emirates (Hybrid). Association for Computational Linguistics.
- Nils Reimers and Iryna Gurevych. 2020. Making monolingual sentence embeddings multilingual using knowledge distillation. In *Proceedings of the* 2020 Conference on Empirical Methods in Natural Language Processing. Association for Computational Linguistics.
- Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. In *Advances in Neural Information Processing Systems*, pages 5998–6008.
- David Vilar, Markus Freitag, Colin Cherry, Jiaming Luo, Viresh Ratnakar, and George Foster. 2023. Prompting PaLM for translation: Assessing strategies and performance. In Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 15406– 15427, Toronto, Canada. Association for Computational Linguistics.

Jitao Xu, Josep Crego, and Jean Senellart. 2020. Boosting neural machine translation with similar translations. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 1580–1590, Online. Association for Computational Linguistics.