Abstract

Despite their success, large pre-trained multilingual models have not completely alleviated the need for labeled data, which is cumbersome to collect for all target languages. Zero-shot cross-lingual transfer is emerging as a practical solution: pre-trained models later fine-tuned on one transfer language exhibit surprising performance when tested on many target languages. English is the dominant source language for transfer, as reinforced by popular zero-shot benchmarks. However, this default choice has not been systematically vetted. In our study, we compare English against other transfer languages for fine-tuning, on two pre-trained multilingual models (mBERT and mT5) and multiple classification and question answering tasks. We find that other high-resource languages such as German and Russian often transfer more effectively, especially when the set of target languages is diverse or unknown a priori. Unexpectedly, this can be true even when the training sets were automatically translated from English. This finding can have immediate impact on multilingual zero-shot systems, and should inform future benchmark designs.

1 Introduction

Developing language technologies for low-resource languages has become a priority in the natural language processing (NLP) community. However, collecting labeled data for the more than 6,000 languages spoken around the world (Hale et al., 1992) would be a massive undertaking. Cross-lingual transfer has emerged as a practical solution, leveraging labeled data from high-resource languages to improve performance on low-resource ones (Ruder et al., 2019). In particular, zero-shot learning has surged in popularity, as it requires no labeled training data in the target language(s). In zero-shot cross-lingual transfer, a large pre-trained multilingual model such as mBERT (Devlin et al., 2018), XLM-R (Conneau et al., 2020) or mT5 (Xue et al., 2020) is fine-tuned with labeled training data presented in a single language, called the source or transfer language. Despite the monolingualism of its labeled corpus, the model can exhibit surprisingly good end-task performance for the other languages seen during pre-training (Pires et al., 2019; Wu and Dredze, 2019). This process is illustrated in Figure 1.

Current studies default to English when selecting the transfer language for fine-tuning, even though this particular choice has not been systematically vetted. In this paper, we ask a question that has been overlooked: Is English the best source language for zero-shot cross-lingual transfer?

The standard of using English as the default source language was adopted by popular multilingual benchmarks such as XTREME (Hu et al., 2020) and XGLUE (Liang et al., 2020), which truncated the training sets of the constituent tasks.
to English, even when the original tasks offered training data in other languages. While more recent benchmarks such as XTREME-R (Ruder et al., 2021) are starting to include cross-lingual training sets, English is still overwhelmingly dominant in this domain. Our standpoint is that adopting English as the de-facto language for transfer without considering alternatives is an opportunity cost, as there might be other languages with better zero-shot transferability. Identifying such languages could boost a system’s zero-shot performance without changes to the training pipeline, by simply collecting labeled data in those languages.

We focus on the scenario in which the complete list of target languages is large and might not even be known a priori, which is common for multilingual systems with an ever-expanding international user base. We also assume a restricted budget for data collection that can acquire labeled examples for fine-tuning in a single language only. This constraint enables us to study transferability of languages in isolation; investigating combinations of source languages is left for future work.

The universality of targeting many languages is particularly challenging. Previous work has addressed the simpler problem of identifying the most effective transfer language(s) for a single target, or a small set of closely related ones. Practitioners either made decisions informed by the phylogenetic language tree (Cotterell and Heigold, 2017) or designed automated rankers that leverage hand-crafted similarity features such as syntactic, morphological, or geographic proximity (Lin et al., 2019). To the best of our knowledge, no previous study investigated general language transferability towards a set of targets that is not predetermined.

Finding a universal answer is intractable: there is an unbounded pool of NLP tasks, and acquiring test data in 6,000+ languages is almost as difficult as acquiring training data. To address these difficulties, we first design metrics that capture, given a source language, its zero-shot transferability towards a fixed set of test languages for which data is readily available. Then, we conduct extensive experiments with mBERT (Devlin et al., 2018) and mT5 (Xue et al., 2020) on multiple tasks, including classification and question answering.

Our experiments reveal two surprising results. First, we find that English is not the most universally transferable language in most settings, with the exception of question answering on mT5; German and Russian are often more effective sources. Second, even more unexpectedly, we find that zero-shot performance can often be improved by fine-tuning on a transfer set that was originally written in English and machine-translated to one of the better source languages. Making this change is effective even when the source language itself is not in the set of target languages. These findings are immediately applicable for building highly multilingual systems.

2 Related Work

2.1 Zero-Shot Cross-lingual Transfer

After the publication of multilingual BERT (mBERT) (Devlin et al., 2018), multiple studies observed its zero-shot capabilities: when fine-tuned for a specific task in language $x$ (most commonly English), it performs well on the same task in another language $y$, without having seen any supervised data in $y$ (Pires et al., 2019; Wu and Dredze, 2019; Hu et al., 2020). With few adjustments, zero-shot transfer can succeed even for languages $y$ that were not included in the original pre-training set (Wang et al., 2020a; Ponti et al., 2020).

Cross-lingual transferability is particularly surprising in the absence of explicit cross-lingual alignment during pre-training. While the transfer mechanism is still not fully understood, there are multiple hypotheses for its success. One debated aspect is vocabulary overlap: some studies observed a positive correlation between the number of shared tokens and transfer compatibility of two languages (Wu and Dredze, 2019); in contrast, others concluded from synthetic experiments that lexical overlap has a negligible effect (K et al., 2020). Another presumed catalyst for transfer is jointly training across multiple languages, shown to encourage cross-lingual alignment of contextual representations (Cao et al., 2020). While models such as mBERT clearly produce cross-lingual representations, there is evidence that they also preserve language-specific information (Wu and Dredze, 2019; Wang et al., 2020b).

2.2 Transfer Language Selection

While popular multilingual zero-shot benchmarks such as XTREME (Hu et al., 2020) and XGLUE
(Liang et al., 2020) provide development and test sets in tens of diverse low-resource languages, their transfer sets are limited to English. Even for tasks such as TyDi QA (Clark et al., 2020) that originally had training data in multiple languages, the authors of the benchmark removed any non-English data from the transfer set. The effect is that most studies mentioned above defaulted their analysis to English as the only transfer language. More recently however, the XTREME-R benchmark (Ruder et al., 2021) introduced two truly cross-lingual retrieval tasks, where both training and evaluation data use a mixture of languages (Roy et al., 2020; Botha et al., 2020).

Previous studies on the effectiveness of source languages focus on a single target language, or a small set of related ones. Lauscher et al. (2020) observe strong correlations between transfer performance and multiple measures of linguistic proximity between the transfer and target language, including syntax and morphology. Lin et al. (2019) automatically identify the most effective transfer languages via a ranker that leverages various distances (geographic, genetic, syntactic, phonological, etc) between a single target language and multiple transfer candidates. In contrast, we seek to find languages that transfer to many targets, potentially not even known a priori.

The pursuit of a language that can help others is also reminiscent of pivot-based machine translation (source → pivot + pivot → target), where a high-resource pivot bridges the gap between pairs of languages with insufficient parallel training data (Cheng et al., 2017; Kim et al., 2019; Dabre et al., 2021). English was shown to not always be the best pivot for machine translation (Paul et al., 2013; Dabre et al., 2015), which prompted us to investigate whether that is also the case for zero-shot cross-lingual transfer.

### 3 Metrics for Language Transferability

In this section, we formally define metrics for measuring the impact of a particular source language on the cross-lingual ability of a model.

Let the relative zero-shot ability \( Z \) of a source language \( S \) to transfer to a target language \( T \) be:

\[
  Z(S \rightarrow T) = \frac{\mathcal{E}(M^S, T)}{\mathcal{E}(M^T, T)}
\]

where \( M^L \) is a pre-trained model \( M \) fine-tuned on a corpus containing labeled data in language \( L \), and \( \mathcal{E} \) is a standard evaluation metric (e.g. accuracy for classification, F1 score for question answering, etc.). \( Z \) measures how much of the quality of a model fine-tuned and evaluated on the same target language \( T \) can be recovered when training it on a different language \( S \) instead. Trivially, \( Z(L, L) = 1.0 \). In our tables, we multiply these values by 100 for readability, so that they can be interpreted as percentages.

Given that English is currently the dominant transfer language, we will often express the transferability of a source \( S \) towards a target \( T \) in terms of its zero-shot advantage over English:

\[
  Z(S \rightarrow T) - Z(\text{en} \rightarrow T)
\]

To measure the transferability of a source \( S \) to a set of target languages \( L \), we average over relative zero-shot abilities:

\[
  Z(S \rightarrow L) = \frac{1}{|L|} \sum_{T \in L} Z(S \rightarrow T)
\]

When \( S \in L \), zero-shot ability is a slight misnomer, since it includes a constant term \( 1/|L| \) for self-transfer. This term cancels out when computing the overall zero-shot advantage over English:

\[
  Z(S \rightarrow L) - Z(\text{en} \rightarrow L)
\]

In other words, the metric in Equation 4 is fully zero-shot, since it disregards self-transfer terms.\(^2\)

For some tasks, the denominator \( \mathcal{E}(M^T, T) \) is not available; to keep the number of experiments manageable, we did not train all models \( M^T \) for every task. In such cases, instead of the relative metric in Equation 1 we will use the un-normalized standard evaluation metric \( \mathcal{E}(M^S, T) \). Note that the self-transfer term is now \( \mathcal{E}(M^S, S) \), which ceases to be constant and no longer cancels out when computing the advantage over English.

### 4 Datasets

In this section, we list the standard multilingual benchmarks we selected for evaluation. The main desideratum for our datasets is that training data is available in multiple languages. Ideally, all such

\(^2\)XTREME defines a cross-lingual transfer gap metric as: \( \frac{1}{|L|} \sum_{S \in L} \mathcal{E}(M^S, S) - \mathcal{E}(M^T, T) \), which is an alternative to Equation 3. If we were to substitute this definition in Equation 4, the self-transfer terms would (undesirably) survive. Also, this metric is oblivious to how difficult it is to solve the task for a target language \( T \), which we capture via the \( \mathcal{E}(M^T, T) \) in the denominator of Equation 1.
training sets would be produced by humans (or verifiably high-quality). In practice however, multilingual training data was obtained by machine-translating an originally human-curated dataset (most often in English) to other languages. Inescapably, this introduces the confound of MT quality; high-resource languages are likely to have good translation systems and therefore merely appear to outperform others on zero-shot cross-lingual transfer. We will be mindful of this when drawing conclusions from our experiments.

To ensure that all language-specific subsets have the same size and informational content, we occasionally depart from the established way of using some of these datasets, as elaborated below.

**XNLI** The Cross-lingual Natural Language Inference corpus (Conneau et al., 2018) consists of premise/hypothesis pairs that are either entailments, contradictions, or neutral. XNLI extends the English MultiNLI dataset (Williams et al., 2018) to 15 languages, including low-resource ones such as Swahili and Urdu; training sets are machine-translated, while the development and test sets are human-translated.

**PAWS-X** The Cross-lingual Paraphrase Adversaries from Word Scrambling corpus (Yang et al., 2019) is a binary classification task for paraphrase identification. Its 6 training sets were machine-translated from the English PAWS dataset (Zhang et al., 2019). The development and test sets were human-translated.

**XQuAD** The Cross-lingual Question Answering Dataset (Artetxe et al., 2020) requires answering questions by identifying answer spans in accompanying paragraphs. XQuAD consists of human translations of the development and test sets of the English SQuAD 1.1 corpus (Rajpurkar et al., 2016) into 10 languages. For training, we automatically translated the SQuAD training set using an in-house MT system. This process is lossy because the translated answers need to be located within the translated paragraphs. We applied the fuzzy matching procedure in Hu et al. (2020), but dropping examples more aggressively (when the edit distance between the closest match and translated answer is >5 instead of >10). When comparing such machine-translated datasets, we ensure equal corpus sizes by taking the intersection of questions whose answers were successfully found in the paragraphs after translation.

**TyDi QA** The Typologically Diverse Question Answering corpus (Clark et al., 2020) gathers human-generated data in 11 languages, for both training and development (the test set is kept private). Specifically, we use its Gold Passage subtask, which has the same format as XQuAD. In contrast to the latter, TyDi QA contains different context/question pairs across languages. In our experiments, we hold the informational content constant by always comparing in-house machine translations of the same human-generated subset. This is similar to XQuAD, except that it allows the source language to be different from English.

**Notation** We attach superscripts to dataset names to indicate whether they are the original version of a corpus (O), human-translated (HT) or machine-translated (MT).

## 5 Models

In our experiments, we fine-tune two widely used pre-trained multilingual language models. We report trends that are consistent between the two model families, and will be less concerned with fully explaining the corner cases when they exhibit different zero-shot behavior.

**mBERT** Multilingual BERT (mBERT) (Devlin et al., 2018) is an encoder model that was jointly trained on 104 languages from Wikipedia, with masked language model and next-sentence prediction objectives. As elaborated in section 2, mBERT has been extensively studied in the context of zero-shot learning, with impressive cross-lingual transfer capabilities.

**mT5** Multilingual T5 (mT5) (Xue et al., 2020) is an encoder-decoder model that was jointly trained on 101 languages from Common Crawl. We use its mT5-Base variant, whose encoder is similar in size to mBERT (mT5-Base has a larger parameter count due to the additional decoder). mT5 was also shown to transfer well to new languages.

The zero-shot cross-lingual strengths of the two models are distributed differently across tasks.
Table 2: XNLI: zero-shot transfer. Values for $en^0$ are relative zero-shot abilities (Equation 1). Values for other languages ($xx^0$) are zero-shot advantages over English (Equation 2). Surprisingly, some machine-translated datasets (such as German and Russian) are more transferable across the board than the original English set.

Compared to mBERT when transferring from English, mT5-Base achieves +10.0 in XNLI accuracy, +4.5 in PAWS-X accuracy, −2.5 in XQuad F1 score and −2.5 in TyDi QA F1 score, among others (Xue et al., 2020). Its generative nature (which poses challenges for extractive contrasts) contrasts with mBERT’s extractive approach.

6 Fine-Tuning Procedure

We measure the zero-shot performance of various languages in isolation, by fine-tuning the pre-trained models listed in section 5 on monolingual corpora. We follow the fine-tuning procedures established by previous work.

mBERT

Similarly to XTREME, we fine-tune mBERT for a fixed number of epochs, with the following hyperparameters: 5 epochs, learning rate 3e-5, training batch size 128. Note that the development set does not contribute to checkpoint selection in any way.

mT5

Following the authors of mT5, we fine-tune it with early stopping. We store checkpoints every 200 steps, for a total of 2000 steps. When using transfer language x, we select the checkpoint with best performance on x’s development set. Finally, we evaluate its zero-shot quality on all other languages using the test set. The only exception is TyDi QA, which kept its test set private: we fine-tune for 500 steps and select the last checkpoint, then evaluate it on the original.

7 Analysis and Results

We find that English is often out-performed by other source languages on standard multilingual benchmarks. Table 1 summarizes our results.

7.1 Sequence Classification

In this set of experiments, we fine-tuned mBERT and mT5-Base separately on all 15 source languages from XNLI (Table 2) and all 7 source languages from PAWS-X (Table 3). For both models, both tasks, and all combinations of source S and target T languages, we computed the relative zero-shot ability $\mathcal{Z}(S \rightarrow T)$ defined in Equation 1.
English is often not the best source language.

Here we tackle our main research question: *Is English the most effective source language for zero-shot cross-lingual transfer?* To explore this question, we compute, for each source language, its relative zero-shot abilities over English, as defined in Equation 2. Results in Table 2 and Table 3 identify multiple source languages that outperform English across the board. For instance, on XNLI (Table 2), German (de\textsuperscript{en}) scores an average advantage of +2.0 on mBERT and +2.2 on mT5, while Russian (ru\textsuperscript{en}) achieves an advantage of +1.6 on mBERT and +2.5 on mT5. Notably, these advantages are consistent across groups of targets; Russian doesn’t only transfer better to related languages such as Bulgarian (bg\textsuperscript{en}), but also to Latin-scripted languages or other scripts such as Thai (th\textsuperscript{en}). Similarly, for PAWS-X (Table 3), German scores +1.3 on mBERT and +1.0 on mT5, with consistent gains across target groups.

Most remarkably, all non-English transfer sets were machine-translated from a corpus initially written in English. The fact that the latter is de-ranked by automated translations is counter-intuitive, since the conversion process is presumed to be imperfect. This finding offers a simple yet effective recipe for improving multilingual systems trained via zero-shot transfer: instead of fine-tuning on English data, translate it first.3

Table 3: PAWS-X zero-shot transfer (averaged over 3 runs). Values for en\textsuperscript{en} are relative zero-shot abilities (Equation 1). Values for xx\textsuperscript{en} are zero-shot advantages over English (Equation 2). Interestingly, German and French both outperform English by a significant margin across the board.

| Train Data | Latin Scripts | Averages |
|------------|---------------|----------|
| Test Data | en\textsuperscript{en} | \textsuperscript{de}\textsuperscript{en} | \textsuperscript{es}\textsuperscript{en} | \textsuperscript{fr}\textsuperscript{en} | \textsuperscript{zh}\textsuperscript{en} | \textsuperscript{ja}\textsuperscript{en} | \textsuperscript{ko}\textsuperscript{en} | Latin | CJK | All |
| mBERT | 100.0 | 97.8 | 97.4 | 98.3 | 93.6 | 94.8 | 93.2 | 98.4 | 93.9 | 96.4 |
| de\textsuperscript{en} | -1.7 | +2.2 | +0.5 | +0.1 | +2.1 | +2.9 | +2.7 | +0.3 | +2.6 | +1.3 |
| es\textsuperscript{en} | -1.0 | -0.1 | +2.6 | +1.4 | +0.9 | +1.2 | +1.1 | +0.7 | +1.1 | +0.9 |
| fr\textsuperscript{en} | -1.7 | -0.6 | +1.7 | +1.7 | +2.0 | +2.3 | +1.3 | +0.3 | +1.9 | +1.0 |
| zh\textsuperscript{en} | -5.1 | -2.6 | -2.7 | -3.4 | +6.4 | +5.9 | +5.0 | -3.5 | +5.8 | +0.5 |
| ja\textsuperscript{en} | -13.8 | -10.2 | -10.3 | -10.3 | +0.3 | +5.2 | +1.7 | -11.3 | +2.4 | +5.4 |
| ko\textsuperscript{en} | -8.4 | -4.3 | -5.3 | -5.6 | +2.1 | +5.6 | +6.8 | -5.9 | +1.9 | -1.3 |

Table 4: XNLI models fine-tuned on translations of the English test set (re-purposed for training), produced either by humans (HT) or by an MT system. Transferability is comparable across the two columns, meaning that the inferior performance of English in Table 2 and Table 3 is not explained by fortunate artefacts of MT.

| Train Data | Average advantage over English (Equation 2) |
|------------|---------------------------------------------|
| Test Data | en\textsuperscript{en} | ar\textsuperscript{en} | bg\textsuperscript{en} | de\textsuperscript{en} | el\textsuperscript{en} | es\textsuperscript{en} | fr\textsuperscript{en} | hi\textsuperscript{en} | ru\textsuperscript{en} | sw\textsuperscript{en} | th\textsuperscript{en} | tr\textsuperscript{en} | ur\textsuperscript{en} | vi\textsuperscript{en} | zh\textsuperscript{en} |
| latex | HT/N/A | MT/N/A | MT/N/A | MT/N/A | MT/N/A | MT/N/A | MT/N/A | MT/N/A | MT/N/A | MT/N/A | MT/N/A | MT/N/A | MT/N/A | MT/N/A | MT/N/A |
| mBERT | 100.0 | 97.8 | 97.4 | 98.3 | 93.6 | 94.8 | 93.2 | 98.4 | 93.9 | 96.4 |
| de\textsuperscript{en} | -1.7 | +2.2 | +0.5 | +0.1 | +2.1 | +2.9 | +2.7 | +0.3 | +2.6 | +1.3 |
| es\textsuperscript{en} | -1.0 | -0.1 | +2.6 | +1.4 | +0.9 | +1.2 | +1.1 | +0.7 | +1.1 | +0.9 |
| fr\textsuperscript{en} | -1.7 | -0.6 | +1.7 | +1.7 | +2.0 | +2.3 | +1.3 | +0.3 | +1.9 | +1.0 |
| zh\textsuperscript{en} | -5.1 | -2.6 | -2.7 | -3.4 | +6.4 | +5.9 | +5.0 | -3.5 | +5.8 | +0.5 |
| ja\textsuperscript{en} | -13.8 | -10.2 | -10.3 | -10.3 | +0.3 | +5.2 | +1.7 | -11.3 | +2.4 | +5.4 |
| ko\textsuperscript{en} | -8.4 | -4.3 | -5.3 | -5.6 | +2.1 | +5.6 | +6.8 | -5.9 | +1.9 | -1.3 |

Does machine translation boost transferability?

In light of the results above, the following question arises: are the gains over the English baseline due to other languages being intrinsically better sources, or from a fortunate side-effect of automated translation (e.g. insertion of noise in the transfer set that makes the model less prone to over-fitting)? To tease these apart, we propose a new experiment using the XNLI dataset: we re-purpose the test set (which was human-generated) for training. We train models on both the human-translated (HT) and their in-house machine translations (MT) and measure how the advantage over English differs in the two scenarios. We use the human-generated development set for evaluation. Table 4 shows that English is outperformed by the same set of languages in both cases, without evidence that machine-translated training sets transfer better than human-generated ones.

**mBERT vs mT5** Across both tasks, mBERT displays larger gaps than mT5 between the highest and lowest performing languages. For instance, for XNLI, Urdu’s average (dis)advantage over English is –11.4 on mBERT and only –0.7 on mT5 (with successful transfer to Hindi in particular). This might be due to mT5’s more comprehensive adaptation after the text was translated. If the budget permits, the alternative is to collect data from scratch in one of the better source languages.

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3This recipe only applies to tasks that accommodate for machine translation, that is, the labels remain valid or can be
pre-training set, and suggests that the handling of a particular language during pre-training can influence its later zero-shot ability during fine-tuning.

### 7.2 Extractive Question Answering (QA)

Next, we investigate whether German and Russian, two of the languages that out-performed English in the experiments above, hold their advantage in question answering tasks. For this purpose, we fine-tune mBERT and mT5 separately on the English SQuAD corpus (en\textsuperscript{en}) and two in-house translations (de\textsuperscript{en} and ru\textsuperscript{en}), and evaluated their transferability to XQuAD. See section 4 for more information on these QA datasets.

**QA on mBERT: Russian transfers better**

Table 5 shows that, when fine-tuning mBERT, English is significantly out-performed by Russian (+2.8 F1→Other) and is on-par with German (+0.5 F1→Other), despite the last two being machine-translated. Zero-shot transfer to Thai (th\textsuperscript{en}) benefits the most: transferring from Russian brings an additional +8.2 F1 over transferring from English. Interestingly, Hu et al. (2020) showed that mBERT generally suffers from impoverished transfer to Thai across multiple tasks. It is remarkable that such a pervasive issue can be partly mitigated by simply transferring from Russian, even when machine-translated.

**QA on mT5: English transfers better**

We repeated the XQuAD experiment on mT5 and, in contrast to all previous results, the original English training set en\textsuperscript{en} performs significantly better than its German translation de\textsuperscript{en} (−3.0 F1→Other) and Russian translation ru\textsuperscript{en} (−4.2 F1→Other). Interestingly however, zero-shot transfer to Thai (th\textsuperscript{en}) is still more effective from both German (+1.2) and Russian (+2.2).

This anomaly could be linked to the purely generative nature of mT5, which is less aligned with the task of extractive QA and is known to produce illegal predictions such as accidental translations (Xue et al., 2020, 2021). Generally, the behavior of zero-shot cross-lingual transfer in generative models is under-studied. The presence of a decoder is yet another variable that can influence cross-lingual transferability, and interact with other aspects of training (model capacity, quality and distribution of pre-training data, language of fine-tuning data, etc.). The reason why fine-tuning mT5 on English leads to better transfer remains an open question. The rest of this section makes observations that can inform future investigations.

**XQuAD contains English-centric content.**

Even though the test sets in XQuAD were human-translated (and therefore likely high-quality), Table 7 shows that some answers consist of English entities that were understandably neither translated nor transliterated (e.g. "Lady Gaga"). We roughly quantify this phenomenon by counting, for each language that doesn’t use the Latin script, how many answers are exclusively ASCII and contain at least one letter (to exclude numeric answers like years). Notably, Greek (el\textsuperscript{en}) is the language with highest proportion of such answers (9.4%), and also the target language that suffers the most when transferring from German (−7.0 F1) or Russian (−9.5 F1) instead of English. This non-negligible portion of English test answers could be...
a reason why the English source scores higher.\footnote{A reasonable counter-argument to this hypothesis is that, when using the same XQuAD dataset to fine-tune mBERT, English was outranked—hence the dataset cannot be the culprit. However, implicit in this hypothesis is the fact that the generative nature of mT5 makes it more susceptible to artifacts in the data compared to mBERT.}

**Translated English still transfers well on mT5.**

In all the experiments above, the English training set was produced by humans, while all others were machine-translated. Our goal here is to test whether the mT5/QA setting is particularly susceptible to this difference. We level the playing field by leveraging the TyDi QA corpus differently from its standard usage. We select the two largest training sets: Arabic (14,000 instances) and Finnish (6,800 instances); in turn, we machine-translate these original sets into English, German, and Russian.

Results in Table 6 and Table 8 show that, surprisingly, the gap between English and the other two transfer languages becomes even more salient. It is possible that these differences stem, at least partly, from uneven translation quality across language pairs. However, the fact that $en^\text{MT}$ scores +2.1 F1 higher than the original dataset $fi^O$ implies that the superior transferability of English compared to $de^\text{MT}$ and $ru^\text{MT}$ on TyDi QA is not just due to better $fi^O\rightarrow en^\text{MT}$ translation quality.

**Under-trained mT5 closes or reverses the gap.**

Another possibility is that the pre-training strategy is responsible for the discrepancy between English and other sources when fine-tuning mT5 on QA. This hypothesis is supported by the following observation: when mT5 is under-trained with 32B tokens (instead of 1T as the published model)

| Model            | Source     | $en^O$ | $ru^O$ | $fi^O$ | $ar^O$ | $bn^O$ | $id^O$ | $ko^O$ | $sw^O$ | $te^O$ | $\rightarrow Other$ | $\rightarrow All$ |
|------------------|------------|--------|--------|--------|--------|--------|--------|--------|--------|--------|---------------------|----------------------|
| mT5-Base         | $fi^O\rightarrow en^\text{MT}$ | 63.3   | 39.4   | 51.6   | 51.1   | 20.0   | 60.1   | 32.2   | 62.7   | 37.5   | 43.9                | 46.4                |
| mT5-Base         | $fi^O\rightarrow de^\text{MT}$  | -8.0   | -4.1   | +0.0   | -5.0   | -1.5   | -3.3   | -1.5   | -3.0   | -14.2  | -4.8                | -4.5                |
| mT5-Base         | $fi^O\rightarrow ru^\text{MT}$  | -13.0  | +10.3  | -10.9  | -9.0   | -5.6   | -7.6   | -6.0   | -13.5  | -13.1  | -10.2               | -8.3                |
| mT5-Base         | $fi^O\rightarrow$               | -5.6   | -2.0   | +8.6   | +0.4   | -3.0   | +1.2   | -2.0   | -2.5   | -6.7   | -2.1                | -1.3                |
| mT5-Uniform      | $fi^O\rightarrow en^\text{MT}$  | 62.2   | -49.1  | 47.4   | 58.1   | 21.7   | 52.7   | 25.3   | 42.8   | 23.8   | 37.4                | 42.6                |
| mT5-Uniform      | $fi^O\rightarrow de^\text{MT}$  | -8.2   | +0.8   | +0.7   | +2.2   | +2.6   | -0.6   | +2.8   | -1.0   | -4.4   | +0.3                | -0.6                |
| mT5-Uniform      | $fi^O\rightarrow ru^\text{MT}$  | -14.6  | -2.4   | -2.1   | +0.7   | +9.0   | -0.4   | +2.0   | -3.2   | -2.9   | +0.9                | -1.5                |
| mT5-Uniform      | $fi^O$                                  | -10.7  | -1.7   | +10.5  | +1.9   | +10.7  | +4.1   | +9.1   | +7.9   | +2.4   | +6.0                | +3.8                |

Table 6: TyDi QA-GoldP (F1 scores) after fine-tuning mT5-Base and mT5-Uniform on datasets that were machine-translated from the original Finnish subset $fi^O$ (6,800 instances). For the English translation $en^O$, we show F1 scores; for all others, we show improvements over $en^O$ F1. mT5-Uniform (trained on 32B tokens) shows smaller gaps between source languages than mT5-Base (trained on 1T tokens). See Table 8 for the same analysis when the source dataset is in Arabic.

| XQuAD Test Set | %ASCII Answers | Examples of ASCII-only test answers in $el^\text{HT}$ |
|---------------|----------------|--------------------------------------------------|
| $ar^\text{HT}$ | 0.4%                   | 120 m                                             |
| $el^\text{HT}$ | 9.4%                   | Lady Gaga                                          |
| $hi^\text{HT}$ | 1.8%                   | State Route 99                                    |
| $ru^\text{HT}$ | 3.4%                   | Toyota Corona Mark II                             |
| $th^\text{HT}$ | 3.3%                   | User Datagram Protocol                            |
| $zh^\text{HT}$ | 2.2%                   | "business as usual" (BAU)                          |

Table 7: Languages with non-Latin scripts have non-negligible proportions of ASCII-only answers (with at least one letter) in the XQuAD test set. Some of these are English-centric entities that cannot be translated.

using a uniform sampling distribution across pre-training languages\footnote{We also pre-trained mT5-Base on 32B tokens with a sampling distribution proportional to dataset sizes (same sampling as the original paper), but observed severe degradation when transferring to lower-resource languages.}, the gap between English and other fine-tuning languages is either closed or reversed (see the mT5-Uniform model in Table 5, Table 6 and Table 8).

8 Conclusion

In this study, we presented empirical evidence that zero-shot cross-lingual transfer from languages other than English can be more effective, especially when the set of target languages is diverse or unknown in advance. Our experiments surface German and Russian as very strong candidates in most settings, even when machine-translated from English. One exception is question answering on mT5; however, when its pre-training strategy is altered, the performance gap between sources is closed or inverted. These findings provide an immediately applicable recipe for improving zero-shot systems (translate them to German or Russian first) and can inform future data collection efforts.
There are multiple future directions for study. Investigating the most effective combinations of transfer languages under a limited data collection budget is a natural next step. Analyzing the relationship between pre-training and the effectiveness of source languages during fine-tuning is another interesting avenue.

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| Model          | Source               | $\text{en}^O$ | $\text{ru}^O$ | $\text{ar}^O$ | $\text{bn}^O$ | $\text{fi}^O$ | $\text{id}^O$ | $\text{ko}^O$ | $\text{sw}^O$ | $\text{te}^O$ | Averages $\rightarrow$Other | Averages $\rightarrow$All |
|----------------|----------------------|---------------|---------------|---------------|---------------|---------------|---------------|---------------|---------------|---------------|-----------------------------|-----------------------------|
| mT5-Base       | $\text{ar}^O \rightarrow \text{en}^H$ | 65.2          | 42.1          | 52.9          | 15.9          | 53.9          | 63.2          | 30.5          | 60.3          | 35.9          | 43.3           | 46.7                        |
| mT5-Base       | $\text{ar}^O \rightarrow \text{de}^H$ | -8.4          | -7.2          | -5.7          | +2.3          | -2.2          | -6.1          | +0.2          | -0.5          | -16.1         | -3.7           | -4.8                        |
| mT5-Base       | $\text{ar}^O \rightarrow \text{ru}^H$ | -17.3         | +5.5          | -9.9          | -2.8          | -12.0         | -11.4         | -6.1          | -16.0         | -15.9         | -10.7          | -9.5                        |
| mT5-Base       | $\text{id}^O$        | -1.0          | +12.3         | +30.0         | +13.6         | +10.4         | +6.9          | +19.4         | +1.8          | +5.2          | +9.6           | +11.0                       |
| mT5-Uniform    | $\text{ar}^O \rightarrow \text{en}^H$ | 61.1          | 48.6          | 58.8          | 21.3          | 47.0          | 52.9          | 26.1          | 40.9          | 22.9          | 35.2           | 42.2                        |
| mT5-Uniform    | $\text{ar}^O \rightarrow \text{de}^H$ | -7.9          | +0.8          | +1.3          | +3.8          | +0.1          | -0.8          | +0.9          | -1.5          | -5.1          | -0.4           | -0.9                        |
| mT5-Uniform    | $\text{ar}^O \rightarrow \text{ru}^H$ | -12.6         | -1.5          | -0.5          | +7.1          | -1.1          | -0.3          | +2.2          | -2.1          | -1.3          | +0.8           | -1.1                        |
| mT5-Uniform    | $\text{id}^O$        | -8.2          | +6.5          | +21.7         | +6.8          | +2.4          | +8.5          | +2.8          | +0.6          | +3.8          | +4.2           | +5.0                        |

Table 8: TyDi QA-GoldP (F1 scores) after fine-tuning mT5-Base and mT5-Uniform on datasets that were machine-translated from the original Arabic subset $\text{ar}^O$ (14,000 instances). For the English translation $\text{en}^H$, we show F1 scores; for all others, we show improvements over $\text{en}^H$ F1. mT5-Uniform (trained on 32B tokens) shows smaller gaps between source languages than mT5-Base (trained on 1T tokens). See Table 6 for the same analysis when the source dataset is in Finnish.