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Beyond English-Centric Multilingual Machine Translation

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Abstract

Existing work in translation demonstrated the potential of massively multilingual machine translation by training a single model able to translate between any pair of languages. However, much of this work is English-Centric, training only on data which was translated from or to English. While this is supported by large sources of training data, it does not reflect translation needs worldwide. In this work, we create a true Many-to-Many multilingual translation model that can translate directly between any pair of 100 languages. We build and open-source a training data set that covers thousands of language directions with parallel data, created through large-scale mining. Then, we explore how to effectively increase model capacity through a combination of dense scaling and language-specific sparse parameters to create high quality models. Our focus on non-English-Centric models brings gains of more than 10 BLEU when directly translating between non-English directions while performing competitively to the best single systems from the Workshop on Machine Translation (WMT). We open-source our scripts so that others may reproduce the data, evaluation, and final M2M-100 model: `https://github.com/pytorch/fairseq/tree/master/examples/m2m_100`.

Keywords: many-to-many, multilingual machine translation, model scaling, bitext mining, neural networks

1. Introduction

Multilingual Machine Translation (MMT) aims to build a single model to translate between any pair of languages. Neural network models have been very successful for bilingual machine translation (Bahdanau et al., 2015; Gehring et al., 2017; Vaswani et al., 2017) and more recently, neural MMT models have shown promising results (Firat et al., 2016; Zhang et al., 2020). Multilingual translation models factorize computation when translating to many languages and share information between similar languages, which benefits low resource directions (Arivazhagan et al., 2019) and enables zero-shot translation (Gu et al., 2019).

However, in the past, these systems have not performed as well as bilingual models when trained on the same language pairs (Johnson et al., 2017), as model capacity necessarily must be split between many languages (Arivazhagan et al., 2019). This has been alleviated by increasing model capacity (Aharoni et al., 2019; Zhang et al., 2020), but increased model size also necessitates larger multilingual training data sets which are laborious and difficult

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to create. To ease this challenge, most prior work has focused on *English-Centric* data sets and models which translate from and to English but not between non-English languages. This English-Centric bias in the data and resulting models is not reflective of how people use translation and empirically leads to lower performance for non-English translation directions.

In this work, we create more diverse multilingual machine translation models by building a large-scale Many-to-Many data set for 100 languages. We considerably reduce the complexity of this task through the automatic construction of parallel corpora (Artetxe and Schwenk, 2019a; Schwenk et al., 2019b) with a novel data mining strategy that exploits language similarity to avoid mining all directions. We also leverage backtranslation to improve the quality of our model on zero-shot and low resource language pairs. Overall, we build the first true Many-to-Many data set comprising 7.5B training sentences for 100 languages, providing direct training data for thousands of translation directions.

The quantity of data in a Many-to-Many data sets increases quadratically with the number of languages, making neural networks with standard capacity underfit rapidly. To that effect, we leverage progress in scaling (Kaplan et al., 2020; Arora et al., 2018) to train models that are over 50 times larger than current bilingual models with model parallelism (Huang et al., 2019a; Shoeybi et al., 2019). Even with these tools, scaling the number of parameters hardly follows the quadratic increase in data induced by the Many-to-Many setting, and we propose several scaling strategies tailored to the specifics of our problem. In particular, we consider a deterministic mixture-of-experts strategy based only on the input language to split the model parameters into non-overlapping groups of languages which we train with a novel re-routing strategy. Language specific capacity also reduce the need to densely update parameters and are more parallelizable in a multi-machine setting. Overall, combining these strategies allows us to scale the capacity of the models to a size of 15.4B parameters and still train them efficiently on hundreds of GPUs.

The resulting method allows us to scale Transformers and directly translate between 100 languages without pivoting through English at a performance that is competitive with bilingual models on many competitive benchmarks, including WMT. Figure 1 illustrates our data mining strategy as well as our model architecture. This paper is organized as follows: first, we introduce several standard components of modern machine translation and explain how they apply in the multilingual setting (Section § 2), then describe our strategy to scale the number of language pairs to create a Many-to-Many data set (Section § 3). We then systematically compare this Many-to-Many data set to an English-Centric approach (Section § 4). Next, we incorporate increased model scale through both dense scaling and sparse mixture-of-experts (Section § 5). Finally, we end with a thorough analysis, including human evaluation, of the quality of our 100x100 Many-to-Many translation system (Section § 6). Our models and code are open-sourced: `https://github.com/pytorch/fairseq/tree/master/examples/m2m_100`.

2. Preliminaries

In this work, we investigate how we can best translate from 100 languages to 100 languages, or 9900 directions, using a single model. We describe our starting point in this section, and provide preliminary context on Transformer-based neural machine translation models.

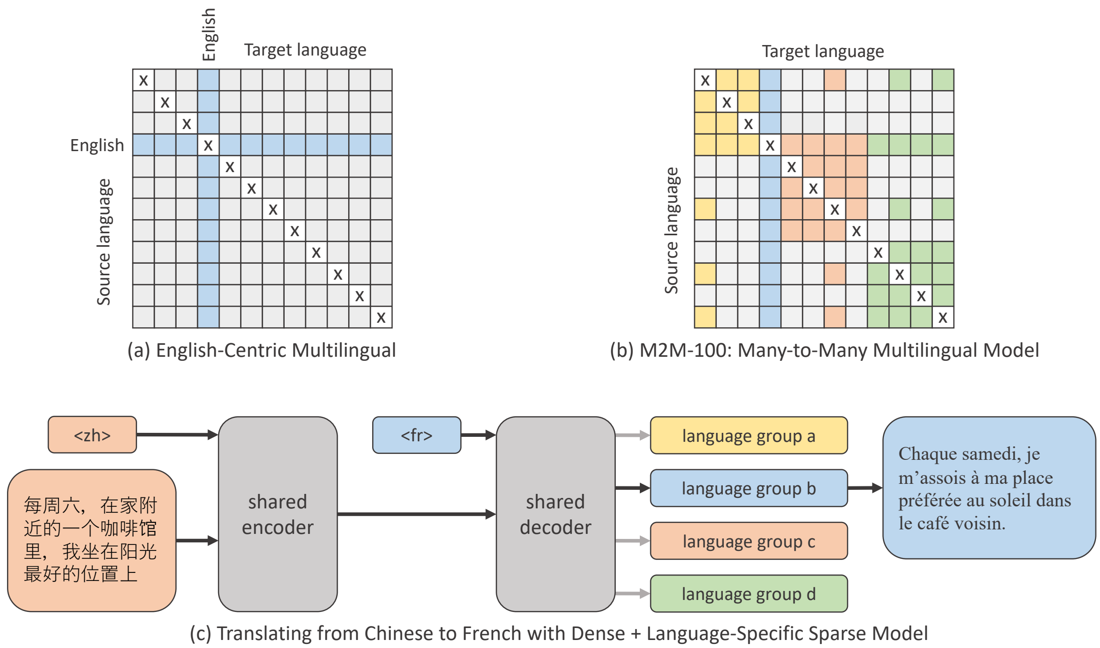


Figure 1: **Summary of our Many-to-Many data set and multilingual model**. English-Centric data (top left) only contains training data to and from English, where as our Many-to-Many multilingual setting (top right) contains data directly through various different directions. Our proposed model, M2M-100, combines dense and sparse language-specific parameters to translate directly between languages (bottom).

Sequence-to-sequence models are trained on pairs of sequences, conditioning on an input sequence to produce an output sequence. Each sentence is split into tokens, that can be words or characters, resulting in pairs of sequences $(w_1, \ldots, w_S)$ and $(v_1, \ldots, v_T)$. Most machine translation systems are trained by maximizing the probability of the target sequence, given the source sentence and the target language ℓ_t:

$$P(v_1,\ \ldots,\ v_T \mid w_1,\ \ldots,\ w_S,\ \ell_t)$$

Modern neural machine translation systems are based on several standard components, namely a subword segmentation method and an encoder-decoder architecture called a Transformer. We describe these components in the context of multilingual translation.

Segmentation with SentencePiece. The input and output of translation systems are sequences of tokens. These tokens are units from a dictionary built with the goal to reconstruct any sentence in any language. Using words as base units is challenging, as it leads either to vocabularies with poor coverage or to large vocabularies. This is especially true in the multilingual setting. Another limitation of word-based systems are languages that are not naturally split into words, like Thai. An alternative approach is to use *subword* units, which are learned directly from data (Sennrich et al., 2015; Kudo and Richardson, 2018). We use SentencePiece[1] as it was designed to work with languages with no segmentation, making it

1. This can be accessed here: `https://github.com/google/sentencepiece`.

particularly suited to our setting. We train a model with 0.9995 character coverage to have sufficient representation of character-based languages[2].

Creating a Multilingual Dictionary. SentencePiece produces subword units depending on their frequency in the training data set. Naively applying it to our corpora would result in low resource languages and languages written in less frequent scripts being underrepresented in the resulting dictionary. Randomly sampling data favors over-represented languages because the probability of picking language ℓ is proportional to its number of sentences, D_ℓ, that is, $p_\ell = \frac{D_\ell}{\sum_i D_i}$. We circumvent this problem by adding monolingual data for low resource languages and by using temperature sampling with $T = 5$. More precisely, the probability p_ℓ is re-scaled to $p_\ell^{\frac{1}{T}}$ where the temperature T controls the distribution. For example, setting T to 1 gives the original data distribution. Note the probability must be re-normalized afterwards to be a valid probability. The resulting dictionary contains 128k unique tokens that are well distributed across languages, as shown in Appendix A.

2.1 Transformers

Our multilingual machine translation model is based on the Transformer sequence-to-sequence architecture, which is composed of two modules: the encoder and the decoder (Vaswani et al., 2017). The encoder transforms the source token sequence into a sequence of embeddings of the same length. Then, the decoder sequentially produces the target sentence, token by token, or autoregressively. More precisely, the encoder takes the sequence of tokens $W = (w_1, \ldots, w_S)$ and the source language ℓ_s, and produces a sequence of embeddings $H = (h_1, \ldots, h_S)$, which are then fed to the decoder with the target language ℓ_t to produce the sequence of target tokens $V = (v_1, \ldots, v_T)$ sequentially, that is,

$$\begin{aligned} H &= \texttt{encoder}(W,\ \ell_s), &(1)\\ \forall i \in [1, \ldots, T],\ v_{i+1} &= \texttt{decoder}(H,\ \ell_t,\ v_1,\ \ldots,\ v_i). &(2) \end{aligned}$$

Both the encoder and decoder are composed of the same type of layers, called Transformer layers. Each Transformer layer takes a sequence of vectors as input and outputs a sequence of vectors. In the encoder, Transformer layers are composed of two sub-layers, a self-attention and a feed-forward layer. These are applied sequentially and are both followed by a residual connection (He et al., 2015) and layer normalization (Ba et al., 2016):

$$\begin{aligned} Z &= \texttt{norm}\left(X + \texttt{self-attention}(X)\right), &(3)\\ Y &= \texttt{norm}\left(Z + \texttt{feed-forward}(Z)\right). &(4) \end{aligned}$$

The self-attention layer is an attention layer that updates each element of the sequence by looking at the other elements, while the feed-forward layer (FFN) passes each element of the sequence independently through a 2-layer MLP. In the decoder, there is an additional third sub-layer, between the self-attention and the feed-forward, which computes attention over the output of the encoder. We refer the reader to Vaswani et al. (2017) for details of these layers.

2. We use the recommended parameter from the SentencePiece repository: `https://github.com/google/sentencepiece`.

Target language token. The Transformer architecture has been designed for the bilingual case, where the target language is fixed. In the case of multilingual machine translation, the target language is not fixed, and several strategies can be applied to condition the network to produce a sentence in the desired target language. Similarly to Ha et al. (2016) and Johnson et al. (2017), we add a special token in the encoder indicating the source language and a special token in the decoder indicating the target language.

Training. Our starting point for improving massively multilingual translation models is a large Transformer model, with 12 Encoder and 12 Decoder layers, with 8192 hidden units in the FFN and 1024 embedding dimension. We share the weight matrices of the input and output embeddings. The total parameter count is 1.2B. We train with the Adam optimizer (Kingma and Ba, 2015) and warmup first for 4000 updates (setting the batch size to 4000 tokens), with label smoothing 0.1 (Szegedy et al., 2015; Pereyra et al., 2017). For regularization, we tune the dropout parameter between $\{0.1, 0.2, 0.3\}$. To stabilize the training of deeper Transformers, we train with LayerDrop (Fan et al., 2019) 0.05 and pre-normalization (Nguyen and Salazar, 2019).

To train with billions of sentences, we split the training data into 256 different shards to manage memory consumption. However, directly dividing mid and low resource languages into shards would reduce the variability of each shard's data for mid or low resource languages. Imagine the extreme case where there are only 100 sentences of a language direction per shard—the model would easily overfit. Thus, each language is divided into a different number of shards based on resource level, such that high resource languages have more shards and the lowest resource languages only have one shard. Subsequently, lower resource shards are replicated until the full number of shards is reached—so sentences from lower resource shards can appear multiple times.

Generation. Unless otherwise specified: for all results, we report single models with no checkpoint averaging, use beam search with beam 5, and do not tune length penalty, keeping it at 1 (meaning the model decides the length).

3. Building a Many-to-Many Parallel Data Set for 100 Languages

In this section, we provide an overview of our Many-to-Many setting: the selection of the 100 languages, the evaluation benchmarks, and the construction of a large-scale training set through data mining (Artetxe and Schwenk, 2019a) and backtranslation (Sennrich et al., 2016a) that provides training data thousands of directions.

3.1 Creating a Multilingual Benchmark

The first step of establishing a Many-to-Many data set is to select 100 languages for which there already exist high-quality, annotated data sets that can be used for model evaluation.

3.1.1 Language Selection

We consider several factors to select which languages to focus on. First, we include widely-spoken languages from geographically diverse language families. We cover a diversity of scripts and resource levels (as shown in Table 1) to have high coverage of languages worldwide.

ISO	Language	Family	Script	ISO	Language	Family	Script
af	Afrikaans	Germanic	Latin	ja	**Japanese**	Japonic	Kanji; Kana
da	Danish	Germanic	Latin	ko	**Korean**	Koreanic	Hangul
nl	**Dutch**	Germanic	Latin	vi	**Vietnamese**	Vietic	Latin
de	**German**	Germanic	Latin	zh	**Chinese Mandarin**	Chinese	Chinese
en	**English**	Germanic	Latin	bn	**Bengali**	Indo-Aryan	Eastern-Nagari
is	Icelandic	Germanic	Latin	gu	Gujarati	Indo-Aryan	Gujarati
lb	Luxembourgish	Germanic	Latin	hi	**Hindi**	Indo-Aryan	Devanagari
no	Norwegian	Germanic	Latin	kn	Kannada	Tamil	Kannada
sv	**Swedish**	Germanic	Latin	mr	Marathi	Indo-Aryan	Devanagari
fy	Western Frisian	Germanic	Latin	ne	Nepali	Indo-Aryan	Devanagari
yi	Yiddish	Germanic	Hebrew	or	Oriya	Indo-Aryan	Odia
ast	Asturian	Romance	Latin	pa	Panjabi	Indo-Aryan	Gurmukhi
ca	Catalan	Romance	Latin	sd	Sindhi	Indo-Aryan	Persian Devanagari
fr	**French**	Romance	Latin	si	Sinhala	Indo-Aryan	Sinhala
gl	Galician	Romance	Latin	ur	Urdu	Indo-Aryan	Arabic
it	Italian	Romance	Latin	ta	**Tamil**	Dravidian	Tamil
oc	Occitan	Romance	Latin	ceb	Cebuano	Malayo-Polyn.	Latin
pt	**Portuguese**	Romance	Latin	ilo	Iloko	Philippine	Latin
ro	Romanian	Romance	Latin	id	**Indonesian**	Malayo-Polyn.	Latin
es	**Spanish**	Romance	Latin	jv	Javanese	Malayo-Polyn.	Latin
be	Belarusian	Slavic	Cyrillic	mg	Malagasy	Malayo-Polyn.	Latin
bs	Bosnian	Slavic	Latin	ms	Malay	Malayo-Polyn.	Latin
bg	Bulgarian	Slavic	Cyrillic	ml	Malayalam	Dravidian	Malayalam
hr	Croatian	Slavic	Latin	su	Sundanese	Malayo-Polyn.	Latin
cs	**Czech**	Slavic	Latin	tl	Tagalog	Malayo-Polyn.	Latin
mk	Macedonian	Slavic	Cyrillic	my	Burmese	Sino-Tibetan	Burmese
pl	**Polish**	Slavic	Latin	km	Central Khmer	Khmer	Khmer
ru	**Russian**	Slavic	Cyrillic	lo	Lao	Kra-Dai	Thai; Lao
sr	Serbian	Slavic	Cyrillic; Latin	th	Thai	Kra-Dai	Thai
sk	Slovak	Slavic	Latin	mn	Mongolian	Mongolic	Cyrillic
sl	Slovenian	Slavic	Latin	ar	**Arabic**	Arabic	Arabic
uk	Ukrainian	Slavic	Cyrillic	he	**Hebrew**	Semitic	Hebrew
et	Estonian	Uralic	Latin	ps	Pashto	Iranian	Arabic
fi	**Finnish**	Uralic	Latin	fa	**Farsi**	Iranian	Arabic
hu	**Hungarian**	Uralic	Latin	am	Amharic	Ethopian	Ge'ez
lv	Latvian	Baltic	Latin	ff	Fulah	Niger-Congo	Latin
lt	**Lithuanian**	Baltic	Latin	ha	Hausa	Afro-Asiatic	Latin
sq	Albanian	Albanian	Latin	ig	Igbo	Niger-Congo	Latin
hy	Armenian	Armenian	Armenian	ln	Lingala	Niger-Congo	Latin
ka	Georgian	Kartvelian	Georgian	lg	Luganda	Niger-Congo	Latin
el	**Greek**	Hellenic	Greek	nso	Northern Sotho	Niger-Congo	Latin
br	Breton	Celtic	Latin	so	Somali	Cushitic	Latin
ga	Irish	Irish	Latin	sw	**Swahili**	Niger-Congo	Latin
gd	Scottish Gaelic	Celtic	Latin	ss	Swati	Niger-Congo	Latin
cy	Welsh	Celtic	Latin-Welsch	tn	Tswana	Niger-Congo	Latin
az	Azerbaijani	Turkic	Latin; Cyrillic Persian	wo	Wolof	Niger-Congo	Latin
ba	Bashkir	Turkic	Cyrillic	xh	Xhosa	Niger-Congo	Latin
kk	Kazakh	Turkic	Cyrillic	yo	Yoruba	Niger-Congo	Latin
tr	**Turkish**	Turkic	Latin	zu	Zulu	Niger-Congo	Latin
uz	Uzbek	Turkic	Latin; Cyrillic	ht	Haitian Creole	Creole	Latin

Table 1: **100 Languages grouped by family.** For each language, we display the ISO code, language name, language family, and script. Languages in bold are *bridge languages* (*Malayo-Polyn.* stands for *Malayo-Polynesian*).

Second, we use languages for which public evaluation data exists, as we must be able to quantify model performance. Lastly, we only use languages for which monolingual data is available, as monolingual data is a critical resource for large-scale mining. Combining these three criteria results creates our full list of 100 languages, summarized in Table 1.

3.1.2 Evaluation Benchmarks

We use publicly available evaluation data sets to evaluate the performance of all of our models. To cover our set of 100 languages, we bring together data from a variety of sources. We describe each evaluation data set below.

- **WMT**—The majority of language pairs from the Workshop on Machine Translatino (WMT) data sets go through English and the data is from the news domain. We consider data for 13 languages (Ondrej et al., 2017; Bojar et al., 2018; Barrault et al., 2019).

- **WAT**—The Workshop on Asian Translation (WAT) covers Asian languages paired with English. We consider data for Burmese-English (Riza et al., 2016), which contains news articles. WAT contains many other evaluation directions, but many of those are covered by WMT or in a specific domain, so we focus on Burmese-English for WAT only.

- **IWSLT**—The International Conference on Spoken Language Translation (IWSLT) contains data from TED talks paired with English translations. We use data for 4 languages (Cettolo et al., 2017).

- **FLORES**—FLORES[3] (Guzmán et al., 2019) pairs two low resource languages, Sinhala and Nepali, with English in the Wikipedia domain.

- **TED**—The TED Talks data set[4] (Ye et al., 2018) contains translations between more than 50 languages; most of the pairs do not include English. The evaluation data is n-way parallel and contains thousands of directions.

- **Autshumato**—Autshumato[5] is an 11-way parallel data set comprising 10 African languages and English from the government domain. There is no standard valid/test split, so we use the first half of the data set for valid and second half for test.

- **Tatoeba**—Tatoeba Challenge[6] covers 692 test pairs from mixed domains where sentences are contributed and translated by volunteers online. The evaluation pairs we use from Tatoeba cover 85 different languages.

3. This can be found here: `https://github.com/facebookresearch/flores`.
4. This can be found here: `https://github.com/neulab/word-embeddings-for-nmt`.
5. This can be found here: `https://repo.sadilar.org/handle/20.500.12185/506`, created by CTexT (Centre for Text Technology, North-West University), South Africa; Department of Arts and Culture, South Africa.
6. This can be found here: `https://tatoeba.org/eng/`. Note that the sentences in this dataset are often very short, and the evaluation is less difficult compared to other data sets.

We evaluate the quality of translations with BLEU (Papineni et al., 2002). We first de-tokenize all data, then apply standard tokenizers for each language before computing BLEU. For most languages, we use the `moses` tokenizer (Koehn et al., 2007).[7] For Chinese we use the SacreBLEU tokenizer (`tok zh`) and convert all traditional characters generated by the model to simplified characters using HanziConv[8] (Post, 2018),[9] for Indian languages we use the Indic NLP library (Kunchukuttan, 2020),[10] for Japanese we use Kytea,[11] for Thai we use PyThaiNLP (Phatthiyaphaibun et al., 2016),[12] for Arabic we use the QCRI Arabic Normalizer,[13] for Korean we use Mecab,[14] for Burmese we use the official segmentation tool provided by Ding et al. (2019), for Romanian we follow Sennrich et al. (2016b) and apply Moses tokenization, special normalization, and remove diacritics for Romanian texts,[15] and finally for Serbian we transliterate the output to Latin characters before computing BLEU.[16] We release the tokenization and evaluation scripts for reproducibility: `https://github.com/pytorch/fairseq/tree/master/examples/m2m_100`. We remove all data from all evaluation sets from our training data[17].

3.2 Covering the Language Matrix by Mining Relevant Parallel Data

Supervised translation systems rely on large quantities of parallel sentences, which we refer to as bitext data, which are traditionally derived from human translations. Most existing bitext data sets go through English, with a few domain specific exceptions such as proceedings from international organizations (Koehn, 2005a; Ziemski et al., 2016). These corpora are limited in size and domain, and an alternative is to *mine* parallel data (Resnik, 1999; Utiyama and Isahara, 2003) in large collections of monolingual data (Conneau et al., 2019; Wenzek et al., 2019). In this work, we leverage and extend the corpus provided by two of these mining projects: CCMatrix (Schwenk et al., 2019b)[18] and CCAligned[19] (El-Kishky et al., 2020). In the following section, we describe our mining strategy and summarize the main ideas of CCMatrix and CCAligned. We refer the reader to the references for a detailed description of the approaches.

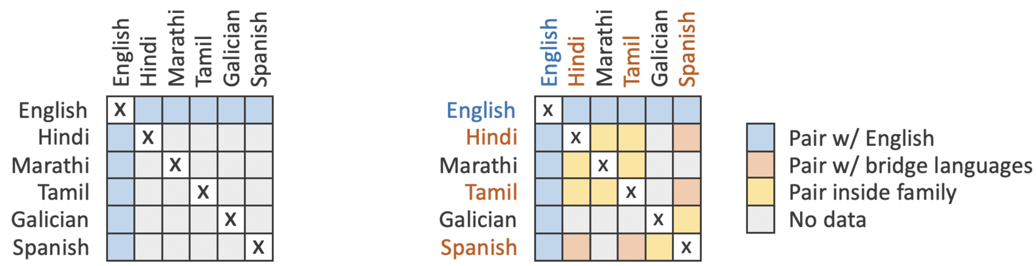
7. This can be found here: `https://github.com/moses-smt/mosesdecoder/blob/master/scripts/tokenizer/tokenizer.perl`.
8. This can be found here: `https://github.com/berniey/hanziconv`.
9. The evaluation data sets for Chinese usually contained simplified characters. However, our training data contains a mix of simplified and traditional characters, and thus the model could generate either. We convert the generated traditional Chinese characters to simplified for consistency.
10. This can be found here: `https://github.com/anoopkunchukuttan/indic_nlp_library`.
11. This can be found here: `https://github.com/neubig/kytea`.
12. This can be found here: `https://github.com/PyThaiNLP/pythainlp`.
13. This can be found here: `http://alt.qcri.org/tools/arabic-normalizer/`.
14. This can be found here: `https://pypi.org/project/python-mecab-ko/`.
15. This can be found here: `https://github.com/rsennrich/wmt16-scripts/blob/master/preprocess/`.
16. In Serbian, both Latin script and Cyrillic script are used, and often intermixed within a sentence in the evaluation data. As the target sentence could be in either script and it is not possible to predict the target script from the input, we transliterate before computing BLEU.
17. This must be done in advance, so all evaluation data needs to be finalized before training begins.
18. This can be downloaded here:`https://github.com/facebookresearch/LASER/tree/master/tasks/CCMatrix`.
19. This can be downloaded here: `http://www.statmt.org/cc-aligned`.

Mining parallel data with LASER. Mining parallel data consists of searching for sentences that could be potential translations in large monolingual corpora. This search requires a measure that captures the semantic similarity between sentences in different languages. Most recent methods build this similarity by comparing the embeddings from a neural network trained on multilingual data (Artetxe and Schwenk, 2019a; Chen et al., 2020; Kvapilíková et al., 2020). We focus on the embeddings generated by the LASER encoder, which enables the comparison of sentences in 94 different languages (Artetxe and Schwenk, 2019b). We then retrieve parallel corpora efficiently using FAISS indexing (Johnson et al., 2019). LASER embeddings generalize to unseen languages, like Asturian, allowing us to mine bitexts for 100 languages. The generic data mining pipeline consists of several steps: **(1)** a large corpus of text is preprocessed and divided into different languages, **(2)** candidate pairs of aligned sentences are embedded and stored in a index, **(3)** indexed sentences are compared to form potential pairs, **(4)** the resulting candidate pairs are filtered in post-processing.

CCMatrix Mining Approach. CCMatrix takes a global approach: all unique sentences in one language are compared with all unique sentences in another language. This *global mining* approach has the advantage of considering all possible documents when searching for the translation of a sentence. CCMatrix works on the large monolingual corpora in the 91 languages of CCNet (Wenzek et al., 2019), but at this scale, the global search is computationally demanding even with fast indexing from FAISS (Johnson et al., 2019). Thus, we apply it to a selected subset of relevant pairs, as detailed in Section § 3.2.1.

CCAligned Mining Approach. CCAligned avoids the scaling challenges of global mining by pre-selecting documents to compare. This *local mining* follows a hierarchical approach: first, document-level language identification along with various rules is applied to find whole documents that are likely to contain mutual translations (El-Kishky et al., 2020). Parallel sentences are then mined using LASER-based alignment within the paired documents only. Filtering (Chaudhary et al., 2019) is performed to remove unaligned data that exists because the original webpage did not have any parallel data, only partial parallel data, or other processing failures. One advantage of this approach is that it is very fast, scalable, and retrieves parallel sentences with high precision. Another advantage is that each English document is aligned to many non-English documents—thus, mining non-English pairs can be quickly performed by joining non-English documents paired to the same source.

Postprocessing. We apply a filtering step to remove sentences of greater than 50% punctuation. The data is then de-duplicated, and we remove any sentence that appears in any validation or test data set—even if it is associated with another language pair. Finally, we apply length and language-specific filtering. The length filtering removes sentences that are too long—more than 250 subwords after segmentation with SPM—or with a length mismatch between the sentence and its translation—if the length ratio is greater than $3\times$. The language-specific filtering removes sentences that contain more than 50% of characters that have not been marked as core to the identified language—specifically, characters that are commonly used in the identified language with the exception of white space, numbers, punctuation, and Latin characters for non-Latin script languages.



(a) Existing Work with English-Centric Data

(b) Bridge Language Family Mining Strategy

Figure 2: **Depiction of an English-Only data mining setting compared to the Bridge Language Mining Strategy**. We display a data matrix, where languages are shown on the X and Y axes. Data is mined in one direction (such as Hindi to Marathi) and used to train bidirectionally.

3.2.1 Bridge Language Group Mining Strategy

Mining data for each and every language pair is prohibitive — previous work circumvents this issue by focusing only on the 99 pairs that go through English (Zhang et al., 2020). An alternative to the extensive computation required to mine all possible combinations of pairs is *sparse mining*, or mining only a select subset of pairs. A straightforward strategy is to *randomly* select pairs to mine, but this does not use any linguistic information on how languages are related and spoken around the world.

In this work, we propose an alternative based on language families and bridge languages that avoids exhaustively mining every possible pair. Our goal is to reduce the number of bitext pairs while preserving translation directions of practical interest. We first group all the 100 languages into 14 *language groupings*. All languages within a grouping are mined against each other. For instance, within the Indic language grouping, we mine all pairs of Bengali, Hindi, Marathi, Tamil, Urdu, and so on. The motivation for this strategy is two-fold. First, people living in areas that speak multiple languages in the same grouping tend to communicate a lot with each other and would benefit from high quality direct translation. Second, systematically mining languages of the same grouping is helpful for training language-specific parameter models (see Section § 5.2).

For the most part, languages are grouped by linguistic similarity, for example Germanic, Slavic, or Malayo-Polynesian languages. However, the size of the resulting groupings varies greatly, resulting in less mined data for the languages in the smallest groupings. We further group languages by geographic and cultural proximity to reduce this discrepancy. For example, Uralic and Baltic languages are gathered into a single group to increase the quantity of mined data. The resulting groupings are shown in Table 1.

To connect languages across groupings, we define 1—3 *bridge languages* in each grouping, usually those with the most resources, such as Bengali, Hindi, and Tamil for the 12 languages in the Indo-Aryan family. All 26 bridge languages are highlighted in Table 1. These bridge languages are mined against all other bridge languages. Finally, all 100 languages are mined

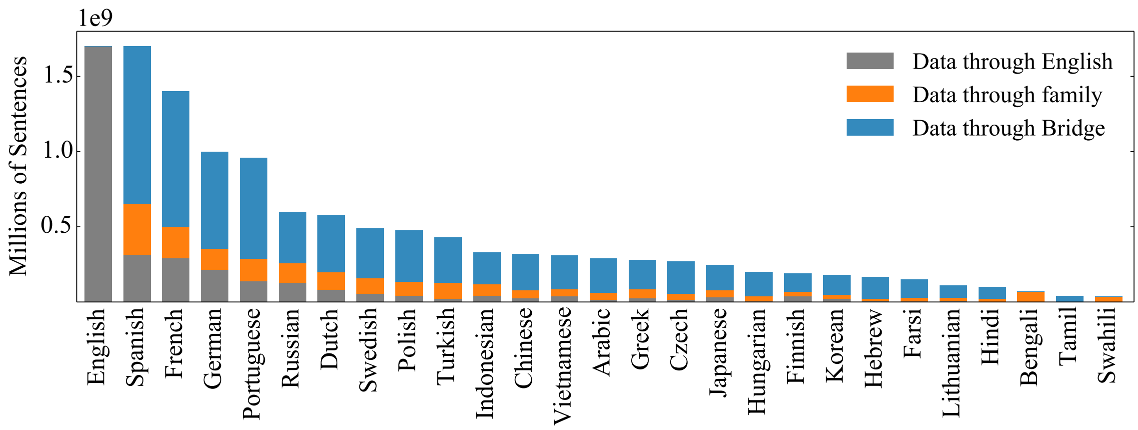


Figure 3: **Total Amount of Data through Bridge Languages on our 100x100 Training Corpus**. We depict the amount of data through English (gray), amount of data through a bridge language not counting English (orange), and amount of data through the language grouping not counting bridge languages (blue).

against English. We illustrate this mining strategy in Figure 2. On the left, we depict what many current approaches model: data only through English. On the right, we depict our Many-to-Many language matrix for several example languages. Compared to English-Centric, our data set has far greater coverage of non-English, direct translation directions.

Training Data Statistics. In total, our final training data set contains 7.5B parallel sentences, corresponding to 2200 directions. We divide these directions by resource level to label high, mid, and low resource language directions. While there is no clear standard, we follow WMT's example to roughly categorize the directions by the quantity of available training data. Low resource languages are directions with less than 500K samples, mid resource are directions with less than 50M samples, and high resource the remaining[20]. In Figure 3, we show all bridge languages and demonstrate how their associated training data is divided between translations with English, within a language grouping, or with bridge languages across language groupings. Of particular interest is the comparison between the additional Many-to-Many data and the data through English. We observe that 5—10 times more parallel data can be mined if using a Many-to-Many strategy, compared to an English-Centric one. This is particularly beneficial for mid- and low-resource languages.

3.2.2 Results

We validate the impact of several decisions made during data construction. First, we study the impact of our bridge language strategy compared to English-Centric mining augmented by other random pairs, as well as fully random mining. Second, we investigate the impact of the level of sparsity chosen in our bridge strategy, focusing on a subset of 50 languages.

20. Note: In WMT20, for example, languages Tamil and Inuktitut were considered low resource directions even though over a million sentences of monolingual data were available for backtransltion. We consider mining and backtranslation similar approaches of augmenting training data with collections of monolingual data online.

Model	All Avg	Supervised Low	Mid	High
Random 80%	11.9	3.6	16.1	31.5
Random 80% w/ En	16.3	8.9	22.4	36.6
Bridge Language, 80%	**17.2**	**10.4**	**23.2**	**37.4**

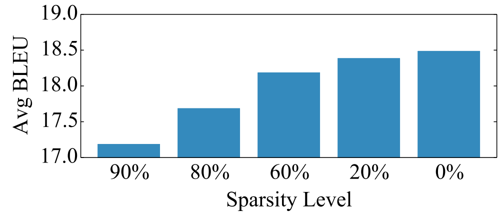


Table 2: **(left) Comparison of Sparse Mining Strategies**, comparing BLEU scores. We first hold the sparsity level fixed at 80% — compared to randomly selecting pairs to mine, the Bridge Language mining strategy performs very well. **(right) Bridge Language Strategy at Different Sparsity Levels**, comparing BLEU scores. We analyze different levels of sparsity in the language matrix to understand how many pairs to mine. Based on these results, we take 60% sparse as a tradeoff point between strong performance and reasonable quantity of mining. 0% indicates no sparsity, or a fully mined language matrix.

Bridge Language strategy versus Random and English-Centric Random. We experimentally evaluate the impact of our bridge language mining strategy on the performance of our baseline model in Table 2 (left). We consider two additional baselines, a fully random mining strategy (Random 20%) and a *English-Centric + Random* strategy (Random 20% w/ En). In the Random strategy, mined pairs are randomly chosen, while in the *English-Centric + Random* strategy, we retain all pairs through English and only select the remaining pairs randomly. We show that fully random mining has a substantial negative impact on performance, as a lot of high quality data is aligned through English, so sampling fully randomly eliminates a large portion of the potential training set. Random 20% w/ En is worse as well. Through examination, we find that randomly sampling pairs to mine often selects pairs that do not produce as much data, as the pairs may not include high resource languages. However, the bridge language strategy ensures that high resource languages are mined, and then focuses on mining languages in related families. This produces a large amount of bitext, and at the same time, covers many language directions.

Impact of Sparsity. We focus on a subset of 50 languages where we have a fully mined matrix to investigate the impact of our sparse mining strategy. We control the sparsity of our language matrix using the number of bridge languages. In Figure 2 (right), we show the impact of sparsity on the performance of our baseline model compared to a fully mined language matrix (0% sparse). We observe that increasing the amount of mined data to make the matrix less sparse is helpful, but fully mining the matrix is not substantially better. The main reason is that our mining strategy prioritizes frequently used pairs which are often associated with the largest bitext, while the discarded pairs are often associated with small bitext. For example, fully mining the matrix would mine a pair such as Icelandic to Chinese, but the amount of data produced by mining this pair is quite low. This case is representative of what occurs as the full matrix is mined—as increasingly more data is mined, the additional pairs begin to add less data which in turn leads to diminishing quality improvements.

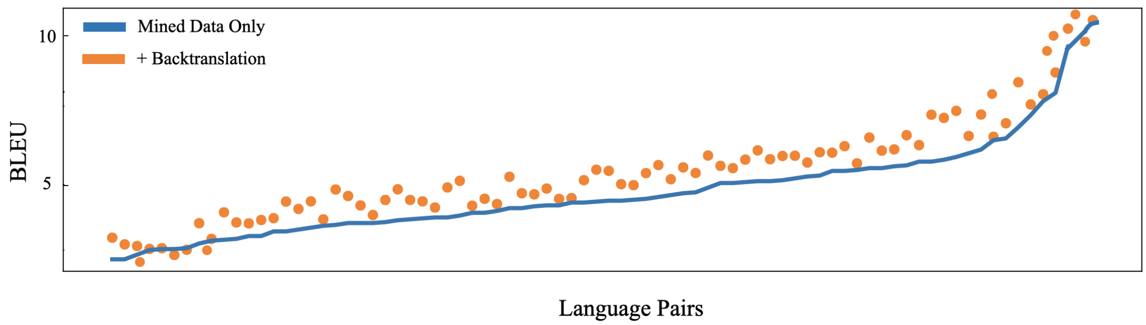


Figure 4: **Improvements from Adding Backtranslated Data.** For each of the 100 language directions we explored by adding backtranslation. The blue line indicates the original model, where directions were selected if they had between 2 and 10 BLEU. The orange scatter indicates the effect of adding backtranslation. Languages are ordered by their original BLEU scores before backtranslation.

3.3 Augmenting Bitext Data with Backtranslation

Backtranslation (BT) creates synthetic bitexts from unaligned monolingual data (Schwenk, 2008; Bojar and Tamchyna, 2011; Sennrich et al., 2016a; Edunov et al., 2018; Hoang et al., 2018). The core idea is to translate monolingual sentences in the backward direction, and add the obtained synthetic translations to the training set. More precisely, when training a model to translate from a source language to a target language, backtranslation generates additional data by translating monolingual target sentences into the source language. Using backtranslation thus requires the ability to translate in both directions, which fits well into the setting of multilingual machine translation (Zhang et al., 2020; Siddhant et al., 2020). However, generating these backtranslations is time consuming even for a single direction, which is compounded in the Many-to-Many case. We thus focus on applying backtranslation on specific pairs to supplement mined data where needed.

Selecting Backtranslation Pairs. Our goal is to translate between 100 languages and to provide good translation quality for as many translation directions as possible. To this end, we use BT to improve directions which have initially lower translation quality. We identify these language directions by measuring the quality of our 1.2B parameter multilingual model before applying BT. Since back-translation is computationally intensive, we focus on 100 directions with a BLEU score of between 2 and 10. For 50 of these directions, we do not have any bitext at all as we did not mine all 4,450 possible language pairs.

Training a Multilingual Model with Additional Backtranslations. For the selected pairs, we first generate synthetic translations that are added to the training set without upsampling. Following Caswell et al. (2019), we add a special encoder-side BT token to these translations to indicate to the model that they are synthetic. For each of the 100 target languages, we randomly sample 50 million unique monolingual sentences from the cleaned CommonCrawl corpus of Wenzek et al. (2019). The synthetic translations are then generated with our 1.2B MMT model. We use a beam search with beam of size 5 and fix all the hyper-parameters, including the length penalty, to the same values for all the directions.

	Supervised				Zero-Shot	All
Data sampling	**Low**	**Mid**	**High**	**Avg**	**Avg**	**Avg**
Uniform	6.1	20.4	38.4	19.0	11.8	15.7
Temperature Rescaling	10.2	23.7	38.0	21.8	13.0	18.1
Sinkhorn Temp. Rescaling	**10.9**	**24.1**	**38.3**	**22.2**	**13.5**	**18.6**

Table 3: **Comparison of Various Sampling Strategies.** We report BLEU on the validation set of our 1.2B base multilingual model trained with different data sampling schemes. Performance is broken down into different resource-setups (low, mid, high) where bitext data exists (supervised) or in the zero-shot setting for pairs without data.

We apply the same filtering to the backtranslations as the original mined training data, which substantially reduces the size of the resulting synthetic bitexts.

Impact of Backtranslated Data. Results are shown in Figure 4, where we compare the original Many-to-Many model used to create the backtranslations (blue line) with the improvements after training a multilingual model with the backtranslation added (orange scatter). Backtranslation almost always improves performance for any direction, regardless of the original BLEU score. As the amount of data generated with BT correlates with the length of training time, we decide to focus on applying BT on directions with low performance (BLEU between 2 and 10) to improve our MMT system where it under-performs.

3.4 Balancing Languages in a Many-to-Many Setting

The data distribution produced by large-scale mining is not balanced between languages, so training a model would favor over-represented languages. A standard solution is to re-balance each language independently with Temperature Sampling (Arivazhagan et al., 2019), for example replacing the probability p_ℓ of a language by $p_\ell^{\frac{1}{T}}$. In the English-Centric case, changing the probability of sampling a language changes the probability of the other languages only through the normalization. However, in the Many-to-Many case, language distributions are more interdependent. For example, some languages are only paired with a subset of other languages or to an over-represented language. Thus, sampling them will affect the probability of these other languages they are paired with. This strategy thus has no guarantee to produce the target balanced distribution between languages. We describe *Sinkhorn Temperature Sampling*, which extends the temperature sampling strategy to the Many-to-Many setting.

Our goal is to design a sampling technique such that the distribution of languages on the source *and* target sides is equal to a given target distribution. Unfortunately, sequentially sampling the source language and then the target would not work, as some languages are only paired with a subset of languages—making it impossible to sample the target language according to a given distribution. Moreover, the sizes and distributions of bitexts greatly vary from a language to another. Instead, we propose directly sampling a pair of languages from a matrix of pair probabilities such that the marginal distributions of languages corresponds to our target distribution. In practice, this means that each row and column of the matrix should sum to the probability of the corresponding language. More precisely, we estimate a square matrix $\mathbf{P}^*$ such that:

$$\max_{\mathbf{P}} \ \text{tr} \ (\mathbf{PQ}) \qquad \text{s.t.} \quad \mathbf{P}1_L = \mathbf{p}^{\frac{1}{T}}, \ \mathbf{P}^\top 1_L = \mathbf{p}^{\frac{1}{T}},$$

where $\mathbf{p}$ is the vector stacking the probabilities of the L languages and $\mathbf{Q}$ is the matrix of pair probabilities. To identify a feasible solution to this problem, we use the Sinkhorn-Knopp algorithm (Sinkhorn, 1964; Sinkhorn and Knopp, 1967). The algorithm works by iteratively operating on the rows and the columns such that it is possible to convergence to a solution where all rows and all columns of the matrix sum to 1[21]. The matrix $\mathbf{Q}$ has entries equal to 0 for pairs with no bitext and this algorithm preserves them in the solution $\mathbf{P}^*$, hence adding no probability mass to missing bitexts. We calculate this once before training and set the temperature T to 5. We initialize the matrix Q with the values from standard temperature sampling methods, for example $p_\ell^{\frac{1}{T}}$, then re-normalizing. In Table 3, we show the benefits of this strategy over temperature sampling with a constant improvement of 0.5 in BLEU.

4. Many-to-Many Compared to English Centric

We have described the starting point of training Transformer-based multilingual translation systems, and detailed how we construct a very large training and evaluation data set covering thousands of directions and 100 languages. In this section, we investigate the importance of our data effort to create a true Many-to-Many data set that can support training direction translation without relying on English-only data. We present a series of experiments to better understand the performance improvements of English-Centric systems and to compare them to our Many-to-Many setting.

Experimental Setting. We train our 1.2B model on the full 100 language Many-to-Many data set and compare it to the same model trained only on data through English. We use the same vocabulary built with SentencePiece on the full data set in both cases. Each model has a different data set size and we train for 500K updates. This number of updates corresponds to one pass over the entire Many-to-Many data set and 3.5 passes on the English-Centric data. We tune the dropout rate for each model over the values $\{0.1, 0.2, 0.3\}$.

4.1 Main Result

In Table 4, we compare the performance of both models on different types of directions, namely, any language to English (To English), English to any language (From English), and all the directions not involving English (Non-English). Performance is aggregated over 150 directions for To English and From English, and over 2500 directions for Non-English. On the pairs including English, both models achieve similar performance, suggesting that a 1.2B model does not underfit even though the additional non-English data represents 98% of the directions and 74% of the data. For the non-English pairs, we consider two translation strategies for the English-Centric model: directly translating as if the model was trained on the pair – by using the corresponding language tokens – or by pivoting through English. Our model outperforms direct translation with the English-Centric model by 10.2

21. There are several constraints to this, please see Sinkhorn and Knopp (1967) for full details.

Setting	**To English**	**From English**	**Non-English**
Bilingual baselines	27.9	**24.5**	8.3
English-Centric	31.0	24.2	5.7
English-Centric with Pivot	—	—	10.4
Many-to-Many	**31.2**	24.1	**15.9**

Table 4: **Comparison of Many-to-Many and English-Centric Systems**, comparing BLEU scores. Many-to-Many matches the performance of English-Centric on evaluation directions involving English, but is significantly better on non English directions.

Setting	**w/ bitext**	**w/o bitext**
En-Centric	5.4	7.6
En-Centric Piv.	9.8	12.4
M2M	**12.3**	**18.5**

Table 5: **Many-to-Many versus English-Centric on zero-shot directions**, comparing BLEU scores. We report performance on language pairs with and without bitext in the Many-to-Many training data set.

Setting	**→En**	**En→**	**Non-En**
En-Centric	**26.4**	17.8	2.4
En-Centric Piv.	—	—	5.1
M2M	25.7	**18.1**	**9.4**

Table 6: **Many-to-Many versus English-Centric on one pass of data**, comparing BLEU scores. We report performance for models after a number of updates equivalent to the size of the English-centric data set.

BLEU and when the English-Centric model uses pivoting by 5.5 BLEU. While this result is not surprising, it confirms that a purely English-Centric model has limited potential on non-English pairs, and there is a fundamental need for training on Many-to-Many data.

4.2 Understanding the Source of Improvement

The main impact of adding Many-to-Many data is on the directions that do not include English. In this section, we provide a detailed study of where we observe the largest improvements with the additional data.

Impact on Zero-shot. Many non-English pairs are not covered by our Many-to-Many model, and we can thus study if the improvements we observe originate primarily from directions associated with bitext data or if we observe the same improvement on directions where the Many-to-Many model generates translations in a zero-shot fashion. In Table 5, we show the performance if the evaluation is split between the Non-English pairs *with* and *without* bitext. On directions with bitext, the Many-to-Many model outperforms the English-Centric model by 7 BLEU for direct translation, and by 3.5 BLEU for English-Centric with pivoting. This demonstrates the importance of diverse data. Not surprisingly, this gap is even bigger on pairs without bitext. Many-to-Many performs nearly 11 BLEU better than the English-Centric model for direct translation, and with pivoting the gain remains over 6 BLEU.

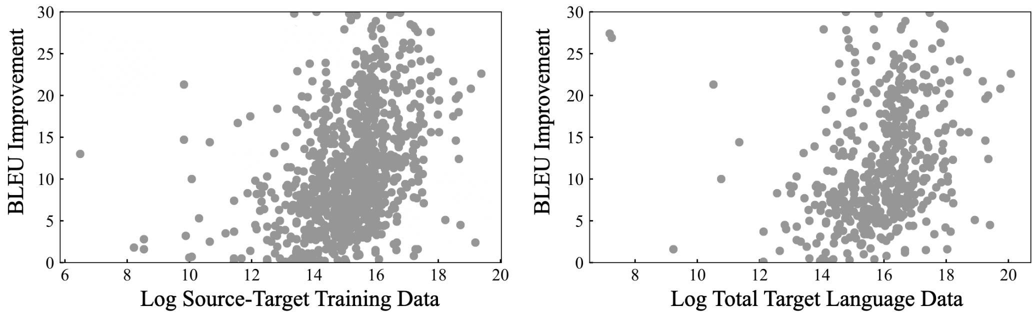


Figure 5: **Improvement of Many-to-Many over English-Centric in BLEU score** with respect to the amount of mined training data (left) and the amount of target side language data (right). Improvement from a Many-to-Many model correlates with greater amounts of bilingual training data with Pearson correlation 0.38 (left) and greater amounts of target language data with Pearson correlation 0.32 (right).

Impact of the quantity of training data. A hypothesis to explain the gain between English-Centric and Many-to-Many models is the effect of additional source and target side training data. Even if the Many-to-Many system has never seen a direction at training time, it benefits from additional source and target side data available through other training pairs. As mining non-English language pairs creates more training data compared to English-Centric data sets, the Many-to-Many model benefits from a larger training set. In Table 6, we compare both models after seeing the same quantity of data. We train both models for one epoch. The English-Centric model performs better on To English directions, likely because it only has one output language to learn, but the Many-to-Many model outperforms on From English directions and Non-English directions.

Which Pairs Improve the Most? The main factor for improvement is the quantity of data associated with either a pair or a language. Pairs that have a large quantity of mined data, such as Spanish-Portuguese, greatly benefit from our Many-to-Many data set. We show this effect in the left panel of Figure 5 (left). A second source of improvement is observed on languages for which the Many-to-Many data set contains a large amount of data across many pairs. This data benefits the decoder-side language model in a way that is comparable with BT. In the right panel of Figure 5, we show the impact of this cumulative monolingual data on the average performance per language. Finally, we also observe a third type of improvements from the similarity in vocabulary and syntax from related languages. A striking example is the quality of translation between English and Belarusian, where the Many-to-Many model achieves 12.7 BLEU on the TED evaluation set, compared to 3.2 BLEU for a bilingual model. The number of bitexts for Belarusian is small, but Belarusian is related to Russian, and the Many-to-Many model transfers its knowledge from Russian to Belarusian.

4.3 Understanding the Performance of English-Centric Systems

In Table 4, we confirm an observation made in Arivazhagan et al. (2019) that an English-Centric model improves the most over bilingual models on the directions into English, while improvement in the other directions (From English) remain more modest. A hypothesis to

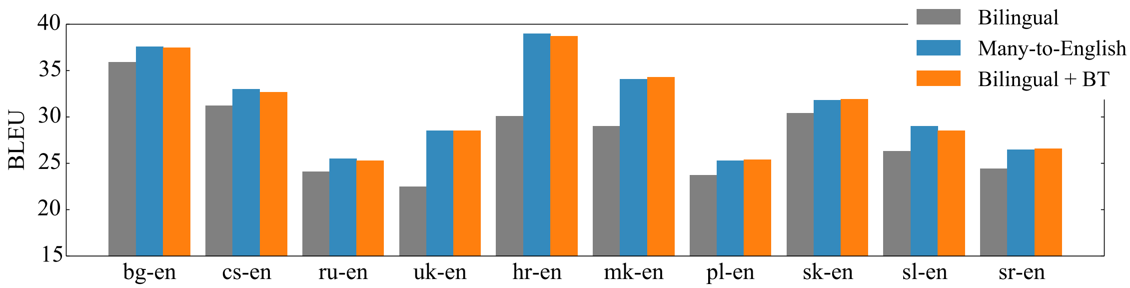


Figure 6: **Performance of many-to-English multilingual translation compared to bilingual baselines trained on mined data and bilingual + backtranslation.** The average performance of many-to-English is 25.1 BLEU compared to 25.2 BLEU for backtranslation while the bilingual system achieves 23.1.

explain this discrepancy between directions from and to English is that the decoder of an English-Centric model learns a better English language model by leveraging the aggregated English data across all through-English directions.

Result. We test this hypothesis with a controlled experiment where we compare a Many-to-English model with bilingual models using backtranslated English data (Section § 3.3). The experiment is based on 11 Slavic languages and we backtranslate the exact same English data as was used to train the Many-to-English model so that both models are trained on the same English data. Figure 6 shows that backtranslation performs comparably to the Many-to-English approach. While this improves our understanding of Many-to-English translation, a multilingual approach nevertheless retains the advantage of combining many directions into a single model which greatly simplifies modeling.

5. Components for Scaling Multilingual Translation Models

Our goal is to build a single model capable of translating $9,900$ language directions covering 100 languages. This creates several challenges for models with insufficient capacity to capture that many languages and scripts adequately. To this end, previous MMT work has considered different types of large capacity models (Arivazhagan et al., 2019; Lepikhin et al., 2020). In this section, we investigate different ways to add capacity to an MMT model. We first investigate dense scaling, where we increase the depth and width of standard Transformer architectures. Then, we identify disadvantages of dense scaling, and propose an alternative to effectively add *language-specific* parameters and exploit the nature of language similarities within the task of multilingual machine translation.

5.1 Dense Scaling

We describe how model parallel is used to scale model width and depth, then describe how to train large model parallel models for multilingual machine translation.

5.1.1 Background: Model Parallel Training

During the training of a neural network, we need to fit its weights, activations, gradients, and optimizer state in memory. This restricts the maximum capacity of a network that we can train on a single accelerated device such as a GPU. In this section, we describe two directions to circumvent this limitation. The first direction focuses on fitting a larger model on single device by reducing the memory required by activations and optimizer states during the training process. The second direction focuses on efficient training of even larger models through model parallelism, for example splitting a model across multiple devices. In this work, we pursue both techniques to densely scale the capacity of Transformers.

Reducing Memory Consumption on a GPU. To reduce the amount of memory, we consider optimizer state sharding and gradient checkpointing. Optimizer state sharding (Rajbhandari et al., 2019) divides the optimizer state across distributed data parallel workers so that each worker only needs to store a fraction of the optimizer state. We also apply gradient checkpointing, which saves memory by discarding intermediate activations before the forward pass finishes (Chen et al., 2016). During the backward pass, these activations are recomputed again as required. This trades time for memory. In the case of a Transformer based architecture, applying gradient checkpointing at pipeline parallel model partition boundaries reduces the memory used by activations by almost 50%.

Models Sharded across Multiple GPUs. Reducing the memory consumption enables fitting greater model capacity on a single GPU, but the physical limitations of a single device still apply. A solution is to split the model into separate components that are dispatched across different GPUs and trained in parallel. This type of solution scales model capacity with the number of GPUs. There are two broad paradigms to split a model: along the width or along the depth. Tensor parallelism (Shoeybi et al., 2019; Shazeer et al., 2018) splits by width, while pipeline parallelism (Huang et al., 2019a; Kim et al., 2020) splits by depth, placing different layers on different GPUs. We use pipeline parallelism, but both methods work equally well with Transformers. We use the implementation from `fairscale`[22].

5.1.2 Training Large Dense Models

We investigate several strategies to increase the capacity of a sequence-to-sequence Transformer model in the context of multilingual machine translation.

How to Scale: Wide or Deep? We consider increasing the capacity of a Transformer by either increasing the number of layers (depth axis) or the dimensions of each layer, including the feed-forward (width axis). The exact model configurations and dimensions are detailed in the Appendix. On the left panel of Figure 7, we analyze which axis to prioritize by comparing models with different sizes, 1B, 2B, and 10B, obtained by growing their depth or width (see Appendix B for model configurations and dimensions). We report their performance in BLEU and their inference speed measured in words per second (WPS). We train these models on a data set that covers 80 languages and evaluate them on 38 different benchmark directions with more than 1k parallel sentences per direction. The main result of this study

22. Please see: `https://github.com/facebookresearch/fairscale`.

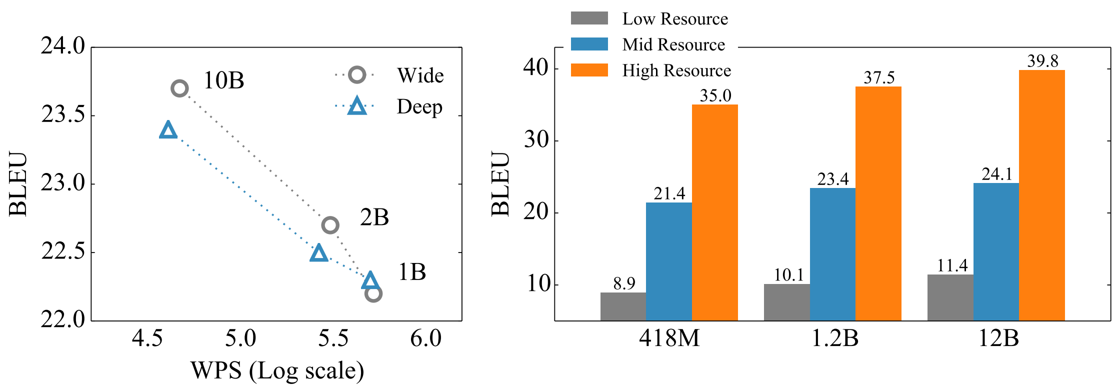


Figure 7: **(left) Comparison between deep versus wide models.** We compare the performance in BLEU for different wide and deep models as a function of their words per second (WPS) at training time, evaluating on a subset of 38 directions. **(right) Performance of wide models for different parameter sizes.** We compare the performance of different wide models on different pairs at low, mid, and high resource levels, evaluating on all supervised evaluation pairs. The white lines indicate comparisons between the different models at the same resource level.

is that wider models scale better than deeper models in terms of performance and WPS. In the rest of this paper, we thus focus on wider models.

Performance as a function of scale. In the right panel of Figure 7, we compare the performance of wide models as we increase their capacity from 418M to 12B parameters. We train these models on the full set of 100 languages and evaluate them on all supervised evaluation pairs. We report their performance in BLEU for pairs with either low, mid or high resource training data. First, as we increase the number of parameters, we observe that the performance increases, *even on low-resource pairs*. This suggest that even a 12B parameter model could be underfitting with our many-to-many multilingual data set. However, improvements increase roughly logarithmically in the number of parameters, and we need to scale model size by an order of magnitude to improve by a few BLEU points, for example, +1.5 BLEU from 1.2B to 12B. As we scale models densely, their runtime and memory usage becomes too prohibitive to justify the gain in performance, and so, we consider alternatives to increase the capacity of our models more efficiently.

5.2 Scaling Model Capacity with Language-Specific Parameters

In this section, we introduce a layer whose parameters are split by language or language group based on similarity in vocabulary. Each translation direction only accesses a subset of these parameters, allowing the model capacity to scale without significantly affecting the training and inference time. The layer is trained with a novel re-routing scheme to improve generalization which we detail below. Compared to previous work (Wang et al., 2018; Bapna and Firat, 2019; Zhang et al., 2020), we focus on allocating entire language-specific layers and using this to scale model size while maintaining training speed.

Parallel Transformer Layer. We follow the sequence-to-sequence Transformer architecture and replace layers by a set of parallel Transformer layers, one for each pre-defined group of languages. More precisely, assuming we have split the languages into K fixed groups, this parallel layer is composed of K parallel Transformer sub-layers, one per language group. For each translation, we then select the corresponding sub-layer among the K possibilities depending on the language direction. If the parallel layer is in the encoder, we select the sub-layer according to the source language, while if it is in the decoder, we select according to the target language. In practice, we only add these layers to either the encoder or decoder, not both. This enables us to split translations along with their sub-layers per GPU, leading to faster training and efficient memory usage. We replace layers of the Transformer model—in the encoder, we replace layers closer to the input, so that the specialized capacity can be used to learn to read different languages and varied scripts. In the decoder, we replace layers closer to the output, so that the specialized capacity can be used to predict different output vocabulary distributions based on the language. Experimentally, we vary the number of layers being replaced to evaluate the effect of adding more specialized capacity to the model. Concretely, if we wanted to add 1 language-specific decoder layer to a Transformer model with 6 encoder layers and 6 decoder layers, the resulting model with have 6 shared encoder layers, 5 shared decoder layers, and 1 language-specific decoder layer closest to the output.

Such a language-specific architecture is reminiscent of a deterministic mixture-of-experts, where one expert is activated based only on the input language. This is a much simplified form of standard mixtures, which often learn weights based on the input data to decide which experts to activate. This architecture is also similar to adapters (Bapna and Firat, 2019; Houlsby et al., 2019). Generally, adapters function by adding small *adapter layers* between the layers of a pre-trained network, and then performing fine-tuning—the adapter layers consist of two projections separated by an activation, followed by a residual connection. The size of the adapters can be modified and tuned to improve performance. Our language-specific layers generalize this adapter strategy to make entire Transformer layers adaptable, allocating much larger quantities of capacity. Adapter layers further focus on adaptation of a pre-trained model, often achieved by freezing the original network (Houlsby et al., 2019) rather than training the entire shared-and-specialized architecture from scratch. Finally, these are all specific instantiations of a larger desire for modular neural networks, where various components can be flexibly added or modified to adjust the level of computation required for a task.

Figure 8 shows an example of the resulting *trunk-and-branch* architecture when the parallel layer is in the decoder.

Grouping Languages by Frequency and Similarity. We group languages based on two criteria: the amount of training data and their vocabulary. The motivation for these criteria is that we can learn a specific layer for a language with enough data, and for the rest, overlapping vocabulary is a good proxy for similar languages. First, each language with more than 100M sentences forms its own group and hence has its own sub-layer. We have 28 languages that fit this criteria: hu, ru, hi, ro, fr, nl, fi, pt, ar, el, vi, en, ms, tr, he, id, pl, cs, sv, fa, zh, bg, de, es, ko, ja, it, da. Second, we group the remaining languages by vocabulary overlap, leading to 18 additional groups. To create these groupings, we calculate the vocabulary overlap between the training data of different languages and cluster those

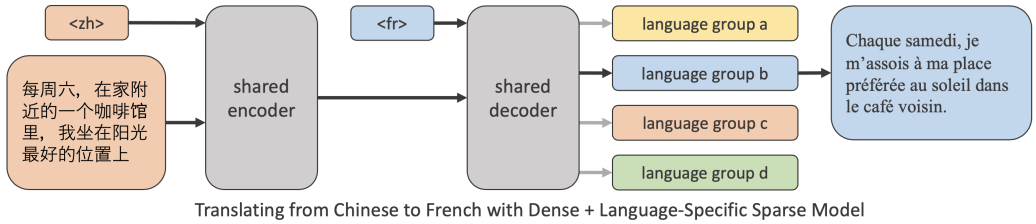


Figure 8: **Language-Specific Parameters** provide specialized capacity to an otherwise fully shared multilingual encoder and decoder.

that have high overlap together. Note that some low resource languages have their own script—such as Kannada—and are not clustered with any similar languages as the script is unique. However, to maintain balance between groups (Wang et al., 2020), we cluster the remaining languages together and roughly balance the amount of training data for each group. In total, we form 46 groups, each with its own sub-layer in a language-specific layer.

Random Re-Routing between Sub-layers. During training and inference, a sub-layer is deterministically selected according to its language direction. This guarantees that our model always uses the same memory and time during inference, regardless of the translation pair. However, during training, this deterministic routing does not share information between similar languages if not associated with the same sub-layer. For example, the sub-layer associated with Ukrainian does not benefit from the large quantity of Russian training data, since Russian has its own isolated sub-layer. We mitigate this shortcoming by *random re-routing* of translations, that is, randomly picking another sub-layer instead of the designated one. This shares information between languages associated with different sub-layers, benefiting low resource languages by training on similar high resource languages. The re-routing is completely random, though could be restricted to re-route only to similar languages.

Adding Language-Specific layers to Pre-Trained Transformers. We can integrate a language-specific layer into an already pre-trained Transformer by adding it either at the end of the decoder or at the beginning of the encoder. We can then freeze the parameters of the pre-trained Transformer and learn the language-specific components. These additional language-specific layers train rapidly as the rest of the model already has strong performance. This strategy means it is straightforward to adapt pre-trained networks to a new domain or language by training a small number of dedicated parallel layers, and could easily be extended to various other applications.

5.2.1 Evaluation of the Language-Specific Layer

We experiment with different scenarios by adding a language-specific layer to the encoder or decoder, or to a pre-trained densely scaled model. We demonstrate the importance of random re-routing. Finally, we validate this strategy by comparing it to scaling models densely.

Parallel layer in Encoder or Decoder? The trunk-and-branch architecture for language-specific layers is general and can be used to specialize capacity for any neural architecture.

Model	Params	BLEU
Language Specific Enc	540M	17.1
	920M	17.5
Language Specific Dec	540M	17.3
	920M	17.8

Table 7: **Comparing Language-Specific Encoders and Decoders** by BLEU score. We add parallel language-specific layers to either the encoder or decoder, with different sizes.

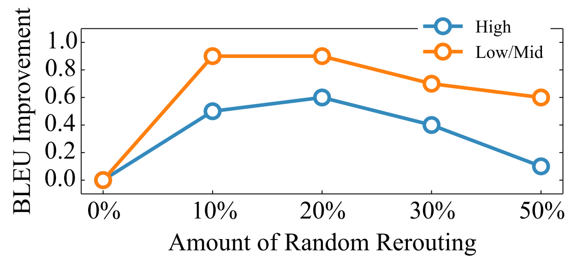


Figure 9: **Impact of Re-routing Rate** on the performance of high resource and low/mid resource languages. We display BLEU score.

We explore adding language-specific capacity in the encoder or decoder using a smaller setting of 10 high-resource languages. Table 7 shows that language-specific parameters are generally more effective when applied to the decoder network. Recent studies show that encoders are more important for bilingual machine translation (Wu et al., 2019; Kasai et al., 2020), however, these studies are based on systems modeling only a single language direction compared to our setting. In our case, increasing the encoder or the decoder does not impact performance significantly, and we focus on decoder for the rest of this paper.

Random Re-routing. Figure 9 shows the impact of the re-routing strategy on performance as we increase the number of training samples routed to random parallel layers as opposed to their assigned layers. With a re-routing rate of 20%, an improvement of about 0.8 BLEU can be achieved over no re-routing for low and mid resource languages, without affecting the performance of high resource languages. Too much stochasticity leads to performance similar to no random re-routing for high resource languages, but still improves mid to low resource performance compared to no re-routing.

Comparison with Large Dense Models. We compare adding language specific capacity with densely scaling model size in Table 8 on 100 languages. As language-specific layers add many parameters, we compare to baseline models at various sizes for multiple points of comparison. Our conclusion is that language-specific layers improve results compared to baselines of similar parameter size, particularly for mid and high resource languages where there is sufficient data to train the language-specific sub-layers. Further, compared to dense scaling, sparse scaling only uses a fraction of the parameters in each forward pass, which maintains fast training speed despite large total model size.

Adding Language-Specific Layers to a Pre-Trained Model. We demonstrate the impact of adding language-specific layers to the decoder of a pre-trained 12B parameter Transformer in Figure 10. We show that adding language-specific layers for five languages improves results on the WMT evaluation data sets. The language-specific layer adds 3.4B parameters and we train it for 20K updates with the rest of the network frozen. The total size of this model is 15.4B parameters. For several directions, we observe gains of more than 1 BLEU, which validates this strategy. On average, we observe gains of 0.9 BLEU.

Model	Params	WPS	Supervised			All
			Low	Mid	High	Avg
Dense Transformer	1.2B	40K	10.1	23.4	37.5	17.5
Dense Transformer	3B	20K	10.3	23.8	38.0	17.9
Dense Transformer	12B	3.5K	**11.8**	24.2	39.9	18.6
Dense Transformer 1.2B						
with 1 Language-Specific Layer	1.9B	38K	10.7	24.1	38.5	18.1
with 3 Language-Specific Layers	3.5B	34K	10.6	**24.7**	39.5	18.8
with 6 Language-Specific Layers	10B	26K	10.5	24.7	**40.3**	**19.2**

Table 8: **Scaling Model Size with Language-Specific Parameters**. We start with a 1.2B parameter baseline with 24 encoder layers and 24 decoder layers. We add increasingly more decoder layers to language specific layers. For example, in the case of 1 language-specific decoder layer, the decoder has 23 shared layers and 1 language-specific layer. We demonstrate the effect of using 1, 3, and 6 language specific layers. The additional parameters for language-specific layers are split across all language groups. We report WPS at training time holding the batch size fixed on 8 GPUs. The 12B baseline uses model parallel. We report BLEU score.

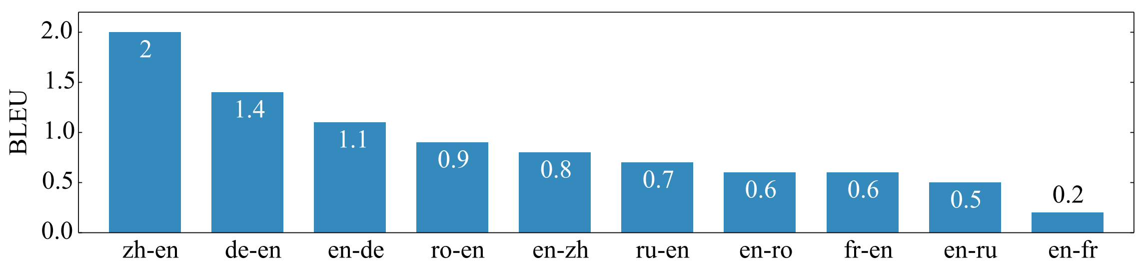


Figure 10: **BLEU Improvement using Dense + Sparse** over Dense alone. We display evaluation on a subset of pairs using the WMT evaluation data sets.

6. Bringing it all Together

We have explored the creation of a true many-to-many data set for the multilingual translation of 100 languages, as well as how to effectively scale Many-to-Many models through a mix of dense and sparse scaling. In this section, we summarize our final results, compare to existing published work—both multilingual benchmarks and competitive directions in WMT—and end with a human evaluation of the overall quality of our translation quality.

6.1 Real-world Settings for Many-to-Many Translation

We highlight that there are several real-world usecases of translation directions not involving English. Many countries have official and regional languages that are not English, which would be natural candidates for direct translation. For example, it is intuitive to translate Kazakh directly to Russian in Kazakhstan. In Table 9, we compare English-Centric models to Many-to-Many on a variety of different non-English directions. We see that across the

	Source	Target	Test Set	BLEU English-Centric	m2m-100	Δ
India	Hindi	Bengali	TED	3.9	8.7	+4.8
	Hindi	Marathi	TED	0.4	8.4	+8.0
	Hindi	Tamil	TED	1.1	7.5	+6.4
South Africa	Afrikaans	Xhosa	Autshumato	0.1	3.6	+3.5
	Afrikaans	Zulu	Autshumato	0.3	3.6	+3.3
	Afrikaans	Sesotho	Autshumato	0.0	2.1	+2.1
	Xhosa	Zulu	Autshumato	0.1	3.6	+3.5
	Sesotho	Zulu	Autshumato	0.1	1.2	+1.1
Chad	Arabic	French	TED	5.3	20.8	+15.5
DR Congo	French	Swahili	Tatoeba	1.8	5.7	+3.9
Kazakhstan	Kazakh	Russian	TED	0.5	4.5	+4.0
Singapore	Chinese	Tamil	TED	0.2	8.0	+7.8
Austria	German	Croatian	TED	9.6	21.3	+11.7
	German	Hungarian	TED	11.3	17.4	+6.1
Belgium	Dutch	French	TED	16.4	25.8	+9.4
	Dutch	German	TED	18.1	26.3	+8.2
Belarus	Belarusian	Russian	TED	10.0	18.5	+8.5
Croatia	Croatian	Serbian	TED	22.4	29.8	+7.4
	Croatian	Hungarian	TED	12.4	17.5	+5.1
	Croatian	Czech	TED	15.2	22.5	+7.3
	Croatian	Slovak	TED	13.8	24.6	+10.8
Cyprus	Greek	Turkish	TED	4.8	12.6	+7.8
Czechia	Czech	Slovak	TED	9.5	28.1	+18.6
Finland	Finnish	Swedish	TED	7.9	19.2	+11.3
Italy	Italian	French	TED	18.9	28.8	+9.9
	Italian	German	TED	18.4	25.6	+7.2
Moldova	Romanian	Russian	TED	8.0	19.0	+11.0
	Romanian	Ukrainian	TED	8.7	17.3	+8.6
Montenegro	Albanian	Croatian	TED	3.0	20.7	+17.7
	Albanian	Serbian	TED	7.8	20.6	+12.8
Romania	Romanian	German	TED	15.0	24.7	+9.7
	Romanian	Hungarian	TED	11.0	16.3	+4.3
	Romanian	Turkish	TED	5.1	12.0	+6.9
	Romanian	Armenian	TED	0.4	8.2	+7.8
Russia	Bashkir	Russian	Tatoeba	0.1	4.3	+4.2
	Ukrainian	Russian	TED	18.0	23.7	+5.7
			Average	8.0	15.6	**+7.6**

Table 9: **Performance translating between official and official regional languages** of several nations, focusing on non-English directions.

board, our m2m-100 model has drastically better performance and on average improves over 7 BLEU across these directions.

6.2 Comparison on Various Translation Benchmarks

Next, we compare our m2m-100 model to various existing work on different benchmarks. While the training data is not the same, we conduct this comparison to provide a reference point for the overall strength of our model. An important note is that for each of these benchmarks, there are various different tokenizers used which affect BLEU—we follow the tokenization and BLEU calculation of each of these benchmarks, rather than the evaluation methodology of our previous results. Thus, the numbers in this subsection are not comparable to the rest of this paper, as they use the tokenization of each benchmark. Further, note this comparison was prepared in advance, so all sentences appearing in these evaluation sets were removed from the training data we used.

Comparison on WMT. First, we compare our Many-to-Many model to submissions to WMT, the premier translation competition. We display results on a variety of different language directions, some of which are standard natural language processing machine translation benchmarks, such as English-French, English-German, and English-Russian. Results are shown in Table 10. [23] Many submissions to the WMT shared task use ensembling, in-domain fine-tuning, or re-ranking methods, which are standard techniques to improve quality. As these could be added to our system at inference time as well, we focus instead on comparing single model results. To identify comparisons, we examine the WMT Shared Task proceedings as well as the submissions at `http://matrix.statmt.org/`.

As seen in Table 10, our m2m-100 system can achieve very competitive performance compared to bilingual models tuned especially for individual WMT translation directions. This shows that our model maintains strong translation quality on individual directions.

Next, we compare our models to other multilingual translation work. Table 11 displays several previously published results on different sets of benchmarks. Note that for each comparison, we follow the published setting in tokenization, evaluation, and whether or not the BLEU is tuned on the validation set to maximize comparability.

Bilingual Models. We first compare to mBART (Liu et al., 2020), which creates bilingual models based on fine-tuning a pre-trained model on individual language directions. After pre-training as a denoising autoencoder, publicly available bitext data is used to create various different bilingual models, one for each evaluation direction. Liu et al. (2020) tune the test set BLEU on the validation set. Following their setting, we tune the generation beam size between {5,10}, and length penalty between {0.5, 1.0, 1.5}, and the number of checkpoints to average between {1, 5, 10}. Our model provides +0.7 BLEU improvement.

We then compare to the bilingual baselines provided in CCMatrix (Schwenk et al., 2019b), which trained individual models for each direction. As these models generate with no tuning, we generate on all pairs with beam size 5 and length penalty 1, using only the

23. **En $\leftrightarrow$ De/En $\leftrightarrow$ Ru:** we evaluated publicly available single model checkpoints prior to finetuning from Ng et al. (2019) on WMT2019. **En $\leftrightarrow$ Zh:** we report results from Li et al. (2019) which contains single model BLEU results on WMT2019. **En $\leftrightarrow$ Lt:** we report results from Pinnis et al. (2019) on WMT2019; both directions are the best single model systems which use unconstrained training data. **En $\rightarrow$ Fr:** we report results from Edunov et al. (2018). **Fr $\rightarrow$ En:** we report results from Johnson et al. (2017) on WMT2014. **En $\leftrightarrow$ Lv:** we report results from Pinnis et al. (2017) on WMT2017. **En $\leftrightarrow$ Tr:** we report results from Sennrich et al. (2017) on WMT17. **En $\leftrightarrow$ Et:** we report results from Pinnis et al. (2018) on WMT18. **En $\leftrightarrow$ Fi:** we report results from Talman et al. (2019) on WMT17.

Direction	Test Set	BLEU Published	m2m-100	Δ
Without Improvement				
English-Chinese (Li et al., 2019)	WMT'19	38.2	33.2	-5.0
English-Finnish (Talman et al., 2019)	WMT'17	28.6	28.2	-0.4
English-Estonian (Pinnis et al., 2018)	WMT'18	24.4	24.1	-0.3
Chinese-English (Li et al., 2019)	WMT'19	29.1	29.0	-0.1
With Improvement				
English-French (Edunov et al., 2018)	WMT'14	43.8	43.8	0
English-Latvian (Pinnis et al., 2017)	WMT'17	20.0	20.5	+0.5
German-English (Ng et al., 2019)	WMT'19	39.2	40.1	+0.9
Lithuanian-English (Pinnis et al., 2019)	WMT'19	31.7	32.9	+1.2
English-Russian (Ng et al., 2019)	WMT'19	31.9	33.3	+1.4
English-Lithuanian (Pinnis et al., 2019)	WMT'19	19.1	20.7	+1.6
Finnish-English (Talman et al., 2019)	WMT'17	32.7	34.3	+1.6
Estonian-English (Pinnis et al., 2018)	WMT'18	30.9	33.4	+2.5
Latvian-English (Pinnis et al., 2017)	WMT'17	21.9	24.5	+2.6
Russian-English (Ng et al., 2019)	WMT'19	37.2	40.5	+3.3
French-English (Edunov et al., 2018)	WMT'14	36.8	40.4	+3.6
English-German (Ng et al., 2019)	WMT'19	38.1	43.2	+5.1
English-Turkish (Sennrich et al., 2017)	WMT'17	16.2	23.7	+7.5
Turkish-English (Sennrich et al., 2017)	WMT'17	20.6	28.2	+7.6
	Average	30.0	31.9	**+1.9**

Table 10: **Comparison of Many-to-Many and public results on WMT data sets.** We compare m2m-100 to published work (best single models) on WMT. To identify previous work, we examine the WMT Shared Task proceedings for the top performing models and check reported results on `http://matrix.statmt.org/`. For these comparisons, we report detokenized BLEU with sacrebleu (Post, 2018) on the test set.

best checkpoint. Our one Many-to-Many multilingual model achieves a 2 BLEU point gain on average compared to training hundreds of individual models.

Multilingual Models. We next compare the performance of our multilingual system to other published multilingual systems. We compare to the English-Centric multilingual model from Zhang et al. (2020) on the OPUS-100 corpus. Their model is trained with noisily aligned through-English data from OPUS (Tiedemann, 2012; Zhang et al., 2020), with online backtranslation to improve the performance of non-English pairs. Note that Zhang et al. (2020) train on 100 directions, but we only overlap a subset of directions. However, we fully cover their full set of non-English evaluation pairs. Finally, the OPUS-100 non-English directions come only with a test set, so we generate with beam size 5, length penalty 1, and use the best checkpoint. As shown in Table 11, we improve by more than 4 BLEU.

6.3 Human Evaluation

We end with a human evaluation study to understand the quality of our model translations. We focus on 20 different directions, none of them involving English. We include languages commonly spoken in the same region, such as Japanese-Chinese, Hindi-Tamil, and Russian-

Benchmark	Model	BLEU
mBART	Previous Work (Liu et al., 2020)	23.9
	m2m-100	**24.6**
CCMatrix	Previous Work (Schwenk et al., 2019b)	16.3
	m2m-100	**18.7**
OPUS100	Previous Work (Zhang et al., 2020)	14.1
	m2m-100	**18.4**

Table 11: **Comparison on various evaluation settings from previous work**. We display the best performing model from the published work and report average BLEU on the test set. For these comparisons, we use the tokenization and BLEU evaluation script used by each work for comparability. Liu et al. (2020) report Low/Mid resource directions into and out of English and High resource directions into English, we average across all. Schwenk et al. (2019b) report the full matrix on 28 languages, we average across all. Zhang et al. (2020) report results on non-English directions, we average across all.

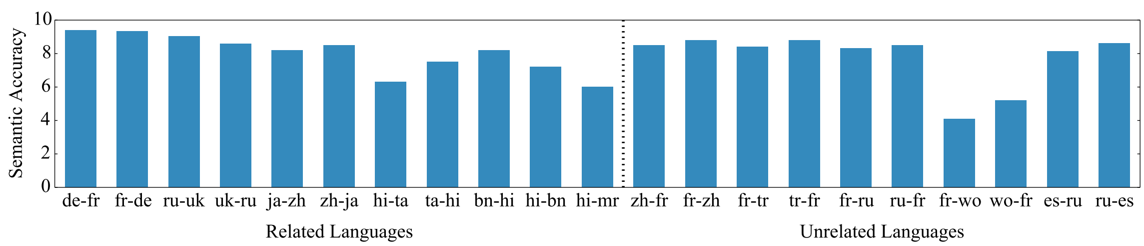


Figure 11: **Human Evaluation of Translation Accuracy of m2m-100 on Non-English Directions.** Evaluators are asked to score the semantic accuracy of translations on a scale of 1 to 10.

Ukrainian, as well as directions that cross language families, such as Chinese-French, French-Arabic, and Russian-Spanish. We also include several very low resource directions, such as French-Wolof, Hindi-Marathi, and Japanese-Mongolian.

We followed the human evaluation done at WMT by asking the same evaluation question with similar setup. To source evaluators, we identified people who were fluent in both non-English languages, and were a native speaker of at least one of the languages they were evaluating. The overall demography of evaluators: our evaluators live across the world, though a number of them are located in France and the United States. The distribution of gender is around 60% male and 40% female. The age ranges from roughly 25 to 65. All evaluators are college graduates. Finally, all evaluators are fluent in English, which is necessary to understand our English-written instructions for the evaluation study.

Each evaluator rates 50 different translations for semantic accuracy on a scale of 1 to 10. Results are shown in Figure 11. On semantic accuracy, most of our evaluations score between 8.5 and 9.5 (with 10 being the best possible score). For lower resource directions, the scores remain reasonable. Hindi to Tamil and Wolof to French score around 7—8. The

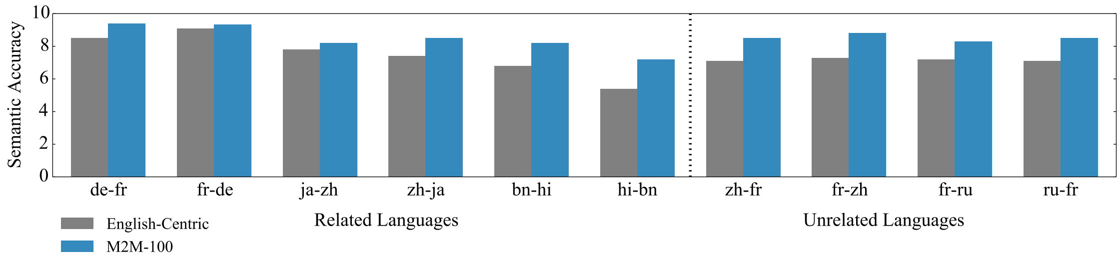


Figure 12: **Human Evaluation of Translation Accuracy of M2M-100 compared to English-Centric on 10 Non-English Directions.** Evaluators are asked to score the semantic accuracy of translations on a scale of 1 to 10.

most challenging direction based on human evaluation is French into Wolof (fr-wo), likely because there is not sufficient target-side Wolof data.

Next, we compare our model with an English-Centric model on 10 directions in Figure 12. Each evaluator is asked to rate 100 sentences, 50 from each model, in a blind test. Across the board, we find that our Many-to-Many system scores better in translation accuracy - both for related and unrelated languages.

6.4 Related Work

Our work builds upon advances in translation quality, both from data and modeling standpoints. In this section, we describe related work in these two areas.

Data Work in machine translation has leveraged natural sources of aligned data. For example, European Parliamentary Proceedings (Koehn, 2005b) and religious text such as the Bible and Quran are translated into numerous languages (Christodouloupoulos and Steedman, 2015; Agić and Vulić, 2019). Many translation efforts contribute data sets of human translations, which can be used for training translation systems. However, beyond human translations, a number of automatic alignment methods have created corpora as well. For example, methods aligned documents on metadata (Resnik, 1999) or sentences based on Jaccard distance or neural representations (Etchegoyhen and Azpeitia, 2016; Buck and Koehn, 2016). Other work expanded to use embeddings from translation systems (Abdul-Rauf and Schwenk, 2009; Bouamor and Sajjad, 2018).

Several previous large-scale translation mining projects have produced data in many directions. For example, efforts have aligned data in Wikipedia (Smith et al., 2010; Tufis et al., 2013) including the Wikimatrix project, which mined 1620 directions (Schwenk et al., 2019a). Wikipedia contains high quality data, but is limited in volume. Other work has identified parallel data in sources such as subtitles, such as the OpenSubtitles project (Lison and Tiedemann, 2016). Efforts such as Paracrawl (Esplà-Gomis et al., 2019) have mined for data on the web and are freely usable. Our work continues this line of scalable mining on the web, but pushes to large-scale mining to produce billions of aligned sentences.

Complementary to the effort of mining training data is to use available monolingual resources. As parallel data is naturally more scarce, monolingual data provides the potential for training high quality models, particularly for low resource languages. Backtranslation (Bojar and Tamchyna, 2011; Sennrich et al., 2016a) has been an effective technique, with several improvements proposed in recent years. For example, how to balance backtranslated data with human translations (Edunov et al., 2018) and how to use backtranslation effectively for low resource languages (Fadaee et al., 2017).

Beyond creating data itself, much work has investigated how to filter noisy data from high quality alignments. This is especially relevant as mined corpora become more prevalent and the scale of backtranslation increases. Shared tasks such as the WMT task on Parallel Corpus Filtering (Koehn et al., 2018a) amongst others challenge the community to innovate and identify techniques to better filter data.

Finally, a long direction of work focuses not on training data but the formation of high quality evaluation data sets. Workshops such as WMT, WAT, and IWSLT have historically contributed very heavily used translation data sets. Work such as the FLORES project (Guzmán et al., 2019), LORELEI (Strassel and Tracey, 2016), and ALT (Riza et al., 2016) contribute data sets for low resource translation directions. Further, community efforts such as masakhane (∀ et al., 2020) and the African Language data sets Challenge (Siminyu et al., 2020), and workshops such as AmericasNLP[24] and Indigenous AI Workshops (Lewis et al., 2020) [25]have contributed to increasing focus on under-resourced languages, the importance of the community driving progress, and the impact of such community contributions.

Models A long history of work exists to create automatic translation systems. Before neural models became widespread, statistical translation models (Koehn, 2009) were used for automatic translation. Improvements in neural systems built off of architectural components such as LSTMs (Hochreiter and Schmidhuber, 1997), convolutions (Gehring et al., 2017), and attention mechanisms (Bahdanau et al., 2015). As they increased in quality, neural methods began to replace statistical translation techniques (Wu et al., 2016).

These improvements in translation not only focused on bilingual translation systems that translate between two languages, but also on multilingual translation. Work encompassed both smaller sets of languages (Firat et al., 2016) as well as investigations with hundreds of languages by training on data from the Bible (Malaviya et al., 2017; Tiedemann, 2018). Similar to work on multilingual sentence representations, investigations probed models to understand if higher level representations such as interlingua were being learned (Lu et al., 2018) or if models encompassed linguistic features (Celikkanat et al., 2020). Several studies examined the architecture choices, resource level of different languages, and the performance of zero-shot cases (Tan et al., 2019b; Gu et al., 2019). Other work focused on exceptionally low resource scenarios, such as fully zero-shot translation (Lakew et al., 2019; Gu et al., 2019; Liu et al., 2020).

Other directions investigate how to create multilingual translation models, proposing multistage fine-tuning (Dabre et al., 2019), slow adaptation from bilingual to multilingual systems (Escolano et al., 2019), and fine-tuning from pre-trained models (Tang et al., 2020). To obtain stronger performance, various work has proposed clustering or grouping languages (Tan et al., 2019a). For translation between non-English languages, much previous work has investigated this. For example, bilingual systems can be trained between any pair of languages given sufficient training data. Other systems propose pivoting (Kim et al., 2019)

24. Please see the following: `http://turing.iimas.unam.mx/americasnlp/`.
25. Please see the following: `http://www.indigenous-ai.net/`.

or training on English-Centric data and zero-shotting non-English directions (Arivazhagan et al., 2019).

On the architectural side, multilingual translation has spurred much research in the direction of improved model architectures. For example, Firat et al. (2016) examined how to share attention mechanisms between languages. Other work has focused on architectures that have specialized components that can be adapted for certain languages, such as adaptor layers (Houlsby et al., 2019; Pfeiffer et al., 2020) or language-specific layer norms and linear transformations (Zhang et al., 2020). Similar to our language-specific trunk-and-branch architecture, these often have deterministic components based on the input language. Other work has focused on learning which model components to use (Li et al., 2020) or how to better train language-specific components (Escolano et al., 2020b,a). Another large body of work focuses on model scaling for multilingual translation applications, such as `gPipe` (Huang et al., 2019b) and `gShard` (Lepikhin et al., 2020).

Finally, translation systems cannot be developed in a vacuum. Multilingual translation systems have clear applications in various usecases. Their quality must be carefully measured, in part with automatic metrics such as BLEU, COMET (Rei et al., 2020), and BLEURT (Sellam et al., 2020), but also with detailed human evaluations to really understand the challenges that still must be overcome. Looking only at numerical scores is far from adequate to understanding the quality of a translation. Further, work has analyzed the presence of bias in automatic translation systems (Prates et al., 2019) as well as the use of translation systems in various applications such as medicine (Vieira et al., 2020). These biases in training, evaluation data, and even architectures (Costa-jussà et al., 2020) require further dedicated efforts and careful examination to understand as a pre-requisite to using these systems broadly.

6.5 Discussion

Curating High-Quality Training Data. Creating high quality data sets to train translation models has been a long-standing area of research. For example, previous work has explored how to best filter noisy data sets (Koehn et al., 2018b, 2019). Our use of large-scale mined training data presents large quantities of data to train multilingual models on, but brings challenges as well. For example, our mining methods mine both simplified and traditional Chinese text, tokenized and de-tokenized text, and many examples with code switching. We apply several data filtering methods, but the cleanliness and quality of alignment is critical for training high-quality translation systems. Further, multilingual translation can be affected by domain mismatch, as people in different parts of the world discuss different topics (Shen et al., 2019), which presents additional challenges for curating good training sets. Thus, we see the continued improvement of data quality as an important direction for multilingual translation systems, which require a lot of data to train well.

Multilinguality at Inference Time Throughout the paper, we explored how to improve the performance of single models, scaling the amount of data as well as the model size, but there remain numerous directions for future investigation of multilinguality. One direction is understanding how to exploit the nature of multilingual translation at inference time as well. A true Many-to-Many system provides several possible directions for exploring this potential.

Model	BLEU
Multilingual	17.3
Multi-Model Ensemble	17.5
Pivoting with Multilingual	17.0
Multi-source Self-Ensemble	17.5

Table 12: **Results on zero-shot language pairs for Multi-Source Self-Ensemble** compared to various baselines. We report the average test BLEU score on 100 randomly sampled pairs.

A known, effective strategy to improve accuracy is to ensemble multiple models at inference time. However, this requires training multiple models which substantially increases the training compute requirements. Instead, we explored self-ensembles as a possible direction, created by applying the multilingual model to the same source sentence in different languages. For example, if we wish to translate Galician to English, then instead of directly translating between the two, we ensemble the translation of Spanish to English with the translation of Galician to English, using the same multilingual model for both directions, and by averaging the predicted token log-probabilities, as for standard multi-model ensembles. The additional source is obtained by translating the input to another *intermediary* language. After this, we ensemble the translation of both sources to the target. This uses the same multilingual model for all steps.

We evaluate both pivoting and self-ensembling on zero-shot directions as these can benefit from better accuracy. We report results on 100 randomly sampled zero-shot translation directions which have at least 1000 examples in the validation and test set. Next, for each translation direction, we choose the intermediary language that resulted in the highest BLEU on the validation set; the same is done to choose the intermediary language for pivoting. We also tune a weight to balance the two language directions (Garmash and Monz, 2016). Table 12 shows that multi-source self-ensembling improves the single model result by 0.2 BLEU on average. It also performs as well as standard multi-model ensembling but requires training only a single model. This is particularly relevant for large models trained on vast quantities of data, which require a lot of compute to be able to perform standard ensembling.

Overall, we find these directions of investigation very interesting—by exploiting multilinguality further at inference time, the large training cost could be reduced and replaced with inference-time techniques that are much faster. We believe further research into these inference-time techniques, focusing on similarity between languages or selecting specific pivot languages, or architectural modifications that can be applied during decoding—such as adding a language model or nearest neighbors search (Khandelwal et al., 2020), are fruitful avenues of future work.

Improvements on Very Low-Resource Languages. Strong performance for low-resource languages remains a critical area for future improvement (Gu et al., 2018; Sennrich and Zhang, 2019). For many languages, our system still requires substantial improvements. Examples include African languages such as Xhosa and Zulu, European languages such as Catalan and Basque, and Southeast Asian languages such as Iloko and Cebuano. For many of these, even monolingual resources on the internet are limited, which strongly affects the quantity and quality of mined data. Using curated data, possibly supplemented by mining, may provide a starting point for future improvement. For example, several resources for African languages exist, including JW300 (Agić and Vulić, 2019) used in the masakhane machine translation effort (∀ et al., 2020) and data sets for Nigerian Pidgin (Ahia and Ogueji, 2020), Wolof (Alla et al., 2020), Fon (Emezue and Dossou, 2020), Igbo (Ezeani et al., 2020), Amharic, Tigrigna, Afan-Oromo, Wolaytta, and Ge'ez (Abate et al., 2018). Other lines of work present resources for low-resource Asian languages, such as the ALT project (Riza et al., 2016; Ding et al., 2016), Mongolian, Uyghur, and Tibetian (Anonymous, 2020), or strategies for improvement on specific directions (Chen et al., 2019). Further research is required to bring together small data sets of higher quality translations, mined data, and monolingual resources to create improved translation systems for very low resource languages.

7. Conclusion

We introduced m2m-100, a new Many-to-Many multilingual translation model that can translate between the 9,900 directions of 100 languages. The underlying data set was mined from CommonCrawl using a novel strategy which exploits language groupings to avoid mining every possible direction while maintaining good accuracy. Such a large data set requires models with increased capacity and to this end we explored densely scaling the number of parameters as well as sparsely, through introducing language-specific parameters trained with a novel random re-routing scheme.

Results show that m2m-100 outperforms English-Centric multilingual models trained on data where either the source or target language is English. The system improves over 10 BLEU on average compared to an English-Centric baseline when translating directly between non-English directions. m2m-100 is competitive with bilingual models from WMT and improves over existing publicly available multilingual translation systems. Human judges indicate that our model translates fluently with high semantic accuracy.

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Appendix A. Additional Information about Data

Dictionary Coverage Figure 13 displays the dictionary coverage for each of our 100 languages.

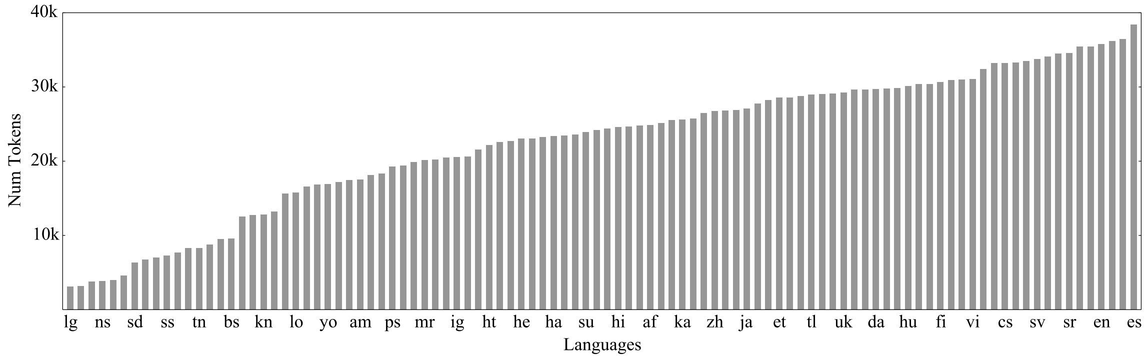

Figure 13: **Dictionary Coverage** per Language

Mining Data with LASER Applying a global bitext mining approach in huge collections like Common Crawl requires a carefully optimized pipeline to tackle the computational challenge. We outline here the main ideas and refer the reader to Schwenk et al. (2019b) for more details. Overall, processing can be structured into four steps:

1. **Text extraction:** extract the textual part of CCNet (Wenzek et al., 2019), segment the paragraphs into sentences and perform language identification;

2. **Index creation:** create an FAISS index for each language using aggressive vector compression based on a 64-bit product-quantizer and 64k cells to partition the search space.[26]

3. **k-nn search:** For each language pair, search the k-nn closest sentences in the FAISS index of the previous step. This search is performed in both directions, that is, source in target and target in source. The k-nn distances and indexes are stored and processed in the next step;

4. **Actual mining:** We follow Artetxe and Schwenk (2019a) and use a margin criterion to decide whether two sentences are parallel or not:

$$\text{margin}(x, y) = \frac{\cos(x, y)}{\sum_{z \in \text{NN}_k(x)} \frac{\cos(x, z)}{2k} + \sum_{z \in \text{NN}_k(y)} \frac{\cos(y, z)}{2k}} \tag{5}$$

   $\text{NN}_k()$ are the k unique nearest neighbors, with $k = 16$. We mine for possible parallel sentences in both directions, that is, source $\leftrightarrow$ target, merge the mined bitexts and remove duplicate sentence pairs.

26. We used FAISS index type `OPQ64,IVF65536,PQ64`.

The data for each language is divided into multiple chunks of approximately 50M sentences which are processed in parallel. This enables to substantially speed up processing when a large cluster is available.Once all parts are processed, data is merged as needed, for example global deduplication in step 1.

Step 1 and 2 process each language independently, while step 3 and 4 loop over all requested language pairs.

The LASER encoder was trained on 93 languages, but not all of them perform equally well. An indication of of the performance of a language pair can be obtained by multilingual similarity search in the embedding space. For each source sentence of a parallel test set, the closest target sentence in the test set is searched and an error is counted if it is not the correct one. Comparative results are given in Tables 1 and 2 in Artetxe and Schwenk (2019b).

Appendix B. Model Details

Training Times The training time for the 418M parameter model was approximately 8 days on 128 GPU. The training time for the 1.2B parameter model was approximately 11 days on 128 GPU. The main bottleneck for training time was the large quantity of data to train through. The models converged very quickly in training but continued improving with additional training time. The 12B model trained for 33 days on 512 GPUs. The model converged within about 17 days with slow, but steady improvement over the remaining time.

Architectures for Deep v. Wide Table 14 shows the various model configurations considered in our experiments when scaling dense models.

Size	Embed	FFN	Layers
1B Wide	1024	16K	14
1B Deep	1024	4K	38
2B Wide	2048	16K	11
2B Deep	1024	8K	48
10B Wide	4096	16K	24
10B Deep	3072	12K	36

Figure 14: **Architecture of Wide and Deep Models.**

Appendix C. Additional Experimental Results

C.1 Language-Specific Parameters

There are various possible constructions to create language-specific parameters. For example, instead of having an architecture where some layers are shared and others are specialized, entire decoders could be specialized. In this section, we analyze various possible approaches to language-specific parameters on a smaller benchmark of 9 languages: Bengali, Czech, Hindi, French, Russian, English, Polish, Spanish, and Chinese.

Model	**Parameters**	**Average BLEU**	**Low-Resource BLEU**
Dense Baseline	620M	15.9	9.1
Fully Separate Decoders			
By Language Family	640M	16.7	9.8
By Language	1.1B	16.9	9.4
Trunk-and-Branch Decoders			
By Language Family	520M	16.6	10.3
By Language	740M	16.3	9.9
Fully Separate Encoders			
By Language Family	640M	16.2	9.2
By Language	1.1B	16.4	9.0
Trunk-and-Branch Encoders			
By Language Family	520M	15.9	9.6
By Language	740M	16.2	9.4

Table 13: **Investigation of Language-Specific Parameter Construction** on a smaller benchmark of 9 languages.

We compare *full separation* of parameters with our proposed *partial sharing*, where certain layers form a shared trunk between all languages and then have separate, specialized layers. We compare the results for encoder-side and decoder-side language-specific parameters. Table 13 breaks down the result by average BLEU and low resource direction BLEU.

We observe a number of trends. First, the decoder side of multilingual translation seems to be more important than the decoder side—the BLEU improvement of adding parameters in the decoder is larger than the similar addition in the encoder. Second, adding parameters can improve the average BLEU, but hurts the BLEU of low resource languages—we hypothesize that low resource directions do not have sufficient data to train these additional parameters, so performance is negatively affected. This problem would be exaggerated extending from the 9 language analysis here to a full set of 100 languages. Finally, comparing if parameters should be allocated by language or by language family, we see similar effects—high resource languages benefit from specialized parameters (for example Russian, French), but low resource languages have decreased performance. Overall, we are interested in strong low resource translation performance, so choose shared and specialized parameters by language family in the decoder.

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