Can Multilinguality benefit Non-autoregressive Machine Translation?

Sweta Agrawal¹ and Julia Kreutzer² and Colin Cherry²

¹Department of Computer Science, University of Maryland
²Google Research
sweagraw@umd.edu, {jkreutzer, colincherry}@google.com

Abstract

Non-autoregressive (NAR) machine translation has recently achieved significant improvements, and now outperforms autoregressive (AR) models on some benchmarks, providing an efficient alternative to AR inference. However, while AR translation is often implemented using multilingual models that benefit from transfer between languages and from improved serving efficiency, multilingual NAR models remain relatively unexplored. Taking Connectionist Temporal Classification (CTC) as an example NAR model and Imputer as a semi-NAR model (Saharia et al., 2020), we present a comprehensive empirical study of multilingual NAR. We test its capabilities with respect to positive transfer between related languages and negative transfer under capacity constraints. As NAR models require distilled training sets, we carefully study the impact of bilingual versus multilingual teachers. Finally, we fit a scaling law for multilingual NAR, which quantifies its performance relative to the AR model as model scale increases.

1 Introduction

Non-autoregressive (NAR) models generate output tokens in parallel instead of sequentially, achieving significantly faster inference speed that no longer depends on sequence length. They depend heavily on sequence-level knowledge distillation to reach the quality of AR models (Gu et al., 2018). As the notion of NAR has expanded to include semi-NAR models that generate their outputs in multiple steps, each time generating several tokens non-autoregressively (Lee et al., 2018; Ghazvininejad et al., 2019), we have begun to see cases where NAR matches the quality of AR. Most prior works have tested the performance of NAR models on a handful of benchmarks of selected language pairs like German (De), Chinese (Zh), Romanian (Ro). To efficiently expand this set of languages, it makes sense to begin exploring multilingual NAR translation models.

Multilingual machine translation models (Dong et al., 2015; Johnson et al., 2017) translate between multiple languages. They have better parameter-efficiency than building one bilingual model per language pair, and they are able to transfer knowledge from high-resource languages to low-resource ones. They have become an attractive solution for expanding the language coverage of AR models (Aharoni et al., 2019; Fan et al., 2021). The capability of doing multilingual modeling is a major feature of the AR regime, and it is one that we should seek to maintain in NAR models.

It is unclear to what extent the properties of multilingual AR models apply to NAR models. Do related languages help each other (positive transfer) as easily? Do unrelated languages interfere with one another (negative transfer) to the same extent? Since NAR models tend to trade target-side modeling for improved modeling of the source, the answer to both questions is unclear. Furthermore, NAR modeling raises a new issue of multilingual distillation. To retain the training-time efficiency of multilingual modeling, it is crucial that NAR works well with multilingual teachers; otherwise, the prospect of training many bilingual teachers would greatly increase the effective training cost. It may actually be the case that multilingual teachers are better suited than bilingual ones, as the effective capacity reduction may result in less complex (Zhou et al., 2019) and less multimodal outputs (Gu et al., 2018).

We present an empirical study of multilingual NAR modeling. Taking CTC (Libovický and Helcl, 2018) as our canonical NAR method, and Imputer (Saharia et al., 2020) as our canonical semi-NAR model, we study how they respond to multilinguality in a 6-language scenario designed to emphasize negative transfer, as well as two-language scenarios designed to emphasize positive transfer.
In doing so, we make the following contributions:

1. We show that multilingual NAR models suffer more from negative transfer and benefit less from positive transfer than AR models.

2. We fit a scaling law for our 6-language NAR scenario, showing that this trend continues as model size increases.

3. We demonstrate that multilingual NAR performs equally well with multilingual and bilingual teachers, even in scenarios where the multilingual teacher has lower BLEU.

Unfortunately, our results indicate that the time is not quite right for multilingual NAR, as least for the models studied here, but our analysis should help future efforts in this space.

2 Non-Autoregressive Multilingual NMT

Let $D^l = (x, y) \in X \times Y$ denote the bilingual corpus of a language pair. Given an input sequence $x$ of length $T'$, an AR model (Bahdanau et al., 2015; Vaswani et al., 2017) predicts the target $y$ with length $T$ sequentially based on the conditional distribution $p(y_t \mid y_{<t}, x_{1:T'}; \theta)$. NAR models assume conditional independence in the output token space; that is, they model $p(y_1:T \mid x_{1:T'}; \phi)$. Due to this conditional independence assumption, training NAR models directly on the true target distribution leads to degraded performance (Gu et al., 2018). Hence, NAR models are typically trained with sequence-level knowledge distillation (Kim and Rush, 2016) to reduce the modeling difficulty.

2.1 Non-Autoregressive NMT with CTC

In this work, we focus on NAR modelling via CTC (Graves et al., 2006) due to its superior performance on NAR generation and the flexibility of variable length prediction (Libovický and Helcl, 2018; Saharia et al., 2020; Gu and Kong, 2021).

CTC models an alignment $\alpha$ that provides a mapping between a sequence of predicted and target tokens. Alignments can be constructed by inserting special blank tokens (“_”) and token repetitions into the target sequence. The alignment is monotonic with respect to the target sequence and is always the same length as the source sequence $x$. However, in MT, the target sequence $y$ can be longer than the source sequence $x$. This is handled via upsampling the source sequence $x$, to $s$ times its original length. An alignment is valid only if when collapsed, i.e., merging repeated tokens and removing blank tokens, it results in the original target sequence. The CTC loss marginalizes over all possible valid alignments $\Gamma(y)$ compatible with the target $y$ and is defined as:

$$p(y \mid x) = \sum_{\alpha \in \Gamma(y)} p(a_{1:T'} \mid x_{1:T'}; \phi).$$

Note that each alignment token $a_{\alpha}$ is modeled independently. This conditional independence allows CTC to predict the single most likely alignment non-autoregressively at inference time, which can then be efficiently collapsed to an output sequence. This same independence assumption enables efficient minimization of the CTC loss via dynamic programming (Graves et al., 2006). While CTC enforces monotonicity between the alignment and the target, it does not require any cross- or self-attention layers inside the model to be monotonic. Hence, CTC should still be able to model language pairs with different word orders between the source and the target sequence. Following Saharia et al. (2020), we train encoder-only CTC models, using a stack of self-attention layers to map the source sequence directly to the alignments.

2.2 Iterative Decoding with IMPUTER

IMPUTER (Saharia et al., 2020) extends NAR CTC modeling by iterative refinement (Lee et al., 2018). At each inference step, it conditions on a previous partially generated alignment to emit a new alignment. While IMPUTER, like CTC, generates all tokens at each inference step, only a subset of these tokens are selected to generate a partial alignment, similar to iterative masking approaches (Ghazvininejad et al., 2019). This is achieved by training with marginalization over partial alignments:

$$p(y \mid x) = \sum_{\alpha \in \Gamma(a)} p(a \mid a_{\text{Mask}}, x; \phi),$$

where $a_{\text{Mask}}$ is a partially masked input-alignment. At training time, the $a_{\text{Mask}}$ alignment is generated using a CTC model trained on the same dataset, and its masked positions are selected randomly. This training procedure enables IMPUTER to iteratively refine a partial alignment over multiple decoding steps at inference time - consuming its own alignments as input to the next iteration. With $k > 1$ decoding steps, the IMPUTER becomes semi-autoregressive, requiring $k$ times more inference passes than pure CTC models.
Table 1: Details on training data used. Target word orders are the ones that are dominating within the language according to (Dryer and Haspelmath, 2013), but there may be sentence-specific variations. English follows predominantly SVO (Subject-Verb-Object) order. Size is measured as the number of parallel sentences in the training data. Source (Src) and Target (Tgt) length are averaged across sentences after word-based tokenization.

| Tgt Word Order | Size  | Script Difference | White Space | Src Length | Tgt Length |
|----------------|-------|-------------------|-------------|------------|------------|
| EN-KK          | SOV   | ✓                 | ✓           | 26.7       | 20.0       |
| EN-DE          | SVO/SOV | ×               | ✓           | 25.7       | 24.3       |
| EN-PL          | SVO   | ×                 | ✓           | 16.2       | 14.6       |
| EN-HI          | SOV   | ✓                 | ✓           | 18.3       | 19.8       |
| EN-JA          | SOV   | ✓                 | ×           | 21.4       | 25.9       |
| EN-RU          | Free  | ✓                 | ✓           | 23.2       | 21.5       |
| EN-FR          | SVO   | ×                 | ✓           | 29.2       | 32.8       |

IMPUTER differs from Conditional Masked Language Modeling (CMLM) (Ghazvininejad et al., 2019) in that it utilizes the CTC loss instead of the standard cross-entropy loss, removing the need for explicit output length prediction. Also, IMPUTER is an encoder-only model that makes one prediction per source token, just like CTC. The cross-attention component from encoder-decoder is replaced by a simple sum between the embeddings of the source sequence and the input alignment ($a_{\text{Mask}}$) before the first self-attention layer.\(^1\)

2.3 Multilingual Modeling

Multilingual MT (Dong et al., 2015; Johnson et al., 2017) extends bilingual MT by training a single model with datasets from multiple language pairs, \(\{D^l\}_l\). To enable multilingual modelling in both AR and NAR models, we prepend each source sequence with the desired target language tag (<2tgt>\(^\text{\text{)}\}) and generate a shared vocabulary across all languages (Johnson et al., 2017). The model encodes this tag as any other vocabulary token, and can use this to guide the generation of the output sequence in the desired target language.

2.4 Efficiency

Inference We refrain from wallclock inference time measurements since these are dependent on implementation, low-level optimization and machines (Dehghani et al., 2021), and instead compare generation speed in terms of the number of tokens that get generated per iteration (Kreutzer et al., 2020), which is < 1 for AR models,\(^2\) \(N\) for fully non-autoregressive models like CTC and \(k\) for iterative semi-autoregressive models like IMPUTER. We acknowledge that other factors like model-depth play a role for inference time, but we assume that both NAR and AR models can be optimized for this aspect (Kasai et al., 2020).

Training At training time, NAR models are less efficient than AR models because their quality depends on distillation (Gu and Kong, 2021). Extra cost is incurred to train a teacher model (usually AR) and to use it to decode the training set.

Multilinguality As discussed above, multilingual models have the advantage of multi-tasking over language pairs, so that a single multilingual model can replace several bilingual models. Thanks to transfer across languages, model size usually needs to be increased less than \(m\)-fold for modeling \(m\) languages instead of a single one.

Considering all of the above factors, an ideal model requires only a few iterations (decoder passes or steps), requires no teacher, and covers several languages, while incurring the smallest drop in quality compared to less efficient models. CTC is desirable as it uses only one pass, while Imputer gives up some efficiency to improve quality. Both require a teacher, but we can try to reduce teacher training costs through distillation.

3 Experimental Setup

Data We perform our experiments on six language pairs, translating from English into WMT-14 German (de), WMT-15 French (fr), WMT-19

\(^1\) We experimented with an encoder-decoder variant of IMPUTER but it did not change the overall output quality in multilingual scenarios or otherwise.

\(^2\) We assumed that both NAR and AR models can be optimized for this aspect (Kasai et al., 2020).

\(^3\) http://www.statmt.org/wmt14/translation-task.html

\(^4\) http://www.statmt.org/wmt15/translation-task.html
Table 2: Multilingual and Bilingual AR and NAR models trained on English → X direction.

| MODEL          | TEACHER     | $N_{gen}$ | EN-FR | EN-DE | EN-PL | EN-RU | EN-HI | EN-JA | AVG. |
|----------------|-------------|-----------|-------|-------|-------|-------|-------|-------|------|
| AR-big         | multi-AR-big| < 1       | 38.8  | 29.0  | 21.4  | 27.2  | 34.6  | 35.4  | 31.1 |
|                | AR-base     | < 1       | 38.5  | 27.0  | 21.6  | 25.3  | 32.6  | 33.6  | 29.3 |

**Bilingual Models**

| MODEL | TEACHER     | $N_{gen}$ | EN-FR | EN-DE | EN-PL | EN-RU | EN-HI | EN-JA | AVG. |
|-------|-------------|-----------|-------|-------|-------|-------|-------|-------|------|
| AR-base | AR-big | 38.2       | 27.6  | 21.2  | 26.2  | 33.8  | 34.8  | 30.3  |      |
| CTC    | multi-AR-big| N        | 35.1  | 24.0  | 17.7  | 20.8  | 30.8  | 28.9  | 26.2 |
| IMPUTER | AR-big | 38.5       | 27.2  | 21.2  | 25.6  | 32.0  | 32.0  | 29.4  |      |

**Multilingual Models**

| MODEL | TEACHER     | $N_{gen}$ | EN-FR | EN-DE | EN-PL | EN-RU | EN-HI | EN-JA | AVG. |
|-------|-------------|-----------|-------|-------|-------|-------|-------|-------|------|
| multi-AR-base | multi-AR-big| < 1       | 35.2  | 24.8  | 19.7  | 23.2  | 30.8  | 31.2  | 27.5 |
| CTC    | AR-big     | 31.6      | 20.5  | 13.0  | 17.7  | 28.2  | 28.1  | 23.2  |      |
| IMPUTER | AR-big       | 34.4       | 22.8  | 14.9  | 21.3  | 29.9  | 29.6  | 25.5  |      |
|        | multi-AR-big| 34.1      | 21.2  | 16.4  | 21.7  | 29.9  | 27.9  | 25.2  |      |

Russian (ru)\(^5\), WMT-20 Japanese (ja), WMT-20 Polish (pl)\(^6\) and Samantar Hindi (hi) (Ramesh et al., 2021). We also use WMT-19 English-Kazakh (kk)\(^7\) in Section 5. The sizes and properties of the datasets are listed in Table 1. Target word order and the writing script differ across these language pairs. We consider translating from English as this is more interesting and difficult direction.

We use SentencePiece (Kudo and Richardson, 2018) to generate a shared subword vocabulary for the source and target language pairs. The proportion of sub-words allocated for each language depends on the size of the language in the combined training data.

**Evaluation Metrics** We evaluate translation quality via BLEU (Papineni et al., 2002) as calculated by Sacrebleu (Post, 2018). For En-Ja we measure Character-level BLEU to be independent of specific tokenizers.

**Architecture** We train the IMPUTER model using the same setup as described in Saharia et al. (2020): We follow their base model with $d_{model} = 512$, $d_{hidden} = 2048$, $n_{heads} = 8$, $n_{layers} = 12$, and $p_{dropout} = 0.1$. AR models follow Transformer-base (Vaswani et al., 2017) and have similar parameter counts. We train both models using Adam with learning rate of 0.0001. We train CTC models with a batch size of 2048 and 8192 sentences for 300K steps for the bilingual and multilingual models respectively. We train the IMPUTER using CTC loss using a Bernoulli masking policy for next 300K steps with a batch size of 1024 and 2048 sentences for the bilingual and multilingual models respectively. We upsample the source sequence by a factor of 2 for all our experiments.\(^8\) We pick the best checkpoint based on validation BLEU for bilingual models and use the last checkpoint for multilingual models.

**Distillation** We apply sequence-level knowledge distillation (Kim and Rush, 2016) from AR teacher models as widely used in NAR generation (Gu et al., 2018). Specifically, when training the NAR models, we replace the reference sequences during training with translation outputs from Transformer-Big AR teacher model with beam = 4. We also report the quality of the AR teacher models. We experiment with two types of teachers, bilingual and multilingual.

4 Negative Transfer Scenario

Our main experiment compares English-to-X models for the six high-resource languages in Table 1.\(^8\)

\(^5\)http://www.statmt.org/wmt19/translation-task.html
\(^6\)https://www.statmt.org/wmt20/translation-task.html
\(^7\)https://www.statmt.org/wmt19/translation-task.html
\(^8\)While increasing the upsampling ratio can provide a larger alignment space, we do not vary the upsampling ratio due to small difference in the performance of the resulting NAR models (See Table 6, Gu and Kong (2021)).
These languages are typologically diverse, and each have enough data so that we do not expect them to benefit substantially from positive transfer. We use this scenario to test the impact of multilingual teachers, and to measure each paradigm’s ability to model several unrelated languages. Results are shown in Table 2.

4.1 Multilingual Teacher Comparison

The top two rows of Table 2 show that in this negative transfer scenario, multilingual teachers have substantially reduced BLEU compared to bilingual teachers. However, as we look at the impact on bilingual students, we see that CTC models trained from the multilingual teacher, multi-AR-big, do not reflect the entirety of this drop in teacher quality when compared to training with the bilingual AR-big. An average teacher gap of $-1.8$ BLEU is mapped to $-1.1$ in the corresponding students. The comparison becomes more interesting as we shift to multilingual students: multilingual CTC does not suffer at all from having a multilingual teacher (average BLEU gap of $-0.1$), and multilingual Imputer likewise suffers very little ($-0.3$). These three results taken together suggest that datasets distilled from multilingual models are likely simpler and easier to model non-autoregressively, which makes up for their lower BLEU. We explore this hypothesis further in Section 4.3. We hope that highly multilingual models, trained with similar target language pairs to exhibit positive transfer (Tan et al., 2019), might be yet better suited to serve as teachers for multilingual NAR models, which we leave to future work.

4.2 Multilingual Model Comparison

Returning to the “Bilingual Models” section of Table 2 with AR-big teachers, we can see that we have reproduced the expected results of Saharia et al. (2020). Bilingual CTC does well for a fully NAR method, but does not come close to AR quality. IMPUTER ably closes the gap with AR, surpassing or coming within 0.2 BLEU of the AR-base models on 3 out of 6 language pairs, with the largest gap in performance for the distant En-Ja. Does this story hold as we move to multilingual NAR students?

To understand each model’s multilingual capabilities, we can compare its bilingual performance to its multilingual performance. Comparing AR-base to multilingual AR-base gives us a baseline average drop of $-2.8$ BLEU, confirming that this is indeed a difficult multilingual scenario that leads to negative transfer. Comparing bilingual CTC to multilingual CTC, both with AR-big teachers, we see an average drop of $-4.1$. This larger drop indicates that CTC suffers more from negative transfer than its AR counterpart. We hypothesize that CTC needs more capacity compared to the AR model to achieve similar multilingual performance, motivating our scaling law experiments in Section 6.

Performing the same bilingual-to-multilingual comparison for IMPUTER shows a similar $-3.9$ average drop due to negative transfer. So although IMPUTER is indeed substantially better than CTC, it does not seem to be necessarily better suited for multilingual modeling in this difficult scenario.

4.3 How do the distilled datasets differ?

Table 3 summarizes different statistics for the original ($R$) and distilled datasets from both multilingual ($M$) and bilingual ($B$) AR teacher models. We report the number of types and average sequence length (in tokens) for the target side of the dataset. We compute the complexity of the dataset based on probabilities from a statistical word aligner (Zhou et al., 2019). The FRS (Talbot et al., 2011) score represents the average fuzzy re-ordering score over all the sentence pairs for the respective language pair as measured in Xu et al. (2021), with higher values suggesting that the target is more monotonic with the source sequence. We also report BLEU for the distilled datasets relative to the original training corpora.

The datasets distilled from the bilingual AR models ($B$) are shorter, less complex, have reduced lexical diversity (in number of types) and are more monotonic compared to the original corpora ($R$), which is aligned with prior work (Zhou et al., 2019; Xu et al., 2021). Interestingly, for En-Ja, we observe that the distilled datasets are less monotonic than the original corpora.

The multilingual distilled datasets ($M$) have further reduced types, are shorter and less complex than the distilled datasets from bilingual teachers. The resulting distilled datasets from the multilingual teacher model specifically have increased monotonicity (FRS) for the more distant language pairs, Japanese and Hindi. As shown in Xu et al. (2021), the reduced lexical diversity and reordering complexity both help NAR learn better alignment between source and target, improving the translation quality of the outputs.
Table 3: Comparison of datasets distilled from Biligual (B) or Multilingual (M) AR models on a subset of 1M samples: Multilingual distilled datasets have fewer types, are less complex and more monotonic than bilingual distilled datasets, despite having lower BLEU.

4.4 Error Analysis

In this section, we present a qualitative analysis to provide some insights on how NAR models differ in output quality across different language pairs when trained in isolation (bilingual) or with other language pairs (multilingual).

**Figure 1**: Brevity penalty (BP) scores for all models for all the language pairs. “-B” and “-M” and bilingual and multilingual models respectively.

**Effect of length** We show the brevity penalty scores from all the languages in Figure 1. Among all the language pairs, both en-pl and en-ja have lowest brevity penalty scores. This could be attributed to the subject pronouns being dropped in both of these target languages. Multilingual modeling of most of the language pairs results in shorter outputs relative to bilingual models for both AR and NAR models. While IMPUTER is generally able to improve the low brevity penalty values compared to CTC models, they still lag behind AR models, suggesting that length of the output might need to be controlled explicitly for these language pairs (Gu and Kong, 2021).

**Invalid Words** Our manual inspection suggested that CTC frequently generates invalid words — tokens that are not present in the target side of the training set or in the test set references. In the Hindi example below, the invalid (or made-up) word in the sentence is marked in red.

We compute the percentage of sequences that include at least one invalid word and report the statistics in Figure 2. CTC generates many invalid words compared to both AR (Average: 0.09-0.14) and IMPUTER (Average: 0.14-0.37), with multilingual modeling leading to an average increase in invalid words by 37%. We attribute this to the limited vocabulary of the model resulting in longer subword segmentation and the conditional independence assumption leading to unrelated adjacent
subwords, which merge to create invalid words.

Figure 2: % Invalid words observed in the outputs from all languages. “B” and “M” and bilingual and multilingual models respectively.

5 Positive Transfer Scenario

In this section we present two experimental setups designed to study positive transfer for similar language pairs, where one or both languages have less than the ideal amount of data.

English→{German, French} To better isolate the effect of transfer via multilingual modelling, we simulate a resource-limited scenario by subsampling 1M samples each from German and French and train bilingual and multilingual models for both AR and NAR paradigms. By pairing two related languages and subsampling down to smaller dataset sizes, we relax the capacity bottleneck and competition amongst the languages for parameters.

Table 4 shows that NAR models benefit from training with multilingual language pairs in the resource-constrained scenario — all models exhibit positive transfer. IMPUTER achieves higher positive transfer than CTC across both the language pairs, but lags behind the AR multilingual model in en-fr. Note however that, for en-fr, the bilingual IMPUTER is already ahead of the bilingual AR model by 0.4 BLEU.

English→{Russian, Kazakh} We test the performance of the multilingual NAR model on the low-resource scenario of En→Kk, where there is not sufficient clean training data to train an AR model in the first place. We instead distill datasets from the publicly available multilingual autoregressive model, PRISM (Thompson and Post, 2020). We then pair with the high-resource Russian to encourage positive transfer to Kazakh. Given the huge difference in dataset sizes for Russian and Kazakh (see Table 1), we sample training data from the two languages based on the dataset size scaled by a temperature value (T), $p^T_l$ (Arivazhagan et al., 2019), where, $p_l = \frac{D_l}{\sum_k D_k}$. We experiment with multiple temperature values: 1, 3, 5, 10, 20, where $T = 1$ implies $p^T_{ru} = 0.995$, $p^T_{kk} = 0.005$ and $T = 20$ results in approximately, $p^T_{ru} = 0.56$, $p^T_{kk} = 0.45$. The best performance on validation set was using $T = 5$ ($p^T_{ru} = 0.75$, $p^T_{kk} = 0.25$).

As can be seen in Table 5, both AR and CTC benefit from positive transfer when translating into Kazakh when trained with Russian. The CTC-M model is able to improve (BLEU: +1.6) over the CTC-B model but the overall quality of the outputs is very low compared to the teacher model (BLEU: -5.3). It highlights that current NAR models do not perform well on very low-resource language pairs and might benefit from additional data augmentation strategies in addition to transfer from other similar language pairs.

6 Impact of Model Scale

Prior work has studied scaling laws for MT to understand the relationship between the output quality
(BLEU), the cross-entropy loss and the number of parameters used for training the model (Ghorbani et al., 2021; Gordon et al., 2021). Based on our hypothesis that CTC might require more capacity than AR models, we study the relationship between the number of parameters used for training the models and the development BLEU averaged across all the language pairs.

We derive the relationship between BLEU and the number of parameters \((N)\) directly from the scaling laws proposed in Gordon et al. (2021) and Ghorbani et al. (2021) as follows:

\[
L(N) \approx L_0 + \alpha_n \left(\frac{1}{N}\right)^\alpha_k \quad \text{(Ghorbani et al., 2021)}
\]

\[
\text{BLEU}(L) \approx C e^{-kL} \quad \text{(Gordon et al., 2021)}
\]

\[
\text{BLEU}(N) \approx a e^{-b\left(\frac{1}{N}\right)^c} \quad \text{(this work)}
\]

where \(L\) is the test loss, \(\{\alpha_n, \alpha_k, L_0, C, k\}\) are fitted parameters from previous power laws, and \(\{a, b, c\}\) are the collapsed fitted parameters of our power law. Ghorbani et al. (2021)’s \(L_0\) corresponds to the irreducible loss of the data, which becomes \(a\) in our formulation.

**Setup** We train seven different models with varying capacity using uniform scaling for both AR and CTC models (see below). We use the same number of layers and model dimension and train both AR and CTC models on distilled datasets from bilingual teacher, AR-big, to make a fair comparison.\(^{10}\)

| # of Layers | Model Size |
|-------------|------------|
| 6           | 128        |
| 6           | 256        |
| 12          | 256        |
| 12          | 512        |
| 24          | 512        |
| 12          | 1024       |
| 24          | 1024       |

Table 6: The feed-forward size is 4 times the size of the model. All AR models have equal number of encoder and decoder layers. The number of attention heads is given by \((8/(512/\text{ModelSize}))\).

**Results** Figure 3 shows the fitted parameters using the model derived using scaling laws respectively — the scaling-law based model is almost able to perfectly describe the relationship between the number of parameters and the development BLEU \((R^2 \text{ AR: 0.99}). When the number of parameters are less than 10M, both AR and CTC model result in approximately similar quality outputs. However, as the number of parameters increases, the gap in BLEU also increases, suggesting that with sufficient number of parameters AR models are able to generate higher quality outputs due to the conditional dependence between tokens. We can also see that CTC needs many more parameters to achieve comparable BLEU to AR models and plateaus early at a BLEU of 26.7, while AR models plateau at 30.8. By projecting the curves out to 1 billion parameters, we can show that increasing the capacity of NAR is insufficient to reach the quality of AR models.

**7 Related Work**

**Non-Autoregressive MT** Multiple approaches with varying architectures (Gu et al., 2018, 2019; Chan et al., 2020; Xu and Carpuat, 2021), custom loss functions (Ghazvininejad et al., 2020; Du et al., 2021) and training strategies (Ghazvininejad et al., 2019; Qian et al., 2021) have been used to enable parallel generation of output tokens for MT. While most of the prior work focuses on better utilization of distilled datasets, we focus on evaluating and understanding the impact of using multilingual distilled datasets for NAR training.

**Multilingual MT** There has been a lot of interest in the AR literature on understanding and proposing models that enable translation between...
more than two language pairs (Dabre et al., 2020). Both supervised and unsupervised (Sun et al., 2020) learning in MT have benefitted from training with multiple languages, especially those that have very little (Siddhant et al., 2020) to no training data (Zhang et al., 2020). However, multilingual modelling has not yet received any attention in the NAR literature. Concurrent to our work, Anonymous (2022) investigate a non-autoregressive multilingual machine translation model with a code-switch decoder. They show that adding code-switched back-translation data to the training of multilingual models improves performance. Our work instead focuses on understanding multilinguality for both the student and the teacher model in the context of NAR training without using any additional data augmentation strategies.

Distillation  
Sequence-level knowledge distillation is one of the key ingredient in the training of NAR models. Recent works have focused on understanding the success of knowledge distillation in NAR training. Zhou et al. (2019) show that distilled datasets have reduced complexity compared to original bitext which is suitable for NAR training. Xu et al. (2021) further show that different types of complexity, i.e. reducing lexical diversity and reordering degree have different impacts on the training. Voita et al. (2021) argue that the complexity of the dataset increases as the training of the AR model progresses and use this to improve the performance of NAR model by distilling from an earlier checkpoint. In this work, we focus on understanding the impact on quality and complexity of distilled datasets from multilingual and bilingual AR teacher models.

Scaling Laws  
While large scale models improve performance, it is practically impossible, time consuming and expensive to train the different variants of the model given different architectures and dataset sizes based on the amount of compute available. Recent works have derived empirical scaling laws that govern the relationship between the performance of the model and these factors (Kaplan et al., 2020; Hernandez et al., 2021; Bahri et al., 2021; Gordon et al., 2021; Ghorbani et al., 2021). However, these scaling laws have not yet been studied for multilingual MT which we explore in our work.

8 Conclusion

While the community has achieved significant progress in improving the performance of NAR and semi-NAR models, the focus on benchmarking on a few language pairs has impeded our understanding of how these models might generalize to multilingual settings. The need for distilled datasets from AR models limits the ceiling on translation quality while adding the expense of training additional models to translate the training set. We have shown that generating distilled datasets from a multilingual model is a good alternative, and have provided insights on how multilingual teachers might differ from bilingual ones in quality and complexity. But as we show in our analysis, generating sequences of the right length and with valid tokens remains a challenge, and one that only grows as we move to either multilingual modeling or to more distant language pairs. We are far from using off-the-shelf models to enable non-autoregressive generation in resource constrained scenario even with positive transfer from similar languages. Moving forward, we need to improve the coverage of language pairs studied in order to set better expectations from multilingual NAR models, and to better understand why our multilingual models are unable to reach the quality of their teachers, even with increased capacity.

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