Beyond the Mode: Sequence-Level Distillation of Multilingual Translation Models for Low-Resource Language Pairs

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Abstract

This paper delves into sequence-level knowledge distillation (KD) of multilingual pre-trained translation models. We posit that, beyond the approximated mode obtained via beam search, the whole output distribution of the teacher contains valuable insights for students. We explore the potential of n-best lists from beam search to guide student's learning and then investigate alternative decoding methods to address observed issues like low variability and under-representation of infrequent tokens. Our research in data-limited scenarios reveals that although sampling methods can slightly compromise the translation quality of the teacher output compared to beam search based methods, they enrich the generated corpora with increased variability and lexical richness, ultimately enhancing student model performance and reducing the gender bias amplification commonly associated with KD.

1 Introduction

Neural machine translation (NMT) is an essential tool for communication and understanding between people who speak different languages. While there are NMT models that offer high performance for translation of high-resource languages, low-resource languages, often with limited available training data, still pose a significant challenge for NMT (Goyal et al., 2020).

Multilingual NMT models have the potential to address this issue by leveraging information from high-resource languages (Tran et al., 2021). A number of multilingual pre-trained models have been released in recent years, often performing better for low-resource languages than bilingual models trained from scratch, such a NLLB-200 (NLLB Team et al., 2022), DeltaLM (Ma et al., 2021) and MADLAD-400 (Kudugunta et al., 2023). Large Language Models (LLM) also take advantage of high-resource languages and provide high quality translations for these high-resource languages, but their results are much worse than traditional encoder-decoder models when working with low-resource languages (Zhu et al., 2024). Despite the performance of multilingual NMT, their hardware requirements make them impractical for general use. Knowledge distillation (KD) (Hinton et al., 2015) offers a solution by transferring knowledge from a large *teacher* model to a smaller *student* model.

KD techniques can be classified into word-level (Hinton et al., 2015) and sequence-level (Kim and Rush, 2016). Word-level KD mimics the teacher's probability distribution for each token, while sequence-level KD uses a synthetic corpus generated by the teacher to train the student model. In both cases, the same corpus used to train the teacher is used for the distillation. Although both approaches have been widely studied in bilingual contexts (Wang et al., 2021; Zhang et al., 2018), they rely on the availability of the training parallel data, often unavailable for pre-trained multilingual models developed by private companies. It is also possible that the desired translation direction works thanks to transfer learning, but there is no parallel corpus available for the target language pair.

In the absence of the parallel corpus used to train the teacher, the way to use sequence-level KD is to translate a monolingual corpus to obtain a synthetic parallel corpus with which to train the student model (Lai et al., 2021; Yu et al., 2021). Sequence-level KD has typically been conducted using beam search (Graves, 2012; Kim and Rush, 2016), but this is detrimental to lexical richness. Beam search prioritises maximising the probability of the generated sequence, leading to repetitions, low

variability (Kulikov et al., 2019) and under-representation of infrequent tokens (Müller and Sennrich, 2021). Consequently, a corpus generated via beam search is less lexically rich compared to a native corpus (Holtzman et al., 2020). The over-representation of the most likely tokens by beam search limits the student model's exposure to a smaller range of plausible translations, as beam search translations are biased towards the most common patterns. This reduces the model's robustness, flexibility and ability to generalise. As demonstrated by Ahn et al. (2022), training with biased data amplifies the social and gender biases present in the teacher model. Beam search's emphasis on high probability results may increase the frequency of stereotypical or biased translations, explaining why distilled models show more bias than the teacher (Vamvas and Sennrich, 2021).

In this paper, we explore whether beam search is the best way to extract knowledge from a large multilingual NMT model for sequence-level KD, and whether sampling methods (Fan et al., 2018a), that generate more human-like text (Holtzman et al., 2020), are a feasible or complementary alternative. We posit that the teacher's full output distribution holds valuable insights for the student, thus supplementing the limited information captured by the approximated mode of the target language distribution obtained via beam search. In order to extract a broader range of knowledge from the teacher, we propose to generate several translations from the same source sentence, using the n-best list of beam search[1] or diverse beam search (Vijayakumar et al., 2018) or multiple iterations with sampling methods. We hypothesise that these multiple translations will reduce the over-representation of the most likely tokens, helping the student model to generalise better and reduce model gender bias.

This leads us to formulate the following research questions:

- RQ1: Is it effective to generate multiple translations from the same source sentence in sequence-level KD?
- RQ2: Is it possible to reduce bias amplification with multiple translations?
- RQ3: Can other decoding methods overcome the limitations of beam search?
- RQ4: What is the influence of factors such as the size of the corpus translated by the teacher and the sampling hyperparameters that control deviation from the mode?

To the best of our knowledge, this is the first paper to compare the properties of decoding methods focused on extracting knowledge from a pre-trained multilingual teacher model using only monolingual corpus.

This paper is structured as follows: next section describes related work. Section 3 presents the decoding methods used, the scenarios studied and the metrics used. Section 4 shows the experiments carried out to analyse the key variables in the distillation process and the results of each experiment, followed by the concluding remarks and future work in Section 5.

2 Related work

Neural models generate output tokens by producing a probability distribution over the target vocabulary at each decoding step. There are two ways for selecting these output token: deterministic methods, which prioritise high-probability tokens but offer low variability (Kulikov et al., 2019), and stochastic methods, which sample from the distribution but can lead to incoherent text (Basu et al., 2021). For *directed generation* tasks, such as NMT, beam search is commonly used because the output is closely tied to the input, and variability is less critical. In contrast, *open-ended* tasks, like story generation, require more diverse and human-like output (Holtzman et al., 2020). While several studies analyse decoding methods (Su et al., 2022; DeLucia et al., 2021; Wiher et al., 2022) and evaluate the quality of the resulting corpus (Pillutla et al., 2021), their focus on LLM and open-ended tasks limits their applicability to NMT.

Concerning NMT, despite some proposed methods to increase translation variability (Kool et al., 2019; Leblond et al., 2021; Hewitt et al., 2022), beam search remains the most widely used, especially for sequence-level KD (Kim and Rush, 2016). The reason for the extensive use of beam search is due to its balance between computational efficiency and

[1] Kim and Rush (2016) suggested using n-best lists from beam search but concluded that the 1-best "worked well".

output quality. Though approaches like Minimum Bayes' Risk (MBR) decoding (Kumar and Byrne, 2004) yield better translation quality, they are too slow for practical use, even with recent optimisations (Freitag et al., 2023; Vamvas and Sennrich, 2024). While the relationship between corpus quality and variability has been explored in open-ended tasks (Zhang et al., 2021), it is understudied for KD in NMT.

Regarding research on KD with multilingual translation models, some studies employ multiple teacher models, multilingual (Do and Lee, 2023) or bilingual (Tan et al., 2019), to distil knowledge into a multilingual student. In contrast, our approach uses a single teacher to distil knowledge into a bilingual student, differing from methods like Gumma et al. (2023), which compress a single multilingual teacher into a multilingual student. Similarly, De Gibert et al. (2023) distil a high-resource pair from NLLB and then fine-tune the student on the low-resource languages. Concerning bilingual student models, some methods use high-resource languages related to low-resource ones for distillation, training the student with both languages as sources and English as the target (Song et al., 2023). In contrast, our study is not limited to English as the target language. Another approach fine-tunes the teacher for specific language pairs and trains the student model with a mix of parallel and synthetic data (Galiano-Jiménez et al., 2023). Recently, MBR has been used to generate sequences with an LLM to fine tune an encoder-decoder translation model (Finkelstein and Freitag, 2024) and the conclusion was that the student model fine-tuned with MBR outputs outperforms the model fine-tuned with beam search translations. The difference with our work is that they used an LLM to translate and generated only one translation.

3 Experimental settings

This section describes the technical details of the experiments carried out. It starts with the decoding methods to be analysed, moves on to the language pairs, the model and the corpora used, and finally explains the features to be evaluated and how to measure each of them.

3.1 Decoding methods

This study focuses on a selected set representing both deterministic and stochastic methods. Beam search and diverse beam search as a deterministic methods and nucleus sampling and top-k sampling as stochastic methods.[2]

Beam search: At each decoding step beam search keeps the n highest probability paths (Graves, 2012). This has the advantage of identifying high probability sequences that start with low probability initial tokens and would have been ignored if the chosen token was always the most probable, as in the case of greedy decoding.

Diverse beam search: It is a variant of beam search that tries to produce more diverse results. Instead of maintaining a single list of the most likely paths, it divides the n paths into G groups and applies a penalty to prevent them from being similar to each other (Vijayakumar et al., 2018). As recommended by the authors, we used n=G, i.e. as many groups as n, with only one sequence per group, and λ=0.5.

Top-k: The k most likely next tokens are filtered and the probability mass is redistributed among them (Fan et al., 2018b). A small k means less variability and progressively more similarity to greedy decoding. For our experiments, we kept the original proposal of k=10 (Fan et al., 2018b), which has proven to work well for generating synthetic corpora for back-translation (Zhang et al., 2020).

Top-p (nucleus sampling): It chooses from the smallest possible set of tokens whose cumulative probability exceeds the probability p (Holtzman et al., 2020). The probability mass is then redistributed among this set of tokens. This way, the size of the set of tokens can dynamically increase and decrease according to the next token's probability distribution. Following Eikema and Aziz (2022), we set p to 0.7 in our experiments.

3.2 Teacher models and language pairs

We used NLLB 1.3B and NLLB 3.3B (NLLB Team et al., 2022) as teacher models to assess

[2]We exclude ancestral sampling from our analysis because the NLLB model was trained using label smoothing, which elevates the likelihood of rare events, leading to translations of significantly lower quality.

Lang. pair	BS	DBS	top-p	top-k
eng-swh	33.1	32.2	25.1	21.5
eng-ibo	16.1	13.7	12.4	10.9
eng-bam	6.8	6.1	4.9	4.6
swh-eng	42.9	42.4	34.8	28.8
ibo-eng	30.3	30.3	24.3	20.9
bam-eng	17.8	16.2	14.4	12.6
bam-swh	11.6	8.3	8.9	8.3

Table 1: BLEU scores of NLLB 1.3B on the FLORES+ devtest dataset when decoding with beam search (BS), diverse beam search (DBS), top-p (average of 3 runs) and top-k (average of 3 runs). The NLLB-3.3B scores follow the same pattern and can be found in the Appendix C.

the generalisation of our approach to different model sizes.

For this study, we selected languages based on the quality of the translations performed by the teacher (Table 1) and the size of the available corpora. Our objective is to have multiple scenarios that allow us to analyse the impact of different variables at generation and training time. The languages we have chosen are English (eng), Swahili (swh), Igbo (ibo) and Bambara (bam). Translation directions to be distilled are as follows:

- **eng-swh, eng-ibo, eng-bam**. Scenario in which we have almost unlimited monolingual source corpora and different qualities of translation.
- **swh-eng, ibo-eng, bam-eng**. Scenario where we have small amount of monolingual data to translate, but enough to try out various sizes in some cases. As the teacher has learned a lot of English and beam search limits the vocabulary we can extract, we theorise that sampling methods allow us to extract more knowledge.
- **bam-swh**. Small amount of monolingual data and low quality translation. The teacher's knowledge is based on transfer learning, generalised from the other translation directions and monolingual knowledge of the source and target languages.

Data: Regarding the availability of data, English and Swahili have the most extensive corpora, from which we selected a subset of 1 million sentences. For Igbo, we used a corpus comprising 451,789 sentences, while for Bambara we employed a corpus containing 108,187 sentences. All corpora used are freely available. Specific details on the corpora can be found in Appendix A.

As development and test sets we use the FLORES+[3] (NLLB Team et al., 2022) *dev* and *devtest* respectively.

3.3 Evaluation metrics

We evaluate two main elements: the synthetic corpora and the models trained on them.

Corpora: We focus on their vocabulary, the fidelity of translations, and the sentence variability. We assess lexical richness by measuring vocabulary diversity using Zipf's Law and counting unique words and sentences to compare corpora. Variability is measured by analysing the diversity of translations generated from the same source sentence using self-BLEU (Zhu et al., 2018), with lower values indicating greater variability.

For translation quality, we rely on BLEU (Papineni et al., 2002) and chrF (Popović, 2015) to evaluate teacher output on FLORES+ dataser, given the lack of neural learnt metrics for these languages. Additionally, we report COMET (Rei et al., 2020) for the supported languages.

All corpora were generated by translating the respective monolingual corpus with the teacher, using the transformers library (Wolf et al., 2020) and the desired decoding method.

Student models: As this study focuses on KD, we have two main metrics. On the one hand, the student's translation quality, measured in the same way as for the teacher. The test set is translated using beam search (n=5). On the other hand, gender biases in the student models. Due to the lack of annotated datasets for these languages, we used contrastive conditioning (Vamvas and Sennrich, 2021) to measure bias, as described in Section 4.4.

Each student model is an encoder-decoder Transformer in its *base* configuration as specified by Vaswani et al. (2017, Tbl. 3). Given that this base model has 65M parameters, our student models are notably compact, operating at just 5% of the size of the NLLB 1.3B model.

[3] https://github.com/openlanguagedata/flores

For more details on architecture and training, see Appendix B.

4 Experiments and results

Our approach is to apply sequence-level KD using different decoding methods and generating multiple translations. The aim is to experiment with different sizes of monolingual corpora and to analyse the features of the generated corpora in order to test how these features affect the quality of the student models.[4]

4.1 Effect on distillation

Sampling methods typically yield lower performance for machine translation compared to beam search and diverse beam search as shown in Table 1. However, in this section, we assess whether, despite this drop in performance, sampling methods offer superior data for training student models.

We translated 100k sentences using beam search (n=10), diverse beam search (n=10=G), top-p, and top-k, generating 10 translations per sentence. While top-p and top-k relied on sampling, beam search and diverse beam search selected the 10 highest-probability candidates. This process yielded a training corpus of 1 million parallel sentences, with each source sentence translated 10 times into the target language. We then divided each corpus into four blocks based on the number of target sentences per source, with the complete corpus containing 10 samples, and the other blocks containing 5, 3, and 1 sample(s). The version with a single sentence from beam search corresponds to standard sequence-level KD. Subsequently, we trained student models on these generated training samples.

Fig. 1 shows the performance of student models for swh-eng and bam-swh, with scores reflecting the average BLEU on three training runs.[5]. Performance trends for other language pairs align closely with those observed for swh-eng (see Appendix C.2). ChrF scores, which exhibit a similar pattern to BLEU, are provided in Appendix C.3. The results of the statistical significance test are shown in the same appendix. We performed the test using

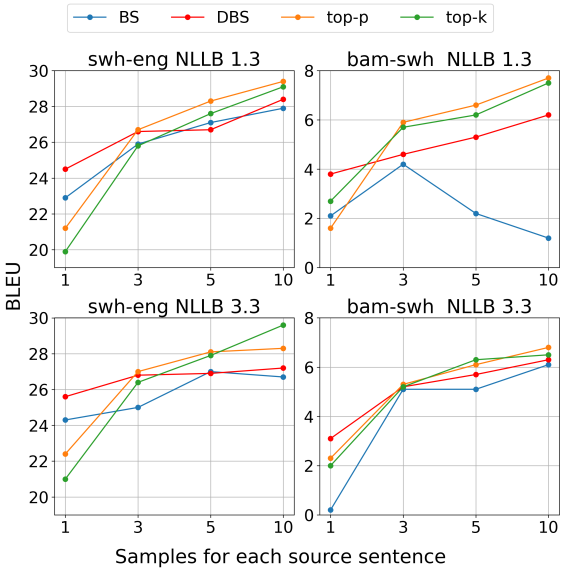

Figure 1: Average BLEU score (y-axis) obtained by student models trained on samples generated with different decoding methods and varying number of translations per source sentence (x-axis).

paired approximate randomization (Riezler and Maxwell, 2005). We compared all student models with the model trained with one translation from beam search as the first baseline and the model trained with 10 translations from beam search as the second baseline.

As expected, student models trained on beam search (or diverse beam search) outputs generally performed best than sampling methods when only one translation per sentence was generated. However, as the number of translations per sentence increased, models trained on top-p and top-k sampled data outperformed those trained with beam search and diverse beam search. Except for the eng-ibo models, all translation directions showed statistically significant differences compared to standard sequence-level KD. When compared to the second baseline, models trained with diverse beam search translations for ibo-eng, bam-eng, and eng-swh did not show differences. The gap between beam search and top-p is especially notable for bam-swh. When distilling NLLB 1.3B, students trained with 5 or 10 beam search translations performed worse than those trained with only 3 or 1 translations. In this case, traditional KD with beam search failed due to the poor quality of translations and lack of data, but sampling methods enabled student models to approach the teacher's performance.

[4]The code is available at https://github.com/***

[5]Note that, for the sampling methods, translations were generated again by the teacher in each training run.

In general, the difference between beam search and top p student models is greater when the target is English. This is in line with our hypothesis that, as the teacher has been trained with so much English and we are working with such small corpora, the sampling methods allow us to extract more information than beam search.

To explain these results, we measured the variability between the translations generated using self-BLEU (Zhu et al., 2018). As expected, deterministic methods produce sentences with low variability (even diverse beam search), whereas sampling methods, particularly top-k, yield more diverse ones (see Appendix C.1). However, top-k and top-p, despite generating more diverse translations, produce repeated translations, specially in the case of top-p, due to a narrow choice window when the model is confident. This, while potentially limiting diversity, can prevent hallucinations that could harm student training. About lexical diversity, Zipf's distribution(Holtzman et al., 2020) analysis shows that corpora amplified with sampling from smaller texts are more similar to native corpora than those produced by beam search with a single translation from larger texts. These results are presented in the Appendix C.1 as they are not novel. Intuitively, the generation of multiple translations by beam search might result in either very similar sentences, adding little value, or hallucinations when the model is forced into less probable paths. This depends on the model's confidence and knowledge of the language.

To ensure that the improvements seen with sampling methods were not simply due to a particularly good translation among the multiple outputs, we conducted an additional experiment. For the eng-swh corpus generated by top-p and 10 translations, we selected the best translation for each sentence based on COMET without reference. We used only these selected translations to train a student model. The resulting performance was similar to that of a model trained with just one translation, confirming that the improvements observed with sampling methods were driven by the diversity of multiple translations.

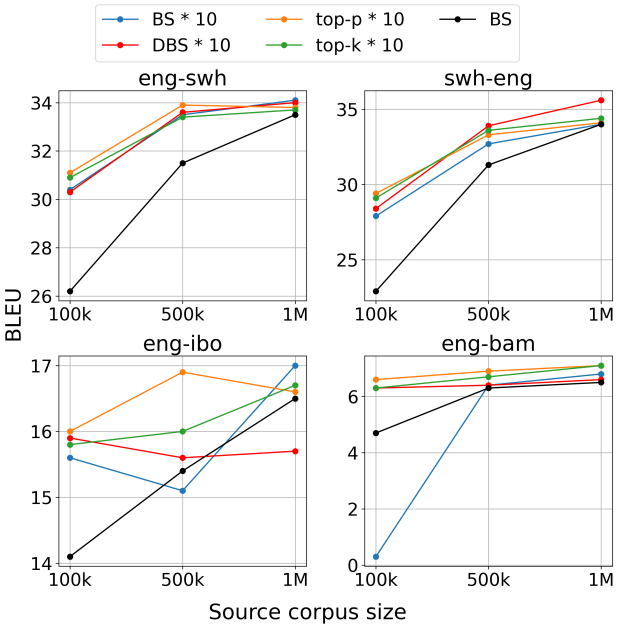

Figure 2: BLEU scores attained for different corpus sizes. BS corresponds to the standard sequence-level KD, and BS×10 correspond to the use of beam search to generate 10 translations per source sentence.

4.2 Impact of source corpus size

The size of the source corpus plays a crucial role, as a larger corpus allows for more knowledge to be extracted from the teacher. To analyse how this affects KD with sampling methods, we translated 100k, 500k and 1 million sentences, generating 10 translations per sentence. We compare each size with the result of translating the same corpus using beam search ($n = 10$) by generating a single translation.

Figure 2 shows the performance of student models trained on samples generated from corpora of different sizes. The results for all translation directions can be found in Appendix C.3. As observed, the discrepancy between different decoding methods decreases as the corpus size increases. For corpora of 500k sentences, sampling methods still outperform beam search, while for corpora of 1 million sentences, sampling methods do not consistently yield superior results. Nonetheless, generating multiple translations remains advantageous. COMET results for the languages it supports are shown in Figure 3.

To explore the importance of lexical richness in the translated corpus, we compared the number of unique words in both the source

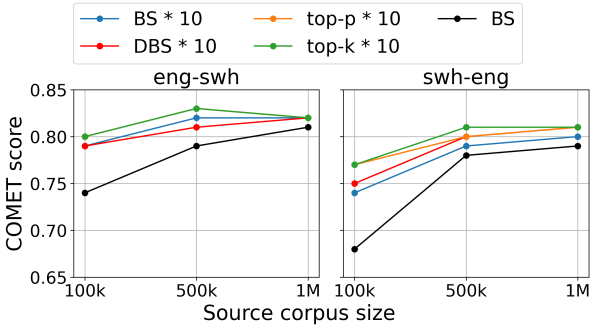

Figure 3: COMET scores by student models on the FLORES+ devtest dataset. The results of top-p and top-k overlap in the eng-swh graph.

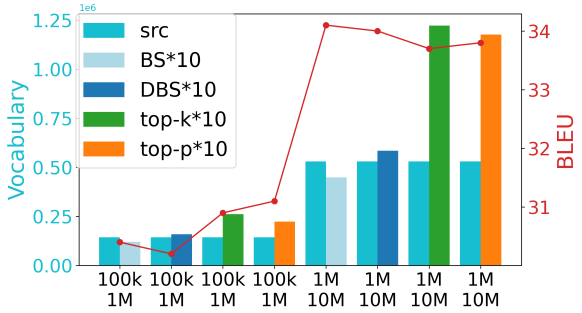

Figure 4: Relationship between the vocabulary of the training corpus and the BLEU of the student models. X-axis markers indicate sentences from the source corpus (first row) and sentences from the generated corpus (second row).

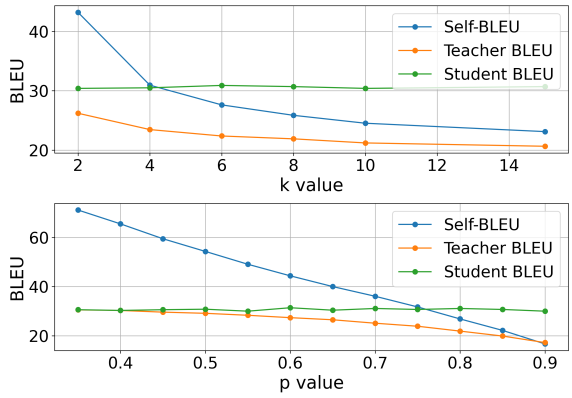

Figure 5: Relationship between the teacher translation quality and variability and the student models score for eng-swh. Initial corpus: 100k sentences

corpus and the generated corpus. Figure 4 illustrates the relationship between the size of the source vocabulary, the vocabulary produced by each decoding method, and the BLEU scores obtained by training student models on these corpora. The results show that sampling methods act as vocabulary amplifiers by generating multiple translations. This is particularly beneficial for smaller source corpora, while beam search may offer advantages for larger corpora and high-resources languages.

During training, models typically use teacher forcing, where the correct previous token is used as input, leading to a mismatch between training and inference. This exposure bias (Ranzato et al., 2015) can be mitigated by using beam search outputs, which are closer to the tokens generated during inference. If the source corpus is sufficiently large, beam search can extract enough vocabulary, and its similarity to the inference process benefits the student model. This also explains the performance of the swh-eng model with a 1 million source corpus using diverse beam search, which maintains the inference similarity of beam search while providing greater diversity.

4.3 Divergence from the mode vs. translation quality.

The adjustment of the sampling parameters affects both output variability and translation quality. To gauge the sensitivity of our approach to the values of p and k, we conducted experiments on eng-swh, translating 100k English sentences. Fig. 5 illustrates the impact of p and k values on both the translation performance of the student and teacher models (measured by BLEU), and the similarity of the translations (measured by self-BLEU). As observed, higher values of p and k result in more diverse translations, albeit with poorer teacher performance, while maintaining similar performance for the student models. Finally, we repeated the experiment with 1 million sentences and found that the results were consistent with previous findings, confirming that the trade-off between quality and variability is independent of corpus size.

4.4 Bias analysis.

Sequence-level KD typically carries a bias amplifitacion respect to the teacher model due to the over-representation of frequent tokens. To measure if this issue can be mitigated by generating multiple translations we used contrastive conditioning (Vamvas and Sennrich, 2021) to evaluate bias, using NLLB 1.3B as an

	eng-swh	eng-ibo	eng-bam
NLLB 1.3B	52.9	52.7	58.3
BS	49.2	49.4	50.8
BS * 10	51.0	50.2	50.3
DBS * 10	50.4	50.4	51.5
top-p * 10	51.7	50.5	52.3
top-k * 10	51.7	50.5	51.3

Table 2: Contrastive conditioning accuracy over WinoMT dataset. Higher scores are better and the blue scores mark the best student models.

evaluator model and WinoMT dataset. This method checks the probability of the translation generated by the evaluated model from the original source sentence using a disambiguated variation as the source of the evaluator model. For each decoding method, we evaluated the model trained with only one translation per source sentence and with 10 translations.

The results in Table 2 show how, for all methods, generating multiple translations for training reduces gender bias compared to training with only one translation.

5 Concluding remarks

This study investigates the effectiveness of generating multiple translations from the same source sentence in sequence-level KD with encoder-decoder models and the effect of different decoding methods.

The results show that increasing the number of translations has a positive effect on the student model performance, especially when monolingual data is limited. Using this method, we achieve similar results to standard sequence-level KD with a much smaller monolingual corpus and improve the results with the same corpus size (RQ1).

This approach also helps to reduce gender bias by increasing translation variability. This finding holds for all decoding methods, demonstrating the generalisability of the approach. Despite the overall good results, sampling methods achieve greater mitigation of bias by avoiding the over-representation of the most likely tokens inherent in beam search (RQ2).

Sampling methods allow for a more diverse corpus for learning when generating multiple translations, which is particularly beneficial for low-resource scenarios (ibo-eng, bam-eng, bam-swh). Nevertheless, with high-resource source languages, the quality of the translations and the mitigation of exposure bias obtained by beam search based methods, can compensate the low variability of these decoding methods, as occurs with eng-ibo, eng-bam and eng-swh. Especially when the teacher model has a lot of knowledge about the source and target language, it is able to produce multiple translations with a high probability. This explains why diverse beam search gives the best result for swh-eng when translating 1 million sentences (RQ3).

Regarding the deviation from the mode with sampling methods, the stability of the student models in the face of changing parameters p and k seems to indicate that the relationship between quality and variability remains balanced, allowing the student models to learn on the basis of one or the other(RQ4).

Future work A promising avenue for future work is to test whether this approach remains effective with LLMs, where sampling methods are commonly used for text generation.

Regarding decoding methods, one possible approach is to combine different techniques to exploit the advantages of each, while another option is to focus on mitigating the weaknesses of certain methods. For example, stopping the generation of translations with beam search or diverse beam search when the generated translations present very low probabilities.

In terms of explainability and interpretability, we plan to explore the precise reasons for the decrease in student translation quality observed in certain language pairs when the number of beam search translations was increased.

6 Limitations

In spite of showing stronger correlations with human judgments than BLEU or chrF, we do not use neural-based machine translation evaluation metrics such as COMET for all languages, as the associated models do not cover the languages involved in our research. Furthermore, our research has specifically focused on a single model at different sizes (NLLB 1.3B and NLLB 3.3B). Our conclusions, therefore, might not be fully applicable to different models. The decision to limit our investigation to this spe-

cific model was primarily due to constraints in computational resources and time.

As regards, other approaches to KD, our approach has not been compared to word-level KD due to the requirement for parallel corpora, which was not completely feasible within some of our constraints. Regarding the decoding methods, our experiments testing the influence of different values of p and k for training student models were limited to the English-Swahili language pair. Consequently, the findings related to particular values of these parameters may not generalise across other language pairs. It is important to note, however, that the approaches we tested are designed to be applicable to any language pair within the multilingual model, offering broad relevance despite this limitation. Moreover, the selection of the values for p and k in our study was guided by established precedents within the literature.

We did not explore combining the synthetic sentences provided by different decoding methods, as our focus was on understanding individual contributions.

Lastly, due to the fact that NLLB was trained with label smoothing (NLLB Team et al., 2022), we were unable to explore ancestral sampling in our experiments. Label smoothing increases the probability of low-frequency events, which could result in lower-quality translations in scenarios that rely on ancestral sampling.

Ethics Statement

Knowledge distillation endeavors to produce smaller, more resource-efficient NMT systems, thereby diminishing energy requirements compared to the original systems and consequently aiding in the reduction of CO_2 emissions. Moreover, it lowers the entry barrier for deploying NMT models, as the resulting models work on lower-power hardware. Our student models are remarkably compact, operating at a mere 5% of the teacher model size. However, delving into knowledge distillation necessitates a substantial number of training iterations, each accompanied by its own energy consumption. For the experiments detailed in this paper, we trained 144 Transformer models employing NVIDIA GeForce RTX 2080 Ti GPUs. Furthermore, all corpora and tools utilized in this study are available under open source licenses, ensuring the complete reproducibility of the presented results.

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A Corpora

The largest corpora correspond to English and Swahili. The English corpus is a fragment of OSCAR-3301 dataset[6] and for Swahili we used Monolingual African Languages from ParaCrawls, a collection of corpora available for the joint task Large-Scale Machine Translation Evaluation for African Languages"at WMT22 (Adelani et al., 2022). The Igbo corpus was obtained from the same collection.

To clean these three corpora, we used `monocleaner` (Sánchez-Cartagena et al., 2018). We used the available ready-to-use language packages for English and Swahili and trained a model for Igbo using the Igbo part of the wmt22_african dataset[7]. We removed all sentences with a `monocleaner` score lower than 0.5 and, for English and Swahili, we then randomly picked one million sentences. For Igbo, our final corpus comprises 451,789 sentences.

For Bambara we collected all available corpora in Hugging Face[8]. For the MADLAD-400 (Kudugunta et al., 2023) corpus we used only the clean part. After concatenating these corpora, we removed duplicated sentences and the result was 108,187 sentences.

[6] https://huggingface.co/datasets/oscar-corpus/OSCAR-2301

[7] https://huggingface.co/datasets/allenai/wmt22_african

[8] https://huggingface.co/datasets/RobotsMaliAI/bayelemabaga, https://github.com/masakhane-io/lafand-mt, https://wortschatz.uni-leipzig.de/en/download/Bambara, https://github.com/facebookresearch/flores/tree/main/nllb_seed, https://huggingface.co/datasets/bigscience/xP3, https://huggingface.co/datasets/allenai/MADLAD-400

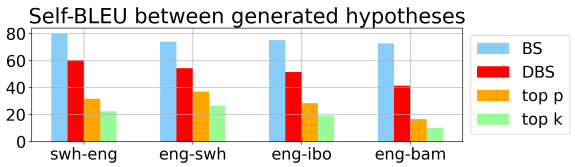

Figure 6: Similarity among the generated translations as evaluated by self-BLEU.

B Student models

Each student model consist of a transformer (Vaswani et al., 2017) with 6 layers for both the encoder and the decoder, embedding dimension of 512, feed-forward inner-layer dimension of 2048, and 8 attention heads. All our models were trained using the `Fairseq` toolkit[9] and a different joint bilingual SentencePiece (Kudo and Richardson, 2018) model for each language pair, trained on the training samples generated from the teacher with a vocabulary of 10,000 tokens. For training we used a learning rate of 0.0007 with the Adam (Kingma and Ba, 2015) optimizer (β_1=0.9, β_2=0.98), 8,000 warm-up updates and 8,000 max tokens. We used parameters dropout of 0.1 and updated the model after 2 training steps. The cross-entropy loss with label smoothing was computed on the development set after every epoch and the best checkpoint was selected after 6 validation steps with no improvement.

C Additional results

This sections reports additional results to measure the effect of decoding methods in sequence-level KD.

C.1 Lexical diversity

This section contains the experiments on lexical variability and diversity discussed in Section 4.1. Figure 6 shows the self-BLEU score obtained by each decoding method when generating 10 translations per source sentence.

Figures 7 compares the Zipf distribution of each generated corpus, translated from English to Swahili, together with the distribution of the native Swahili corpus of 1M sentences (mono_1M in the plot). The figure also includes the distribution of a corpus generated

[9] https://github.com/facebookresearch/fairseq

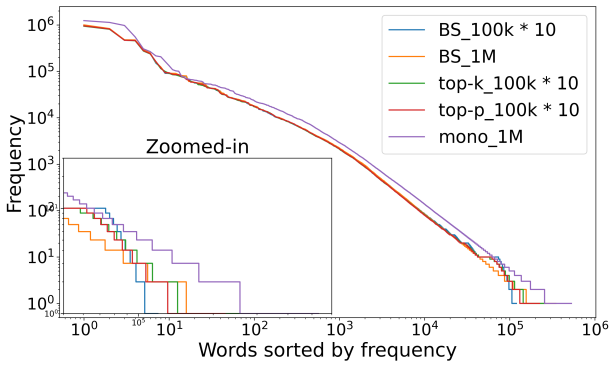

Figure 7: Zipf's distribution over Swahili corpora. Similar patterns were observed for the other languages.

by translating the English corpus of 1M sentences with beam search, but with only one translation for each source sentence (BS_1M). It can be seen that sampling methods produced corpora closer to native language corpora than beam search, even in those cases in which a small corpus is amplified via sampling.

C.2 Experiments with 100k sentences

Figure 8, 9, and 10 show the student models trained on the 100k corpora translated by NLLB 1.3B, with the exception of bam-swh, which is shown in Section 4.1. The results obtained using NLLB 3.3B are shown in Figure 11, 12, and 13

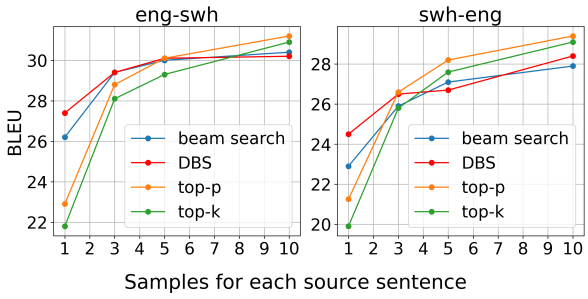

Figure 8: BLEU of eng-swh and swh-eng student models trained with corpora generated by different decoding methods and varying number of translations per source. Teacher: NLLB 1.3B.

C.3 Experiments with 500k and 1 million sentences

Tables 3 and 4 show the BLEU and chrF scores of the trained student models together with the teacher score. The results in Table 3 correspond to those in Figure 2, together with the

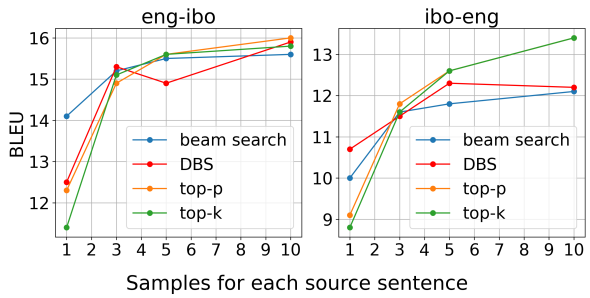

Figure 9: BLEU of eng-ibo and ibo-eng student models trained with corpora generated by different decoding methods and varying number of translations per source. Teacher: NLLB 1.3B.

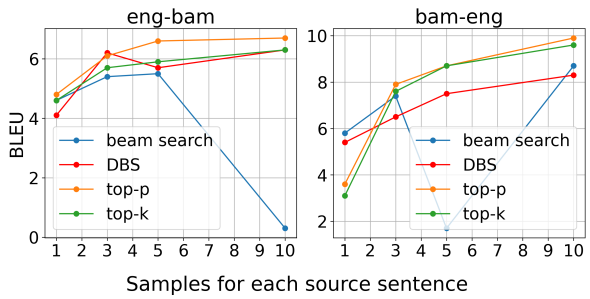

Figure 10: BLEU of eng-bam and bam-eng student models trained with corpora generated by different decoding methods and varying number of translations per source. Teacher: NLLB 1.3B.

directions for which the available corpus does not reach one million sentences.

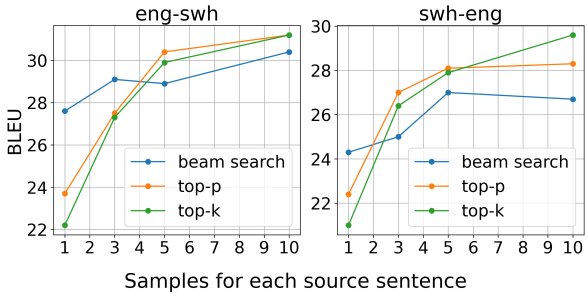

Figure 11: BLEU of eng-swh and swh-eng student models trained with corpora generated by different decoding methods and varying number of translations per source. Teacher: NLLB 3.3B.

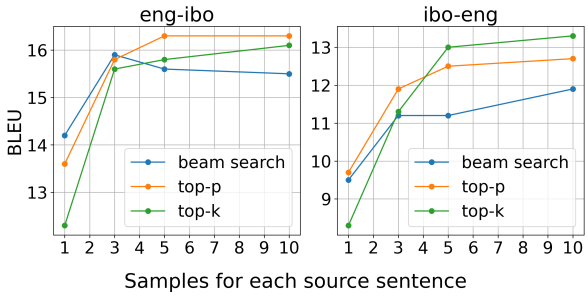

Figure 12: BLEU of eng-ibo and ibo-eng student models trained with corpora generated by different decoding methods and varying number of translations per source. Teacher: NLLB 3.3B.

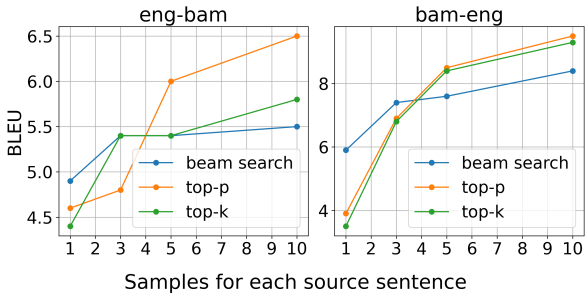

Figure 13: BLEU of eng-bam and bam-eng student models trained with corpora generated by different decoding methods and varying number of translations per source. Teacher: NLLB 3.3B.

	eng-swh	eng-ibo	eng-bam	swh-eng	ibo-eng	bam-eng	bam-swh
NLLB 1.3B	33.1	16.1	6.8	42.9	30.7	17.8	11.6
100k BS	26.2	14.1	4.7	22.9	10.0	5.8	2.1
100k BS * 10	30.4	**15.6**	0.3	27.9	12.1	8.7	1.2
100k DBS * 10	**30.2**	**15.9**	6.3	28.4	**12.4**	**8.3**	6.1
100k top-p * 10	31.1	**16.0**	6.6	29.4	13.4	9.9	7.7
100k top-k * 10	**30.9**	**15.8**	6.3	29.1	13.4	9.7	7.5
500k BS	31.5	15.4	6.3	31.3	14.2	–	–
500k BS * 10	33.5	15.1	6.4	32.7	15.5	–	–
500k DBS * 10	33.4	15.6	6.5	33.1	16.4	–	–
500k top-p * 10	33.9	16.9	6.9	33.3	16.2	–	–
500k top-k * 10	33.4	16.0	6.7	33.6	17.1	–	–
1M BS	33.5	16.5	6.5	34.0	–	–	–
1M BS * 10	34.1	17.0	6.8	34.5	–	–	–
1M DBS * 10	34.0	15.7	6.6	35.6	–	–	–
1M top-p * 10	33.8	16.6	7.1	34.1	–	–	–
1M top-k * 10	33.7	16.7	7.1	34.4	–	–	–

Table 3: BLEU scores on the FLORES+ devtest for several student models and the teacher. Underlined results are those that show no statistically significant difference compared to beam search with a single translation. Bolded results are those that show no statistically significant difference compared to beam search with 10 translations.

	eng-swh	eng-ibo	eng-bam	swh-eng	ibo-eng	bam-eng	bam-swh
NLLB 1.3B	61.8	43.2	33.3	64.8	54.0	40.2	38.3
100k BS	54.8	39.5	29.8	49.0	34.3	27.1	9.6
100k BS * 10	59.3	41.6	13.8	52.9	37.1	30.6	22.7
100k DBS * 10	59.0	41.9	30.8	53.6	37.6	31.0	31.4
100k top-p * 10	59.9	41.9	32.3	54.1	38.3	32.0	33.5
100k top-k * 10	59.4	41.8	31.7	54.1	38.2	32.1	33.6
500k BS	60.2	42.1	32.8	56.0	38.8	–	–
500k BS * 10	61.7	42.3	33.0	57.1	40.8	–	–
500k DBS * 10	61.2	42.4	32.9	57.8	41.0	–	–
500k top-p * 10	61.9	43.3	33.1	57.6	41.3	–	–
500k top-k * 10	61.7	42.5	33.1	58.1	41.7	–	–
1M BS	61.4	42.9	32.7	57.9	–	–	–
1M BS * 10	62.2	43.7	33.3	58.3	–	–	–
1M DBS * 10	62.0	42.6	32.3	59.6	–	–	–
1M top-p * 10	61.7	43.1	33.2	58.2	–	–	–
1M top-k * 10	61.8	43.2	33.2	58.5	–	–	–

Table 4: chrF scores on the FLORES+ devtest for several student models and the teacher model.