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Improving Fuzzy Match Augmented Neural Machine Translation in Specialised Domains through Synthetic Data

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Abstract

Previous studies have demonstrated the effectiveness of fuzzy match (FM) augmentation in improving the performance of Neural Machine Translation (NMT) models. However, this approach exhibits limitations when applied to scenarios where limited parallel datasets are available for NMT training. This study investigates the effectiveness of leveraging additional monolingual data to improve FM-augmented NMT performance by generating synthetic parallel datasets in domain-specific scenarios. To this end, we adopt a simple strategy for combining two data augmentation methods for NMT, namely back-translation and Neural Fuzzy Repair (NFR). Experiments conducted on three language directions, namely English→Ukrainian, English→French and French→English, two domains and various dataset sizes show that this simple approach yields significant and substantial improvements in estimated translation quality.

1. Introduction

In recent years, the field of neural machine translation (NMT) has undergone rapid advancements, first with the emergence of the (encoder-decoder) transformer models (Vaswani et al., 2017), and more recently with the (decoder-only) large language models (LLMs), exemplified by BLOOM (Scao et al., 2022), Mistral (Jiang et al., 2023), and Llama 3 (Dubey et al., 2024). Despite the growing enthusiasm for utilising LLMs for MT and the additional capabilities they possess over specialised NMT models, such as instruction following (Ouyang et al., 2022; Wei et al., 2022), their adoption does not guarantee superior performance in translation tasks, especially in specialised domains (Kocmi et al., 2023; Jiao et al., 2023; Peng et al., 2023; Son and Kim, 2023).

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In domain-specific scenarios, specialised NMT systems, as well as LLMs, have demonstrated a capacity to leverage translations of similar sentences retrieved from the training data or external databases (also referred to as 'fuzzy matches'; FMs) effectively, resulting in remarkable gains in translation quality (Bulté and Tezcan, 2019; Xu et al., 2020; Khandelwal et al., 2021; Moslem et al., 2023a). Despite the differences in the way FMs are utilised by existing approaches, the fundamental concept unifying all of them lies in their capacity to steer the MT output towards translations of retrieved FMs.

In the context of specialised NMT models, previous studies showed that FM-augmented NMT models attain their maximum potential in high-resource, domain-specific scenarios characterised by the availability of large bilingual datasets, which enhance the likelihood of retrieving FMs with higher similarity levels (Bulté and Tezcan, 2019; Tezcan and Bulté, 2022; Xu et al., 2023; Reheman et al., 2023). To address this limitation, some efforts have been undertaken to leverage additional monolingual data in the target language for directly retrieving similar translations through employing multilingual sentence embeddings, resulting in further improvements in translation quality (Cai et al., 2021; Tamura et al., 2023). More related to our work, in the context of general-domain scenarios, Pham et al. (2020) and Xu et al. (2021) proposed a simple yet novel approach for leveraging additional monolingual data in the target language for FM augmentation where synthetic source sentences are generated through back-translation in the first place. However, this approach showed mixed results regarding its impact on translation performance. As both of these studies acknowledged, the challenge of effectively utilising this approach in general domain scenarios is finding highly similar translations for a given input (high FMs).

Following up on previous work, we consider FM augmentation through the generation of synthetic source sentences more suitable for domain-specific scenarios, which are focused on specific subject areas characterised by high levels of repetitiveness in vocabulary, structure, and style. To this end, in this study, we adopt previously proposed methods for in-domain scenarios by combining two data augmentation techniques for NMT: (i) back-translation, a commonly used technique for generating synthetic data in the source language from monolingual data in the target language (Sennrich et al., 2016), and (ii) 'Neural Fuzzy Repair' (NFR), which integrates FMs into NMT through concatenating source sentences with translations of retrieved FMs (Bulté and Tezcan, 2019).

Our experimental results, spanning three language pairs and two specialised domains, demonstrate that combining the two data augmentation approaches yields significant improvements in estimated translation quality in all tested settings. Additionally, we present insights into the effectiveness of this approach by employing reduced sizes of bilingual and additional monolingual datasets and contrast it with state-of-the-art LLMs, as well as NMT systems trained under an alternative scenario, where high-quality translations for the additional monolingual data are available.

2. Related Research

Within the domain of FM-augmented NMT, various approaches have been implemented in the past, resulting in enhanced translation performance. Some examples include integrating FMs to the transformer-based NMT architectures through modifying the decoding process (Cao and Xiong, 2018; Gu et al., 2018; Khandelwal et al., 2021; Reheman et al., 2023), adding a lexical memory to the NMT architecture (Feng et al., 2017), attaching rewards for matched translation pieces from FMs into the NMT output layer (Zhang et al., 2018), introducing additional attention layers to capture relevant information from translation memories (TMs) (He et al., 2021), or modifying the whole architecture, enabling it to edit FMs to obtain a final translation (Gu et al., 2019; Bouthors et al., 2023).

Whereas most of the approaches that utilise FMs for NMT require modifications to the NMT architectures or decoding algorithms, FMs have also been successfully integrated into NMT through data augmentation techniques (Bulté and Tezcan, 2019; Xu et al., 2020; Tezcan et al., 2021). These studies vary in their approaches to measuring FM similarity, employing N-best FMs, or combining FMs with different characteristics. Nonetheless, a shared characteristic among these studies is the reliance on seeking FMs through source text similarity and augmenting source sentences during training and inference times with the translations of retrieved FMs in the target language.

Previous studies have shown that the quality of retrieved samples plays a crucial role in the effectiveness of FM augmentation. Specifically, the translation quality of FM-augmented models improves as the similarity of the retrieved FMs to the input sentence increases, with optimal results observed in high-resource scenarios (Bulté and Tezcan, 2019; Tezcan and Bulté, 2022; Xu et al., 2023; Reheman et al., 2023). As a result, in the domain of European legislation—a dataset also employed in this study—Bulté and Tezcan (2019) found that the NFR approach starts to become effective with at least 300K sentence pairs as training data.

In order to extend the capabilities of FM-augmented NMT systems beyond their reliance on parallel sentences for FM retrieval, some studies proposed leveraging additional monolingual data in the target language. For example, Cai et al. (2021) used sentence encoders to measure the similarity between sentences from the source and target languages and conditioned the translation model on both the retrieved FMs from the target language and the input from the source language to generate translations. On the other hand, Tamura et al. (2023) expanded the usefulness of the NFR approach by leveraging additional monolingual data. To this end, they trained NFR models as proposed by Bulté and Tezcan (2019) but extended the pool of sentences for FM retrieval and augmentation with the additional monolingual data during inference by measuring the similarity of source sentences with sentences in the target language through multilingual sentence embeddings. Both studies, which used additional monolingual data for FM augmentation, reported significant improvements in translation performance. In another relevant study, multilingual sentence embeddings have also been used to support translators by retrieving FMs from additional monolingual data in a TM-based computer-assisted translation environment (Esplà-Gomis et al., 2022).

Apart from these studies, a substantial body of literature exists on leveraging monolingual data in the target language to improve the translation quality of NMT systems. Some effective approaches include incorporating target-side language models into the NMT decoding step (Gulcehre et al., 2015) or for re-ranking the NMT output (Jean et al., 2015), as well as leveraging additional monolingual data through *back-translation*. In this process, a reverse NMT model is trained on existing parallel data to translate monolingual target-language data into the source language, thereby generating additional synthetic parallel training data. (Sennrich et al., 2016; Fadaee et al., 2017; Edunov et al., 2018). Notably, Xu et al. (2019) have further demonstrated that the positive effect of the synthetic training data generated through back-translation on NMT performance gradually waned with increasing sizes due to the noisy nature of source sentences. While other researchers have drawn similar conclusions regarding the performance decrease with increasing ratios of high-quality to synthetic training dataset sizes, the optimal ratios varied considerably across different studies, typically ranging from 1:1 to 1:5 (Sennrich et al., 2016; Edunov et al., 2018; Ng et al., 2019).

Our work stems from the technique explored by Pham et al. (2020) and Xu et al. (2021), which leverages additional monolingual data in the target language for FM augmentation with a different strategy. Both studies extended the pool of source sentences for FM retrieval and augmentation with the synthetically generated source sentences via back-translation, as well as using the same sentence pairs as extra training data, applying this approach in general domain settings. In one set of experiments, for the English→French language direction, this approach yielded limited gains in translation performance compared to FM-augmented NMT systems using only the available parallel datasets, consisting of approx. 4.5M sentence pairs from different domains, resulting in +0.6 and +1.8 BLEU scores in the news and Wikipedia domains, respectively (Pham et al., 2020). Notably, to achieve the improvements from additionally employing the synthetically generated data for FM augmentation, approx. 83.5M (news) and 6.5M (Wikipedia) monolingual sentences in the target language were required. Furthermore, in the same study, this approach was outperformed by a standard NMT system trained only on the original parallel sentences (without FM augmentation) in the news domain (-0.6 BLEU). Overall, despite having access to extensive monolingual datasets, FM-augmentation with backtranslated sentences in these general domain experiments resulted in limited effectiveness.

In a second set of experiments, this approach was applied to the news domain and for domain adaptation, using 10M additional sentences in the target languages[1] (Xu et al., 2021). When applied to the news domain, this approach generally resulted in lower BLEU scores compared to simply using synthetically generated datasets via back-translating target sentences, as additional training data (-2.6 BLEU and -0.1 BLEU on the WMT'19 translation test set; and -3.6 BLEU and +0.2 BLEU on the WMT'20 translation test set for the French→German and German→French language directions, respectively). Similar to the findings of Pham et al. (2020), Xu et al. (2021) demonstrated that FM-augmentation with back-translated sentences for NMT was generally ineffective for improving MT performance in general domain settings[2].

In the same study, this approach was also used for domain adaptation for the German→French language direction, where the bilingual and monolingual news data was used for training and FM augmentation for translating a test set extracted from the European Central Bank (ECB) corpus. The experiments showed that using back-translated sentences (paired with hand-crafted target sentences) both as extra training data and additionally for FM augmentation was detrimental to translation performance, yielding -0.8 BLEU scores for both types of systems compared to a standard NMT system trained on the available parallel datasets (without FM augmentation). Further experiments on increasing the minimum similarity threshold up to $\lambda \geq 0.85$ for FM retrieval also resulted in mixed outcomes in both experiments.

In addition to the aforementioned studies that focus on improving specialised NMT models, FMs and previously seen translations in the same domain as the input have recently been utilised to improve the translation quality of LLMs, by integrating them into the prompts used for generating translations, a method referred to as in-context learning (Mu et al., 2023; Moslem et al., 2023a), and into the fine-tuning process (Alves et al., 2023; Moslem et al., 2023b).

3. Methodology

3.1. Neural Fuzzy Repair

For implementing NFR, we followed the work of Tezcan et al. (2021)[3]: for a given bilingual dataset, consisting of source/target sentence pairs S, T, we augmented each source sentence $s_i \in S$ with the translations $\{t_1, \ldots, t_n\} \in T$ of the most similar

[1]While the authors stated that they used all available parallel data for the WMT'21 translation task with the exception of the ParaCrawl data, the exact size of the parallel data used for training was not explicitly provided.

[2]Neither study included statistical significance analyses for these reported differences in estimated translation performance.

[3]`https://github.com/lt3/nfr`

source sentence in the same dataset[4] $\{s_1, \ldots, s_n\} \in S$ (i.e., fuzzy match; FM), where $s_i \notin \{s_1, \ldots, s_n\}$, given that the FM score is sufficiently high (i.e., above the given threshold): $\lambda \geq 0.5$. To this end, we measured FM score $FM(s_i, s_j)$ between two source sentences s_i and s_j as the cosine similarity between their sentence embeddings e_i and e_j:

$$FM(s_i, s_j) = \frac{e_i \cdot e_j}{\|e_i\| \times \|e_j\|} \tag{1}$$

where $\|e\|$ is the magnitude of vector e.

To generate sentence embeddings, we used sent2vec (Pagliardini et al., 2018), and for efficient retrieval of FMs, we built a FAISS index (Johnson et al., 2021). The hyperparameters used for generating sentence embeddings and building the FAISS index are provided in Appendices A.1 and A.2, respectively. Prior to retrieving FMs, all sentences were segmented into sub-words using SentencePiece (Kudo and Richardson, 2018), using the XLM-RoBERTa (base) tokenizer[5]. An example of the FM retrieval and data augmentation process is provided in Table 1.

S	Debt, breakdown by **residual** maturity
score	0.9812
FM_S	Debt, breakdown by **initial** maturity
FM_T	Dette, ventilation par échéance **initiale**
S'	Debt, breakdown by **residual** maturity $< sep >$ Dette, ventilation par échéance **initiale**
T	Dette, ventilation par échéance **résiduelle**

Table 1. An example of FM retrieval and source augmentation (S') for a given source sentence (S) for the EN→FR language direction, with the translation 'T'. 'FM_S' and 'FM_T' refer to the source and target sides of the retrieved FM, respectively. The sentence similarity score is indicated as 'score'.

The NFR model is trained with an off-the-shelf NMT toolkit, namely the OpenNMT-py toolkit (Klein et al., 2017), using the combined dataset, which consists of the original and the augmented source/target sentence pairs S, T and S', T, respectively. Combining the original parallel data with the source-augmented parallel data allows the NFR model to handle both the augmented and non-augmented source sentences as input (Bulté and Tezcan, 2019). Each source sentence is augmented at inference time using the same FM retrieval method described above. Following previous work,

[4]We used "@@@" as a separator between the source sentence and the translation of the retrieved FM.

[5]https://huggingface.co/docs/transformers/v4.22.2/en/model_doc/xlm-roberta#overview

we used a minimum similarity threshold of $\lambda \geq 0.5$ for FM retrieval (Tezcan et al., 2021). If no FMs are found with a match score above this threshold, the original, non-augmented source sentence is used as input to the FM-augmented NMT model. While different minimum similarity thresholds have been tested in previous studies (Pham et al., 2020; Xu et al., 2020; Tezcan et al., 2021), we keep this value fixed in this study.

3.2. Combining Neural Fuzzy Repair and back-translation

In the context of NMT, NFR and back-translation can be considered complementary data augmentation techniques. While NFR aims to use existing training data more efficiently by steering the MT output for a given input towards the translation of the most similar sentence found in the same data, back-translation aims to generate additional parallel data for training, where the source side consists of synthetically generated sentences. Therefore, following the work of Bulté and Tezcan (2019), Pham et al. (2020), and Xu et al. (2021), by combining these two data augmentation approaches, we expect to leverage gains in translation quality in domain-specific scenarios from two angles: first, by expanding the pool of source sentences for retrieving FMs with high similarity, even if they are partially synthetic; and subsequently, by generating additional, synthetic training data, which is augmented with the translations of retrieved FMs, consisting of non-synthetic, high-quality texts from the target language.

The methodology used in this study, which combines back-translation and NFR, is illustrated in Figure 1. First, we train a back-translation model using the original parallel data to translate in the reverse language direction. Next, we utilise this back-translation model to translate the additional monolingual sentences in the target language to the source language. Finally, we combine the resulting synthetic parallel data with the original training data and implement NFR training and inference, as described in the previous section.

4. Experimental Setup

This section outlines the datasets (Section 4.1), the implementation details of the different NMT systems (Section 4.2), as well as the evaluation methodology used in this study (Section 4.3).

4.1. Data

The first set of experiments was conducted for the English→Ukrainian (EN→UK) language direction, using bilingual and monolingual datasets in the legal domain, collected from the European Language Resource Coordination (ELRC-SHARE) Reposi-

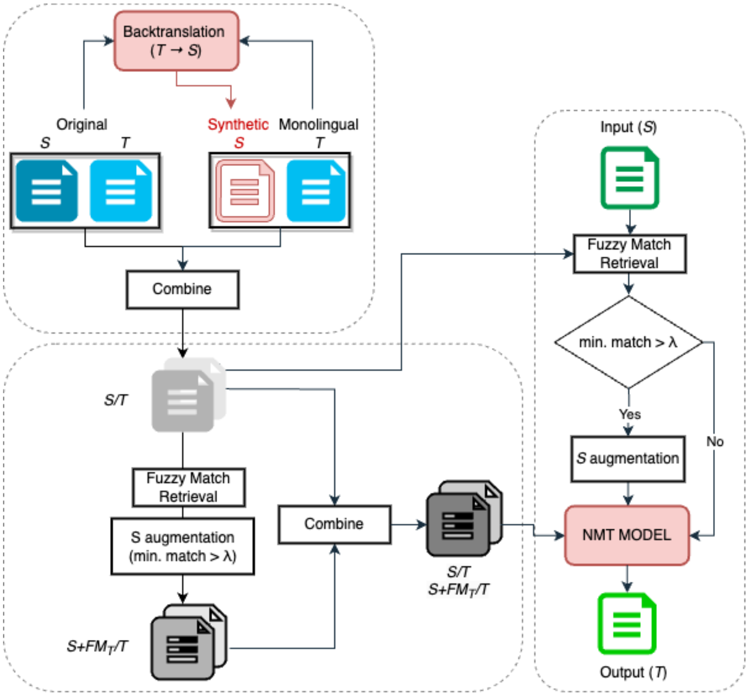

Figure 1. Overview of the methodology used in this study, which utilises the 'Original' source (S) and target (T) sentences to build a back-translation model and translates the additional monolingual data in the target language 'Monolingual T' to source language 'Synthetic S' (top-left), then implements the NFR training (bottom-left), and finally the NFR inference (bottom-right) steps.

tory[6]. The bilingual dataset consisted of the translations of the EU acts into Ukrainian[7] (EN→UK) and the translations of the Ukrainian laws into English, collected from the official web-portal of the Parliament of Ukraine[8,9] (UK→EN). The monolingual Ukrainian data consisted of a random subset of sentences collected from the documents of the official web portal of the Ukrainian parliament[10] and the Legal Ukrainian

[6] `https://elrc-share.eu/`, CC-BY-4.0 license

[7] EU acts in Ukrainian

[8] Abstracts of Ukrainian Laws in English

[9] Ukrainian Laws in English

[10] Legal documents of the Parliament of Ukraine

Crawling Corpus[11], which is built from web documents collected from legislation websites, and governmental sites. The number of sentences in each dataset is provided in Table 2.

Dataset	**Language(s)**	**No. sentences**
EU acts	EN–UK	129941
Ukrainian laws	EN–UK	177270
Ukrainian Parliament	UK	665000
Legal Ukrainian Crawling	UK	1000000

Table 2. An overview of the datasets used for the EN→UK experiments.

Prior to training NMT engines, both the additional monolingual and the original bilingual datasets underwent an automatic cleaning process[12]. This entailed removing empty segments, duplicate segments, segments copied from source to target, HTML codes, segments containing more than 100 tokens, and normalising punctuation marks. In addition, sentences that consisted of Russian were removed from the target side of the bilingual data, as well as from the monolingual data[13]. After the automatic cleaning process, the bilingual dataset was randomly partitioned into training, validation and test sets. The randomly selected test sets, consisting of 2000 sentence pairs per language direction, were also manually reviewed to eliminate noisy sentence pairs, such as unaligned sentences, partial translations, sentences consisting only of dates or alphanumeric codes, and sentence pairs with fewer than three tokens on either the source or target side. The additional monolingual data was further utilised for generating synthetic, bilingual training data (EN→UK) through back-translation. The number of segments after cleaning and partitioning the original data is provided in Table 3.

	Train	**Validation**	**Test**
Bilingual (EN–UK)	286417	2000	1899
Monolingual (UK)	1461320	–	–

Table 3. The number of sentences used as training, validation and test sets for the EN→UK experiments.

[11] The Legal Ukrainian Crawling Corpus

[12] `filter.py` script from `https://github.com/ymoslem/MT-Preparation`.

[13] `https://github.com/pemistahl/lingua-py`

The second set of experiments was conducted for the English↔French (EN↔FR) language directions. To this end, we used the TM of the European Commission's translation service[14] (DGT-TM) (Steinberger et al., 2012), which consists of texts regarding European legislation, comprising the treaties, regulations and directives adopted by the European Union. The DGT-TM was cleaned using the same steps as described above, and a random subset was collected, consisting of bilingual and monolingual datasets of similar sizes to the EN–UK data, with the monolingual data containing five times more sentences than the bilingual data. Unlike the EN–UK dataset, where the collected monolingual sentences in the target language did not have any translations in the source language, monolingual datasets in EN and FR were extracted from the parallel dataset for EN–FR. Similar to the EN–UK dataset, these extracted monolingual datasets were utilised for generating synthetic bilingual training data through back-translation. The number of sentences in the different partitions of the EN–FR dataset is provided in Table 4.

	Train	**Validation**	**Test**
Bilingual (EN–FR)	300000	2000	1609
Monolingual (FR)	1499436	–	–
Monolingual (EN)	1499436	–	–

Table 4. The number of sentences used as training, validation and test sets for the EN↔FR experiments.

The resulting bilingual datasets, consisting of approximately 300K sentence pairs, is a meaningful starting point to test our hypotheses, as it enables us to evaluate our methodology in a scenario where the NFR approach achieved comparable results to a baseline system trained solely on the original bilingual training data, as previously observed with the DGT datasets (Bulté and Tezcan, 2019). To assess the effectiveness of this approach under varying data conditions, particularly when data resources are scarcer, we conducted additional experiments by gradually reducing the number of sentences in both the bilingual (down to 33% of the original amount) and the monolingual (down to 20% of the original amount) datasets. The resulting datasets used for training the MT systems in this study are available on HuggingFace[15].

4.2. NMT Systems

We trained six types of baseline systems. Among them, four were aimed at assessing the effectiveness of the proposed approach in comparison to existing alternatives

[14]`https://opus.nlpl.eu/DGT/corpus/version/DGT`

[15]`https://huggingface.co/collections/LT3/nfr-bt-nmt-66bcf9db6f39f76a39456df5`

in the literature: (i) NMT systems using only the original bilingual data for training (*BASE*); (ii) *NFR* (Tezcan et al., 2021), as described in Section 3.1; (iii) NFR_{mono}, an adaptation of the NFR approach, which further utilises the additional monolingual data for retrieving FMs during inference (Tamura et al., 2023) using multilingual sentence embeddings generated by LaBSE (Feng et al., 2022); and (iv) *BT*, NMT systems that are trained using a combination of original and synthetic bilingual data, where the synthetic source sentences are generated through back-translation (Sennrich et al., 2016). An overview of the training set sizes used for training these NMT systems is provided in Appendix A.3.

Furthermore, to better understand the limitations of using synthetically generated source sentences compared to an alternative scenario, where large, high-quality parallel datasets are available instead, we trained two additional baseline systems for the EN↔FR language directions: (v) a baseline NMT system, *BASE_HQ*, which utilises high-quality translations for the additional monolingual data in the target language for training, without any additional FM-augmentation (i.e. approx. 1.8M high-quality sentence pairs in total); and (vi) an NFR variant of this system, *NFR_HQ*, which utilises the same high-quality parallel data for training and FM-augmentation. Given that high-quality translations for the monolingual data in the target language were only available for EN↔FR language directions (see Section 4.1), these baseline systems are not available for the EN→UK language direction.

All the systems were trained using the Transformer architecture (Vaswani et al., 2017) and the OpenNMT-py toolkit[16] (Klein et al., 2017). Prior to training, all sentences were segmented into sub-words using SentencePiece, as described in Section 3.1. The resulting vocabulary sizes per system that was trained using all available bilingual and monolingual datasets, per language direction are provided in Appendix A.3. All systems were trained with early stopping with 10 validation rounds in terms of accuracy and perplexity. All training runs were initialised using the same seed. For the systems that did not utilise NFR, the maximum source and target lengths were defined as 200 tokens. The same settings have been used to train NMT systems for back-translation, using the reverse language direction in each case. Maximum source length was doubled to 400 tokens for the systems that utilised NFR, which were trained with augmented source sentences. Other details regarding the hyper-parameters used for training the NMT systems are provided in Appendix A.4.

Finally, using the same test sets, we evaluated four state-of-the-art LLMs for the MT task (Kocmi et al., 2024), namely, GPT4o[17], Llama3.1-Instruct (8b[18] and 70b[19]

[16] `https://github.com/OpenNMT/OpenNMT-py`, v. 3.5.1.

[17] `https://openai.com/index/gpt-4o-system-card/`, translations generated on 27th of October, 2024.

[18] `https://huggingface.co/meta-llama/Llama-3.1-8B-Instruct`

[19] `https://huggingface.co/meta-llama/Llama-3.1-70B-Instruct`

models) (Dubey et al., 2024) and TowerInstruct-Mistral-7b[20] (Alves et al., 2024). Although this study primarily focuses on evaluating the effectiveness of back-translated sentences in improving FM-augmented NMT systems trained from scratch, the comparison offers additional insights into the relative performance of FM-augmented NMT systems alongside state-of-the-art LLMs for MT. From the selected LLMs, while GPT4o and Llama can be regarded as general-purpose multilingual LLMs, TowerInstruct has been further specialized for the MT task through continued pretraining on Mistral using translation data and fine-tuning on translation-relevant instructions. All four LLMs were evaluated on the three language directions, except TowerInstruct for EN→UK, as this language pair is not officially supported.

4.3. Evaluation Methodology

We make use of automated evaluation metrics SacreBLEU[21] (Post, 2018), chrF (Popović, 2015), and COMET[22] (Rei et al., 2020) to assess the quality of the (detokenised) MT output. To verify whether differences between the automated quality metric scores of the different MT systems are statistically significant, we used bootstrap resampling tests (Koehn, 2004). Both the automated evaluations and bootstrap resampling tests have been performed using the MATEO toolkit[23] (Vanroy et al., 2023) with the default settings for each metric.

5. Results

In this section, we first compare the translation performance of the proposed system (*BT+NFR*) with the baseline NMT systems using all the bilingual and monolingual datasets available for training, as well as the LLMs (Section 5.1). Subsequently, we also analyse the effectiveness of this approach using the reduced datasets (Section 5.2).

5.1. System performance with full datasets

Table 5 provides the automated evaluation results for the translations generated by the different MT systems on the corresponding test sets per language direction.

Firstly, looking at the four baseline systems that were trained using the original datasets (upper section), we see that *BT* leads to consistent improvements for all language directions and all metrics over the *BASE* system, confirming the usefulness of back-translation in scenarios where additional monolingual datasets are available in

[20] `https://huggingface.co/Unbabel/TowerInstruct-Mistral-7B-v0.2`

[21] `https://github.com/mjpost/sacrebleu`, v. 2.4.1. (SacreBLEU and chrF)

[22] `https://huggingface.co/Unbabel/wmt22-comet-da`

[23] `https://mateo.ivdnt.org/`

System	EN→UK			EN→FR			FR→EN		
	BLEU	chrF	COMET	BLEU	chrF	COMET	BLEU	chrF	COMET
BASE	54.85	75.95	91.23	51.50	71.21	84.22	53.95	71.61	85.01
BT (*Sennrich et al., 2016*)	56.21	76.93	92.18	54.88	73.34	85.27	56.99	74.23	86.72
NFR (*Tezcan et al., 2021*)	57.73	77.52	91.78	52.67	71.82	84.50	54.43	71.94	85.26
NFR_{mono} (*Tamura et al., 2023*)	60.39	78.89	92.03	52.39	71.68	84.45	55.54	72.62	85.44
BT+NFR (*This work*)	**66.95**	**82.39**	**92.78**	**61.91**	**77.54**	**87.13**	**64.69**	**78.65**	**87.79**
BASE_HQ	–	–	–	59.13	76.28	87.40	61.56	77.04	88.03
NFR_HQ	–	–	–	64.58	79.32	88.36	67.75	80.53	88.61
GPT4o	41.66	67.95	92.35	43.47	67.93	86.75	44.58	68.82	86.87
TowerInstruct-Mistral-7b	–	–	–	39.99	64.66	83.06	42.11	52.14	82.32
Llama3.1-Instruct-8b	18.12	52.77	85.27	26.44	57.96	80.39	27.74	57.94	81.19
Llama3.1-Instruct-70b	27.81	60.14	88.70	44.90	68.57	86.37	49.37	70.49	86.56

Table 5. Results of the automatic evaluations performed on systems using all available datasets.

the target language. While the NFR approach leads to consistent improvements over *BASE* for all metrics for the EN→UK language direction, it only leads to marginal gains for the EN↔FR language directions. The performance of the NFR approach for the DGT datasets is in line with previous research, which showed that the NFR approach did not yield notable improvements with similar training set sizes (Bulté and Tezcan, 2019). While *BT* outperforms *NFR* for the EN↔FR language directions, an opposite observation can be made for the EN→UK language direction, with the exception of COMET scores. Considering all the baseline systems, NFR_{mono} outperforms *NFR* and *BASE* with respect to all metrics for EN→UK, while yielding mixed results for EN↔FR.

Secondly, when we compare the results of *BT+NFR* with the best-performing baseline system per metric, per language direction (upper section), a clear trend emerges: *BT+NFR* consistently outperforms all baseline systems for all language directions and metrics, with improvements of +6.56, +7.03, +7.70 BLEU points over the best baseline system for EN→UK, EN→FR, and FR→EN, respectively. For all language directions, the improvements achieved by *BT+NFR* over all baseline systems are measured to be statistically significant, with $p < 0.001$. Compared to the baseline systems that only utilise the original bilingual datasets (*BASE*), *BT+NFR* yields improvements of up to +12.10 BLEU points (EN→UK).

Thirdly, by comparing the performance of *BT+NFR* to two systems that can be trained in an alternative scenario, where high-quality translations for the monolingual sentences are available in the source language (middle section), we can make two important observations. On the one hand, employing high-quality bilingual datasets alongside FM-augmentation (*NFR_HQ*) results in optimal translation performance for both language directions and across all metrics. While these results highlight the constraints associated with employing synthetically generated source texts alongside the NFR approach, they also offer a clear indication of the upper boundary that can be achieved in terms of translation quality when training NMT models from scratch using these datasets. Consequently, using 1.5M synthetically generated source sentences, instead of high-quality translations, results in decreased MT performance, with reductions of -2.67 BLEU, -1.78 chrF, and -1.23 COMET scores for EN→FR, and -3.06 BLEU, -1.88 chrF, and -0.82 COMET scores for FR→EN. These differences are measured to be statistically significant, with $p < 0.001$.

On the other hand, *BT+NFR* surpasses *BASE_HQ* in BLEU and chrF scores for both language directions but does not yield higher COMET scores. Given the disagreement among the three metrics, we can argue that utilising back-translation and FM-augmentation with limited high-quality bilingual data alongside additional monolingual data in the target language produces results comparable to those of a conventional (i.e., non-augmented) NMT system trained on a large, high-quality dataset. In this particular scenario, by using only a monolingual dataset of five times the size of the bilingual data, this combined approach achieved MT performance comparable to that of a conventional NMT system requiring the same amount of additional bilingual data.

Finally, in the lower section, we present the MT performance of four LLMs. Comparative analysis shows that *GPT4o* achieves the best results across all metrics for EN→UK, while it performs similarly to *Llama3.1-Instruct-70b* for EN↔FR, given the mixed rankings each model attains per metric. The larger Llama model also shows clear improvements over the smaller model (70b vs. 8b). Additionally, despite having a similar parameter count, *TowerInstruct-Mistral-7b* performs noticeably better than *Llama3.1-Instruct-8b*.

BT+NFR outperforms all four LLMs in every setting, with improvements that are more pronounced in BLEU and chrF scores than in COMET across all language directions. For each language direction and metric, the improvements over the best-performing LLM are statistically significant, with $p < 0.001$ for BLEU and chrF, and $p < 0.005$ for COMET scores. Notably, *BASE*, which is trained with approx. 300K sentence pairs per language direction, also outperforms all LLMs in terms of BLEU and chrF scores, while being outperformed only by *GPT4o* and *Llama3.1-Instruct-70b* in terms of COMET scores.

5.2. System performance with reduced datasets

In Figure 2, we provide the BLEU scores for different systems for all language directions in two specific lower-resource scenarios, where: (i) the original bilingual datasets are combined with gradually decreasing sizes of monolingual datasets in the target language (upper section), and (ii) the original additional monolingual datasets in the target language are combined with gradually decreasing sizes of bilingual datasets (lower section). The BLEU, chrF and COMET scores for each system are further provided in Appendix A.7.

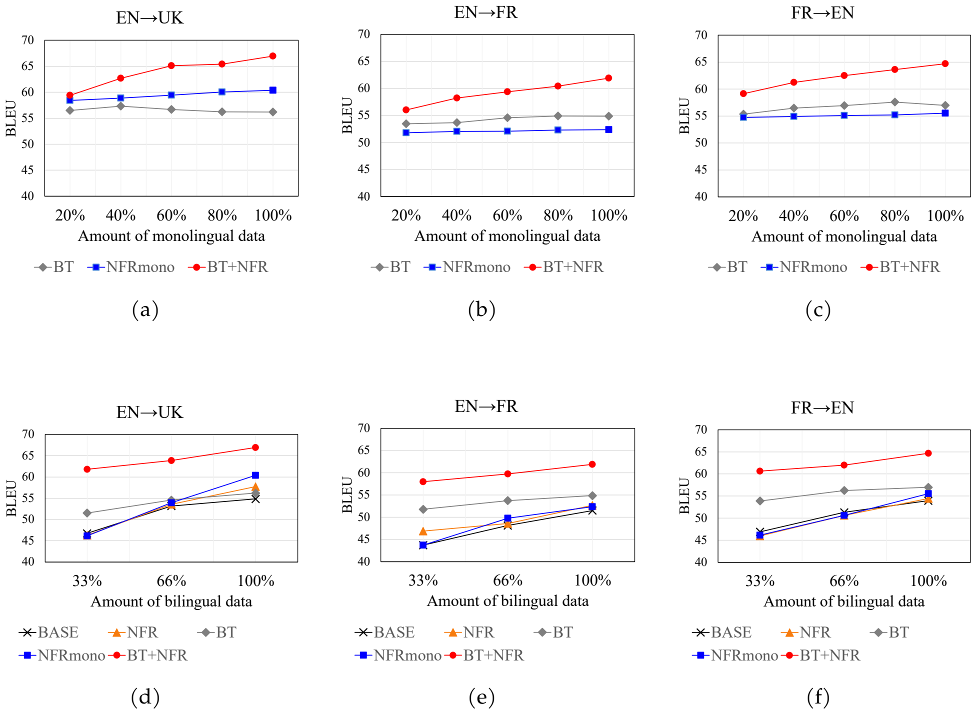

Figure 2. Results of BLEU evaluations performed on systems using gradually decreasing sizes of (i) additional monolingual data in the target language (a, b and c), and (ii) the original bilingual data (d, e and f).

In the upper section of Figure 2, we provide the results for the three systems that employ the extra monolingual data in the target language, namely *BT*, *NFR$_{mono}$* and *BT+NFR*, as the *BASE* and *NFR* systems are not affected from this adaptation. In this figure, we observe that *BT+NFR* outperforms both baseline systems in all data settings, where the size of the additional monolingual data available in the target language is gradually decreased from 100% down to 20% (approx. 300K sentences) for each language direction, resulting in a 1:1 ratio between the high-quality to synthetic training dataset sizes. Moreover, the performance of *BT+NFR* experiences continuous improvement as larger monolingual datasets become available. While *NFR$_{mono}$* also shows a performance increase with larger datasets, though, at a much slower pace, this pattern is not observed for *BT*, for which the optimal performance begins to diminish starting with ratios of high-quality to synthetic bilingual data sizes ranging from 1:2 to 1:4 (%40 to %80).

In the lower section, alongside the systems mentioned earlier, we provide the BLEU scores for *BASE* and *NFR*, taking into account the adjustments made to the sizes of the bilingual datasets. These results show that *BT+NFR* system consistently outperforms all baseline systems across all settings by a substantial margin, even when the bilingual dataset size is reduced down to 33%, approx. 100K sentence pairs per language direction. It is worth noting that such clear improvements in MT performance are observed even when the reduction in training set sizes also adversely affects the MT performance of the back-translation systems employed within the proposed approach. Please refer to Appendix A.6 for an overview of the MT performances of the back-translation systems trained in this study. The trends observed for the BLEU scores in both analyses are also reflected in chrF and COMET scores for all systems (see Appendix A.7).

For all configurations with reduced monolingual and bilingual data sets, for all language directions and evaluation metrics (see Appendix A.7), the improvements achieved by *BT+NFR* over the best-performing alternative are measured to be statistically significant (with $p < 0.001$, except for one experiment[24]).

6. Discussion

6.1. Comparison of NMT systems with LLMs

In Table 5, we provided the results of the automated evaluations of the translation quality of the NMT systems built from scratch and three LLMs. While this comparison aims to provide additional perspective on the translation performance of the proposed method, these results should be cautiously interpreted due to three factors: (i) the NMT systems in this study use relatively small training datasets of similar sizes per language direction aimed at investigating the effectiveness of FM-augmentation in low(er)-resource settings, with potential for improvements in MT performance if larger datasets were used; (ii) the LLMs we used in our experiments were not fine-tuned with domain-specific translation data, nor did they leverage FMs through in-context learning, both of which could enhance their MT performance (Moslem et al., 2023a; Alves et al., 2023); and (iii) there is a possibility that the test sets used in this study may (fully or partially) be included in the LLMs' training data, potentially resulting in data leakage and inflated translation performance. While fully preventing data leakage in the LLMs used in this study is challenging, future research could aim for a more balanced comparison between these two types of MT approaches.

Despite challenges in achieving a fully fair comparison and mitigating potential data leakage, these experiments demonstrate that, in these specific settings, the NMT

[24]For EN→UK, when 20% of the monolingual data set is used, the improvements *BT+NFR* yields over *NFR_mono* are observed to be significant with with $p < 0.005$ for all evaluation metrics.

systems trained from scratch with the proposed data augmentation approach outperform state-of-the-art LLMs in translation quality across all automated metrics.

While all three metrics confirm that *BT+NFR* achieves superior translation quality compared to the tested LLMs, the improvements in BLEU and chrF scores are significantly greater than those indicated by COMET scores across all comparisons. The notably higher BLEU and chrF scores for *BT+NFR* suggest that this system generates translations that more closely align with the word order and vocabulary of reference translations than the evaluated LLMs, as these metrics reward translations with overlapping word and character n-grams with the reference translations (Papineni et al., 2002; Popović, 2015). COMET, on the other hand, evaluates the translation quality of a given MT output based on its semantic similarity to the reference, without explicitly measuring word and character n-gram overlaps (Rei et al., 2020). The discrepancy between the improvements achieved by *BT+NFR* against the best-performing LLM with respect to BLEU and chrF (large improvements), in comparison to COMET scores (smaller improvements) suggests that while these LLMs do not produce translations that closely match the reference in vocabulary or word order, they maintain a higher accuracy in conveying the correct meaning. Considering the different dimensions of translation quality highlighted by these metrics, a manual assessment by human evaluators with domain expertise and knowledge of field-specific translation guidelines is crucial to accurately capture and evaluate these nuanced aspects.

6.2. FM similarity

In this study, we argue that FM augmentation using synthetically generated source sentences is most beneficial for domain-specific scenarios, where the chances of finding high FMs for a given input would be considered high due to the repetitive nature of such domains. While the results obtained in different experiments demonstrate the clear benefit of this approach in terms of MT performance, to have a better understanding of the measured level of similarity in the datasets we used in our experiments (i.e. cosine similarity between sent2vec embeddings), we analysed the mean, median, and standard deviation values of the similarity scores of the retrieved FMs for the sentences in the test sets, for all language directions. These statistics, which were analysed for *NFR* and *BT+NFR* (see Table 5) are provided in Tables 6 and 7, respectively. For *BT+NFR*, we also calculated the percentage of FMs retrieved from the additional synthetic source sentences generated via back-translation, which accounts for approximately 1.5 million additional sentences in each language direction.

Given the overall high mean and median FM similarity scores, as well as low standard deviation values, for all language directions, these statistics support the hypothesis that specialised domains are better suited for FM augmentation, whether or not additional synthetic datasets are used. This aligns with earlier research showing a strong positive correlation between FM scores and MT performance in FM-augmented MT systems (Bulté and Tezcan, 2019; Xu et al., 2023; Reheman et al., 2023), with the largest

NFR	**EN→UK**	**EN→FR**	**FR→EN**
Mean	0.8705	0.8554	0.8394
Median	0.8635	0.8384	0.8211
St. Dev.	0.0826	0.0853	0.0883

Table 6. FM similarity statistics for the NFR systems.

BT+NFR	**EN→UK**	**EN→FR**	**FR→EN**
Mean	0.8109	0.8030	0.7923
Median	0.8142	0.7990	0.7867
St. Dev.	0.1219	0.1235	0.1252
FMs from BT	63.73%	86.16%	86.23%

Table 7. FM similarity statistics for the BT+NFR systems, as well as the percentage of FMs retrieved from the additional synthetically generated source sentences via back-translation (FMs from BT).

improvements in MT performance occurring when FM scores exceed 0.8 (Tezcan and Bulté, 2022). These results also demonstrate that when back-translated target sentences into source are added to the pool for FM retrieval, in the test sets, a large portion of the FMs are retrieved from these additional sentences for all language directions despite these sentences being synthetically generated.

On the other hand, the FM scores calculated for the two types of systems indicate a noticeable difference. Considering the higher MT performance achieved by *BT+NFR*, it could be expected that, in the test set, the mean and median FM scores for *BT+NFR* would be higher than for *NFR*. However, our measurements indicate the opposite, showing lower mean and median FM scores for *BT+NFR*. We observed that the disparity between the statistics for both types of systems arises from the differences in the datasets used for creating the corresponding sent2vec models (approx. 300K sentences for *NFR* vs. approx. 1.5M additional sentences for *BT+NFR*). This difference in dataset size leads to distinct vector representations, resulting in different FM scores, even for the same FMs retrieved from the original training data in both systems. As a result, direct comparisons across systems that use different datasets become challenging. While the FM scores still provide a good indication of the level of textual similarity in these specialised domains, this observation should be taken into account in future studies, especially when different minimum similarity thresholds are defined for FM retrieval using sent2vec models with different datasets. It should be highlighted that in all FM-augmented systems used in this study, every sentence in the test set was augmented with an FM, using the minimum similarity threshold of $\lambda \geq 0.5$, as described in Section 3.1.

6.3. Impact of FM retrieval on computational costs

We make a final observation regarding the overhead introduced by FM retrieval in the translation process. As FM retrieval in FM-augmented systems is an additional processing step compared to a standard NMT system, it increases the total time required for generating translations. In the scenario where the full datasets are used for FM retrieval and FM augmentation (see Table 5) – the slowest scenario in our experiments – we observed the total time required for generating an output per sentence using the FM-augmented NMT systems (*BT+NFR*) when FM retrieval and inference are combined, to be approximately 1.5 times the inference time of the standard NMT systems[25] (*BASE_HQ*) across all language directions (approx. 0.078 seconds vs. 0.053 seconds, respectively). It should also be noted that while creating the sent2vec model, FAISS indexing and FM retrieval/augmentation on the source side of the training data also incur additional computational costs (approx. 775 seconds, 62 seconds and 314 minutes in our experiments, respectively, when full data sets are used), these steps are performed only once for NMT training and any translations to be generated via FM augmentation.

7. Conclusion

In this study, we adopted a simple yet effective approach for improving FM-augmented NMT in domain-specific scenarios where limited bilingual datasets are accompanied by additional monolingual data in the target language. Following earlier work, the adopted strategy combines two data augmentation techniques for NMT, namely back-translation and neural fuzzy repair (NFR), without modifying the underlying NMT architecture. Our results show that this approach outperforms NMT systems that employ (i) additional back-translated data for training, (ii) FM-augmentation via NFR, and (iii) a variant of NFR, which utilises additional monolingual data for FM retrieval at inference, yielding substantial improvements in estimated translation quality across two domains and three language directions. These results demonstrate that, unlike previous studies that focus on general-domain scenarios, combining FM augmentation with back-translation is a highly effective strategy for improving NMT systems in specialised domains. Additionally, this approach extends the applicability of FM augmentation to scenarios where bilingual datasets are limited, but additional monolingual datasets in the target language are available. In the specific dataset configurations used in this study, by leveraging monolingual datasets five times the size of the original bilingual datasets, this method effectively matched the performance of traditional NMT systems that would typically rely on the same amount of additional bilingual datasets. Moreover, despite the challenges in ensuring a fair comparison, this straightforward data augmentation method allowed us to develop NMT systems

[25] We used an NVIDIA A100-SXM4-80GB GPU for our experiments.

that outperformed state-of-the-art LLMs across all metrics and language directions, affirming the effectiveness of training NMT systems from scratch for specialized domains.

Our analysis of employing smaller sizes of additional monolingual data reveals a positive correlation between the size of such additional data and MT performance, indicating the potential for further improving such FM-augmented NMT systems through access to larger monolingual datasets. However, this hypothesis needs to be confirmed in future studies. Furthermore, the results demonstrate that combining back-translation with FM augmentation remains an effective method for enhancing NMT performance even in scenarios with smaller bilingual datasets, despite the reduction in high-quality training data and the decline in back-translation performance.

The findings of this study raise interesting research questions for future exploration. These include investigating whether (i) similar improvements can be observed by using the same approach through in-context learning methods when using LLMs for MT; (ii) LLMs can effectively replace back-translation models in lower resource scenarios; and (iii) whether LLMs can be further used to improve the performance this approach by generating additional monolingual sentences in the target language.

Limitations

The experiments were only conducted in two domains, albeit for three language pairs. Additional experiments would be required to confirm these results for other language directions and domains. Moreover, we relied on automated MT evaluation metrics only and did not conduct any experiments involving human evaluation of MT quality.

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A. Appendix

A.1. Sent2vec hyper-parameters

To train sent2vec models, we used the same hyper-parameters that are suggested in the description paper (Pagliardini et al., 2018) for a sent2vec model trained on Wikipedia data containing both unigrams and bigrams. The hyper-parameters values are provided in Table 8.

Hyper-Parameter	Value
embedding dimension	700
minimum word count	8
minimum target word count	20
initial learning rate	0.2
epochs	9
sub-sampling hyper-parameter	5×10^{-6}
bigrams dropped per sentence	4
number of negatives sampled	10

Table 8. Hyper-parameters for training sent2vec models.

A.2. FAISS hyper-parameters

We created a Flat index with an inner product metric for brute-force search. We used cosine similarity as the match metric effectively by adding the L2-normalised vectors of the sentence representation to the index and using an L2-normalised sentence vector as an input query. For more information on FAISS, please see `https://github.com/facebookresearch/faiss/wiki`.

A.3. NMT training data and vocabulary sizes

System	EN→UK	EN↔FR
BASE	286417	300000
NFR	572731	600000
NFR_{mono}	572731	600000
BT	1747737	1799436
BT+NFR	3491066	3598872
BASE_HQ	1747737	1799436
NFR_HQ	3491066	3598872

Table 9. The total number of bilingual sentence pairs used for training the NMT systems using all available data, per language direction.

For training the NFR systems by using the minimum FM similarity threshold of $\lambda = 0.5$, we were able to retrieve FMs for all source sentences in our experiments. As a result, combining the augmented and the non-augmented sentence pairs in the NFR approach simply doubled the training data sizes for all systems and all language directions (e.g. *BASE* vs. *NFR*, and *BT* vs. *BT+NFR*). It is also worth highlighting that *NFR* and NFR_{mono} use the same NMT training data. The key difference is that NFR_{mono} additionally employs FM retrieval and augmentation (only) on the test set using the additional available monolingual data.

System	EN→UK	EN→FR	EN→FR
BASE	21906/17612	36252/35550	35550/36252
NFR	33075/17612	39924/35550	39731/36252
NFR_{mono}	33075/17612	39924/35550	39731/36252
BT	21906/30683	36253/50611	35551/51089
BT+NFR	38466/30683	47726/50611	47501/51089
BASE_HQ	–	51089/50611	50611/51089
NFR_HQ	–	53874/50611	53592/51089

Table 10. Vocabulary sizes (source/target) of the NMT systems using all available data, per language direction.

A.4. NMT hyper-parameters

Hyper-Parameter	Value
source/target embedding dimension	512
size of hidden layers	512
feed-forward layers	2048
number of heads	8
number of layers	6
batch size	32
gradient accumulation	4
dropout	0.1
warm-up steps	8000
optimizer	Adam
validation steps	2000

Table 11. Common hyper-parameter values used for training the NMT systems.

A.5. LLM implementation details

All LLMs in the experiments were prompted using consistent templates and configurations to ensure fair comparison. Each model's native chat template format was utilised while maintaining identical prompt content across all models. The default sampling parameters were used for inference, as their respective developers recommended. Table 12 shows the prompt template used across all models. While the actual formatting varied according to each model's chat template, the content structure remained consistent:

```
Translate the following text from {source_language} into {target_language}.
{source_language}: {source_sentence}
{target_language}:
```

Table 12. Prompt template used across all models. The actual formatting followed each model's specific chat template while maintaining this content structure.

In some cases, the models exhibited consistent patterns of overgeneration, such as adding parenthetical notes (e.g., "\n Note that...") after the translation itself. These extra generations followed predictable patterns and were systematically filtered out before evaluation. The final hypotheses used for comparison against the references contained only the models' core translations.

A.6. Back-translation performance

System	BLEU	chrF	COMET
UK→EN 100%	59.54	76.66	86.27
UK→EN 66%	55.67	74.12	85.04
UK→EN 33%	50.69	70.60	82.89
FR→EN 100%	53.95	71.61	85.01
FR→EN 66%	51.30	69.52	83.49
FR→EN 33%	46.90	66.05	80.56
EN→FR 100%	51.50	71.21	84.22
EN→FR 66%	48.14	68.77	82.48
EN→FR 33%	43.71	65.26	77.88

Table 13. Results of the automatic evaluations performed on back-translation systems using different sizes of bilingual data, in reverse language direction, on the reversed test sets.

A.7. System performance using reduced datasets

System	EN→UK			EN→FR			FR→EN		
	BLEU	chrF	COMET	BLEU	chrF	COMET	BLEU	chrF	COMET
BT 100%	56.21	76.93	92.18	54.88	73.34	85.27	56.99	74.23	86.72
BT 80%	56.22	76.95	91.98	54.91	73.56	85.74	57.60	74.77	86.83
BT 60%	56.68	77.24	92.04	54.58	73.28	85.63	56.95	74.47	86.78
BT 40%	57.33	77.53	92.14	53.70	72.79	85.41	56.48	73.94	86.35
BT 20%	56.49	76.96	91.79	53.48	72.88	85.20	55.36	72.92	86.07
NFR_{mono} *100%*	60.39	78.89	92.03	52.39	71.68	84.45	55.54	72.62	85.44
NFR_{mono} *80%*	60.03	78.72	92.02	52.32	71.58	84.37	55.19	72.43	85.39
NFR_{mono} *60%*	59.44	78.39	91.97	52.11	71.47	84.37	55.11	72.37	85.36
NFR_{mono} *40%*	58.87	78.08	91.92	52.07	71.51	84.29	54.92	72.27	85.40
NFR_{mono} *20%*	58.42	77.85	91.90	51.83	71.34	84.29	54.72	72.16	85.38
BT+NFR 100%	66.95	82.39	92.78	61.91	77.54	87.13	64.69	78.65	87.79
BT+NFR 80%	65.40	81.53	92.66	60.44	76.76	86.85	63.62	78.02	87.32
BT+NFR 60%	65.11	81.27	92.69	59.38	76.04	86.39	62.51	77.14	87.06
BT+NFR 40%	62.68	80.14	92.57	58.24	75.39	86.40	61.25	76.26	86.87
BT+NFR 20%	59.42	78.42	92.22	56.04	74.04	85.77	59.15	74.92	86.55

Table 14. Results of the automatic evaluations performed on systems using the original bilingual data and gradually decreasing sizes of additional monolingual data in the target language.

System	EN→UK			EN→FR			FR→EN		
	BLEU	chrF	COMET	BLEU	chrF	COMET	BLEU	chrF	COMET
BASE 100%	54.85	75.95	91.23	51.5	71.21	84.22	53.95	71.61	85.01
BASE 66%	53.18	74.62	90.18	48.14	68.77	82.48	51.30	69.52	83.49
BASE 33%	46.76	70.23	87.47	43.71	65.26	77.88	46.90	66.05	80.56
NFR 100%	57.73	77.52	91.78	52.67	71.82	84.50	54.43	71.94	85.26
NFR 66%	53.56	74.86	90.43	48.60	69.03	82.26	50.61	69.05	83.10
NFR 33%	46.31	70.05	87.07	46.90	67.70	81.01	45.96	65.58	80.23
BT 100%	56.21	76.93	92.18	54.88	73.34	85.27	56.99	74.23	86.72
BT 66%	54.56	75.83	91.43	53.75	72.72	85.19	56.25	73.65	86.21
BT 33%	51.52	73.79	90.32	51.80	71.11	83.92	53.88	72.28	85.06
NFR_{mono} *100%*	60.39	78.89	92.03	52.39	71.68	84.45	55.54	72.62	85.44
NFR_{mono} *66%*	53.96	75.16	90.54	49.77	69.77	82.93	50.62	69.09	83.16
NFR_{mono} *33%*	46.15	70.03	87.28	43.72	65.27	78.68	46.14	65.65	80.17
BT+NFR 100%	66.95	82.39	92.78	61.91	77.54	87.13	64.69	78.65	87.79
BT+NFR 66%	63.89	80.29	92.01	59.75	76.20	86.40	61.99	76.38	86.49
BT+NFR 33%	61.83	78.96	91.30	58.01	74.75	85.23	60.62	76.11	85.92

Table 15. Results of the automatic evaluations performed on systems using all additional monolingual data in the target language and gradually decreasing sizes of the original bilingual data.

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