Iterative Training of Unsupervised Neural and Statistical Machine Translation Systems

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Recent work achieved remarkable results in training neural machine translation (NMT) systems in a fully unsupervised way, with new and dedicated architectures that only rely on monolingual corpora. However, previous work also showed that unsupervised statistical machine translation (USMT) performs better than unsupervised NMT (UNMT), especially for distant language pairs. To take advantage of the superiority of USMT over UNMT, and considering that SMT suffers from well-known limitations overcome by NMT, we propose to define UNMT as NMT trained with the supervision of synthetic parallel data generated by USMT. This way we can exploit USMT up to its limits while ultimately relying on full-fledged NMT models to generate translations. We show significant improvements in translation quality over previous work and also that further improvements can be obtained by alternatively and iteratively training USMT and UNMT. Without the need of a dedicated architecture for UNMT, our simple approach can straightforwardly benefit from any recent and future advances in supervised NMT. Our systems achieve a new state-of-the-art for unsupervised machine translation in all of our six translation tasks for five diverse language pairs, surpassing even supervised SMT or NMT in some tasks. Furthermore, our analysis shows how crucial the comparability between the monolingual corpora used for unsupervised training is in improving translation quality.

CCS Concepts: • **Computing methodologies** → **Machine translation**;

Additional Key Words and Phrases: Machine translation, phrase table induction, low-resource language pair, semantic similarity, knowledge acquisition

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1 INTRODUCTION

Machine translation (MT) systems usually require a large amount of bilingual parallel data, produced by humans, as supervision for training. However, finding such data remains challenging for most language pairs, as it may not exist or may be too costly to manually produce.

In contrast, a large amount of monolingual data can be easily collected for many languages. Previous work proposed many ways for taking advantage of monolingual data in order to improve

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translation models trained on parallel data [12, 34]. These methods usually exploit existing accurate translation models to generate synthetic parallel data that can be used to augment the training data of the NMT systems. Recent work has also shown remarkable results in training MT systems using only monolingual data in the source and target languages in so-called unsupervised statistical (USMT) and neural (UNMT) machine translation [2, 5, 24]. However, existing approaches for UNMT rely on dedicated architectures significantly different from the well-established architectures designed for supervised NMT. Existing UNMT architectures relatively remain unoptimized and under-explored with many specific hyper-parameters difficult to set. On the other hand, running existing USMT only requires slight modifications of well-known SMT frameworks and consistently outperforms UNMT in translation quality as demonstrated by Artetxe et al. [2]. Nonetheless, SMT architecture has well-known limits that are overcome by NMT. Exploiting an NMT architecture for unsupervised MT seems intuitive to perform as close as possible to supervised MT.

Following our promising preliminary experiments presented in [26], we propose, in order to exploit USMT up to its limits while ultimately relying on full-fledged NMT models, a new approach for unsupervised MT in which USMT and UNMT are assisting each other through an iterative training, only using synthetic parallel data for supervision. We answer the following research questions:

- Can synthetic bilingual data generated by a given unsupervised MT system be used to train from scratch an MT system better than the given unsupervised MT system?
- How do the language pairs and the comparability between the monolingual corpora impact on the translation quality in unsupervised MT?

In our way toward answering these questions, we report on the following outcomes:

- We propose a *simplified USMT framework*, which is easier to set up and train than the existing frameworks.
- We propose to cast UNMT with a standard NMT framework by simply replacing manually produced parallel data with synthetic parallel data generated by USMT. This *pseudo-supervision strategy* enables us to use well-established and well-optimized NMT architectures with all their features, without assuming any relatedness between targeted languages in contrast to previous work.
- We propose a new *unsupervised iterative training approach* in which USMT and UNMT assist each other for training.
- We demonstrate that *the feasibility of unsupervised MT* depends largely on the language pair and the comparability of the monolingual corpora used.

The remainder of this article is organized as follows. We first discuss in Section 2 how we define “unsupervised.” In Section 3, we introduce our architecture for USMT and then in Section 4 we present our approach for an UNMT trained on synthetic parallel data. In Section 5, we describe our approach to combine the advantages of USMT and UNMT using an iterative training framework. In Section 6, we evaluate our USMT, UNMT, and their iterative training on six translation tasks and present an analysis of the results. We conduct further experiments and analyses in Section 7, in settings where we have more comparable monolingual corpora to train our systems. Section 8 exposes the concurrent work and highlights strengths and weaknesses of other approaches for unsupervised MT. Finally, Section 9 concludes this article.

2 WHAT IS UNSUPERVISED IN THIS ARTICLE?

Since the term “unsupervised” may be ambiguous, we present in this section what aspects of this work are assumed to be unsupervised.

Fig. 1. Our USMT framework for the translation direction $L1 \rightarrow L2$ of a given language pair $L1-L2$. It is analogous for $L2 \rightarrow L1$.

As previous work, we define “unsupervised MT” as MT that does not use manually produced translation pairs as parallel data for training. Nonetheless, MT still needs some supervision for training and we use synthetic parallel data generated from monolingual data for this purpose.

In this article, “unsupervised” only qualifies the training of MT systems on parallel data of which at least one side is synthetic. For tuning, i.e., finding the best model weights for USMT or selecting the best model for UNMT, it is supervised in all our experiments using a small development set of manually produced sentence pairs. We assume that this development set can be inexpensive to create manually or automatically. Nonetheless, we discuss “unsupervised tuning” in Section 3.2 and report on experimental results in Section 6.5. For evaluation, it must be fully supervised since we use a manually produced test set to evaluate the translation quality.

Even if our systems are trained without manually produced parallel data, we can still argue that the monolingual corpora used to generate synthetic parallel data have been produced by humans. Monolingual corpora in our experiments (see Section 6.1) could include comparable parts that could have a significant impact on the translation quality. Moreover, we cannot ensure that they do not contain any human-made translations from which our systems can take advantage during training. Finally, we use SMT and NMT architectures with their hyper-parameters (for instance, the default parameters of the Transformer model [39]) that have already shown to give good results in MT.

3 USMT

Our USMT framework, as illustrated in Figure 1, is based on the same architecture proposed by previous work [2, 24]: a phrase table is induced from monolingual data and used to compose the

initial USMT system that is then refined iteratively using synthetic parallel data. We propose various modifications in this section to better ground each step required to set up an USMT system. An ablation study is reported in Section 6.4 to evaluate the impact of our modifications.

3.1 Phrase Table Induction

In USMT, phrase table induction is regarded as the process of creating a phrase table using only monolingual resources. It takes as inputs a set of phrases in the source language, another set of phrases in the target language, and their respective embeddings.

3.1.1 Previous Work. Artetxe et al. [2] regarded the most frequent unigrams, bigrams, and trigrams in the monolingual data as phrases. The embedding of each n -gram is computed with a generalization of the skipgram algorithm [27]. Then, source and target n -gram embedding spaces are aligned in the same bilingual embedding space without supervision [1]. Lample et al. [24]’s method also works at n -gram level using the method by Mikolov et al. [27]¹ that was also used by Marie and Fujita [25] in the context of phrase table induction.

3.1.2 Phrase Collection. We induce our phrase tables with phrases collected as in Marie and Fujita [25]. This method can collect more meaningful phrases than only the most frequent n -grams [2]. Whereas Mikolov et al. [27]’s phrase collection method was originally proposed to identify non-compositional phrases, we rather choose to enforce the collection of more compositional phrases,² for which embeddings are easier to estimate, because of the following reasons:

- Very few phrases are non-compositional in standard SMT systems [41].
- Most of them are not very frequent.
- Useful representation of compositional phrases can easily be obtained compositionally [43].

Consequently, we obtain a set of phrases mainly made of compositional phrases for which phrase embeddings can be compositionally computed [24, 43].

3.1.3 Phrase Pair Scoring. To obtain the pairs of source and target phrases that populate the induced phrase table, we use the equation proposed by Lample et al. [24]:³

$$p(t_j|s_i) = \frac{\exp(\beta \cos(\text{emb}(t_j), \text{emb}(s_i)))}{\sum_k \exp(\beta \cos(\text{emb}(t_k), \text{emb}(s_i)))}, \quad (1)$$

where t_j is the j -th phrase in the target phrase list, s_i the i -th phrase in the source phrase list, β a parameter to tune the peakiness of the distribution [35],⁴ and $\text{emb}(\cdot)$ a function returning the bilingual embedding of a given phrase. $p(s_i|t_j)$ is computed analogously for the other translation direction.

We also compute two lexical translation probabilities for each phrase pair, using the equation proposed by Song and Roth [37] that computes a similarity score between two phrases, i.e.,

¹The exact method used is not mentioned in the article and is not in the publicly released implementation. We found this information at <https://github.com/facebookresearch/UnsupervisedMT/issues/64#issuecomment-471700200>. However, note that we could not confirm whether it was used for the experiments of the paper [24].

²This is done by using a low value for the parameter δ , the discount coefficient in Equation (6) in Mikolov et al. [27], which prevents us from collecting infrequent phrases. We set $\delta = 10$ in all our experiments.

³We could not obtain results similar to the results reported in Lample et al. [24] by using their Equation (3) with $\beta = 30$ as they proposed. We have confirmed through personal communications with the authors that Equation (1), as we wrote, with $\beta = 30$, generates the expected results. We do not use the equation computing ϕ in Artetxe et al. [2], since it produces a negative value as a probability when cosine similarity is negative.

⁴We set $\beta = 30$ since it is the default value proposed in the code released by Smith et al. [35]: https://github.com/Babylonpartners/fastText_multilingual.

sequences of words, given word embeddings:

$$\text{lex}(t_j|s_i) = \frac{1}{L} \prod_{l=1}^L \max_{k=1}^K p(t_j^k|s_i^l), \quad (2)$$

where K and L are the number of words in t_j and s_i , respectively, and $p(t_j^k|s_i^l)$ the translation probability of the k -th target word t_j^k of t_j given the l -th source word s_i^l of s_i given by Equation (1). $\text{lex}(s_i|t_j)$ is computed analogously for the other translation direction. Note that, unlike Song and Roth [37] and Kajiwara and Komachi [18], we do not use a threshold value under which $p(t_j^k|s_i^l)$ is ignored, since it would be costly to tune for each translation task.

After the computation of the above four scores for each phrase pair in the induced phrase table, the phrase table is plugged in an SMT system to perform what we denote in the remainder of this article as step 0 of USMT.⁵

3.2 Discussion about Unsupervised Tuning

State-of-the-art supervised SMT performs the weighted log-linear combination of different models [28] for decoding. The model weights are tuned given a small development set of sentence pairs. For fully unsupervised SMT, we cannot assume the availability of this development set. Model weights must be tuned without the supervision of manually produced parallel data.

Lample et al. [24] used some pre-existing default weights that work reasonably well. On the other hand, Artetxe et al. [2] used 10,000 monolingual sentences paired with their back-translations as a development set. Nonetheless, to create this development set, they also relied on the same pre-existing default weights used by Lample et al. [24]: the default weights of the Moses framework [20].

However, regarding the use of default weights as “unsupervised tuning” is arguable, since these default weights have been manually determined for European languages. For translation between very distant languages, these default weights would likely result in a very poor translation quality. We argue that unsupervised tuning remains one of the main issues in current approaches for USMT.

While manually creating large training parallel data for a particular language pair is very costly, which is one of the fundamental motivations of unsupervised MT, we can assume that a small set of sentence pairs⁶ required for tuning is already available⁷ or can be created at a reasonable cost. In this work, we present results with supervised tuning only and leave for future work the study of unsupervised methods for generating development data. For a comparison, we present results of USMT and our whole framework without using any development set in Section 6.5.

3.3 Refinement

3.3.1 Previous Work. Artetxe et al. [2] and Lample et al. [24] proposed so-called refinement steps. Those steps use USMT to generate synthetic parallel data to train a new phrase table, with refined translation probabilities. This can be repeated for several iterations to improve USMT. The initial system at step 0 uses the induced phrase table (see Section 3.1), while the following steps

⁵Klementiev et al. [19] showed that lexicalized reordering models for the phrase pairs in the induced phrase table can be computed from monolingual data, and they are potentially helpful. However, for the sake of simplicity, we do not compute these lexical reordering models for step 0.

⁶For instance, the WikiMatrix project (<https://github.com/facebookresearch/LASER/tree/master/tasks/WikiMatrix>) proposes a small set of sentence pairs for 1,620 language pairs extracted from Wikipedia that could be used for tuning purposes.

⁷As in the unsupervised MT shared task of WMT19: <http://www.statmt.org/wmt19/>.

use only a phrase table and a reordering model trained on the synthetic parallel data generated by USMT.

In previous work, for a given language pair $L1-L2$, the synthetic parallel data were generated through back-translation: the $L2 \rightarrow L1$ USMT system was used to back-translate $L2$ sentences. Then, $L2$ sentences paired with their translations in $L1$ were used as synthetic parallel data to train a new $L1 \rightarrow L2$ USMT system. Using back-translation in SMT has been proven useful by previous work [21]. It has also been proposed to improve NMT systems [34] with a specific motivation to enhance the decoder by exploiting fluent sentences in $L2$. However, using only back-translation for training USMT lacks motivation. Since the source side of the synthetic parallel data, i.e., decoded results of USMT, tends to not be fluent, USMT will learn a phrase table with many ungrammatical $L1$ phrases or untranslated words in $L2$ that will never be seen in $L1$, meaning that many phrase pairs in the phrase table will never be used while skewing the translation probability distribution. Moreover, possible and frequent source phrases, or even source words, may not be generated via back-translation and will be consequently absent from the trained phrase table.

3.3.2 Refinement with Forward Translations. To ensure that the phrase tables will contain fluent target phrases, we keep using back-translations for the refinement steps. Nevertheless, to compensate for the shortcomings of exclusive use of back-translations, we also use synthetic parallel data made of $L1$ sentences translated into $L2$ by the $L1 \rightarrow L2$ USMT system, i.e., “forward translation.” Actually, the idea of retraining an SMT system on synthetic parallel data generated by an $L1 \rightarrow L2$ system has already been proven beneficial [38].

At each iteration, we randomly sample Q $L1$ and Q $L2$ sentences from their respective monolingual corpus and translate them with the latest $L1 \rightarrow L2$ and $L2 \rightarrow L1$ USMT systems, respectively, to generate a total of $2Q$ synthetic sentence pairs that can be used to train both $L1 \rightarrow L2$ and $L2 \rightarrow L1$ USMT systems. In contrast, using only either back-translation or forward translation requires twice the computational cost for generating both of them independently with $L2 \rightarrow L1$ and $L1 \rightarrow L2$ systems, in order to obtain two different sets of $2Q$ synthetic sentence pairs for both translation directions.

3.3.3 Phrase Table Pruning. Since we train phrase tables on noisy synthetic parallel data, we prune the phrase tables as proposed by Johnson et al. [16] to remove less reliable phrase pairs without any significant drop of the translation quality. This pruning also speeds up decoding for generating synthetic parallel data for the next step since numerous translation options are removed in advance.

4 UNMT AS NMT TRAINED EXCLUSIVELY ON SYNTHETIC PARALLEL DATA

4.1 Previous Work

Many methods [4, 23, 24, 40] proposed dedicated architectures for UNMT, such as denoising autoencoders, shared latent representations, weight sharing, pre-trained embeddings, and adversarial training. However, as the following and concurrent studies [2, 24] have demonstrated, existing UNMT frameworks hardly realize systems significantly better than USMT systems, especially in translation tasks for which SMT performs well.

4.2 Training UNMT on Synthetic Parallel Data

We propose to train UNMT systems exclusively on synthetic parallel data, simply using existing frameworks for supervised NMT without any modification. Our approach is substantially different from the “PBSMT+NMT” configuration in Lample et al. [24] in the following three aspects.

Fig. 2. Our UNMT framework for a given language pair L1–L2.

- (1) While their method uses synthetic parallel data generated by USMT only to further tune their dedicated UNMT architecture, ours uses it as ordinary parallel data for training NMT.
- (2) They assumed a certain level of relatedness between languages, which is a prerequisite to jointly pre-train bilingual sub-word embeddings. Our approach does not make this assumption.
- (3) We do not rely on a particular architecture and therefore are free to use any available NMT frameworks, maximally benefiting from their up-to-date features and efficiency.

4.3 Back-Translation and Data Filtering

To obtain better UNMT systems, we propose the following procedure (see also Figure 2).

Assuming that USMT produces translations of a reasonable quality, we first train L1→L2 and L2→L1 UNMT systems on Q sentence pairs respectively generated by back-translating monolingual data with L2→L1 and L1→L2 USMT systems. Since USMT may generate very ungrammatical translations, we only keep for training the $\alpha \cdot Q$ ($0 < \alpha \leq 1$)⁸ sentence pairs with the most fluent translations generated by USMT according to a normalized language model score:

$$ppl(S) = \frac{lm(S)}{len(S) + 1}, \quad (3)$$

where S is an output of USMT, i.e., synthetic source sentence, $lm(\cdot)$ the language model score, and $len(\cdot)$ a function returning the number of tokens in the sentence. We add 1 to the denominator to account for the special token used by NMT that marks the end of a sentence.

There are many ways to make use of the above score during NMT training. For instance, weighting the sentence pairs with this score during training is a possible alternative, and this idea is close to the joint training framework for NMT proposed by Cheng et al. [8]. However, given that many of the synthetic sentence pairs would be noisy, we rather choose to exclude potentially noisy pairs for training. We also expect this filtering to significantly speed up convergence during training since it uses smaller training data.

⁸This ratio was arbitrarily set to 0.5 in all our experiments.

4.4 Refinement

To fully exploit the potential of NMT in generating more fluent sentences than SMT, especially for morphologically rich languages and for language pairs requiring long-distance reordering, we retrain from scratch the $L1 \rightarrow L2$ UNMT system on P synthetic parallel sentences generated by back-translating $L1$ sentences using the $L2 \rightarrow L1$ UNMT system, mixed with those generated by the $L2 \rightarrow L1$ USMT system. The entire set of synthetic parallel sentences is also filtered in the same manner as in Section 4.3 to keep the best $\alpha \cdot (P + Q)$ sentence pairs for training.

5 ITERATIVE TRAINING OF USMT AND UNMT

In contrast to supervised NMT where synthetic parallel data are added to manually produced parallel data, we can presumably use as much synthetic parallel data as possible, since seeing more fluent target sentences will help training a better UNMT decoder while we can assume that the quality of the synthetic source side remains constant. In practice, since the decoder focuses on the head of the model distribution, it leads to back-translations likely to be very regular by favoring the same translations in case of ambiguity and with a poor coverage of the true data distribution [12]. Generating a larger quantity of synthetic parallel data is also costly and provides only limited improvements, if any, as also confirmed by previous work on USMT by Lample et al. [24, Figure 3].

We propose an alternative framework to improve our USMT and UNMT systems iteratively. Assuming that our approach for UNMT can generate translations of a better quality than the translations generated by USMT, we train a new USMT system on synthetic parallel data generated by UNMT and expect to obtain an USMT system better than the previous USMT system. This procedure can be repeated for several iterations to improve USMT and UNMT. Within each iteration, USMT and UNMT are trained from scratch to make sure that they are not biased by the synthetic data generated earlier, already used for previous training, and presumably of a lower quality. The training of UNMT is always initialized by synthetic parallel data generated by the last USMT system, while the training of USMT is initialized by synthetic parallel data generated by the UNMT system of the previous iteration, except for the first iteration for which USMT is initialized with an induced phrase table (Section 3.1).

The number of iterations to perform is pre-set and the best MT systems, among all the systems trained, can be selected using a development set.

6 EXPERIMENTS

In order to evaluate the feasibility and the performance of our USMT, UNMT, and of their iterative training, we conducted experiments in various settings, including high-resource and low-resource language pairs.

6.1 Experimental Settings

We experimented with five language pairs: English–German (en-de), English–French (en-fr), English–Japanese (en-ja), English–Indonesian (en-id), and Japanese–Indonesian (ja-id). We performed six translation tasks only using monolingual corpora for training, development data for tuning USMT and for model selection of UNMT, and test data for evaluation, presented in Table 1.

For en-de and en-fr, we used the same data used in previous work [24] to conduct comparable experiments. Since the monolingual corpora are clean and comparable to some degree, we can expect a reasonable translation quality. We can have the same expectation for en-ja-NTCIR; even though this task involves much more distant languages, the difficulty of training unsupervised bilingual word embeddings is alleviated by the comparability of the source and target monolingual corpora [36]. Moreover, a good coverage of the dev/test sets by the induced phrase tables is ensured,

Table 1. Data Used in Our Experiments for Each Translation Task

Language pair (L1–L2-task)	Monolingual corpora (domain)		dev/test (domain)
	(#tokens in L1)	(#tokens in L2)	
en-de-news	News Crawl (newswire) (2007–2017, 5.3 B) (2007–2017, 4.3 B)		Newstest2015/Newstest2016 (newswire)
en-fr-news	News Crawl (newswire) (2007–2017, 5.3 B) (2007–2014, 0.9 B)		Newstest2013/Newstest2014 (newswire)
en-ja-NTCIR	NTCIR (patent) (3.0 B) (3.9 B)		NTCIR dev/test-10 (patent)
en-id-ALT	Common Crawl (any) (1.8 B) (2.2 B)		ALT dev/test (newswire)
en-ja-ALT	Common Crawl (any) (1.8 B) (1.9 B)		ALT dev/test (newswire)
ja-id-ALT	Common Crawl (any) (1.9 B) (2.2 B)		ALT dev/test (newswire)

News Crawl corpora, English Common Crawl, and Newstest data are provided by the Conference on Machine Translation [7]. NTCIR data are provided by the NTCIR patent translation task [13]. We obtained the Common Crawl corpora for Japanese and Indonesian from the official Web site. ALT dev/test are provided by the Asian Language Treebank project [32].

since the monolingual corpora and the dev/test sets belong to the same domain. In contrast, the three ALT tasks are expected to be much more difficult, since the involved monolingual data, i.e., Common Crawl corpora,⁹ are essentially crawled Web pages from any domain and thus potentially extremely noisy. ja-id and en-id can be considered as extremely low-resource language pairs for which unsupervised MT may have applications.

All our English, German, French, and Indonesian data were pre-processed with the tokenizer and truecaser of Moses.¹⁰ The statistics for truecasing were learned from 10 M sentences randomly sampled from the monolingual data. We tokenized Japanese data with MeCab.¹¹

For the phrase table induction, the source and target word embeddings were learned from the entire monolingual data with the default parameters of fastText [6],¹² except that we set the number of dimensions to 512. We retained only the embeddings for the 300,000 most frequent words, following previous work, in order to limit computational cost. Word embeddings for each pair of languages were then aligned in the same space using the `--unsupervised` option of vecmap.¹³ From the entire monolingual data, we collected phrases of up to six tokens in each language using word2phrase,¹⁴ but retained only the 300,000 most frequent phrases made of words among the 300,000 most frequent words in the corresponding monolingual data for a reasonably fast computation. We also conserved only the 300-best target phrases for each source phrase according to Equation (1), resulting in an induced phrase table for USMT containing 90 M (300,000×300) phrase pairs.¹⁵

⁹<http://commoncrawl.org/>.

¹⁰<https://github.com/moses-smt/mosesdecoder>.

¹¹<https://taku910.github.io/mecab/>.

¹²<https://fasttext.cc/>.

¹³<https://github.com/artetxem/vecmap>.

¹⁴<https://code.google.com/archive/p/word2vec/>.

¹⁵We intended to reduce the significant computational cost for computing $p(s_i|t_j)$, $lex(t_j|s_i)$, and $lex(s_i|t_j)$. Using many more phrases, as in Artetxe et al. [2], can significantly improve coverage and potentially translation quality.

We used Moses and its default parameters to conduct experiments for USMT with four refinement steps. At each step, we sampled 1.5 M monolingual sentences from the source and target monolingual corpora, i.e., $Q = 1.5 \times 10^6$, and translate them, using cube-pruning for fast decoding [15], to generate synthetic parallel data. We then trained a phrase table and a lexicalized reordering model on the synthetic parallel data using `fast_align` [11].¹⁶ We used 4-gram language models trained with LMPLZ [14] on the entire monolingual data. For tuning, we used `kb-mira` [9].

For UNMT, we used the Transformer [39] model implemented in Marian [17]¹⁷ with the hyperparameters proposed by Vaswani et al. [39] but using only four layers to speed up training and decoding. We reduced the vocabulary size by using byte pair encoding (BPE) with 8,000 sub-words independently learned on 10 M sentences randomly sampled from each set of monolingual data. BPE was then applied to the entire source and target monolingual data.¹⁸ For training, $3Q$ sentences were sampled from monolingual data ($P = 3Q$), back-translated, and then the resulting synthetic parallel data were mixed with the Q sentence pairs generated by the last iteration of USMT. The data were filtered according to an RNN language model¹⁹ to keep only $2Q (= \alpha \cdot (P + Q))$, with $\alpha = 0.5$ and $P = 3Q$ sentence pairs for training. During training, our models were validated according to their perplexity computed on the development set.

We report on results for two iterations of iterative training for USMT and UNMT. We performed only two refinement steps for training USMT at iteration 2 since we did not observe any noticeable improvements on the development data when performing more steps. Note also that each iteration of UNMT used the same size of synthetic parallel data for training, i.e., Q and P remained constant.

Our baseline USMT and (Transformer-based) UNMT systems were respectively trained on 3 M back-translated data, generated from sentences randomly sampled, at each refinement step, and on 10 M sentences sampled from source and target monolingual corpora, with the original implementation of Lample et al. [24].²⁰ For these systems, we also exploited the development data for supervised tuning and validation. However, despite our best efforts, we could not reproduce the results of their “PBSMT+NMT” configuration.²¹

For reference, we also trained supervised SMT and NMT, with Moses and Marian, respectively, on 5.6 M, 26.7 M, and 3.1 M sentence pairs,²² respectively, for the en-de, en-fr, and en-ja-NTCIR tasks. For the ALT tasks, we used the 18k parallel sentences provided for training.

We evaluated our systems with detokenized and detruccased BLEU-cased [29] for all languages except for Japanese. Note that our results should not be directly compared with the tokenized BLEU scores reported in previous work, as discussed in Post [30].²³ For Japanese, we report on tokenized BLEU-cased.

6.2 Results

6.2.1 Translation Quality. Our results are presented in Table 2 for en-de, en-fr, and en-ja-NTCIR tasks, and in Table 3 for ALT tasks. We exclude en-ja-ALT and ja-id tasks from this part of our analysis, and will discuss them in Section 6.2.2.

¹⁶mgiza may provide better results, especially for difficult language pairs [10], but for a much greater computational cost.

¹⁷<https://marian-nmt.github.io/>, version 1.6.

¹⁸We did not use BPE for USMT.

¹⁹Trained with Marian on the entire monolingual data, without BPE, with a vocabulary size of 100,000.

²⁰We used the default parameters assuming that they are the parameters used for the experiments reported in their paper. We could reproduce their results for en-fr and de-en pairs with these parameters.

²¹Their implementation for this configuration has not been released to the best of our knowledge while the details in the paper are too scarce to re-implement it by ourselves.

²²All the en-de and en-fr parallel data provided by WMT, except the ParaCrawl corpus, and all the en-ja parallel data provided by NTCIR.

²³For instance for French, tokenized BLEU computes scores are several BLEU points higher than detokenized BLEU.

Table 2. Results for the en-de-news, en-fr-news, and en-ja-NTCIR Tasks

System	Newstest				NTCIR		#
	de→en	en→de	fr→en	en→fr	ja→en	en→ja	
Lample et al. [24]’s USMT	22.1	17.5	26.2	23.9	20.5	21.6	1
Lample et al. [24]’s UNMT	20.3	17.0	23.6	22.9	15.8	17.2	2
USMT-1	23.4	18.8	26.7	25.3	21.3	22.0	3
↳ UNMT-1	29.4	22.8	28.8	28.1	25.3	27.8	4
↳ USMT-2	26.6	21.4	28.0	27.3	21.6	25.0	5
↳ UNMT-2	30.4	24.3	29.2	29.0	25.9	29.2	6
UNMT-1 ($P = 8.5 \times 10^6$)	29.8	22.8	28.9	28.4	26.0	28.0	7
Supervised SMT	30.4	26.4	35.3	32.7	27.6	31.3	8
Supervised NMT	35.8	32.9	35.9	37.2	43.5	48.7	9

#1–2 are baseline systems built using the framework by Lample et al. [24]. #3–6 are our USMT and UNMT systems after one (#3–4) and two iterations (#5–6). #7 is our UNMT systems at iteration 1 with $P = 8.5 \times 10^6$ instead of $P = 4.5 \times 10^6$ for #2. #8 and #9 are respectively SMT and NMT systems trained on manually produced parallel data.

Table 3. Results for the ALT Tasks

System	ALT						#
	id→en	en→id	ja→en	en→ja	id→ja	ja→id	
Lample et al. [24]’s USMT	27.3	22.9	5.0	5.5	6.0	4.4	1
Lample et al. [24]’s UNMT	20.5	18.7	1.9	2.2	0.8	0.5	2
USMT-1	29.1	24.5	6.0	6.4	6.6	4.4	3
↳ UNMT-1	32.3	28.4	5.7	6.5	6.6	4.4	4
↳ USMT-2	29.6	28.7	5.2	6.6	6.2	4.4	5
↳ UNMT-2	33.0	29.3	5.4	6.9	6.9	4.8	6
UNMT-1 ($P = 8.5 \times 10^6$)	32.0	28.7	6.0	6.7	7.0	5.0	7
Supervised SMT	35.5	35.3	10.9	15.0	13.8	8.9	8
Supervised NMT	21.6	23.4	7.1	12.1	9.8	5.0	9

Definition of each system (#ID) follows those in Table 2.

We confirmed that USMT (#1, #3) outperforms Lample et al. [24]’s UNMT (#2) for all tasks. We also observed that our USMT (#3) outperforms Lample et al. [24]’s USMT (#1), mainly thanks to better refinement steps (see Section 6.3).

Our approach for UNMT (#4) is significantly better than USMT (#1, #3) and #2, demonstrating that it can successfully exploit the synthetic parallel data generated by USMT. Improvements over #2 range from 5.2 (fr→en) to 11.8 (id→en) BLEU points, bringing unsupervised MT to a dramatically better level of translation quality than previous work. The difference between #4 and #2 is especially large for distant languages, such as en-ja-NTCIR and en-id, presumably due to the fact that #2 relies on shared sub-word units that may be too rare in these language pairs. Moreover, sub-word units are not semantic units, i.e., a particular shared sub-word may have a very different meaning depending on the language, and consequently should not share the same embedding across distant languages. Lample et al. [24] observed slight drops of translation quality with their unsupervised “PBSMT+NMT” configuration, including for their en-fr task for which we used the same data. In contrast, we observed consistent and significant improvements with UNMT-1 over USMT-1.

USMT-2 (#5) outperformed USMT-1 (#3) for all tasks but underperformed UNMT-1 (#4). Finally, our best results were achieved by UNMT-2 (#6) with consistent improvements over UNMT-1 (#4),

ranging from 0.4 (fr→en) to 1.5 (en→de) BLEU points. Iterative training of USMT and UNMT also brought larger improvements than using more back-translated data for training UNMT-1 (#7).

For some of our translation tasks, our systems reached the performance of supervised SMT systems trained on millions of parallel sentences, such as for de→en. It also outperformed supervised NMT trained on much less data for the en-id pair.

6.2.2 en-ja-ALT and ja-id-ALT. We obtained only a poor translation quality for these two tasks with unsupervised MT. This is the consequence of the poor quality of the synthetic parallel data generated by USMT that are not useful for initializing UNMT. USMT remains difficult to train presumably due to the difficulty of the language pair, for which unsupervised bilingual word embeddings are difficult to train and also due to the low comparability between the monolingual corpora used for training [36] (see Section 6.6).

6.2.3 Computational Cost. We used 20 CPUs to train USMT-1 (#3), during approximately 4 days for each task to complete all the steps of iteration 1. Training of Lample et al. [24]’s USMT (#1) was slower due to the need of generating twice more back-translated data: it consumed around 6 days for training.

Training time of Lample et al. [24]’s UNMT (#2) was fairly unstable, varying from less than 2 days (for all ALT tasks) to 12 days (for en-fr). On the other hand, one iteration of our approach of UNMT required between 4 and 6 days of computation for each task. One advantage of our approach is that we can use an existing well-optimized NMT framework, such as Marian that is known to be very fast thanks to its native implementation in C++ and the possibility to use multi-GPU training and decoding. For instance, we used four GPUs for our UNMT, while the original implementation of #2 that we used exploited only one GPU. Note also that we could further reduce the training time of our approach using other features implemented in Marian, such as decoding with many CPUs or with averaged attention [42].

6.3 Learning Curves

Our USMT and UNMT (#3–6) include internal refinement steps, as described in Sections 3.3 and 4.4, respectively. Figure 3 presents the improvement of BLEU scores according to this refinement, i.e., the learning curves, for all our translation tasks. The curves for en-de, en-fr, en-ja-NTCIR, and en-id are similar. There was a remarkable improvement in translation quality between step 0 and the first refinement step of USMT. The following refinement steps improved translation quality to a lesser extent, but we observed that they were more effective in our USMT framework than the refinement steps of Lample et al. [24]’s USMT (#1). For our UNMT systems, the first system trained on back-translations generated by UNMT brought the largest improvements in most of our tasks, while the first step of UNMT led to a slight drop of translation quality, especially when translating into English.

The first refinement step of USMT-2 resulted in a significant drop of translation quality compared to UNMT-1. The second refinement step of USMT-2 did not bring improvements, or further worsened the translation quality. However, it surpassed USMT-1 in most tasks. By successfully exploiting the new outputs of USMT, subsequently, UNMT-2 recovered from the drop of translation quality.

6.4 Ablation Study for USMT

In this section, we present an ablation study to highlight the impact of our choices in our USMT pipeline that differentiate our systems from those in previous work. We evaluated the impact of the following.

Fig. 3. Learning curves for all our tasks. #ID refers to the systems presented in Tables 2 and 3.

Table 4. BLEU Scores of Our Ablation Study for USMT

Configuration	System	en-de		en-fr		en-ja-NTCIR	
		de→en	en→de	fr→en	en→fr	ja→en	en→ja
This work	USMT-1	23.4	18.8	26.7	25.3	21.3	22.0
	UNMT-2	30.4	24.3	29.2	29.0	25.9	29.2
(a) frequent n -grams	USMT-1	23.1	17.8	24.9	24.0	21.4	22.5
	UNMT-2	30.0	23.4	27.4	28.0	25.9	29.3
(b) backward only	USMT-1	22.0	18.5	25.8	25.3	19.6	21.7
	UNMT-2	29.5	23.5	28.3	28.8	24.5	29.0
	USMT-1	22.5	18.6	26.3	25.7	20.4	21.5
	UNMT-2	29.7	24.0	28.7	29.1	25.0	29.1
(c) not pruned	USMT-1	23.1	18.9	26.4	25.3	21.0	22.1
	UNMT-2	30.4	24.5	29.3	29.0	25.8	29.0

- (a) Phrases: collected with the word2phrase algorithm against using the most frequent n -grams, with n up to 3.
- (b) Synthetic parallel data for refinement steps: mixture of synthetic parallel data generated by forward and backward USMT systems against only using synthetic data generated by backward or forward USMT.
- (c) Re-trained phrase table: pruned or not using significance testing.

We performed this study on the tasks en-de, en-fr, and en-ja-NTCIR to highlight the impact of our choices where USMT performs reasonably well and for distant languages. The results for USMT, i.e., USMT-1, and UNMT after two training iterations, i.e., UNMT-2, are reported in Table 4.

For (a), we observed that using frequent n -grams as phrases to induce the phrase table, instead of phrases extracted via word2phrase, performs lower for en-de and en-fr pairs. The BLEU score of USMT-1 decreases up to 1.8 BLEU points for fr→en. On the other hand, for en-ja-NTCIR, the use of frequent n -grams was slightly better, with a gain of 0.5 BLEU points for USMT-1 en→ja. To sum up, the use of frequent n -grams was significantly harmful for three translation directions, en→de, fr→en, and en→fr, while we observed only slight improvements or similar BLEU scores for the other three translation directions, de→en, ja→en, and en→ja.

For (b), our results confirmed our assumptions given in Section 3.3: using only synthetic parallel data generated through back-translation, as in previous work, i.e., for which the source side is synthetic, is sub-optimal as many generated source phrases will never be used when decoding manually produced texts. They also skew the probability distribution by considering phrases unseen in the source language. For these reasons, we observed better results using forward translations in five configurations out of six, i.e., except for en→ja, thanks to the ability of the language model in dealing with noisy target phrases and in producing locally probable sequences of words.

Finally, for (c), we observed similar BLEU scores with and without pruning the phrase tables trained on synthetic parallel data. In all our configurations, pruning with significance testing removed more than 85% of the phrase pairs, while the BLEU scores remained stable, highlighting the high ratio of unlikely and noisy phrase pairs learned from the synthetic parallel data.

Interestingly, for all the different configurations, the impact on the translation quality for USMT-1 is approximately carried over to UNMT-2. From this empirical observation, we can speculate that the final performance of UNMT-2 is dependent on the performance of the first USMT-1 system and that efforts to improve USMT-1 may lead to similar improvement for UNMT-2.

Table 5. BLEU Scores With and Without Using Development Data

Configuration	System	en→fr	en→ja-NTCIR
USMT-1	w/ dev. data	25.3	22.0
	w/o dev. data	23.4	17.2
UNMT-2	w/ dev. data	29.0	29.2
	w/o dev. data	27.2	24.5

6.5 Impact of Using Development Data

In this work, we assumed the existence of development data for the reasons detailed in Section 3.2 and performed a supervised tuning of USMT and model selection for UNMT.

In this section, to evaluate the impact of this choice on the final result of our approach, we compare two configurations using or not using development data. The configuration using development data is the same one used in previous sections. For the configuration that does not use development data, we perform unsupervised tuning of USMT by using the default weights of Moses and use the UNMT model obtained after 10 training epochs.²⁴ We experiment on en→fr and en→ja-NTCIR and expect to have a larger drop of translation quality for en→ja-NTCIR than for en→fr, since previous work has shown that default Moses weights already perform well for en→fr [24].

Results are reported in Table 5. We observed that while the translation quality decreases by less than 2.0 BLEU points for en→fr, it decreases by more than 4.0 BLEU points for en→ja-NTCIR. Again, the drop in USMT-1 is carried over UNMT-2. The difference of translation quality between using or not using development data remains the same for USMT-1 and UNMT-2. We can then argue that most of the drop of the translation quality happens due to the unsupervised tuning of USMT with default weights of Moses that are particularly unsuitable for en→ja-NTCIR. While the unsupervised tuning method proposed by Artetxe et al. [2] is more elaborated than just using the Moses's default weights, it still depends on them for initialization and we may expect it to perform poorly for en→ja-NTCIR. Unsupervised tuning for distant languages remains an open challenge.

6.6 Impact of the Comparability of Monolingual Corpora

For en→ja-ALT and ja→id tasks, USMT failed in generating useful synthetic parallel data to initialize our UNMT. The reasons for this failure may be related to the difficulty of the language pairs, since, for instance, English and Japanese are distant languages, relatively for instance to English and German. However, for en→ja-NTCIR we observed that USMT can also generate useful synthetic parallel data for this language pair. Consequently, we hypothesize that, in addition to the language pair, the most important factors to consider for a success in USMT and eventually UNMT are the following two:

- (a) the comparability of the L1 and L2 monolingual corpora used for training, and
- (b) the similarity between the domain of the monolingual data and the domain of dev/test data.

To test these hypotheses, we performed further experiments in USMT, taking en→fr as an example, by only modifying the combination of monolingual corpora used for phrase table induction and

²⁴The number of epochs was arbitrarily chosen but we confirmed that it is more epochs than the number of epochs performed with supervised validation.

Table 6. BLEU Scores of USMT for en-fr Obtained Using Different English Monolingual Corpora

English corpora	BLEU		English OOV ratio
	fr→en	en→fr	
News Crawl	26.7	25.3	7.8%
Common Crawl	22.5	22.6	9.5%
NTCIR	2.5	3.2	36.9%

The “OOV ratio” is the ratio of the English token types in the test data that are not in the vocabulary of the English monolingual corpus.

during the refinement steps. As English data, we used either News Crawl, Common Crawl, or NTCIR corpora, while the French data remained the News Crawl corpus.

The resulting BLEU scores are summarized in Table 6. We observed that while en-fr can be considered as an easy language pair for USMT, replacing the News Crawl corpus with either a very noisy corpus (Common Crawl) or a clean but out-of-domain corpus (NTCIR) brought a significant drop in translation quality. In particular, the phrase table induced from NTCIR corpus had a very low coverage of the dev/test sets. For instance, in the English side of the test set, 7.8% (800/10,308), 9.5% (979/10,308), and 36.9% (3,805/10,308) of the token types were out-of-vocabulary for the phrase tables induced either from English News Crawl, English Common Crawl, or English NTCIR corpora, respectively. In this case, the noisier and smaller Common Crawl corpus was much more helpful than the cleaner and larger but out-of-domain NTCIR corpus.

We also confirmed in additional experiments for en-ja-ALT that none of all the possible combinations of our monolingual corpora achieved better results than using Common Crawl data, while using any other combination of our monolingual corpora than using NTCIR corpora for en-ja-NTCIR led to scores below 5.0 BLEU points for this task.

These results confirm how critical the selection of the monolingual data used to train USMT is, regarding (a) the comparability of the corpora for both languages and (b) the similarity of their domains to the domain of the dev/test data.

7 FURTHER EXPERIMENTS WITH WIKIPEDIA AS MONOLINGUAL DATA

From our observations in Section 6.6, we concluded that domain similarity of the monolingual data plays a crucial role in the success of unsupervised MT. In this section, we describe further experiments by using Wikipedia as monolingual data. Wikipedia corpora are especially interesting as we can consider that from one language to another the style of the corpus will remain similar. Moreover, while the Wikipedia corpus is a mixture of many domains, we can expect many articles to have a semantically similar content across languages; some may even be translations.²⁵ Given these properties of the Wikipedia corpora, we can expect to achieve a better translation quality than with configurations using very large but less-related monolingual data.

7.1 Data

The architectures and hyper-parameters of our MT systems are identical to those used in Section 6. For highlighting the impact of using more comparable monolingual data, we perform new experiments on the three ALT tasks, using Wikipedia corpora instead of the Common Crawl corpora. All the steps of our pipeline, along with the training of the models, such as word embeddings, have been done using Wikipedia corpora.

²⁵For instance, Schwenk et al. [33] extracted 135 M sentence pairs from Wikipedia that can be used to train NMT systems.

Table 7. Statistics of the Pre-Processed Wikipedia Corpora

	English	Indonesian	Japanese
#tokens	2.8 B	71.9 M	457 M

Table 8. Results for the ALT Tasks

System	ALT						#
	id→en	en→id	ja→en	en→ja	id→ja	ja→id	
USMT-1 (cc)	29.1	24.5	6.0	6.4	6.6	4.4	3
UNMT-2 (cc)	33.0	29.3	5.4	6.9	6.9	4.8	6
USMT-1 (wiki)	30.8	28.1	7.5	8.6	7.7	4.7	3
↳ UNMT-1 (wiki)	33.3	31.0	9.3	8.6	6.6	6.6	4
↳ USMT-2 (wiki)	31.0	30.4	8.7	6.6	6.5	4.4	5
↳ UNMT-2 (wiki)	34.0	31.3	9.3	9.1	7.3	5.0	6
Supervised SMT	35.5	35.3	10.9	15.0	13.8	8.9	8
Supervised NMT	21.6	23.4	7.1	12.1	9.8	5.0	9

Definition of each system (#ID) follows those in Table 2. “(wiki)” denotes the use of Wikipedia corpora to train the systems, while “(cc)” denotes the use of Common Crawl corpora.

We extracted raw texts from the English, Indonesian, and Japanese Wikipedia dumps of 2017/06/01. Then, we applied the same pre-processing steps described in Section 6.1. Statistics of our Wikipedia data after pre-processing are presented in Table 7. One obvious disadvantage of using these corpora is that they are significantly smaller than the Common Crawl corpora. Smaller training data may lead to much less accurate word embeddings, for instance. We assume that the better comparability of the Wikipedia corpora may compensate this disadvantage to some extent.

7.2 Results

As reported in Table 8, the use of Wikipedia corpora brought a better translation quality in all our ALT tasks, despite the use of much smaller monolingual data. Comparing #6 (cc) and #6 (wiki), the largest improvement is for ja→en, with a gain of 3.9 BLEU points, while ja→id remains extremely difficult with only a slight improvement of 0.2 BLEU points. These results confirm that the quality and the comparability of the monolingual corpora used for training unsupervised MT are indeed crucial. We also noticed that improvements observed at USMT-1 (#3) are carried over UNMT-2 (#6).

8 CONCURRENT WORK

After our preliminary experiments [26], several concurrent works that combine USMT and UNMT or improve UNMT have been published. In this section, we discuss the main similarities and differences between them and ours.

A framework proposed by Ren et al. [31] uses USMT to guide the training of UNMT models in an iterative back-translation process. One of the main differences with our work is that it uses a simpler version of USMT, word-based and without refinement steps, and relies on a unified EM framework for training iteratively USMT and UNMT.

The work in Artetxe et al. [3] is very close to ours. It first proposes to improve USMT using mixed forward and backward translations as synthetic training parallel data for the refinement steps, as we did in Section 3.3, and also proposes, among other modifications, a new feature for the induced phrase table based on the orthographic similarity between the source and target phrases. The resulting USMT system outperforms the USMT system proposed in their previous work [2],

on European language pairs. However, this work does not provide any ablation study to highlight how the modifications perform individually and we can expect that orthographic similarity features will not be useful, or even misleading, for distant languages that do not share the same writing systems. It also proposes to combine USMT and NMT similarly to what we proposed in [26] by incrementally training NMT on more and more synthetic parallel data. The originality of their approach is that during the training, the training data are progressively switched from data generated by USMT to data back-translated by NMT. They compared with our preliminary results in [26] and reported on higher BLEU scores for the same en-de and en-fr tasks presented in Section 6. However, it remains unclear to what extent their approach depends on the initial quality of the synthetic parallel data generated by USMT. Their proposed UNMT system reaches a significantly better translation quality than ours while they used an NMT system with Transformer “Big” model. For a fair comparison, we consistently used a standard Transformer model (Transformer “Base”) and with only four layers to speed up experiments. Last but not least, they did not present any results on truly low-resource and/or distant language pairs or Asian languages.

More recently, a new architecture for pre-training cross-lingual language models, called XLM, has been proposed by Lample and Conneau [22]. In their evaluation, they show that XLM can be used to initialize UNMT training, i.e., using an architecture similar to their previous one but replacing bilingual sub-word embeddings with XLM. They empirically demonstrate that XLM initializes UNMT better than bilingual sub-word embeddings, allowing UNMT to reach a new state-of-the-art performance in several translation tasks. In future work, we plan to investigate the promising combination of USMT and UNMT initialized by XLM.

These three works have in common that they performed experiments only on high-resource European language pairs, and with source and target monolingual data that are comparable to some extent. None of them explored the feasibility of their approach in much more difficult settings, i.e., for very distant language pairs and noisy or less-related monolingual corpora, in contrast to this article.

9 CONCLUSION AND FUTURE WORK

We proposed a new approach for UNMT that can be straightforwardly exploited with well-established architectures and frameworks used for supervised NMT without any modifications. It only assumes for initialization the availability of synthetic parallel data that can be, for instance, generated by USMT. Our approach for unsupervised MT achieved a much higher level of translation quality than previous work. We also showed that ensuring some comparability between the monolingual corpora used for both languages as well as some similarity between their domains and the domain of the dev/test sets is critical for the success of unsupervised MT.

For future work, we will extend our study on the impact of the comparability of monolingual corpora used in unsupervised MT and study methods for selecting useful monolingual corpora without supervision, as well as methods exploiting a weighted combination of out-of-domain and in-domain monolingual corpora. We also plan to propose new applications of our approach in weakly supervised scenarios where a small amount of manually produced parallel sentences is available for training.

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