Non-Autoregressive Machine Translation with Translation Memories

Jitao Xu† Josep Crego‡ François Yvon†

†Université Paris-Saclay, CNRS, LISN, 91400, Orsay, France
‡SYSTRAN, 5 rue Feydeau, 75002 Paris, France
{jitao.xu,francois.yvon}@limsi.fr, josep.crego@systrangroup.com

Abstract
Non-autoregressive machine translation (NAT) has recently made great progress. However, most works to date have focused on standard translation tasks, even though some edit-based NAT models, such as the Levenshtein Transformer (LevT), seem well suited to translate with a Translation Memory (TM). This is the scenario considered here. We first analyze the vanilla LevT model and explain why it does not do well in this setting. We then propose a new variant, TM-LevT, and show how to effectively train this model. By modifying the data presentation and introducing an extra deletion operation, we obtain performance that are on par with an autoregressive approach, while reducing the decoding load. We also show that incorporating TMs during training dispenses to use knowledge distillation, a well-known trick used to mitigate the multimodality issue.

1 Introduction
Non-autoregressive neural machine translation (NAT) has been greatly advanced in recent years (Xiao et al., 2022). NAT takes advantage from parallel decoding to generate multiple tokens simultaneously and speed up inference. This is often at the cost of a loss in translation quality when compared to autoregressive (AR) models (Gu et al., 2018). This gap is slowly closing and methods based on iterative refinement (Ghazvininejad et al., 2019; Gu et al., 2019; Saharia et al., 2020) and on connectionist temporal classification (Libovický and Helcl, 2018; Gu and Kong, 2021) are now reporting similar BLEU scores as strong AR baselines.

Most works on NAT focus on the standard machine translation (MT) task, where the decoder starts from an empty translation, with the exception of Susanto et al. (2020); Xu and Carpuat (2021), who use NAT to incorporate lexical constraints in decoding. However, some edit-based NAT models, such as the Levenshtein Transformer (LevT) of Gu et al. (2019), seem to be a natural candidate to perform translation with Translation Memories (TM). LevT is designed to iteratively edit an initial target sequence by performing insertion and deletion operations until convergence. This design also matches the concept of using TMs in MT, where given a source sentence, we aim to edit a candidate translation retrieved from a TM (Koehn and Senellart, 2010; Bulte and Tezcan, 2019). This setting is relevant for high-quality MT in technical domains, where the translation of terms and phraseology benefits from examples in a TM.

Our main goal in this study is to train a model that can revise candidate translations retrieved from a TM using edit-based NAT models. We first show that the original LevT cannot perform well on this task and explain why this is the case. We fix this issue with TM-LevT, which includes an additional initial deletion operation. Next, we improve the training procedure in two ways: (a) by also including the initial candidate translation on the source side, as done in AR decoding with TMs (Bulte and Tezcan, 2019; Xu et al., 2020); (b) by simultaneously training with empty and non-empty initial target sentences. In our experiments, TM-LevT achieves comparable performance to the AR approach on various domains when translating with TMs, with a reduced decoding load. We also observe that incorporating an initial translation on both source and target sides makes Knowledge Distillation (KD, Kim and Rush, 2016) useless, even when translating from scratch. This contrasts with standard NAT models, which resort to KD to alleviate the multimodality issue (Gu et al., 2018). As far as we know, we are the first to perform NAT with TMs and match AR model scores in this setting.

2 Using Translation Memories in NAT

2.1 Background
Translation Memory Retrieval  Given a source sentence \( f \), we aim to retrieve a TM match \( \tilde{e} \) from
the TM. For this, we search in the TM for a pair of sentences \((\tilde{f}, \tilde{e})\), where \(\tilde{f}\) is similar to \(f\). The corresponding target \(\tilde{e}\) is then used to initiate the translation of \(f\). The similarity between \(f\) and \(\tilde{f}\) is:

\[
\text{sim}(f, \tilde{f}) = 1 - \frac{\text{ED}(f, \tilde{f})}{\max(|f|, |\tilde{f}|)},
\]

where \(\text{ED}(f, \tilde{f})\) is the edit distance between \(f\) and \(\tilde{f}\), and \(|f|\) is the length of \(f\). The intuition is that the closer \(f\) and \(\tilde{f}\) is, the more suited \(\tilde{e}\) will be. We only use TM matches when the similarity score exceeds a threshold \(\alpha\), otherwise translate from scratch.

**Levenshtein Transformer** LevT is an edit-based NAT model proposed by Gu et al. (2019). It performs translation by iteratively editing an initial target sequence with insertion and deletion operations until convergence. The insertion operation first predicts the number of placeholders to insert for each position, then generates a token for each inserted placeholder. The deletion operation makes a binary decision for each token, indicating whether it should be deleted or kept. During training, a noised initial target sequence \(e'\) is first generated by randomly dropping tokens from the reference \(e\). The insertion operation is first applied to \(e'\), followed by the deletion operation which erases wrong predictions made by the model. During inference, the deletion operation is applied before insertion in each refinement iteration, except for the initial empty input (\(e' = []\)), where no deletion can happen. We refer to Gu et al. (2019) for details.

### 2.2 TM-LevT

Even though the edit-based nature of LevT seems to suit the task of MT with TMs, it has mostly been used to perform standard MT, where the decoder starts with an empty sentence. This means that \(e'\) is always a subsequence of \(e\), and the deletion operation is only trained to detect prediction errors made by the model. However, this training scheme does not suit for MT with TMs, as TM matches \(\tilde{e}\) retrieved from the TM will often contain tokens unrelated to the reference that should be removed (Figure 1 shows an example of TM match \(\tilde{e}\) containing an unrelated word "eating"). The distribution of these unrelated tokens may greatly differ from token prediction errors made by LevT. Our preliminary experiments (+tgt TM in Table 1) show that, given a trained LevT model, when we initialize the inference with \(\tilde{e}\) instead of an empty sequence, LevT is not able to make proper edits and almost considers \(\tilde{e}\) as the final translation.

**TM-LevT** aims to fix this issue. For this, we modify the training regime and add an extra deletion operation (init-del) before the insertion operation. As illustrated in Figure 1, init-del is trained to detect unrelated tokens from the initial sequence \(e'\), while the final deletion (final-del) aims to delete prediction errors, therefore making TM-LevT able to detect both unrelated tokens and its own errors. We apply the initial deletions to \(e'\) during training by taking the union of reference and predicted deletions in the init-del operation, resulting in a subsequence \(e''\) which is then passed to the insertion operation. We use the same deletion classifier for both the init-del and the final-del operations, which means that TM-LevT does not contain any extra parameters. During inference, TM-LevT performs the same as LevT, iteratively applying deletions and insertions to an initial candidate translation.

### 2.3 Incorporating TMs with TM-LevT

For each pair of sentences \((f, e)\), we use the TM match \(\tilde{e}\) retrieved from TM to initialize decoding \((e' = \tilde{e})\). As TM-LevT only supports deletion and insertion, reordering operations can only be obtained by first deleting a token, then reinserting it at another position. As these operations are performed independently, they may cause the erasure of a valid word from \(\tilde{e}\). To mitigate this risk, we make sure that \(\tilde{e}\) is always fully available to the decoder, by concatenating \(f\) and \(\tilde{e}\) (see Figure 1), as in (Bulte and Tezcan, 2019; Xu et al., 2020).
Finally, in order to perform both MT with TMs (when a good match is found) and standard MT (in absence of match), our training data exemplifies these two tasks and is prepared as follows: with a probability \( p = 0.5 \), we decide either to decode with a retrieved TM match \( \tilde{e} \) or to decode from scratch. In the former case, the decoder is initialized with \( \tilde{e} \), while in the latter case, we use a noised subsequence \( e' \) generated as in Gu et al. (2019). TM-LevT is then jointly trained on both tasks.

3 Experiments

3.1 Datasets

Our experiments use the same corpus as Xu et al. (2020). This corpus contains texts from a diverse set of 11 domains for the English-French direction, downloaded from OPUS\(^1\) (Tiedemann, 2012). For each source sentence, we retrieve from the same domain the top 3 TM matches according to the similarity score in Equation (1), further requiring a score greater than \( \alpha = 0.4 \) and strictly less than 1. For each domain, we prepare two test sets with 1,000 sentences: one containing randomly selected sentences having a close match (\( \text{sim} > 0.6 \)) in the TM, the other containing sentences with an acceptable match (\( \text{sim} \in [0.4, 0.6] \)). The remaining data is used for training. Details about these corpora are in Appendix A. We use all retrieved (up to 3) TM matches for training and only the best match for testing. The initial set of 4.4M parallel sentences is thus augmented with about 5M examples for which a TM match is available. Using these data, we build a shared source-target vocabulary with 32K Byte Pair Encoding (BPE) units (Sennrich et al., 2016).

3.2 Experimental Settings

TM-LevT is based on the Transformer architecture (Vaswani et al., 2017), implemented with fairseq\(^2\) (Ott et al., 2019).\(^3\) Details about hyperparameters are in Appendix B. For inference, the maximum number of iterations is 10. We compare TM-LevT with a strong AR approach (Bulte and Tezcan, 2019) and the original LevT model.\(^4\) These baselines use the same training data as TM-LevT, and process examples with and without TM matches. Contrarily to TM-LevT, TM matches only appear concatenated to the source sentence and translation always starts from scratch. We report results of a "do-nothing" baseline which simply outputs the TM matches. Performance is measured by SacreBLEU (Post, 2018) and COMET (Rei et al., 2020).

4 Results and Analysis

We evaluate the performance of standard MT and MT with TMs on the two test sets introduced in Section 3.1. We report in the main text aggregated results computed on the concatenation of all domains (11k sentences). Detailed results with a breakdown by domain are in Appendix C. As shown in Table 1, the AR TM-based baseline yields higher BLEU and COMET scores than the standard MT approach. LevT can also make good use of TM matches, but its performance lags way behind the AR strategy. Our TM-LevT, on the contrary, when using TM matches, almost closes the gap with the AR approach on BLEU, especially for the subset containing close matches.\(^5\) The gap in COMET score between TM-LevT and the AR model is much smaller than reported by Helcel et al. (2022), indicating that TM-LevT outputs valid translations. TM-LevT does remarkably well when translating from scratch, even surpassing on BLEU the AR model on the "close" match set, which is arguably easier.

| BLEU | \( \text{sim} > 0.6 \) | \( \text{sim} \in [0.4, 0.6] \) |
|------|-----------------|-----------------|
| copy | w/o TM | w/ TM | w/o TM | w/ TM |
| AR   | 51.2 | 67.1 | 46.1 | 55.7 |
| LevT | 46.5 | 60.4 | 40.8 | 49.3 |
| +tgt TM | 52.8 | 52.9 | 35.0 | 35.0 |
| TM-LevT | 52.6 | 65.9 | 45.7 | 53.3 |
| COMET | w/o TM | w/ TM | w/o TM | w/ TM |
| copy | 0.1330 | - | -0.3784 | - |
| AR   | 0.6143 | 0.6985 | 0.5379 | 0.5900 |
| LevT | 0.4251 | 0.5767 | 0.3429 | 0.4404 |
| +tgt TM | - | 0.1639 | - | -0.3478 |
| TM-LevT | 0.5314 | 0.6454 | 0.4263 | 0.4889 |

Table 1: BLEU and COMET scores on multi-domain test sets for various TM similarity ranges. w/o TM is standard MT, w/ TM adds a retrieved match on the source side. Copy copies \( \tilde{e} \) in the output. +tgt TM refers to using TM matches as the initial target for LevT.

AR approaches are known to improperly copy "unrelated tokens" from TM matches into output translations (Xu et al., 2020). We define unrelated tokens as those present in \( \tilde{e} \) but not in \( e \). Table 2 reports the percentage of such unrelated tokens:

\(^1\)https://opus.nlpl.eu/
\(^2\)https://github.com/pytorch/fairseq
\(^3\)We will open-source our code.
\(^4\)https://github.com/facebookresearch/fairseq/tree/main/examples/nonautoregressive_translation
\(^5\)The effect of using TM matches greatly varies across domains. See details in Appendix C.
TM-LevT seems slightly less prone than AR model to recopy unrelated parts of the TM matches.

| Unrelated rate ↓ sim > 0.6 | sim ∈ [0.4, 0.6] |
|----------------------------|------------------|
| AR                        | 28.42            |
| TM-LevT                   | 26.67            |

Table 2: Percentage of unrelated tokens from the retrieved TM matches appearing in the final translations.

4.1 Knowledge Distillation

KD is the "by default" technique used in most NAT models, as it reduces the complexity and lexical diversity of target sentences, thereby helping NAT approaches to mitigate the multimodality issue (Zhou et al., 2020; Xu et al., 2021). We conduct here experiments with KD to evaluate its effectiveness in MT with TMs. We train a Transformer-base model on the 4.4M parallel data and use it for distillation. As expected, using KD does improve the scores of TM-LevT on standard MT (Table 3). However, KD seems unnecessary when editing an initial translation and yields a large drop in scores compared to using real data. Furthermore, applying KD also to TM matches hurts the performance on both tasks.

| sim > 0.6 | sim ∈ [0.4, 0.6] |
|-----------|------------------|
| BLEU      | w/o TM w/ TM     | w/o TM w/ TM |
| TM-LevT   | 52.6 65.9        | 45.7 53.3    |
| +KD       | 54.3 57.1        | 47.6 49.3    |
| +KD TM    | 53.8 56.0        | 47.3 48.5    |

Table 3: BLEU scores for KD contrast. +KD applies KD to the training references. +KD TM applies KD to both references and TM matches.

4.2 Ablation Analysis

We study the effectiveness of each component of our method, training a new model for each contrast. Training without TM matches on the target side vastly degrades the scores in both conditions, indicating that standard MT can also benefit from training with TMs as initial targets. Training without TM matches on the source side, however, improves standard MT, as also pointed out by Bulte and Tezcan (2019), but has a negative impact when translating with TMs (Table 4). We also compare with alternative implementations of the deletion operation. Results in Table 4 (- final-del) show that removing the final deletion operation mostly impacts TM-LevT in the standard MT setting, where the detection of wrong predictions matters most (Huang et al., 2022). Last, we experiment with using only reference deletion labels to train the insertion operation, instead of using both the reference and model predictions (see Section 2.2). We observe (- self-pred) a small performance drop with respect to the baseline policy.

| sim > 0.6 | sim ∈ [0.4, 0.6] |
|-----------|------------------|
| BLEU      | w/o TM w/ TM     | w/o TM w/ TM |
| TM-LevT   | 52.6 65.9        | 45.7 53.3    |
| - tgt TM  | 46.6 60.7        | 40.7 49.6    |
| - src TM  | 53.2 64.3        | 45.9 52.2    |
| - final-del | 38.5 64.2    | 32.7 50.8    |
| - self-pred | 52.6 65.2   | 45.6 52.7    |

Table 4: BLEU scores for various configurations. - tgt TM (resp. - src TM) is the model trained without TM match on the target (resp. source) side. - final-del is trained without the final-del operation. - self-pred only applies reference deletions during training.

4.3 Reducing Decoding Load with TMs

Using TMs in MT is expected to not only improve the translation quality, but also reduce the decoding load. However, the latter is not really reduced in AR approaches nor with LevT, as decoding always starts from scratch. TM-LevT, on the contrary, uses an initial translation to speed up decoding. We measure the average number of iterations required in inference in Table 5, and observe that TM-LevT needs fewer iterations than LevT in all conditions.

| Decoding iter | sim > 0.6 | sim ∈ [0.4, 0.6] |
|---------------|-----------|------------------|
| BLEU          | w/o TM w/ TM | w/o TM w/ TM |
| TM-LevT       | 2.027 1.899 | 2.544 2.538 |
| +KD TM        | 1.781 1.348 | 2.260 1.880 |

Table 5: Averaged decoding iterations per sentence.

5 Conclusion

In this paper, we study the task of NAT with TMs. We propose TM-LevT which adds an initial deletion operation during training to detect possible unrelated tokens present in the TM matches. We show by copying the TM matches both on the source side and on the target side, as an initial target sequence, our model vastly outperforms the vanilla LevT model and achieves BLEU scores that approach those of a strong AR model both when decoding from scratch and when editing a TM match. TM-LevT also generates translations that contain less unrelated tokens and reduces the decoding load with fewer iterations. Finally, we demonstrate that training with TMs helps to improve NAT performance on standard MT without resorting to KD.
Limitations

NAT models such as LevT are more difficult to train than AR models, as they require larger batch size to converge. Our TM-LevT adds an initial deletion operation during training, therefore lengthening the training time by approximately $\times 1.2$ with respect to the basic LevT model. Due to computational limits, we have not conducted experiments on other language pairs, especially on more distant language pairs to further validate the TM-LevT model.

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A Details of Data Processing
We use a multi-domain corpus with 11 domains for English-French direction, collected from OPUS: documents from the European Central Bank (ECB); from the European Medicines Agency (EMEA); Proceedings of the European Parliament (Epps); legislative texts of the European Union (JRC); News Commentaries (News); TED talk subtitles (TED); parallel sentences extracted from Wikipedia (Wiki); localization files (GNOME, KDE and Ubuntu) and manuals (PHP). All these data are deduplicated prior to training. Table 6 reports statistics of the ratio of TM matches for various similarity ranges; these ratios vary greatly across domains. We tokenize all data using Moses and build a shared source-target vocabulary with 32K BPE learned with subword-nmt.\footnote{https://github.com/rsennrich/subword-nmt}

| Domain | Raw | sim > 0.6 | sim ∈ [0.4, 0.6] |
|--------|-----|-----------|------------------|
| ECB    | 195,956 | 51.73%    | 14.06%           |
| EMEA   | 373,235  | 65.68%    | 12.65%           |
| Epps   | 2,009,489 | 10.12%    | 25.30%           |
| GNOME  | 55,391  | 39.31%    | 11.06%           |
| JRC    | 503,437 | 50.87%    | 16.67%           |
| KDE    | 180,254 | 36.00%    | 10.81%           |
| News   | 151,423 | 2.12%     | 9.65%            |
| PHP    | 16,020 | 34.92%    | 12.06%           |
| TED    | 159,248 | 11.90%    | 26.64%           |
| Ubuntu | 803,704 | 19.87%    | 17.32%           |
| Wiki   | 9,314 | 20.32%    | 8.26%            |
| Total  | 4,457,471 | 24.27%   | 20.00%           |

Table 6: Dataset statistics, with ratios of sentences with at least one TM match for various similarity ranges.

B Model Configurations
TM-LevT is based on the Transformer architecture using a hidden size of 512 and a feedforward size of 2,048. We optimize with Adam with a maximum learning rate of 0.0005, an inverse square root decay schedule, and 10,000 warmup steps. We share the decoder parameters for both two deletions and the insertion operation. We also tie all input and output embedding matrices (Press and Wolf, 2017). We train TM-LevT with a mixed precision for 300k iterations with a batch size of 8,192 tokens on 8 V100 GPUs. The vanilla LevT model is trained similarly, while the AR baseline (Bulte and Tezcan, 2019) is trained with a maximum learning rate of 0.0007, with 4,000 warmup steps for 300k iterations on 4 V100 GPUs.
Table 7: BLEU and COMET scores for each domain, the task is standard MT with sim > 0.6. All is computed by concatenating all test sets (11k sentences in total). Copy refers to copying the TM match into the output.

| BLEU | ECB | EMEA | Epps | GNOME | JRC | KDE | News | PHP | TED | Ubuntu | Wiki | All |
|------|-----|------|------|-------|-----|-----|------|-----|-----|--------|------|-----|
| copy | 59.8 | 64.5 | 34.4 | 70.3  | 67.6| 55.3| 12.0 | 38.6| 30.8| 51.6   | 47.4 | 52.6|
| AR   | 58.7 | 53.8 | 55.8 | 35.0  | 68.8| 53.9| 27.1 | 18.2| 62.0| 54.0   | 65.0 | 51.2|
| LevT | 46.6 | 30.7 | 51.8 | 51.0  | 62.3| 47.0| 23.6 | 12.5| 58.7| 50.0   | 61.9 | 46.5|
| TM-LevT | 53.0 | 49.7 | 53.2 | 51.5  | 64.7| 50.8| 24.5 | 37.1| 59.5| 50.4   | 64.0 | 52.6|
| COMET| 0.4006 | 0.4625 | -0.0797 | 0.4893 | 0.6993 | 0.1150 | -0.6083 | -0.1977 | -0.4184 | 0.3296 | 0.5768 | 0.7335 |
| AR   | 0.6333 | 0.6402 | 0.8137 | 0.9057 | 0.5116 | 0.3241 | -0.0556 | 0.7848 | 0.7031 | 0.7786 | 0.6143 |
| LevT | 0.4251 | 0.1322 | 0.7460 | 0.6181 | 0.8291 | 0.3879 | 0.2037 | 0.6912 | 0.5636 | 0.6947 | 0.4251 |
| TM-LevT | 0.5637 | 0.5559 | 0.7513 | 0.6355 | 0.8477 | 0.4218 | 0.1660 | 0.6929 | 0.5768 | 0.7335 | 0.5314 |

Table 8: BLEU and COMET scores for each domain, the task is MT with TMs with sim > 0.6. All is computed by concatenating all test sets (11k sentences). Copy refers to copying the TM match into the output.

| BLEU | ECB | EMEA | Epps | GNOME | JRC | KDE | News | PHP | TED | Ubuntu | Wiki | All |
|------|-----|------|------|-------|-----|-----|------|-----|-----|--------|------|-----|
| copy | 47.3 | 47.6 | 12.7 | 52.6 | 53.0 | 42.7 | 5.8  | 29.7 | 8.2  | 35.1   | 13.0 | 34.5|
| AR   | 52.3 | 52.7 | 44.7 | 54.4  | 64.7| 53.2| 30.0 | 17.9 | 41.7 | 49.2   | 42.2 | 46.1|
| LevT | 40.7 | 31.4 | 42.6 | 51.0  | 59.8| 46.8| 27.6 | 11.9 | 38.7 | 45.7   | 40.2 | 40.8|
| TM-LevT | 47.9 | 47.7 | 41.5 | 51.6  | 61.1| 50.1| 26.8 | 34.3 | 38.0 | 46.8   | 41.0 | 45.7|
| COMET| 0.0310 | 0.1527 | -0.7608 | 0.1416 | 0.1919 | -0.1703 | -0.9719 | -0.6279 | -1.1419 | -0.1837 | -0.8222 | -0.3784 |
| AR   | 0.5229 | 0.5920 | 0.7735 | 0.7048 | 0.8854 | 0.5522 | 0.4688 | -0.1819 | 0.5501 | 0.6363 | 0.4157 | 0.5379 |
| LevT | 0.2908 | 0.1245 | 0.6996 | 0.5956 | 0.8069 | 0.4140 | 0.3567 | -0.7332 | 0.3979 | 0.5194 | 0.3011 | 0.3429 |
| TM-LevT | 0.4370 | 0.5231 | 0.6515 | 0.6205 | 0.8116 | 0.4576 | 0.2948 | -0.2343 | 0.3655 | 0.5035 | 0.2600 | 0.4263 |

Table 9: BLEU and COMET scores for each domain, the task is standard MT with sim ∈ [0.4, 0.6]. All is computed by concatenating all test sets (11k sentences). Copy refers to copying the TM match into the output.

C Detailed Results on Each Domain

BLEU and COMET scores for each domain are in Tables 7, 8, 9, 10. The variation in scores across domains is large, confirming that TM matches can be very beneficial for some technical domains (e.g. ECB, EMEA, GNOME, KDE, JRC), for which we often find good matches that help to greatly increase the performance. On the other hand, News, Wiki and TED yield less matches, and these only help when the similarity is high (sim > 0.6).
|       | ECB | EMEA | Epps | GNOME | JRC | KDE | News | PHP | TED | Ubuntu | Wiki | All |
|-------|-----|------|------|-------|-----|-----|------|-----|-----|--------|------|-----|
| copy  | 47.3| 47.6 | 12.7 | 52.6  | 53.0| 42.7| 5.8  | 29.7| 8.2 | 35.1   | 13.0 | 34.5|
| AR    | 62.3| 62.8 | 44.9 | 69.6  | 75.4| 62.1| 29.9 | 39.2| 42.6| 58.1   | 43.9 | 55.7|
| LevT  | 52.3| 47.1 | 42.7 | 65.7  | 71.9| 57.6| 27.5 | 23.8| 39.0| 55.0   | 40.8 | 49.3|
| +tgt TM| 47.4| 48.0 | 13.2 | 53.2  | 53.5| 42.9| 6.0  | 29.7| 9.1 | 37.1   | 13.2 | 35.0|
| TM-LevT| 59.7| 61.9 | 41.4 | 68.1  | 73.0| 61.4| 26.4 | 39.1| 37.5| 56.1   | 39.7 | 53.3|
| COMET | ECB | EMEA | Epps | GNOME | JRC | KDE | News | PHP | TED | Ubuntu | Wiki | All |
| copy  | 0.0310 | 0.1527 | -0.7608 | 0.1416 | 0.1919 | -0.1705 | -0.9719 | -0.6279 | -1.1419 | -0.1837 | -0.8222 | -0.3784 |
| AR    | 0.5814 | 0.6607 | 0.7740 | 0.8380 | 0.9220 | 0.6217 | 0.4741 | -0.1140 | 0.5543 | 0.7453 | 0.4344 | 0.5900 |
| LevT  | 0.4283 | 0.2846 | 0.6998 | 0.7697 | 0.8746 | 0.5437 | 0.3660 | -0.4900 | 0.4107 | 0.6676 | 0.2910 | 0.4404 |
| +tgt TM| 0.0487 | 0.1569 | -0.7208 | 0.1883 | 0.2167 | -0.1151 | -0.9508 | -0.6205 | -1.0949 | -0.1234 | -0.8100 | -0.3478 |
| TM-LevT| 0.5102 | 0.6281 | 0.6368 | 0.8142 | 0.8741 | 0.5814 | 0.2781 | -0.1853 | 0.3523 | 0.6727 | 0.2172 | 0.4889 |

Table 10: BLEU and COMET scores for each domain, the task is MT with TMs with \( \text{sim} \in [0.4, 0.6] \). All is computed by concatenating all test sets (11k sentences). Copy refers to copying the TM match into the output.