Maximising TM Performance through Sub-Tree Alignment and SMT

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Abstract

With the steadily increasing demand for high-quality translation, the localisation industry is constantly searching for technologies that would increase translator throughput, in particular focusing on the use of high-quality Statistical Machine Translation (SMT) supplementing the established Translation Memory (TM) technology. In this paper, we present a novel modular approach that utilises state-of-the-art sub-tree alignment and SMT techniques to turn the fuzzy matches from a TM into near-perfect translations. Rather than relegate SMT to a last-resort status where it is only used should the TM system fail to produce the desired output, for us SMT is an integral part of the translation process that we rely on to obtain high-quality results. We show that the presented system consistently produces better-quality output than the TM and performs on par or better than the standalone SMT system.

1. Introduction

As the world becomes increasingly interconnected, ideas, products and services need to be communicated to the widest audience possible. This requires localisation for as many languages cultures and locales as possible, with translation being one of the main parts of the localisation process. Because of this, the amount of data that needs professional high-quality translation is continuing to increase well beyond the capacity of the world's human translators.

Current efforts in the localisation industry are mostly directed at the reduction of the amount of data that needs to be translated manually from scratch. Such efforts mainly include the use of Translation Memory (TM) systems, where earlier translations are stored in a database and offered as suggestions when new data needs to be translated. As TM systems were originally limited to providing translations only for (almost) exact matches of the new data, the integration of Machine Translation (MT) techniques is often seen as the only feasible development that has the potential to significantly reduce the amount of manual translation.

Currently, the most widely used method to enhance TMs is to employ Example-Based Machine Translation (EBMT) techniques to suggest translations for new data by combining parts of sentences from the TM database, rather than simply looking for (almost) exact matches.[1] With recent advances in the performance and quality of Statistical Machine Translation (SMT) systems, many commercial TM systems offer the user the option to obtain SMT-generated translations for new data. Such translations, however, are usually only obtained for cases where the TM system could not produce a good-enough translation (cf. Heyn, 1996). Given that the SMT system used is presented with the "hard" translation cases (strings not seen in the TM) and is usually trained only on the data available in the TM, it tends to have only few examples from which to construct the translation, thus often producing fairly low quality output. Because of this, and since translators are used to TMs as an integral part of their working environment but less so to MT, SMT output is still often scorned upon by professional translators.

Another major problem with the TM-SMT approach is the fact that, unlike the Fuzzy-Match

[1] See e.g. the Déjà Vu TM system (http://www.atril.com/overview), as well as Chapter 3 in (Carl and Way, 2003). For an in-depth comparative review of TM systems and EBMT, see (Somers and Fernández Díaz, 2004).

Scores (FMS) provided by TM systems, currently there is no reliable way to automatically ascertain the quality of SMT-generated translations, so that the user could at a glance make a judgement as to the amount of effort that might be needed to post-edit the suggested translation (Simard and Isabelle, 2009). Not having such automatic quality metrics also has the side effect of it being impossible for a Translation-Services Provider (TSP) company to reliably determine in advance the increase in translator productivity due to the use of MT and to adjust their resources-allocation and cost models correspondingly.

We present a new system implementing a different type of TM/MT integration. The system incorporates TM, SMT and automatic Sub-Tree Alignment (STA) backends. When a new sentence needs to be translated, first a Fuzzy-Match Score (FMS) is obtained from the TM backend, together with the suggested matching sentence and its translation. For sentences that receive a reasonably high FMS, the STA backend is used to find the correspondences between the input sentence and the TM-suggested translation, as well as the parts of the input sentence that still need to be translated, i.e. the parts of the input sentence that do not directly correspond to part of the TM-suggested translation. Using this information, the SMT backend is employed to obtain the final translation of the input sentence, which should be of higher quality than the translation originally suggested by the TM.

In Section 2, we present the technical details of the design of our system, together with motivation for the particular design choices we took. Section 3 details the experimental setup we build and the data set we used for the evaluation results in Section 4. In Section 5, we discuss some related research employing similar TM/MT integration techniques. We present improvements that we plan to investigate in further work in Section 6, and provide concluding remarks in Section 7.

2. Integration Framework

We present a system that uses an SMT backend to translate the mismatched parts of a TM-suggested translation, generating higher-quality output.

2.1. Translation Memory Backend

Although the intention is to use a full-scale TM system as the translation memory backend, to have complete control over the process for this initial research we decided to build a simple prototype TM backend ourselves.

We employ a database setup using the PostgreSQL v.8.4.3[2] relational database management (RDBM) system. The segment pairs from a given TM are stored in this database and assigned unique IDs for further reference. When a new sentence is supplied for translation, the database is searched for (near) matches, using an FMS based on character-based Levenshtein edit distance (Levenshtein, 1965). To speedup the computation, we use a recursive wrapper around the PostgreSQL-internal implementation of the `levenstein()` function, taken from the TinyTM project.[3]

In this way, for each input sentence, from the database we obtain the matching segment with the highest FMS, its translation and the score itself.

2.2. Sub-Tree Alignment Backend

The system presented in this paper uses sub-tree alignment (Zhechev, 2010) to discover parts of the input sentence that correspond to parts of the suggested translation extracted from the TM database. This is done in a three-step process. First, the plain TM match and its translation are aligned, which produces a sub-tree aligned phrase-based tree pair with pseudo non-terminal nodes with the label '*X*'. We call this step *bilingual alignment*.

In the second step, called *monolingual alignment*, the phrase-based tree-annotated version of the TM match is aligned to the plain-text input sentence. The reuse of the structure for the TM match allows us to use it in the third step as an intermediary to establish the available sub-tree alignments between the input sentence and the translation suggested from the TM.

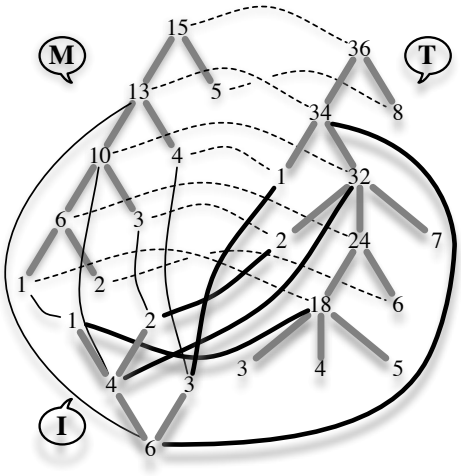
During this final alignment, we identify matched and mismatched portions of the input sentence and their possible translations in the TM suggestion and, thus, this step is called *matching*. Additionally, the sub-tree alignments implicitly provide us with reordering information, telling us where the

[2] `http://www.postgresql.org`

[3] `http://tinytm.sourceforge.net/en/technology/fuzzymatch.html`

portions of the input sentence that we translate should be positioned in the final translation.

The alignment process is exemplified in Figure 1. The tree marked 'I' corresponds to the input sentence, the one marked 'M' to the TM match and the one marked 'T' to the TM translation. Due to space constraints, we only display the node ID numbers of the non-terminal nodes in the phrase-structure trees—in reality all nodes carry the label '*X*'. These IDs are used to identify the sub-sentential alignment links. The lexical items corresponding to the leaves of the trees are presented in the table below the graph.



I	1	2	3					
input	sender	email	address					
M	1	2	3	4	5			
match	sender	's	email	address	.			
T	1	2	3	4	5	6	7	8
trans-lation	adresse	électro-nique	de	l'	expé-diteur	du	mes-sage	.

Figure 1. Example of sub-tree alignment between an input sentence, TM match and TM translation

The alignment process can be visually represented as starting at a linked node in the **I** tree and following the link to the **M** tree. Then, if available, we follow the link to the **T** tree and this leads us to the **T**-tree node corresponding to the **I**-tree node we started from. In Figure 1, this results in the **I–T** alignments *I1–T18*, *I2–T2*, *I3–T1*, *I4–T32* and *I6–T34*. The first three links are matches, because the lexical items covered by the **I** nodes correspond exactly to the lexical items covered by their **M** node counterparts. Such alignments provide us with direct TM translations for our input. The last two links in the group are mismatched, because there is no lexical correspondence between the **I** and **M** nodes (node *I4* corresponds to the phrase *sender email*, while the linked node *M10* corresponds to *sender 's email*). Such alignments can only be used to infer reordering information. In particular in this case, we can infer that the target word order for the input sentence is *address email sender*, which produces the translation *adresse électronique de l' expéditeur*.

We decided to use sub-tree-based alignment, rather than plain word alignment (e.g. GIZA++ – Och and Ney, 2003), due to a number of factors. First, sub-tree-based alignment provides much better handling of long-distance reorderings, while word– and phrase-based alignment models always have a fixed limit on reordering distance that tends to be relatively low to allow efficient computation.

The alignments produced by a sub-tree alignment model are also precision-oriented, rather than recall-oriented (cf. Tinsley, 2010). This is important in our case, where we want to only extract those parts of the translation suggested by the TM for which we are most certain that they are good translations.

Out of the three currently available open-source sub-tree alignment systems, two can only operate when at least one language-side of the data that needs to be aligned is pre-parsed (Ambati et al., 2009, Tiedemann, 2010) and one of them needs a hand-crafted parallel treebank as training data (Tiedemann, 2010).

As these requirements necessitate the acquisition of human-annotated data besides the data available in the TM, we decided to use the system described in (Zhechev, 2010) instead. It can produce aligned phrase-based-tree pairs from unannotated (i.e. unparsed) data. It can also function fully automatically without the need for any training data.

The only resource necessary for the operation of this system is a probabilistic bilingual dictionary covering the data that needs to be aligned. For the *bilingual alignment* step, such a bilingual dictionary is produced as a byproduct of the training of the SMT backend and therefore available. For the *monolingual alignment* step, the required probabilistic dictionary is generated by simply listing each unique token seen in the source-language data in the TM as translating only as itself with probability 1.

2.3. Statistical Machine Translation Backend

Once the *matching* step is completed, we have identified the parts of the input sentence for which translations will be extracted from the TM suggestions, as well as the parts that need to be translated from scratch. The lengths of the non-translated segments vary depending on the FMS, but are in general relatively short (one to three tokens). In the system presented in this paper, we explore two approaches to handling the translation of these outstanding fragments.

The first approach is extremely straightforward, in that the non-translated segments of the input sentence are sent severally to the SMT backend for translation without any context information. The segments translated using TM data and the ones translated using the SMT backend are then simply concatenated in the target-language word order, as determined implicitly by the sub-tree alignment information. The most serious drawback of this approach is that translating the individual segments out of context might often lead to improper lexical choice by the SMT backend, which could have been properly resolved given the context of the whole input sentence. Also, for certain cases (particularly with low FMS) the target-language word order may not be discernible for all input-sentence segments and the translations of the segments with undetermined placement are simply appended to the end of the generated translation. Still, the simplicity of this approach makes it a good baseline benchmark against which to evaluate improvements. This approach is referred to as *comb* below.

The second approach to handling non-translated input-sentence segments relies on a specific feature of the SMT backend we use, namely the Moses system (Koehn et al., 2007). We decided to use this particular system as it is the most widely adopted open-source SMT system, both for academic and commercial purposes. In this approach, we annotate the segments of the input sentence for which translations have been found from the TM suggestion using XML tags with the translation corresponding to each segment given as an attribute to the encapsulating XML tag.[4] The SMT backend is supplied with a string consisting of the concatenation of the XML-enclosed translated segments and the plain non-translated segments in the target-language word order, as established by the alignment process. The SMT backend is instructed to translate the string as a whole, while keeping the translations supplied via the XML annotation. This mode of operation provides the SMT backend with the necessary context information to come up with proper lexical choice for the non-translated fragments and allows it to introduce reordering on its own, based on the SMT reordering models derived during training. We refer to this approach as *xml*.

2.4. Auxilliary Tools

It must be noted that in our approach the SMT backend sees the data it needs to translate in the target-language word order (e.g. it is asked to translate an English sentence that has French word order). This, however, does not correspond to the data found in the TM, which we use for deriving the SMT models. Because of this discrepancy, we developed a pre-processing tool that goes over the TM data performing *bilingual alignment* and outputting reordered versions of the sentences it processes by using the information implicitly encoded in the sub-tree alignments. In this way, we obtain the necessary reordered data to train a translation model where the source language already has the target-language word order. For translation in our system, we use both this model and the proper-word-order model.

One specific aspect of real-world TM data that we need to deal with is that they often contain meta-tag annotations of various sorts. Namely, annotation tags specific to the file format used for storing the TM data, XML tags annotating parts of the text as appearing in Graphical User Interface (GUI) elements, formatting tags specific to the file format the TM data was originally taken from, e.g. RTF, OpenDoc, etc. Letting any MT system try to deal with these tags in a probabilistic manner can easily result in ill-formed, mistranslated and/or out-of-order meta-tags in the translation.

This motivates the implementation of a rudimentary handling of meta-tags in the system presented in this paper, in particular handling the XML tags found in the TM data we work with, as described in Section 3. The tool we built for this purpose

[4] A similar strategy has been adopted by Smith and Clark (2009) for the integration of EBMT-derived translations in SMT.

simply builds a map of all unique XML tags per language and replaces them in the data with short placeholders that are designed in such a way that they would not interfere with the rest of the TM data.[5] A special case that the tool has to take care of is when an XML tag contains an attribute whose value needs to be translated. In such situations, we decided to not perform any processing, but rather leave the XML tag as is, so that all text may be translated as needed. The proper treatment of meta-tags is beyond the scope of the current paper and will be investigated separately.

We also had to build a dedicated tokeniser/detokeniser pair to handle real world TM data containing meta-tags, e-mail addresses, file paths, etc., as described in Section 3. Both tools are implemented as a cascade of regular expression substitutions in Perl. However, due to the nature of the data, the detokeniser is not always able to fully detokenise the data, especially in cases that include quotation marks, and we expect this to have a slight impact on the evaluation results.

Finally, we use a tool to extract the textual data from the TM. That is, we strip all tags specific to the format in which the TM is stored, as they can in general be recreated and thus do not need to be present during translation. In our particular case, the TM is stored in the XML-based TMX format.[6]

2.5. Complete Workflow

Besides the components described above, we also performed two further transformations on the data. First, we lowercase the TM data before using it to train the SMT backend models. This also means that the alignment steps from Section 2.2 are performed on lowercased data, as the bilingual dictionary used there is obtained during the SMT training process.[7]

Additionally, the SMT and sub-tree alignment systems that we use cannot handle certain characters, which we need to mask in the data. For the SMT backend, this includes '|', '<' and '>' and for the sub-tree aligner—'(' and ')'. The reason these characters cannot be handled is that the SMT system uses '|' internally to separate data fields in the trained models and '<' and '>' cannot be handled whilst using XML tags to annotate pre-translated portions of the input. The sub-tree aligner uses '(' and ')' to represent the phrase-based tree structures it generates and the presence of these characters in the data may create ambiguity when parsing the tree structures. All these characters are masked by substituting in high-Unicode counterparts, namely '|', '<', '>', '（' and '）'. Visually, there is a very slight distinction and this is intentionally so to simplify debugging. However, the fact that the character codes are different alleviates the problems discussed above. Of course, in the final output, the masking is reversed and the translation contains the regular versions of the characters.

The complete pre-processing workflow is presented in Figure 2, where the rectangles with vertical bars represent the use of open-source tools, while the plain rectangles represent tools developed by the authors of this paper. First, the textual data is extracted from the original TM format, producing one plain-text file for each language side. These data can either be pre-loaded in a PostgreSQL database at this time, or during the first run of the translation system.

Next, the meta-tag-handling tool is used to generate the substitution tables for the source and target languages, as well as new files for each language with the tags substituted by the corresponding identifiers (cf. Section 2.4). These files are then tokenised, lowercased and all conflicting characters are masked, as described in Section 2.4.

The pre-processed files are then used to produce a file containing pairs of sentences in the input format of the sub-tree aligner, as well as to generate the probabilistic dictionary required for the *monolingual alignment* and to train the SMT model on the data in the proper word order. The SMT training produces the necessary bilingual dictionary for use by the sub-tree aligner, which is run to obtain a parallel-treebank version of the TM data. The parallel treebank is then used to retrieve bilingual alignments for TM data, rather than gen-

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[5] In the current implementation, the XML tags are replaced with the string ␣<tag_id>␣, where <tag_id> is a unique numeric identifier for the XML tag that is being replaced.

[6] http://www.lisa.org/fileadmin/standards/tmx1.4/tmx.htm

[7] Currently, we do not use a recaser tool and the translations produced are always in lowercase. This component, however, will be added in a future version of the system.

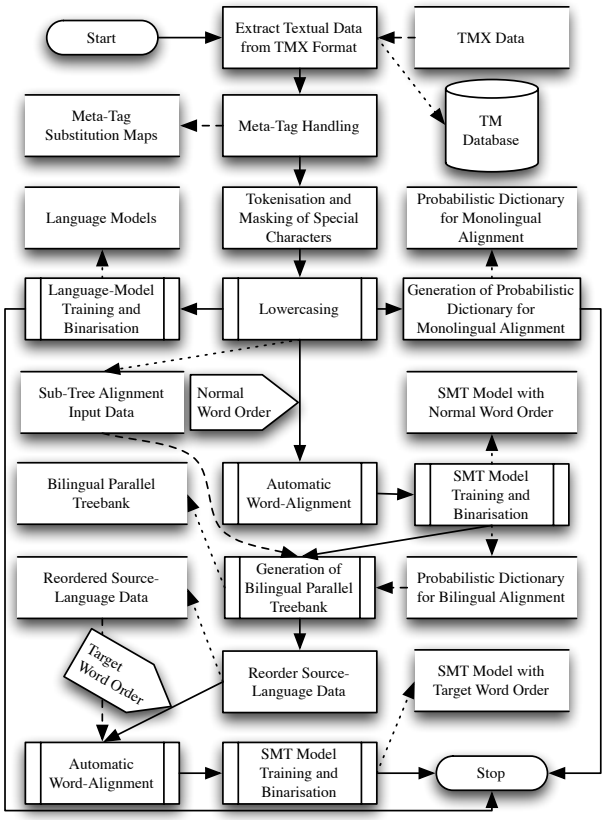

Figure 2. Pre-Processing Workflow

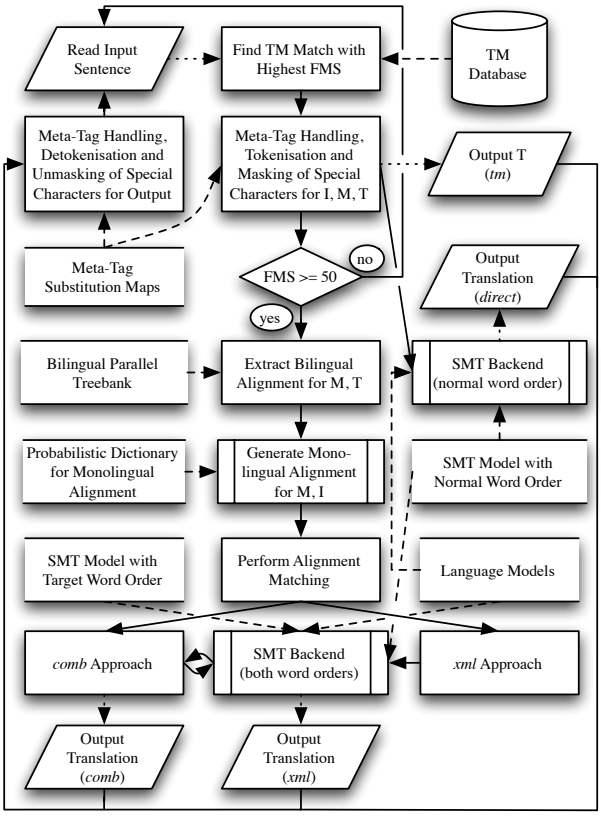

Figure 3. Translation Workflow

erate them on the fly during translation. This is an important design decision, as the complexity of the alignment algorithm is (very) high for plain-text alignment (cf. Zhechev, 2010).

Once we have generated the bilingual parallel treebank, we run the reordering tool, which generates a new plain-text file for the source language, where the sentences are modified to conform to the target-language word order, as implied by the data in the parallel treebank. This is then matched with the proper-order target-language file to train the SMT backend for the actual use in the translation process.

Once all the necessary files have been generated and all pre-processing steps have been taken, the system is ready for use for translation. The translation workflow is shown in Figure 3, 'I', 'M' and 'T' having the same meanings as in Figure 1. The two translation approaches from Section 2.3 are represented by their labels *comb* and *xml*, while *tm* and *direct* denote the unmodified outputs of the TM and SMT backends respectively.

During translation, the first step after an input sentence has been read in is to find the TM match with the highest FMS. This is done using the original plain non-pre-processed data to simulate real-life operation with a proper TM backend. After the best TM match and its translation are extracted from the TM, they—together with the input sentence—are pre-processed by tokenisation, lowercasing, meta-tag and special-character substitution.

Next, the corresponding tree pair is extracted from the bilingual parallel treebank to establish the tree structure for the TM source-language match. This tree structure is then used to perform the *monolingual alignment*, which allows us to perform the *matching* step next. After the *matching* is complete, we generate two possible translations as described in Section 2.3. Finally, the translations are de-tokenised and the XML tags and special characters are unmasked.

3. Experimental Setup

We use real-life TM data provided by Symantec Ireland, an industrial partner of CNGL. The TM was generated during the translation of RTF-formatted customer support documentation. The data is in TMX format and originally contains 108 967 English–French translation segments, out of which 14 segments either have an empty lan-

guage side or have an extreme discrepancy in the number of tokens for each language side and were therefore discarded.

A particular real-life trait of the data is the presence of a large number of XML tags. Running the tag-mapping tool described in Section 2.5, we gathered 2 049 distinct tags for the English side of the data and 2 653 for the French side. Still, there were certain XML tags that included a `label` argument whose value was translated from one language to the other. These XML tags were left intact so that our system could handle the translation correctly.

The TM data also contain a large number of file paths, e-mail addresses, URLs and others, which makes bespoke tokenisation of the data necessary. Our tokenisation tool ensures that none of these elements are tokenised, keeps RTF formatting sequences non-tokenised and properly handles non-masked XML tags, minimising their fragmentation.

Due to the nature of TM data, translation segments rarely occur more than once in the data set. This explains the high number of unique tokens (measured after pre-processing) that we observe for the two languages—41 379 for English and 49 971 for French—out of 108 953 segment pairs. The average sentence length is 13.2 for English and 15.0 for French.

For evaluation, we use a data set of 4977 English–French segments that were obtained from a different set of documents than the ones, for whose translation the TM presented above was used. The sentences in the test set — with average length 9.2 tokens for English and 10.9 for French — are significantly shorter compared to the TM.

It must be noted that we used SMT models with maximum phrase length of 3 tokens, rather than the standard 5 tokens, and for decoding we used a 3-gram language model. This results in much smaller models than the ones usually used in mainstream SMT applications. (The standard for some tools goes as far as 7-token phase-length limit and 7-gram language models.)

4. Evaluation Results

For the evaluation of our system, we used a number of widely accepted automatic metrics, namely BLEU (Papineni et al., 2002), METEOR (Banerjee and Lavie, 2005), TER (Snover et al., 2006) and inverse F-Score based on token-level precision and recall.

We setup our system to only fully process input sentences for which a TM match with an FMS over 50% was found, although all sentences were translated directly using the SMT backend for control purposes (marked as *direct*). The TM-suggested translations were also output for all input sentences (*tm*).

The results of the evaluation are given in Figure 4, where the *tm* and *direct* scores are also given for the FMS range [0%; 50%)∪{100%}. Across all metrics we see a uniform drop in the quality of TM-suggested translations, which is what we expected, given that these translations contain one or more incorrect words. We believe that the relatively high scores recorded for the TM-suggested translations at the high end of the FMS scale are a result of the otherwise perfect word order and lexical choice. For *n*-gram-match-based metrics like the ones we used, such a result is expected and predictable. Although the inverse F-score results show the potential of our setup to translate the outstanding tokens in a 90%–100% TM match, it appears that the SMT system produces word order that does not correspond to the reference translation and because of this receives lower scores on the other metrics.

The inverse F-score results also confirm our prediction that the *comb* translation approach is prone to lexical-choice errors due to the lack of context during translation. These errors seem to be the major factor leading to significantly worse performance compared to the *xml* approach.

The unexpected drop in scores for perfect TM matches is due to discrepancies between the reference translations in our test set and the translations stored in the TM. We believe that this issue affects all FMS ranges, albeit to a lower extent for non-perfect matches. Unfortunately, the exact impact cannot be ascertained without human evaluation.

We observe a significant drop-off in translation quality for the direct output below FMS 50%. This suggests that sentences with such low FMS should be translated either by a human translator from scratch, or by an SMT system trained on different/more data.

The *xml* setup of our system clearly outperforms the direct SMT translation for FMS between 80% and 100% and has comparable performance between FMS 70% and 80%. Below FMS 70%, the SMT backend has the best performance. Although these results are positive, we still need to investigate

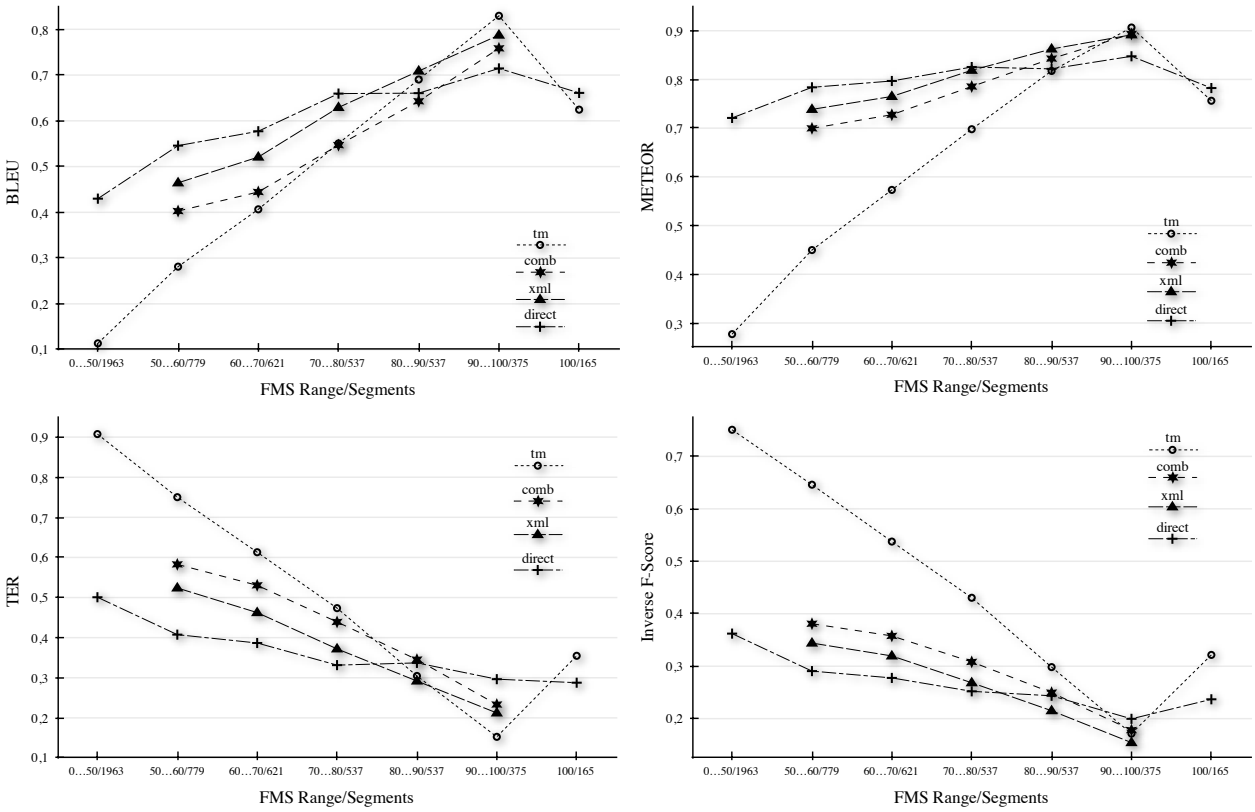

Figure 4. Evaluation results for English-to-French translation, broken down by FMS range

why our system has poor performance at lower FMS ranges. Theoretically, it should outperform the SMT backend across all ranges, as its output is generated by supplying the SMT backend with good pre-translated fragments. The Inverse F-Score graph suggests that this is due to worse lexical choice, but only manual evaluation can provide us with clues for solving the issue.

The discrepancy between the results in the Inverse F-Score graph and the other metrics suggests that the biggest problem for our system is producing output in the expected word-order.

5. Related Research

In this section, we look at earlier proposals for the use of MT (or MT techniques) to modify TM output to produce better translations.

Kranias and Samiotou (2004) present research similar to the *comb* approach discussed in our paper. Using automatically established alignments between the input sentence and the TM match, as well as between the TM match and the TM translation, they identify the transformations that need to be performed on the TM translation to obtain a translation of the source sentence. The operations are *Insertion* (during which an input-sentence segment is translated using MT and inserted in the translation), *Deletion* (during which words are deleted from the translation) and *Replacement* (during which an input-sentence segment is translated using MT and the result replaces a segment in the translation). The described algorithm, however, relies on the word-alignment information used to find the correspondences between the TM match and its translation being present as part of the TM. The handling of reordering is rudimentary and relies on the quality of the word-alignment data. Kranias and Samiotou also use heuristics to increase the FMS of the translation with each modification to represent the improvement in quality.

The system of Feiliang et al. (2007) also operates similarly to the *comb* approach. Here, once the necessary modifications required to produce a translation from the TM suggestion are identified, they are compiled into a Finite-State Transducer (FST), which is then used for the fast generation of the output. The biggest difficulties Feiliang et al. come across are with the handling of insertions, where they need a complex system of states to de-

cide at what position to insert a word in the translation and how to handle the lexical choice properly so that the resulting translation is fluent. The problem is exacerbated by the fact that they only use simple dictionary lookup for the translation of mismatched fragments. The system from (Feiliang et al., 2007) uses a purpose-built algorithm for finding the best TM match for the pair Chinese–Japanese, which makes it difficult to integrate with an existing TM system.

Hewavitharana et al. (2005) and Simard and Isabelle (2009) present systems akin to our *xml* approach. They, however, do not work with an existing SMT system that can handle pre-translated fragments and need to implement the functionality themselves. Therefore and due to the complexity of the translation task, Hewavitharana et al. (2005) only evaluate their system on exact TM matches and TM matches where only one word differs from the input sentence.

Simard and Isabelle (2009) also concentrate in their evaluation on the case where the TM match is used only if it is a perfect match and otherwise the MT output is used. However, they also present results, where the matching translation segments are supplied to an SMT system as a heavily biased additional phrase table. This, however, does not guarantee the use of the TM suggestions and they implement additional features that guide the SMT system towards producing a translation that maximally exploits information from the TM suggestion. Their features, however, proved costly to compute.

Biçici and Dymetman (2008) come very close to our *xml* system, with the difference that they extract at most one matched source-target segment (possibly containing a limited number of gaps), which is simply given as an option to the SMT backend, while we fix as many segments as possible before translation. It also relies on the proprietary MATRAX SMT system (Simard et al., 2005) to handle gapped phrases for translation.

6. Future Work

First, our main goal is to integrate our system with a standalone commercial or open-source TM system so that it can become a part of a fully integrated localisation workflow. Our system would be first evaluated on a small, but representative, set of data to establish the FMS level at which the system performs at its best and set the appropriate thresholds accordingly for the further use of the system. This can be linked to a translation-quality estimator, when such tools become available.

In addition, the reordering tool needs to be developed further, with emphasis on properly handling situations where the appropriate position of an input-sentence segment cannot be reliably established.

Finally, a user study evaluating the effect of the use of our system on post-editing speeds should be performed. We expect the findings of such a study to show a significant increase of throughput that will significantly reduce the costs of translation for large-scale projects.

7. Conclusions

In this paper we presented a novel modular approach to the integration of MT and TM techniques for use in localisation workflows.

The system we developed uses precise sub-tree-based alignments to reliably determine correspondences between an input sentence and a TM-suggested translation, which ensures the utilisation of the high-quality translation data stored in the TM database. It uses an SMT backend to translate the mismatched parts of the input sentence and produce a complete translation with higher quality than the TM suggestion.

Our evaluation shows that the system presented in this paper significantly improves the quality of SMT output when using TM matches with FMS above 80% and produces results on par with the pure SMT output for SMT between 70% and 80%. Still, further investigation is needed to properly diagnose the drop in quality for FMS below 70%. We expect improvements to the reordering functionality of our system to result in higher-quality output even for lower FMS ranges.

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