Exploring Different Representational Units in English-to-Turkish Statistical Machine Translation

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Abstract

We investigate different representational granularities for sub-lexical representation in statistical machine translation work from English to Turkish. We find that (i) representing both Turkish and English at the morpheme-level but with some selective morpheme-grouping on the Turkish side of the training data, (ii) augmenting the training data with “sentences” comprising only the content words of the original training data to bias root word alignment, (iii) re-ranking the n-best morpheme-sequence outputs of the decoder with a word-based language model, and (iv) using model iteration all provide a non-trivial improvement over a fully word-based baseline. Despite our very limited training data, we improve from 20.22 BLEU points for our simplest model to 25.08 BLEU points for an improvement of 4.86 points or 24% relative.

1 Introduction

Statistical machine translation (SMT) from English-to-Turkish poses a number of difficulties. Typologically English and Turkish are rather distant languages: while English has very limited morphology and rather fixed SVO constituent order, Turkish is an agglutinative language with a very rich and productive derivational and inflectional morphology, and a very flexible (but SOV dominant) constituent order. Another issue of practical significance is the lack of large scale parallel text resources, with no substantial improvement expected in the near future.

In this paper, we investigate different representational granularities for sub-lexical representation of parallel data for English-to-Turkish phrase-based SMT and compare them with a word-based baseline. We also employ two-levels of language models: the decoder uses a morpheme based LM while it is generating an n-best list. The n-best lists are then rescored using a word-based LM.

The paper is structured as follows: We first briefly discuss issues in SMT and Turkish, and review related work. We then outline how we exploit morphology, and present results from our baseline and morphologically segmented models, followed by some sample outputs. We then describe discuss model iteration. Finally, we present a comprehensive discussion of our approach and results, and briefly discuss word-repair – fixing morphologically malformed words – and offer a few ideas about the adaptation of BLEU to morphologically complex languages like Turkish.

2 Turkish and SMT

Our previous experience with SMT into Turkish (Durgar El-Kahlout and Oflazer, 2006) hinted that exploiting sub-lexical structure would be a fruitful avenue to pursue. This was based on the observation that a Turkish word would have to align with a complete phrase on the English side, and that sometimes these phrases on the English side could be discontinuous. Figure 1 shows a pair of English and Turkish sentences that are aligned at the word (top) and morpheme (bottom) levels. At the morpheme level, we have split the Turkish words into their lexical morphemes while English words with overt morphemes have been stemmed, and such morphemes have been marked with a tag.

The productive morphology of Turkish implies potentially a very large vocabulary size. Thus, sparseness which is more acute when very modest

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parallel resources are available becomes an important issue. However, Turkish employs about 30,000 root words and about 150 distinct suffixes, so when morphemes are used as the units in the parallel texts, the sparseness problem can be alleviated to some extent.

Our approach in this paper is to represent Turkish words with their morphological segmentation. We use lexical morphemes instead of surface morphemes, as most surface distinctions are manifestations of word-internal phenomena such as vowel harmony, and morphotactics. With lexical morpheme representation, we can abstract away such word-internal details and conflate statistics for seemingly different suffixes, as at this level of representation words that look very different on the surface, look very similar.\(^1\) For instance, although the words *evinde* ‘in his house’ and *masasında* ‘on his table’ look quite different, the lexical morphemes except for the root are the same: \(\text{ev}+\text{sH}+\text{ndA}\) vs. \(\text{masa}+\text{sH}+\text{ndA}\).

We should however note that although employing a morpheme based representations dramatically reduces the vocabulary size on the Turkish side, it also runs the risk of overloading distortion mechanisms to account for both word-internal morpheme sequencing and sentence level word ordering.

The segmentation of a word in general is not unique. We first generate a representation that contains both the lexical segments and the morphological features encoded for all possible segmentations and interpretations of the word. For the word *emeli* for instance, our morphological analyzer generates the following with lexical morphemes bracketed with (..):

\[
\text{(em)}\text{em}+\text{Verb}+\text{Pos}+(y\text{AlH})^\text{DB}+\text{Adverb}+\text{Since} \\
\text{since (someone) sucked (something)} \\
\text{(emel)}\text{emel}+\text{Noun}+\text{A3sg}(+\text{sH})+\text{P3sg}+\text{Nom} \\
\text{his/her ambition} \\
\text{(emel)}\text{emel}+\text{Noun}+\text{A3sg}+\text{Pnon}(+\text{yH})+\text{Acc} \\
\text{ambition (as object of a transitive verb)}
\]

These analyses are then disambiguated with a statistical disambiguator (Yüreğ and Tür, 2006) which operates on the morphological features.\(^2\) Finally, the morphological features are removed from each parse leaving the lexical morphemes.

Using morphology in SMT has been recently addressed by researchers translation from or into morphologically rich(er) languages. Niessen and Ney (2004) have used morphological decomposition to improve alignment quality. Yang and Kirchhoff (2006) use phrase-based backoff models to translate words that are unknown to the decoder, by morphologically decomposing the unknown source word. They particularly apply their method to translating from Finnish – another language with very similar structural characteristics to Turkish. Corston-Oliver and Gamon (2004) normalize inflectional morphology by stemming the word for German-English word alignment. Lee (2004) uses a morphologically analyzed and tagged parallel corpus for Arabic-English SMT. Zolmann et al. (2006) also exploit morphology in Arabic-English SMT. Popovic and Ney (2004) investigate improving translation qual-

\(^1\)This is in a sense very similar to the more general problem of lexical redundancy addressed by Talbot and Osborne (2006) but our approach does not require the more sophisticated solution there.

\(^2\)This disambiguator has about 94% accuracy.
ity from inflected languages by using stems, suffixes and part-of-speech tags. Goldwater and McClosky (2005) use morphological analysis on Czech text to get improvements in Czech to English SMT. Recently, Minkov et al. (2007) have used morphological postprocessing on the output side using structural information and information from the source side, to improve SMT quality.

3 Exploiting Morphology

Our parallel data consists mainly of documents in international relations and legal documents from sources such as the Turkish Ministry of Foreign Affairs, EU, etc. We process these as follows: (i) We segment the words in our Turkish corpus into lexical morphemes whereby differences in the surface representations of morphemes due to word-internal phenomena are abstracted out to improve statistics during alignment.\(^3\) (ii) We tag the English side using TreeTagger (Schmid, 1994), which provides a lemma and a part-of-speech for each word. We then remove any tags which do not imply an explicit morpheme or an exceptional form. So for instance, if the word book gets tagged as +NN, we keep book in the text, but remove +NN. For books tagged as +NNS or booking tagged as +VVG, we keep book and +NNS, and book and +VVG. A word like went is replaced by go +VVD.\(^4\) (iii) From these morphologically segmented corpora, we also extract for each sentence, the sequence of roots for open class content words (nouns, adjectives, adverbs, and verbs). For Turkish, this corresponds to removing all morphemes and any roots for closed classes. For English, this corresponds to removing all words tagged as closed class words along with the tags such as +VVG above that signal a morpheme on an open class content word. We use this to augment the training corpus and bias content word alignments, with the hope that such roots may get a chance to align without any additional “noise” from morphemes and other function words.

From such processed data, we compile the data sets whose statistics are listed in Table 1. One can note that Turkish has many more distinct word forms (about twice as many as English), but has much less number of distinct content words than English.\(^5\) For language models in decoding and n-best list rescoring, we use, in addition to the training data, a monolingual Turkish text of about 100,000 sentences (in a segmented and disambiguated form).

A typical sentence pair in our data looks like the following, where we have highlighted the content root words with bold font, coindexed them to show their alignments and bracketed the “words” that evaluation on test would consider.

\[\begin{align*}
T: & \text{kat} + \text{hl} + \text{ma} \ [\text{ortaklık} + \text{sh} + \text{nhn}] \\
& \text{uygula} + \text{hn} + \text{ma} + \text{sh} \ [,] \ [\text{ortaklık}] \\
& \text{anlaşma} + \text{sh} \ [\text{çerceve} + \text{sh} + \text{nda}] \\
& \text{izle} + \text{hn} + \text{yacak} + \text{dhr} \ [] \\
E: & \text{the implementation} + \text{of the accession} + \text{partnership} + \text{will be monitor} + \text{vvn} + \text{in the framework} + \text{of the association} + \text{agreement} + \text{.}
\end{align*}\]

Note that when the morphemes/tags (starting with a +) are concatenated, we get the “word-based” version of the corpus, since surface words are directly recoverable from the concatenated representation. We use this word-based representation also for word-based language models used for rescoring.

We employ the phrase-based SMT framework (Koehn et al., 2003), and use the Moses toolkit (Koehn et al., 2007), and the SRILM language modelling toolkit (Stolcke, 2002), and evaluate our decoded translations using the BLEU measure (Papineni et al., 2002), using a single reference translation.

| Turkish | Sent. | Words (UNK) | Uniq. Words |
|---------|-------|-------------|-------------|
| Train   | 45,709| 557,530     | 52,897      |
| Train-Content | 56,609 | 436,762 | 13,767 |
| Tune    | 200   | 3,258       | 1,442       |
| Test    | 649   | 10,334 (545)| 4,355       |

Table 1: Statistics on Turkish and English training and test data, and Turkish morphological structure.

\(^3\)So for example, the surface plural morphemes +ler and +lar get conflated to +ler and their statistics are hence combined.

\(^4\)Ideally, it would have been very desirable to actually do derivational morphological analysis on the English side, so that one could for example analyze access to access plus a marker indicating nominalization.

\(^5\)The training set in the first row of 1 was limited to sentences on the Turkish side which had at most 90 tokens (roots and bound morphemes) in total in order to comply with requirements of the GIZA++ alignment tool. However when only the content words are included, we have more sentences to include since much less number of sentences violate the length restriction when morphemes/function word are removed.
### Table 2: BLEU results for baseline experiments.

| Moses Dec. Parms. | BLEU  | BLEU-c |
|-------------------|-------|--------|
| Default           | 16.29 | 16.13  |
| dl = -1, -weight-d = 0.1 | 20.16 | 19.77  |

BLEU is for the model trained on the training set augmented with the content words. BLEU-C is for the model trained on training set augmented with the content words after the alignment phase. The resulting models fared slightly worse though we do not yet understand why.

### 3.1 The Baseline System

As a baseline system, we trained a model using default Moses parameters (e.g., maximum phrase length = 7), using the word-based training corpus. The English test set was decoded with both default decoder parameters and with the distortion limit (-dl in Moses) set to unlimited (-1 in Moses) and distortion weight (-weight-d in Moses) set to a very low value of 0.1 to allow for long distance distortions. We also augmented the training set with the content word data and trained a second baseline model. Minimum error rate training with the tune set did not provide any tangible improvements. Table 2 shows the BLEU results for baseline performance. It can be seen that adding the content word training data actually hampers the baseline performance.

### 3.2 Fully Morphologically Segmented Model

We now trained a model using the fully morphologically segmented training corpus with and without content word parallel corpus augmentation. For decoding, we used a 5-gram morpheme-based language model with the hope of capturing local morphotactic ordering constraints, and perhaps some sentence level ordering of words. We then decoded and obtained 1000-best lists. The 1000-best sentences were then converted to "words" (by concatenating the morphemes) and then rescoring with a 4-gram word-based language model with the hope of enforcing more distant word sequencing constraints. For this, we followed the following procedure: We tried various linear combinations of the word-based language model and the translation model scores on the tune corpus, and used the combination that performed best to evaluate the test corpus. We also experimented with both the default decoding parameters, and the modified parameters used in the baseline model decoding above.

The results in Table 3 indicate that the default decoding parameters used by the Moses decoder provide a very dismal results – much below the baseline scores. We can speculate that as the constituent orders of Turkish and English are very different, (root) words may have to be scrambled to rather long distances along with the translations of functions words and tags on the English side, to morphemes on the Turkish side. Thus limiting maximum distortion and penalizing distortions with the default higher weight, result in these low BLEU results. Allowing the decoder to consider longer range distortions and penalizing such distortions much less with the modified decoding parameters, seem to make an enormous difference in this case, providing close to almost 7 BLEU points improvement.

We can also see that, contrary to the case with the baseline word-based experiments, using the additional content word corpus for training actually provides a tangible improvement (about 6.2% relative (w/o rescoring)), most likely due to slightly better alignments when content words are used. Rescoring the 1000-best sentence output with a 4-gram word-based language model provides an additional 0.79 BLEU points (about 4% relative) – from 20.22 to 21.01 – for the model with the basic training set, and an additional 0.71 BLEU points (about 3% relative) – from 21.47 to 22.18 for the model with the augmented training set. The cumulative improvement is 1.96 BLEU points or about 9.4% relative.

### 3.3 Selectively Segmented Model

A systematic analysis of the alignment files produced by GIZA++ for a small subset of the training sentences showed that certain morphemes on the
Table 3: BLEU results for experiments with fully morphologically segmented training set

| Moses Dec.Parms.  | BLEU | BLEU-c |
|-------------------|------|--------|
| Default           | 13.55| NA     |
| dl = -1, -weight-d = 0.1 | 20.22| 21.47  |
| + word-level LM rescoring | 21.01| 22.18  |

Turkish side were almost consistently never aligned with anything on the English side: e.g., the compound noun marker morpheme in Turkish (+sh) does not have a corresponding unit on the English side since English noun-noun compounds do not carry any overt markers. Such markers were never aligned to anything or were aligned almost randomly to tokens on the English side. Since we perform derivational morphological analysis on the Turkish side but not on the English side, we noted that most verbal nominalizations on the English side were just aligned to the verb roots on the Turkish side and the additional markers on the Turkish side indicating the nominalization and agreement markers etc., were mostly unaligned.

For just these cases, we selectively attached such morphemes (and in the case of verbs, the intervening morphemes) to the root, but otherwise kept other morphemes, especially any case morphemes, still by themselves, as they almost often align with prepositions on the English side quite accurately.\(^\text{11}\)

This time, we trained a model on just the content-word augmented training corpus, with the better performing parameters for the decoder and again did 1000-best rescoring.\(^\text{12}\) The results for this experiment are shown in Table 4. The resulting BLEU represents 2.43 points (11% relative) improvement over the best fully segmented model (and 4.39 points 21.7% compared to the very initial morphologically segmented model). This is a very encouraging result that indicates we should perhaps consider a much more detailed analysis of morpheme alignments to uncover additional morphemes with similar status. Table 5 provides additional details on the BLEU scores for this model, for different ranges of (English source) sentence length.

4 Sample Rules and Translations

We have extracted some additional statistics from the translations produced from English test set. Of the 10,563 words in the decoded test set, a total of 957 words (9.0 %) were not seen in the training corpus. However, interestingly, of these 957 words, 432 (45%) were actually morphologically well-formed (some as complex as having 4-5 morphemes!) This indicates that the phrase-based translation model is able to synthesize novel complex words.\(^\text{13}\) In fact, some phrase table entries seem to capture morphologically marked subcategorization patterns.

13 Though whether such words are actually correct in their context is not necessarily clear.

| Range | Sent. | BLEU-c |
|-------|-------|--------|
| 1 - 10 | 172 | 44.36 |
| 1 - 15 | 276 | 34.65 |
| 5 - 15 | 217 | 33.00 |
| 1 - 20 | 369 | 28.84 |
| 1 - 30 | 517 | 27.88 |
| 1 - 40 | 589 | 24.90 |
| All   | 649 | 24.61 |

\(^{11}\)It should be noted that what to selectively attach to the root should be considered on a per-language basis; if Turkish were to be aligned with a language with similar morphological markers, this perhaps would not have been needed. Again one perhaps can use methods similar to those suggested by Talbot and Osborne (2006).

\(^{12}\)Decoders for the fully-segmented model and selectively segmented model use different 5-gram language models, since the language model corpus should have the same selectively segmented units as those in the training set. However, the word-level language models used in rescoring are the same.
We have not included the content word corpus in these experiments, as (i) our few very preliminary experiments indicated that using a morpheme-based models in subsequent iterations would perform worse than word-based models, and (ii) that for word-based models adding the content word training data was not helpful as our baseline experiments indicated. The models were tested by decoding the output of the previous model for original test data. For word-based decoding in the additional iterations we used a 3-gram word-based language model but reranked the 1000-best outputs using a 4-gram language model. Table 6 provides the BLEU results for these experiments corresponding to two additional model iterations.

We then trained the next model using $T_1^{Train}$ and $T_1^{Train}$, to build a model that hopefully will improve upon the output of the previous model, $T_1^{Test}$, to bring it closer to $T_2^{Test}$. This model when applied to $T_1^{Train}$ and $T_1^{Test}$ produce $T_2^{Train}$ and $T_2^{Test}$ respectively.

The BLEU result for the second iteration, 25.08, represents a cumulative 4.86 points (24% relative) improvement over the initial fully morphologically segmented model using only the basic training set and no rescoring.

### 6 Discussion
Translation into Turkish seems to involve processes that are somewhat more complex than standard statistical translation models: sometimes words on the Turkish side are synthesized from the translations of two or more (SMT) phrases, and errors in any translated morpheme or its morphotactic position render the synthesized word incorrect, even though the rest of the word can be quite fine. If we just extract the root words (not just for content words but all words) in the decoded test set and the reference set, and compute root word BLEU, we obtain $30.62$, $[64.6/35.7/23.4/16.3]$. The unigram precision score shows that we are getting almost 65% of the root words correct. However, the unigram precision score with full words is about 52% for our best model. Thus we are missing about 13% of the words although we seem to be getting their roots.
correct. With a tool that we have developed, BLEU+ (Tantuğ et al., 2007), we have investigated such mismatches and have found that most of these are actually morphologically bogus, in that, although they have the root word right, the morphemes are either not the applicable ones or are in a morphotactically wrong position. These can easily be identified with the morphological generator that we have. In many cases, such morphologically bogus words are one morpheme edit distance away from the correct form in the reference file. Another avenue that could be pursued is the use of skip language models (supported by the SRILM toolkit) so that the content word order could directly be used by the decoder.\textsuperscript{14}

At this point it is very hard to compare how our results fare in the grand scheme of things, since there is not much prior results for English to Turkish SMT. Koehn (2005) reports on translation from English to Finnish, another language that is morphologically as complex as Turkish, with the added complexity of compounding and stricter agreement between modifiers and head nouns. A standard phrase-based system trained with 941,890 pairs of sentences (about 20 times the data that we have!) gives a BLEU score of 13.00. However, in this study, nothing specific for Finnish was employed, and one can certainly employ techniques similar to presented here to improve upon this.

### 6.1 Word Repair

The fact that there are quite many erroneous words which are actually easy to fix suggests some ideas to improve unigram precision. One can utilize a morpheme level “spelling corrector” that operates on segmented representations, and corrects such forms to possible morphologically correct words in order to form a lattice which can again be rescored to select the contextually correct one.\textsuperscript{15} With the BLEU+ tool, we have done one experiment that shows that if we could recover all morphologically bogus words that are 1 and 2 morpheme edit distance from the correct form, the word BLEU score could rise to 29.86, [60.0/34.9/23.3/16.] and 30.48 [63.3/35.6/23.4/16.4] respectively. Obviously, these are upper-bound oracle scores, as subsequent candidate generation and lattice rescoring could make errors, but nevertheless they are very close to the root word BLEU scores above.

Another path to pursue in repairing words is to identify morphologically correct words which are either OOVs in the language model or for which the language model has low confidence. One can perhaps identify these using posterior probabilities (e.g., using techniques in Žens and Ney (2006)) and generate additional morphologically valid words that are “close” and construct a lattice that can be rescoring.

### 6.2 Some Thoughts on BLEU

BLEU is particularly harsh for Turkish and the morpheme based-approach, because of the all-or-none nature of token comparison, as discussed above. There are also cases where words with different morphemes have very close morphosemantics, convey the relevant meaning and are almost interchangeable:

- \textit{gel+hyor} (geliyor - he is coming) vs. \textit{gel+makta} (gelmekte - he is (in a state of) coming) are essentially the same. On a scale of 0 to 1, one could rate these at about 0.95 in similarity.

- \textit{gel+yacak} (gelecek - he will come) vs. \textit{gel+yacak+dhr} (gelecektir - he will come) in a sentence final position. Such pairs could be rated perhaps at 0.90 in similarity.

- \textit{gel+dh} (geldi - he came (past tense)) vs. \textit{gel+mhs} (gelmiş - he came (hearsay past tense)). These essentially mark past tense but differ in how the speaker relates to the event and could be rated at perhaps 0.70 similarity.

Note that using stems and their synonyms as used in METEOR (Banerjee and Lavie, 2005) could also be considered for word similarity.

Again using the BLEU+ tool and a slightly different formulation of token similarity in BLEU computation, we find that using morphological similarity our best score above, 25.08 BLEU increases to 25.14 BLEU, while using only root word synonymy and very close hypernymy from Wordnet, gives us 25.45 BLEU. The combination of rules and Wordnet match gives 25.46 BLEU. Note that these increases are much less than what can (potentially) be gained from solving the word-repair problem above.

### 7 Conclusions

We have presented results from our investigation into using different granularity of sub-lexical representations for English to Turkish SMT. We have found that employing a language-pair specific representation somewhere in between using full word-forms and fully morphologically segmented representations and using content words as additional
data provide a significant boost in BLEU scores, in addition to contributions of word-level resoring of 1000-best outputs and model iteration, to give a BLEU score of 25.08 points with very modest parallel text resources. Detailed analysis of the errors point at a few directions such as word-repair, to improve word accuracy. This also suggests perhaps hooking into the decoder, a mechanism for imposing hard constraints (such as morphotactic constraints) during decoding to avoid generating morphologically bogus words. Another direction is to introduce exploitation of limited structures such as bracketed noun phrases before considering full-fledged syntactic structure.

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