

Large-Scale Machine Translation between Arabic and Hebrew: Available Corpora and Initial Results

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Abstract

Machine translation between Arabic and Hebrew has so far been limited by a lack of parallel corpora, despite the political and cultural importance of this language pair. Previous work relied on manually-crafted grammars or pivoting via English, both of which are unsatisfactory for building a scalable and accurate MT system. In this work, we compare standard phrase-based and neural systems on Arabic-Hebrew translation. We experiment with tokenization by external tools and subword modeling by character-level neural models, and show that both methods lead to improved translation performance, with a small advantage to the neural models.

1 Introduction

Arabic and Hebrew are Semitic languages spoken by peoples with complicated cultural and political relationships. They share important similar characteristics in all linguistic levels, including orthography, morphology, syntax, and lexicon. Yet there is relatively little previous research on machine translation between the two languages, despite its potential benefit for promoting understanding between their speakers. The main reason for this lacuna is a lack of parallel Arabic-Hebrew texts. This has led researchers to consider alternative approaches, including pivoting via English (El Kholly and Habash, 2014; El Kholly and Habash, 2015) and developing transfer-based systems built with synchronous context free grammars (Shilon et al., 2012). Both approaches are unsatisfactory: the transfer-based system relies on manually-crafted grammars and lexicons, therefore suffering from robustness issues, and

pivoting via a morphologically-poor language like English leads to under-specification of potentially useful features.

Recently, a number of large-scale parallel Arabic-Hebrew corpora have been compiled, mostly from multilingual transcriptions of spoken language available online (Cettolo et al., 2012; Lison and Tiedemann, 2016). These resources finally allow for training full-scale statistical machine translation systems on the Arabic-Hebrew pair. Our first contribution is in evaluating such standard systems on a clearly-defined dataset. We compare phrase-based machine translation (PBMT) with neural machine translation (NMT), using state-of-the-art implementations.

Like other Semitic languages, Arabic and Hebrew feature rich morphology and frequent cliticization (joining of prepositions, conjunctions, etc. to the main word). These characteristics lead to increased ambiguity and pose a challenge to machine translation. A common solution is to apply tokenization by external tools, shown to help translation between Arabic/Hebrew and English (El Kholly and Habash, 2012; Singh and Habash, 2012). Our second contribution is thus in evaluating tokenization by external tools for the Arabic-Hebrew language pair. We also experiment with character-level neural models that have recently become popular for dealing with morphologically-rich languages (Kim et al., 2016).

In this work, we focus on Arabic-to-Hebrew translation. Arabic has relatively more available resources such as tokenizers and morphological analyzers, making this translation direction more approachable. We leave the investigation of Hebrew-to-Arabic translation for future work.

Our results show that phrase-based and neural MT systems reach comparable performance, with a small advantage to neural models. We also ascertain the importance of sub-word modeling, where neural character models rival or surpass morphology-aware tokenization by standard tools. We conclude by pointing to potential directions for future research.

2 Related Work

There is relatively little previous research on machine translation between Arabic and Hebrew, despite cultural and political relations between their speakers, and despite their linguistic similarities. The most relevant work is by Shilon et al. (2012), who built a statistical transfer-based system for translating from Arabic to Hebrew and vice versa. Their work relies on synchronous context free grammars and lexicons in the two languages, an approach that they advocate as being better suited to this pair for two main reasons: (a) a lack of available parallel corpora; and (b) the rich morphology of Arabic and Hebrew that requires linguistic knowledge. Here, we explore an alternative to this approach by exploiting Arabic-Hebrew parallel texts that have recently become available, enabling us to train standard statistical MT systems.¹ We further explore methods for handling morphology both by using traditional tools for morphological analysis and tokenization, and by training a *character*-level neural MT system.

Other work directly targeting machine translation between Arabic and Hebrew includes (El Kholly and Habash, 2014), which used pivoting via English. They improved translation quality by carefully designing the alignment symmetrization process in a phrase-based system. In later work, El Kholly and Habash (2015) incorporated morphological constraints for pivoting in a phrase-based system, which they augmented with parallel Arabic-Hebrew data (from an earlier version of the corpus we use in this paper). While pivoting is an appealing solution to scarcity in parallel corpora, Shilon et al. (2012) convincingly show how pivoting through a morphologically-poor language like English leads to under-specification of linguistic features and loss of information.

¹Cettolo (2016) describes the corpus and baseline MT systems in work concurrent with this paper.

There is a fairly decent body of work on translation between Arabic and English, using a variety of methods; see the survey in (Alqudsi et al., 2014). In particular, the importance of morphology-aware tokenization when translating from and to Arabic has been confirmed in phrase-based (Badr et al., 2008; Habash and Sadat, 2006; El Kholly and Habash, 2012), hybrid (Devlin et al., 2014), and end-to-end neural machine translation (Almahairi et al., 2016). Work on Hebrew translation is more limited, but previous studies on translating Hebrew to English also demonstrated the need for morphological analysis and tokenization (Lavie et al., 2004; Lembersky et al., 2012; Singh and Habash, 2012).

3 Linguistic Description

We give here a short description of similarities and differences between Arabic and Hebrew, referring to (Shilon et al., 2012) for a comprehensive discussion.

As Semitic languages, Arabic and Hebrew share several characteristics. Both orthographies commonly omit vowels and other diacritics in writing, leading to increased ambiguity. The scripts are distinct, but there is substantial overlap in the alphabets. Many clitics (prepositions, conjunctions, definite articles) are prefixed or suffixed to words. Both languages have a rich morphology with a complex system of verbal inflection. Their inflection paradigms partially, but not completely, overlap. Syntactically, the languages have both verbal and verbless sentences. Arabic, in particular, has a more complicated agreement system. Some systematic word order patterns can be noted (SVO for Hebrew, VSO for Arabic), but these have exceptions and depend on genre.

Shilon et al. (2012) discuss the challenges such characteristics pose for machine translation between Arabic and Hebrew. In this work, we mostly address orthographic and morphological challenges, which call for solutions like tokenization and representing sub-word elements.

4 Parallel Corpora

Until recently, there were not many available parallel corpora of Arabic and Hebrew. Shilon et al. (2012) prepared a parallel corpus of several hundred sentences from the news domain, too small for training a statistical system but potentially useful for

Corpus	Sents	Ar words	He words
OpenSubtitles	14.6M	108M	111M
OpenSubtitles-Alt	9.5M	71M	76M
WIT ³	0.2M	3.4M	3.1M
GNOME	0.6M	2.1M	2.6M
KDE	80.5K	0.5M	0.4M
Ubuntu	51.3K	0.2M	0.2M
Shilon et al.	1.6K	28K	25K
Tatoeba	0.9K	90K	0.6M
GlobalVoices	76	3.2K	3.7K

Table 1: Statistics of parallel Arabic-Hebrew corpora. See text for references and more details.

evaluation. Since then, two large resources have become available. First, WIT³ provides multilingual transcriptions of TED talks (Cettolo et al., 2012) and its 2016 release includes about 3 million words of Arabic-Hebrew parallel texts (Cettolo, 2016). As a corpus of TED talks, it has several interesting features: diversity of topics, spoken language transcriptions, and user-generated translations, although the review process ensures a reasonable translation quality. The original transcriptions are segmented at the caption level and WIT³ automatically joins them into sentences.

Second, OPUS provides a collection of translation texts from the web. The largest Arabic-Hebrew parallel corpus is OpenSubtitles, comprising automatically aligned movie and TV subtitles. The 2016 release contains more than 100 million words (Lison and Tiedemann, 2016). In addition, OPUS provides a version with alternative translations, with some 70 million words of Arabic-Hebrew texts (Tiedemann, 2016). Having alternative translations can be valuable for evaluation with multiple references, although many alternatives are simply duplicates. While this is by far the largest available Arabic-Hebrew parallel corpus, it suffers from the usual problems of OpenSubtitles texts: user-generated content, questionable translation quality, and automatic caption alignment. In addition, the right-to-left scripts cause problems with punctuation marks such as misplacement and wrong tokenization.

Smaller Arabic-Hebrew corpora in OPUS include localization files (Ubuntu, KDE, GNOME), each totaling between 200 thousand to 2 million words, as well as user-contributed translations from Tatoeba, and news stories from GlobalVoices (Tiedemann, 2009; Tiedemann, 2012). Table 1 summarizes statistics about available Arabic-Hebrew corpora.

5 Experimental Setup

5.1 Machine Translation Systems

Phrase-Based MT We use Moses (Koehn et al., 2007) to build a standard PBMT system. Word alignment is extracted by `fast_align` (Dyer et al., 2013) and symmetrized with the grow-diag-final-and strategy, and lexical reordering follows the `msd-bidirectional-fe` configuration. Sentences longer than 80 words are filtered during training. We train a 5-gram language model on the training set target side using KenLM (Heafield et al., 2013) and tune with MERT to optimize BLEU. These are common Moses settings that have also been used in Arabic-English translation (Almahairi et al., 2016).

Neural MT We use a Torch (Collobert et al., 2011) implementation of attention sequence-to-sequence learning (Kim, 2016) to train a translation model. We keep the default settings and experiment with two architectures: a small 2-layer 500 unit LSTM (on both encoder and decoder sides) and a larger 4-layer 1000 unit LSTM. Sentences are limited to 50 words and the vocabulary size is limited to 50,000 on both source and target sides. The model is trained on a single GPU using SGD. Decoding is done with beam search using a width of 5.

5.2 Tokenization and Sub-Word Models

Morphological processing and tokenization are considered crucial for machine translation from and to Semitic languages like Arabic and Hebrew (Section 2). This is typically applied as a preprocessing step, requiring language-specific tools. An alternative option is to incorporate language-agnostic sub-word elements inside the training algorithm. We describe the two options next.

Tokenization We experiment with tokenization of the Arabic source side using two tools: MADAMIRA (Pasha et al., 2014), a standard morphological analyzer and disambiguator, and the Farasa segmenter (Abdelali et al., 2016), a much faster ranker that has been shown to perform comparably to MADAMIRA. In both cases we segment the Arabic according to the ATB scheme that tends to perform better than other schemes in translating between Arabic and English (El Kholy and Habash, 2012; Sajjad et al., 2013). This scheme separates all

	Train	Tune	Test
Sents	0.2M	7.3K	874
Ar words	3.2M	102.2K	13.7K
He words	3.0M	93.1K	12.7K

Table 2: Number of sentences and (space-delimited) words in the WIT³ corpus of TED talks used in our experiments.

clitics other than the definite article. While it is possible that other schemes will work better for Arabic-Hebrew translation, exploring this option is left for future work. The tokenized text is also normalized with the tools’ default settings. On the Hebrew side, we only separate punctuation marks.

Character-level models Character-level models have been shown to benefit neural MT, especially for languages with large vocabularies. For instance, Sennrich et al. (2016) convert words to sub-word elements using byte-pair encoding and obtain significant gains on English-German/Russian translation. The method was also applied to Arabic-English translation (Abdelali et al., 2016). Here we experiment with a character-level convolutional neural network (charCNN) that replaces input word vectors with learned representations based on character vectors (Kim et al., 2016). We use the default settings in (Kim, 2016).

5.3 Data and Evaluation

We mainly experiment with the WIT³ corpus of TED talks (Section 4). It is a fairly large corpus (3 million words), with high-quality translations and diverse topics. We use the designated train.tags files for training, IWSLT16.TED.tst2010-2014 for tuning, and IWSLT16.TED.dev2010 for testing. We keep IWSLT16.TED.tst2015-2016 as a held-out set for future evaluations. Table 2 provides some statistics about the datasets.

We also performed initial separate experiments with the OpenSubtitles corpus. However, the translation quality was very poor, mostly due to the extremely noisy nature of the dataset. Therefore we leave the exploration of this corpus for future work.

We compute BLEU scores using the `multi-bleu.perl` script included with Moses. Significance testing follows (Koehn, 2004; Riezler and Maxwell, 2005). We also report Meteor scores (version 1.5), using Meteor Universal (Denkowski and Lavie, 2014) to build language resources based on the phrase table learned by the PBMT system.

System	BLEU	Meteor	PPL
PBMT	9.31	32.30	478.4
PBMT+Tok-Farasa	9.51	33.38	335.5
PBMT+Tok-MADAMIRA	9.63	32.90	342.5
NMT	9.91	30.55	2.275
NMT Large	9.92	30.46	2.214
NMT+UNK Replace	10.12	31.84	2.275
NMT+charCNN	10.65	32.43	2.239
NMT+charCNN+UNK Repl.	10.86	33.61	2.239

Table 3: Results on WIT³. Differences in BLEU scores in the first block are not statistically significant (at $p < 0.05$); differences between the two blocks are significant; the difference between small and large NMT models is not significant; differences between word and character NMT models are significant. Perplexity (PPL) scores are computed from the PBMT language model and the NMT decoder’s classification loss, respectively.

6 Results

Table 3 summarizes the results for Arabic-to-Hebrew translation on the WIT³ corpus of TED talks. As expected, tokenization helps phrase-based MT, although the differences in BLEU scores are not statistically significant. In terms of BLEU, neural MT performs significantly better than phrase-based MT, and char-based models lead to substantial and statistically significant improvement. Another small improvement is gained by replacing generated unknown words with translations of their aligned source words based on the attention weights (Jean et al., 2015). Using a larger and deeper NMT model does not lead to significant improvement, possibly due to the size of the training data.

We note that the generally low BLEU scores can be attributed to the single-reference evaluation mode, as well as the challenging nature of the data (spoken language transcripts, automatically aligned captions, diverse topics). Similar BLEU scores were reported for translating from English into Arabic and Hebrew in previous evaluations of TED talks translation (Cettolo et al., 2014).

Looking at Meteor scores, we again see that tokenization helps, but this time the basic NMT system is inferior to PBMT. However, as Meteor Universal uses the phrase-table learned by the PBMT system, it might be biased towards PBMT. Using a character-based model and UNK replacement can close this gap, leading to the best performing system.

7 Conclusion and Future Work

We presented initial experiments in large-scale Arabic-to-Hebrew machine translation, comparing both phrase-based and neural MT. We also evaluated the contribution of tokenization to the PBMT system and of character-level models to the NMT system.

This work is a first step that can be extended in a number of ways. First, experimenting with the Hebrew-to-Arabic direction might reveal new insights. Second, other combinations of tokenization and character-level models can be explored (e.g. character-level neural models on tokenized or byte-pair encoded text). The parallel corpora can also be cleaned and improved, especially by adding multiple reference translations. Finally, modeling interrelations between the two languages in a more direct manner is an appealing direction, given the similarities across linguistic levels.

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