

A Recipe for Arabic-English Neural Machine Translation

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Abstract

In this paper, we present a recipe for building a good Arabic-English neural machine translation. We compare neural systems with traditional phrase-based systems using various parallel corpora including UN, ISI and Ummah. We also investigate the importance of special preprocessing of the Arabic script. The presented results are based on test sets from NIST MT 2005 and 2012. The best neural system produces a gain of +13 BLEU points compared to an equivalent simple phrase-based system in NIST MT12 test set. Unexpectedly, we find that tuning a model trained on the whole data using a small high quality corpus like Ummah gives a substantial improvement (+3 BLEU points). We also find that training a neural system with a small Arabic-English corpus is competitive to a traditional phrase-based system.

1 Introduction

Neural networks succeed to show impressive results as part of a statistical machine translation (SMT) system in the work of Devlin et al. (2014). Since then, the research shifted more towards an end-to-end approach. Currently, neural machine translation (NMT) has become the dominant approach in the field achieving state-of-the-art results in many translation tasks (Bojar et al., 2017).

Junczys-Dowmunt et al. (2016) investigate 30 translation directions using the UN corpus (around 335M words). The experiments, based on test sets from the same corpus, show that NMT is superior to the traditional approach (i.e. phrase-based SMT). One of the investigated task is translation between Arabic and English but without special preprocessing for Arabic. Large improvement is observed (around 3 BLEU points) over phrase-based SMT in both directions.

Almahairi et al. (2016) compared a neural system against phrase-based one in Arabic-English

translation task and found them to be comparable based on NIST 2005 test set. It is also observed that NMT is superior to SMT in an out-of-domain test set. In all cases, preprocessing of Arabic script did improve the translation quality.

In this paper, we further investigate Arabic to English translation using several corpora including Ummah, ISI, UN and many others. We compare the performance of NMT against phrase-based SMT. In our experiments, we applied Arabic preprocessing, which includes normalization and tokenization, to see its impact on both NMT and SMT systems. Our results is based on NIST MT sets for the year 2005, 2006 and 2012.

In the next section, we give a brief introduction to neural machine translation. Section 3 lists the parallel corpora will be used and show some statistics. Section 4 presents our SMT and NMT experiments followed by the conclusion.

2 Neural Machine Translation

Kalchbrenner and Blunsom (2013) set the foundation of neural machine translation by proposing an end-to-end encoder-decoder approach. Convolutional neural networks (CNN) are used to encode a source sentence then generates its translation by recurrent neural networks (RNN).

Long sentences propose a challenge for RNN where there are long distance reordering. Sutskever et al. (2014) develop sequence-to-sequence models that use RNN for both encoding and decoding. Standard RNN units are replaced with Long Short-Term Memory (LSTM) units to capture long-term dependencies. Cho et al. (2014) introduce Gated Recurrent Unit (GRU) which is simpler than LSTM.

In the previous work, a source sentence is encoded into a fixed-length vector which is a bottleneck holding NMT from being compet-

itive to SMT particularly in long sentences. Bahdanau et al. (2015) introduce the powerful **attention mechanism** that allows the decoder to focus on different words while translating.

These advancements and other such as byte **pair encoding** (Sennrich et al., 2016b), to achieve **open vocabulary** NMT, pave the way for new state-of-the-art translation systems.

Mathematically, the probability of a translation sentence ($\mathbf{y} : y_1, \dots, y_I$) of an input sentence ($\mathbf{x} : x_1, \dots, x_J$) is computed as follows:

$$p(\mathbf{y}|\mathbf{x}) = \prod_{i=1}^I p(y_i|y_1, \dots, y_{i-1}, \mathbf{x}) \quad (1)$$

$$p(y_i|y_1, \dots, y_{i-1}, \mathbf{x}) = g(y_{i-1}, s_i, c_i) \quad (2)$$

where $s_i = f(s_{i-1}, y_{i-1}, c_i)$ is a hidden state in the RNN decoder while c_i is the context vector computed from all hidden states (h) in the RNN encoder as follows:

$$c_i = \sum_{j=1}^J \alpha_{ij} h_j \quad (3)$$

$$\alpha_{ij} = \frac{\exp(a(s_{i-1}, h_j))}{\sum_{k=1}^J \exp(a(s_{i-1}, h_k))} \quad (4)$$

where $h_j = f(h_{j-1}, x_j)$, α_{ij} is its weight and $a(\cdot)$ is an alignment model shows the importance of the input word j in translating the output word i . This mechanism allows the decoder to just pay attention to the related input words. Note that, the function f that produces the next hidden state in the encoder and decoder can be defined as LSTM or GRU.

Usually, an input sentence is **encoded by a forward RNN but a backward RNN, that reads the sentence in a reverse order**, is found to improve the performance (Sutskever et al., 2014). A bidirectional RNN also has been successful (Bahdanau et al., 2015). It reads the sentence in both directions then concatenates the forward and backward hidden states as follows:

$$h_j = [\vec{h}_j^T; \overleftarrow{h}_j^T]^T \quad (5)$$

3 Corpora

There are many parallel corpora available for building Arabic-English translation systems. The UN corpus¹ is an obvious choice for many researchers and will be used in our experiments.

¹<https://conferences.unite.un.org/uncorpus>

It is composed of parliamentary documents of the United Nations since 1990 for Arabic, Chinese, English, French, Russian, and Spanish (Ziems et al., 2016).

There are also 11 LDC² corpora have been selected. These include Ummah and ISI with catalogue numbers LDC2004T18 and LDC2007T08, respectively. Ummah corpus contains news stories while ISI was extracted automatically from Arabic Gigaword and English Gigaword. The rest are mostly from GALE project with catalogue numbers LDC2004T17, LDC2005T05, LDC2008T09, LDC2009T09, LDC2013T10, LDC2013T14, LDC2015T05, LDC2015T07 and LDC2015T19.

Besides that, we used all Arabic-English corpora available on OPUS³ website (Tiedemann, 2012; Rafalovitch and Dale, 2009; Wok and Marasek, 2014). We exclude MultiUN because we already have larger version. Open-Subtitles and Tanzil are also excluded due to their low quality.

Table 1 shows statistics of all corpora. The total number of all English words is close to half a billion words.

No.	Corpus	Sentences	Ar-En words	
1	Ummah	80k	2.3m	2.9m
2	ISI	1.1m	28.9m	30.8m
3	LDC2004T17	19k	441k	581k
4	LDC2005T05	5k	106k	135k
5	LDC2008T09	3k	55k	68k
6	LDC2009T09	10k	145k	198k
7	LDC2013T10	8k	182k	240k
8	LDC2013T14	5k	89k	124k
9	LDC2015T05	18k	285k	379k
10	LDC2015T07	20k	330k	440k
11	LDC2015T19	6K	156k	210k
12	OPUS	639k	13.8m	13.8m
13	UN	185m	398m	448m

Table 1: Statistics of all Arabic-English corpora (m: million, k: thousand).

4 Experiments

We present SMT and NMT results on Arabic-English based on NIST MT sets for the year 2005, 2006 and 2012 (see Table 2). As commonly used in machine translation, we evaluated the transla-

²<http://ldc.upenn.edu/>

³<http://opus.nlpl.eu/>

tion performance by BLEU score (Papineni et al., 2002).

	Ar-En Sentences		Ar-En words	
MT06 (dev)	1797	1797	42k	54k
MT05 (test)	1056	4224	26k	130k
MT12 (test)	1378	5512	35k	191k

Table 2: Statistics of NIST MT sets.

The systems are trained on different datasets ranging from small to very large. Training corpora in Table 1 are grouped into 4 sets:

- Set A: Ummah corpus
- Set B: Ummah, ISI and LDC2004T17
- Set C: all corpora except UN
- Set D: all corpora

The reasons for this setting are the following. Low-resource MT task is a known challenge for NMT (Koehn and Knowles, 2017). We would like to see if this is the case for Arabic-English task (Set A). Almahairi et al. (2016) report the first result on Arabic NMT therefore Set B are chosen for comparison. Finally, UN corpus might add no benefit (Devlin et al., 2014) since it is not the news domain (Set C and D).

Preprocessing In our experiments, we applied Arabic preprocessing, which includes normalization and tokenization (ATB scheme), to see its impact on both SMT and NMT systems. We used Farasa (Abdelali et al., 2016), a fast Arabic segmenter. The maximum sentence length is 100.

Phrase-based MT We use Moses toolkit (Koehn et al., 2007) with its default settings. The language model is a 5-gram built from the English side with interpolation and Kneser-Ney smoothing (Kneser and Ney, 1995) built by KenLM (Heafield et al., 2013). Word alignments are extracted by `fast_align` (Dyer et al., 2013). We tune the system using MERT technique (Och, 2003). The chosen option for the reordering model is `msd-bidirectional-fe`.

Neural MT We use Marian, an efficient and fast NMT system written in C++ (Junczys-Dowmunt et al., 2018). The system has implemented several models. The `s2s` option is chosen which is equivalent to Nematus models (Sennrich et al., 2017) that are RNN encoder-decoder based with attention mechanism. The basic training script provided is used. To achieve

open vocabulary, we apply byte pair encoding (BPE) (Sennrich et al., 2016b) setting the maximum size of the joint Arabic-English vocabulary to 90,000.

Table 3 reports BLEU scores of many phrase-based SMT systems trained on various datasets. Clearly, preprocessing of the Arabic side is important. Substantial gain is observed when the training data is small (Set A). Note that adding UN corpus to the training data improves the BLEU score as in set D.

Set	System	MT05	MT12	avg
A	baseline	39.49	22.50	31.00
	+ ar preprocessing	42.17	31.87	37.02
B	baseline	49.71	34.25	41.98
	+ ar preprocessing	51.65	37.06	44.35
C	baseline	51.32	38.12	44.72
	+ ar preprocessing	52.76	40.80	46.78
D	baseline	52.57	40.02	46.30
	+ ar preprocessing	53.45	41.11	47.28

Table 3: BLEU scores of Arabic-English SMT.

Table 4 presents NMT systems’s performance in BLEU. Compared to Table 3, NMT is superior to SMT in all cases. The best NMT system produces a gain of +13 BLEU points in NIST MT12 test set. Unexpectedly, NMT is similar or better than SMT even with a small dataset (Set A is less than 3 million English words). Note that the gap in BLEU between NMT and SMT increases with more training data. Arabic preprocessing improves the performance as in Table 3 which indicates that BPE is not sufficient. We find that tuning a model trained on the whole data using a high quality corpus like Ummah (Set A) gives us a substantial improvement. Finally, an independent ensemble of 5 best models boosts the score with +1.5 BLEU.

Set	System	MT05	MT12	avg
A	baseline	41.62	19.47	30.55
	+ ar preprocessing	44.15	31.86	38.01
B	baseline	53.27	38.19	45.73
	+ ar preprocessing	54.69	40.07	47.38
C	baseline	57.02	45.73	51.38
	+ ar preprocessing	58.35	47.04	52.70
D	baseline	57.31	45.81	51.56
	+ ar preprocessing	58.43	47.74	53.09
	+ tuning	61.26	52.53	56.90
	+ ensemble of 5	62.98	54.27	58.63

Table 4: BLEU scores of Arabic-English NMT.

Training the whole data on a single GPU took 4 days⁴. The disk size of the best model is just 645 MB. It is very compact compared to the phrase table alone in SMT which is 8.5 GB.

During the experiments, other models have been tried like `transformer` (Vaswani et al., 2017) but no improvement is gained. It is also the case for the joint vocabulary’s size.

5 Conclusion

We present Arabic to English machine translation using various training datasets. We compare neural systems with traditional ones (i.e. phrase-based SMT). We also investigate the importance of special preprocessing of the Arabic script. The systems are tested on NIST MT 2005 and 2012.

After the experiments, we draw the following conclusions. In both NMT and SMT systems, Arabic preprocessing improves the translation quality as found by Almahairi et al. (2016). Although UN corpus is not in the news domain, a gain is observed in both systems. Neural MT is superior to phrase-based MT in all cases. NMT able to perform very well given a small corpus. Finally, tuning a model trained on the whole data using a small high quality corpus (i.e. Ummah) gives a substantial improvement. The best NMT system produces a gain of +13 BLEU points in NIST MT12 test set.

There are techniques we have not considered in this work but might improve the translation quality such as back translation (Sennrich et al., 2016a).

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⁴NVidia GTX 1080 Ti, CPU 4.20GHz and Hard disk SSD

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