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Two Ways to Use a Noisy Parallel News corpus for improving Statistical Machine Translation

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Abstract

In this paper, we present two methods to use a noisy parallel news corpus to improve statistical machine translation (SMT) systems. Taking full advantage of the characteristics of our corpus and of existing resources, we use a bootstrapping strategy, whereby an existing SMT engine is used both to detect parallel sentences in comparable data and to provide an adaptation corpus for translation models. MT experiments demonstrate the benefits of various combinations of these strategies.

1 Introduction

In Statistical Machine Translation (SMT), systems are created from parallel corpora consisting of a set of source language texts aligned with its translation in the target language. Such corpora however only exist (at least are publicly documented and available) for a limited number of domains, genres, registers, and language pairs. In fact, there are a few language pairs for which parallel corpora can be accessed, except for very narrow domains such as political debates or international regulatory texts. Another very valuable resource for SMT studies, especially for under-resource languages, are comparable corpora, made of pairs of monolingual corpora that contain texts of similar genres, from similar periods, and/or about similar topics.

The potential of comparable corpora has long been established as a useful source from which to extract bilingual word dictionaries (see e.g. (Rapp, 1995; Fung and Yee, 1998)) or to learn multilingual terms (see e.g. (Langé, 1995; Smadja et al., 1996)).

More recently, the relative corpus has caused the usefulness of comparable corpora be reevaluated as a potential source of parallel fragments, be they paragraphs, sentences, phrases, terms, chunks, or isolated words. This tendency is illustrated by the work of e.g. (Resnik and Smith, 2003; Munteanu and Marcu, 2005), which combines Information Retrieval techniques (to identify parallel documents) and sentence similarity detection to detect parallel sentences.

There are many other ways to improve SMT models with comparable or monolingual data. For instance, the work reported in (Schwenk, 2008) draws inspiration from recent advances in unsupervised training of acoustic models for speech recognition and proposes to use self-training on in-domain data to adapt and improve a baseline system trained mostly with out-of-domain data.

As discussed e.g. in (Fung and Cheung, 2004), comparable corpora are of various nature: there exists a continuum between truly parallel and completely unrelated texts. Algorithms for exploiting comparable corpora should thus be tailored to the peculiarities of the data on which they are applied.

In this paper, we report on experiments aimed at using a noisy parallel corpus made out of news stories in French and Arabic in two different ways: first, to extract new, in-domain, parallel sentences; second, to adapt our translation and language models. This approach is made possible due to the specificities of our corpus. In fact, our work is part of a project aiming at developing a platform for processing multimedia news documents (texts, interviews, images and videos) in Arabic, so as to streamline the...
work of a major international news agency. As part
as the standard daily work flow, a significant por-
tion of the French news are translated (or adapted)
in Arabic by journalists. Having access to one full
year of the French and Arabic corpus (consisting, to
date, of approximately one million stories (150 mil-
ion words)), we have in our hands an ideal compa-
rable resource to perform large scale experiments.

These experiments aim at comparing various
ways to build an accurate machine translation sys-
tem for the news domain using (i) a baseline system
trained mostly with out-of-domain data (ii) the com-
parable dataset. As will be discussed, given the very
large number of parallel news in the data, our best
option seems to reconstruct an in-domain training
corpus of automatically detected parallel sentences.

The rest of this paper is organized as follows.
In Section 2, we relate our work to some exist-
ing approaches for using comparable corpora. Sec-
tion 3 presents our methodology for extracting par-
allel sentences, while our phrase-table adaptation
strategies are described in Section 4. In Section 5,
we describe our experiments and contrast the results
obtained with several adaptation strategies. Finally,
Section 6 concludes the paper.

2 Related work

From a bird’s eye view, attempts to use comparable
corpora in SMT fall into two main categories: first,
approaches aimed at extracting parallel fragments;
second, approaches aimed at adapting existing re-
sources to a new domain.

2.1 Extracting parallel fragments

Most attempts at automatically extracting parallel
fragments use a two step process (see (Tillmann and
Xu, 2009) for a counter-example): a set of candidate
parallel texts is first identified; within this short list
of possibly paired texts, parallel sentences are then
identified based on some similarity score.

The work reported in (Zhao and Vogel, 2002)
concentrates on finding parallel sentences in a set of
comparable stories pairs in Chinese/English. Sen-
tence similarity derives from a probabilistic align-
ment model for documents, which enables to recog-
nize parallel sentences based on their length ratio,
as well as on the IBM 1 model score of their word-
to-word alignment. To account for various levels of
parallelism, the model allows some sentences in the
source or target language to remain unaligned.

The work of (Resnik and Smith, 2003) considers
mining a much larger ”corpora” consisting of docu-
ments collected on the Internet. Matched documents
and sentences are primarily detected based on sur-
face and/or formal similarity of the web addresses
or of the page internal structure.

This line of work is developed notably in
(Munteanu and Marcu, 2005): candidate parallel
texts are found using Cross-Lingual Information Re-
trieval (CLIR) techniques; sentence similarity is in-
directly computed using a logistic regression model
aimed at detecting parallel sentences. This formal-
ism allows to enrich baseline features such as the
length ratio, the word-to-word (IBM 1) alignment
scores with supplementary scores aimed at reward-
ing sentences containing identical words, etc. More
recently, (Smith et al., 2010) reported significant im-
provements mining parallel Wikipedia articles us-
ing more sophisticated indicators of sentence par-
allelism, incorporating a richer set of features and
cross-sentence dependencies within a Conditional
Random Fields (CRFs) model. For lack of find
enough parallel sentences, (Munteanu and Marcu,
2006; Kumano and Tokunaga, 2007) consider the
more difficult issue of mining parallel phrases.

In (Abdul-Rauf and Schwenk, 2009), the authors,
rather than computing a similarity score between a
source and a target sentence, propose to use an ex-
isting translation engine to process the source side
of the corpus, thus enabling sentence comparison to
be performed in the target language, using the edit
distance or variants thereof (WER or TER). This
approach is generalized to much larger collections
in (Uszkoreit et al., 2010), which draw advantage
of working in one language to adopt efficient parallelism detection techniques (Broder, 2000).

2.2 Comparable corpora for adaptation

Another very productive use of comparable corpora
is to adapt or specialize existing resources (dictio-
naries, translation models, language models) to spe-
cific domains and/or genres. We will only focus here
on adapting the translation model; a review of the
literature on language model adaptation is in (Bella-
garda, 2001) and the references cited therein.
The work in (Snover et al., 2008) is a first step towards augmenting the translation model with new translation rules: these rules associate, with a tiny probability, every phrase in a source document with the most frequent target phrases found in a comparable corpus specifically built for this document.

The study in (Schwenk, 2008) considers self-training, which allows to adapt an existing system to new domains using monolingual (source) data. The idea is to automatically translate the source side of an in-domain corpus using a reference translation system. Then, according to some confidence score, the best translations are selected to form an adaptation corpus, which can serve to retrain the translation model. The authors of (Cettolo et al., 2010) follow similar goals with different means: here, the baseline translation model is used to obtain a phrase alignment between source and target sentences in a comparable corpus. These phrase alignments are further refined, before new phrases not in the original phrase-table, can be collected.

The approaches developed below borrow from both traditions: given (i) the supposed high degree of parallelism in our data and (ii) the size of the available comparable data, we are in a position to apply any of the above described technique. This is all the easier to do as all stories are timestamped, which enables to easily spot candidate parallel texts. In both cases, we will apply a bootstrapping strategy using as baseline a system trained with out-of-domain data.

3 Extracting Parallel Corpora

This section presents our approach for extracting a parallel corpus from a comparable in-domain corpus so as to adapt a SMT system to a specific domain. Our methodology assumes that both a baseline out-of-domain translation system and a comparable in-domain corpus are available, two requirements that are often met in practice.

As shown in Figure 1, our approach for extracting an in-domain parallel corpus from the in-domain comparable corpus consists in 3 steps and closely follows (Abdul-Rauf and Schwenk, 2009):

- **translation**: translating the source side of the comparable corpora;
- **document pairs selection**: selecting, in the comparable corpus, documents that are similar to the translated output;
- **sentence pairs selection**: selecting parallel sentences among the selected documents.

The main intuition is that computing document similarities in one language enables to use simple and effective comparison procedures, instead of having to define ad hoc similarities measures based on complex underlying alignment models.

The translation step consists here in translating the source (Arabic) side of the comparable corpus using a baseline out-of-domain system, which has been trained on parallel out-of-domain data.

The document selection step consists in trying to match the automatic translations (source:target) with the original documents in the target language. For each (source:target) document, a similarity score with all the target documents is computed. We contend here with a simple association score, namely the Dice coefficient, computed as the number of words in common in both documents, normalized by the length of the (source:target) document.

* A priori knowledge, such as the publication dates
of the documents, are used to limit the number of document pairs to be compared. For each source document, the target document that has the best score is then selected as a potential parallel document. The resulting pairs of documents are then filtered depending on a threshold $T_d$, so as to avoid false matches (in the experiments described below, the threshold has been set so as to favor precision over recall).

At the end of this step, a set of similar source and target document pairs has been selected. These pairs may consist in documents that are exact translations of each other. In most cases, the documents are noisy translation and only a subset of their sentences are mutual translation.

The sentence selection step then consists in performing a sentence level alignment of each pair of documents to select a set of parallel sentences. Sentence alignment is then performed with the hunalign sentence alignment tool (Varga et al., 2005), which also provides alignment confidence measures. As for the document selection step, only sentence pairs that obtain an alignment score greater than a predefined threshold $T_s$ are selected, where $T_s$ is again chosen to favor prevision of alignments of recall. From these, 1:1 alignments are retained, yielding a small, adapted, parallel corpus. This method is quite different from (Munteanu and Marcu, 2005)'s work where the sentence selection step is done by a Maximum Entropy classifier.

4 Domain Adaptation

In the course of mining our comparable corpus, we have produced a translation into French for all the source language news stories. This means that we have three parallel corpora at our disposal:

- The **baseline training corpus**, which is large (a hundred million words), delivering a reasonable translation performance quality of translation, but out-of-domain;
- The **extracted in-domain corpus**, which is much smaller, and potentially noisy;
- The **translated in-domain corpus**, which is of medium-size, and much worse in quality than the others.

Considering these three corpora, different adaptation methods of the translation models are explored. The first approach is to concatenate the baseline and in-domain training data (either extracted or translated) to train a new translation model. Given the difference in size between the two corpus, this approach may introduce a bias in the translation model in favor of out-of-domain.

The second approach is to train separate translation models with baseline on the one hand, and with in-domain on the other data and to weight their combination with MERT (Och, 2003). This alleviates the former problem but increases the number of features that need to be trained, running the risk to make MERT less stable.

A last approach is also considered, which consists in using only the in-domain data to train the translation model. In that case, the question is the small size of the in-domain data.

The comparative experiments on the three approaches, using the three corpora are described in next section.

5 Experiments and results

5.1 Context and data

The experiments have been carried out in the context of the Cap Digital SAMAR\footnote{http://www.samar.fr} project which aims at developing a platform for processing multimedia news in Arabic. Every day, about 250 news in Arabic, 800 in French and in English\footnote{The English news have not been used in this study.} are produced and accumulated on our disks. News collected from December 2009 to December 2010 constitute the comparable corpora, containing a set of 75,975 news for the Arabic part and 288,934 news for the French part (about 1M sentences for Arabic and 5M sentences for French).

The specificity of this comparable corpus is that many Arabic stories are known to be translation of news that were first written in French. The translations may not be entirely faithful: when translating a story, the journalist is in fact free to rearrange the structure, and to some extend, the content of a document (see example Figure 2).

In our experiments, the in-domain comparable corpus then consists in a set of Arabic and French
And he added, we in Hamas don’t have a problem to resume indirect negotiations about the deal from the point at which it ended and at which Netanyahu tried to fail.

Le porte-parole a réaffirmé que le Hamas était prêt à reprendre les tractations au point où elles s’étaient arrêtées.

The spokesperson reaffirmed that Hamas was ready to resume negotiations at the point where they stopped.

Figure 2: An example of incorrect/inexact translation in a pair of similar documents.

documents which are parallel, partly parallel, or not parallel at all, with no explicit link between Arabic and French parts.

5.2 Baseline translation system

The baseline out-of-domain translation system was trained on a corpus of 7.6 million of parallel sentences (see Table 1), that was harvested from publicly available sources on the web: the United Nations (UN) document database, the website of the World Health Organization (WHO) and the Project Syndicate Web site. The “UN” data constitutes by far the largest portion of this corpus, from which only the Project Syndicate documents can be considered as appropriate for the task at hand.

A 4-gram backoff French language model was built on 2.4 billion words of running texts, taken from the parallel data, as well as notably the Giga-word French corpus.

| Corpus          | ar #tokens | ar voc | fr #tokens | fr voc |
|-----------------|------------|--------|------------|--------|
| baseline        | 162M       | 369K   | 186M       | 307K   |
| extracted       | 3.6M       | 72K    | 4.0M       | 74K    |
| translated      | 20.8M      | 217K   | 22.1M      | 181K   |

Table 1: Corpus statistics: total number of tokens in the French and Arabic sides, Arabic and French vocabulary size. Numbers are given on the preprocessed data.

Arabic is a rich and morphologically complex language, and therefore data preprocessing is necessary to deal with data scarcity. All Arabic data were preprocessed by first transliterating the Arabic text with the BAMA (Buckwalter, 2002) transliteration tool. Then, the Arabic data are segmented into sentences. A CRF-based sentence segmenter for Arabic was built with the Wapiti³ (Lavergne et al., 2010) package. A morphological analysis of the Arabic text is then done using the Arabic morphological analyzer and disambiguation tool MADA (Nizar Habash and Roth, 2009), with the MADA-D2 since it seems to be the most efficient scheme for large data (Habash and Sadat, 2006).

The preprocessed Arabic and French data were aligned using MGiza++⁴ (Gao and Vogel, 2008). The Moses toolkit (Koehn et al., 2007) is then used to make the alignments symmetric using the grow-diag-final-and heuristic and to extract phrases with maximum length of 7 words. A distortion model lexically conditioned on both the Arabic phrases and French phrases is then trained. Feature weights were set by running MERT (Och, 2003) on the development set.

5.3 Extraction of the in-domain parallel corpus

We follow the method described in Section 3: Arabic documents are first translated into French using the baseline SMT system. For the document selection step each translated (ar:fr) document is compared only to the French documents of the same day. The thresholds for document selection and sentence selection were respectively set to 0.5 and 0.7. For a pair of similar documents, the average percentage of selected sentences is about 43%.

The document selection step allows to select documents containing around 35% of the total number of sentences from the initial Arabic part of the comparable corpus, a percentage that goes down to 15% after the sentence alignment step. The resulting in-domain parallel corpus thus consists in a set of 156K pairs of parallel sentences. Data collected during the last month of the period was isolated from the resulting corpus, and was used to randomly extract a development and a test set of approximately 1,000

³http://wapiti.limsi.fr
⁴http://geek.kyloo.net/software/doku.php/mgiza:overview
Reference: Le ministre russe des Affaires étrangères, Sergueï Lavrov a prèvenu mercredi [...]  
Baseline: Pronostiquait Ministre des affaires étrangères russe, Sergei Lavrov mercredi [...]  
Extracted: Le ministre russe des Affaires étrangères, Sergueï Lavrov a averti mercredi [...]  
Reference: Le porte-parole de Mme Clinton, Philip Crowley, a toutefois reconnu [...]  
Baseline: Pour ukun FILIP Cruau porte-parole de Clinton a reconnu ...  
Extracted: Mais Philip Crowley, le porte-parole de Mme Clinton a reconnu [...]

Figure 3: Comparative translations using the baseline translation and the extracted translation systems of two sentences: “Russian Minister of Foreign Affairs, Sergueï Lavrov, informed Wednesday [...]” and “The spokesman for Mrs. Clinton, Philip Crowley, however, acknowledged [...]”.

5.4 Translation Results

Translation results obtained on the test set are reported in terms of BLEU scores in Table 2, along with the corresponding phrase table sizes. The different adaptation approaches described in Section 4 were experimented with both extracted and translated corpora as adaptation corpus (see Section 3). As expected, adapting the translation model to the

| SMT System      | #Phrase pairs | BLEU |
|-----------------|---------------|------|
| baseline        | 312.4M        | 24.0 |
| extracted       |               |      |
| baseline+extracted (1 table) | 10.9M | 29.2 |
| baseline+extracted (2 tables) | 321.6M | 29.0 |
| translated      | 39M           | 26.7 |
| extracted+translated (2 tables) | 9.9M + 39M | 28.2 |

Table 2: Arabic to French translation BLEU scores on a test set of 1000 sentences

news domain is very effective. Compared to the baseline system, all adapted systems obtain much better results (from 2 to 6 BLEU points). The extracted system outperforms the baseline system by 5 BLEU points, even though the training set is much smaller (3.6M compared to 162M tokens). This result indirectly validates the precision of our methodology.

Concatenating the baseline and extracted data to train a single translation model does not improve the smaller extracted system, thus maybe reflecting the fact that the large out-of-domain corpus overwhelms the contribution of the in-domain data. However, a log-linear combination of the corresponding phrase tables brings a small improvement (0.8 BLEU point).

Another interesting result comes from the performance of the system trained only on the translated corpus. Without using any filtering of the automatic translations, this artificial dataset enables to build another system which outperforms the baseline system by 2.5 BLEU points. This is another illustration of the greater importance of having matched domain data, even of a poorer quality, than good parallel out-of-domain sentences (Cettolo et al., 2010).

In the last experiment, all the available in-domain data (extracted and translated) are used in conjunction, with a separate phrase-table trained on each corpus. However, this did not enable to match the results of the extracted system, a paradoxical result that remains to be analyzed more carefully. Filtering automatic translations may be an issue.

A rapid observation of the translations provided by both the baseline system and the extracted system shows that the produced output are quite different. Figure 3 displays two typical examples: the first one illustrates the different styles in Arabic (“News” style often put subject “Le ministre russe des affaires étrangères” before verb “ a prévenu” or “a averti” — which are semantically equivalent — whereas “UN” style is more classical, with the verb “Pronostiquait” followed by the subject “ministre russe des Affaires étrangères”). The second one shows how adaptation fixes the transla-
tion of words (here “Philip Crowley”) that were not (correctly) translated by the baseline system (“ukun FILIP Cruau”).

6 Conclusion

We have presented an empirical study of various methodologies for (i) extracting a parallel corpus from a comparable corpus (the so-called “Noisy Corpus”) and (ii) using in-domain data to adapt a baseline SMT system. Experimental results, obtained using a large 150 million word Arabic/French comparable corpus, allow to jointly validate the extraction of the in-domain parallel corpus and the proposed adaptation methods. The best adapted system, trained on a combination of the baseline and the extracted data, improves the baseline by 6 BLEU points. Preliminary experiments with self-training also demonstrate the potential of this technique.

As a follow-up, we intend to investigate the evolution of the translation results as a function of the precision/recall quality of the extracted corpus, and of the quality of the automatically translated data. We have also only focused here on the adaptation of the translation model. We expect to achieve further gains when combining these techniques with LM adaptation techniques.

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