MATREX: DCU Machine Translation System for IWSLT 2006

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Abstract

In this paper, we give a description of the machine translation system developed at DCU that was used for our first participation in the evaluation campaign of the International Workshop on Spoken Language Translation (2006).

This system combines two types of approaches. First, we use an EBMT approach to collect aligned chunks based on two steps: deterministic chunking of both sides and chunk alignment. We use several chunking and alignment strategies. We also extract SMT-style aligned phrases, and the two types of resources are combined.

We participated in the Open Data Track for the following translation directions: Arabic-English and Italian-English, for which we translated both the single-best ASR hypotheses and the correct recognition results. We report the results of the system for the provided evaluation sets.

1. Introduction

In this paper, we present the Data-Driven MT system developed at DCU, MATREX (Machine Translation using Examples). This system is a hybrid system which exploits both EBMT and SMT techniques to extract a dataset of aligned chunks [1].

The EBMT data resources are extracted using a two-step approach. First, the source and the target sentences are chunked using several different methods. In the case of English and Italian, we employ a marker-based chunker [2, 3]. In the case of Arabic, we use the chunker provided with the ASVM toolkit [4]. The chunks are then aligned thanks to a dynamic programming algorithm which is similar to an edit-distance algorithm while allowing for block movements [5, 6]. This aligner relies on the identification of relationships between chunks, which can be defined and computed in several ways. We also extract SMT-style aligned phrases from word alignments, as described in [7]. These two types of resources are then combined and given to the decoding module, currently a wrapper around a phrase-based SMT decoder.

We participated in the Open Data Track for the following translation directions: Arabic-English and Italian-English, for which we translated both the single-best ASR hypotheses and the text input. We report the results of the system for the provided evaluation sets.

This paper is organized as follows. In section 2, we describe the various components of the system; in particular, we give details about the various chunking and chunk alignment strategies. In Section 3, we report experimental results obtained for the two language pairs. In Section 4, we conclude, and provide avenues for further research.

2. The MaTrEx System

The MATREX system used in our experiments is a modular data-driven MT engine, built following established Design Patterns [8]. It consists of a number of extendible and re-implementable modules, the most important of which are:

- *Word Alignment Module*: takes as its input an aligned corpus and outputs a set of word alignments.

- *Chunking Module*: takes in an aligned corpus and produces source and target chunks.

- *Chunk Alignment Module*: takes the source and target chunks and aligns them on a sentence-by-sentence level.

- *Decoder*: searches for a translation using the original aligned corpus and derived chunk and word alignments.

The Word Alignment and the Decoder modules are currently wrappers around existing tools, namely GIZA++ [9] and PHRAMER.[1] In our experiments we investigated a number of different chunking and alignment strategies which we describe in more detail in what follows.

An overview of the entire translation process is given in Figure 1: the aligned source-target sentences are passed in turn to the word alignment, chunking and chunk alignment modules, in order to create our chunk and lexical example databases. These databases are then given to the decoder to translate new sentences.

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[1]http://www.utdallas.edu/~mgo031000/phramer/.

Figure 1: Translation Process

2.1. Chunking Strategies

2.1.1. Marker-Based Chunking

One method for the extraction of chunks, used in the creation of the example database, is based on the Marker Hypothesis [3], a psycholinguistic constraint which posits that all languages are marked for surface syntax by a specific closed set of lexemes or morphemes which signify context. Using a set of closed-class (or "marker") words, such as determiners, conjunctions, prepositions, possessive and personal pronouns, aligned source-target sentences are segmented into chunks [2] during a pre-processing step. A chunk is created at each new occurrence of a marker word, with the restriction that each chunk must contain at least one content (or nonmarker) word. In addition to the set of marker words used in the experiments of [2, 10], punctuation is also used to segment the aligned sentences – with the punctuation occurring in chunk-final, rather than initial, position. An example of such a chunking is given in Figure 2, for English and Italian.

2.1.2. Arabic Chunking

The language characteristics of Arabic makes the direct application of the Marker-Based chunker described above more difficult. In the case of Arabic, determiners, prepositions, and pronouns do not usually form independent tokens but are usually part of a token which also contains a noun, an adjective, or a verb. Consequently, in order to identify the markers, one would need to perform some disambiguation at different levels, in particular tokenization and POS tagging. We would thus lose one of the main strengths of the Marker-Based approach, which is simplicity.[2]

Another option is to use an already available chunker, such as ASVM [4]. This choice is also motivated by our previous work on Basque-English MT [6], in which we used a chunker specifically designed for Basque: we found that the chunks obtained in this manner are actually comparable

to the chunks extracted with the marker-based chunker. The ASVM toolkit is based on Support Vector Machines, a Machine Learning algorithm, and has been trained on the Arabic Penn Treebank [11]. The chunking process is achieved through a pipeline approach: tokenization, lemmatisation, POS tagging, and finally chunking are performed in turn.

2.1.3. Remarks about Chunking

Since each module of the system can be changed independently of the others, it is possible to use a variety of chunkers. The Marker-Based approach has several obvious advantages: it is simple (linear complexity), easily adaptable, and does not need expensive training on Treebanks. Adapting this chunker to a new language simply amounts to providing the system with a list of marker words. For example, in the case of Italian, we easily extracted a list of markers from the MorphIt lexicon [12], making it possible to apply the Marker-Based chunker to Italian.

However, we do not exclude the possibility to use different types of chunkers that may be available. In particular, in the case of English, several statistical chunkers have been developed, notably in the context of the CoNLL 2000 shared task [13]. A summary of the strategies used for each language is displayed in Figure 3.

Language	Chunking Strategy
English	Marker-Based Chunker
Arabic	ASVM
Italian	Marker-Based Chunker

Figure 3: Chunking strategies

2.2. Alignment Strategies

2.2.1. Word alignment

Word alignment is performed using the GIZA++ statistical word alignment toolkit and we followed the "refined" method of [7] to extract a set of high-quality word alignments

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[2]Note that these observations do not invalidate the Marker Hypothesis; they only stress the difficulty of its application in some contexts.

English: *[it felt okay] [after the game] [but then] [it started turning black-and-blue] [is it serious ?]*
Italian: *[era a posto] [dopo la partita] [ma poi] [ha cominciato] [a diventare livida] [è grave ?]*

Italian: *[nel mio caso] [solitamente] [per affari] [raramente] [per piacere]*
English: *[in my case] [it is usually] [on business] [seldom] [for pleasure]*

Figure 2: English and Italian Marker-Based chunking

from the original uni-directional alignment sets. These along with the extracted chunk alignments were passed to the translation decoder.

2.2.2. Chunk alignment

In order to align the chunks obtained by the chunking procedures described in Section 2.1, we make use of a "edit-distance style" dynamic programming alignment algorithm.

In the following, a denotes an alignment between a target sequence e and a source sequence f, with $I = |e|$ and $J = |f|$. Given two sequences of chunks, we are looking for the most likely alignment $\hat{a}$:

$$\hat{a} = \underset{a}{\operatorname{argmax}} \, \mathbb{P}(a|e, f) = \underset{a}{\operatorname{argmax}} \, \mathbb{P}(a, e|f). \qquad (1)$$

We first consider alignments such as those obtained by an edit-distance algorithm, i.e.

$$a = (t_1, s_1)(t_2, s_2) \ldots (t_n, s_n),$$

with $\forall k \in [\![1, n]\!], t_k \in [\![0, I]\!]$ and $s_k \in [\![0, J]\!]$, and $\forall k < k'$:

$$t_k \leq t_{k'} \text{ or } t_{k'} = 0,$$
$$s_k \leq s_{k'} \text{ or } s_{k'} = 0,$$
$$I \subseteq \cup_{k=1}^n \{t_k\}, J \subseteq \cup_{k=1}^n \{s_k\},$$

where $t_k = 0$ (resp. $s_k = 0$) denotes a non-aligned target (resp. source) chunk.

We then assume the following model:

$$\mathbb{P}(a, e|f) = \Pi_k \mathbb{P}(t_k, s_k, e|f) = \Pi_k \mathbb{P}(e_{t_k}|f_{s_k}), \qquad (2)$$

where $\mathbb{P}(e_0|f_j)$ (resp. $\mathbb{P}(e_i|f_0)$) denotes an "insertion" (resp. "deletion") probability.

Assuming that the parameters $\mathbb{P}(e_{t_k}|f_{s_k})$ are known, the most likely alignment is computed by a simple dynamic-programming algorithm.[3] Moreover, this algorithm can be easily adapted to allow for block movements or "jumps", following the idea introduced in [5] in the context of MT evaluation. This adaptation can be necessary if the order of constituents is significantly different in the source and target languages. In our previous work, we found out that it was useful in the case of Basque-English [6], but not for Spanish-English [1]. In our experiments, we thus decided to include this adapted algorithm for Arabic, but not for Italian (cf. Figure 4).

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[3]This algorithm is actually a classical edit-distance algorithm in which distances are replaced by opposite-log-conditional probabilities.

Language Pair	Alignment Strategy
Arabic-English	"Edit-Distance" with Jumps
Italian-English	"Edit-Distance"

Figure 4: Alignment strategies

Instead of using an Expectation-Maximization algorithm to estimate these parameters, as commonly done when performing word alignment [9, 14], we directly compute these parameters by relying on the information contained within the chunks. The conditional probability $\mathbb{P}(e_{t_k}|f_{s_k})$ can be computed in several ways. In our experiments, we have considered three main sources of knowledge: (i) word-to-word translation probabilities, (ii) word-to-word cognates and (iii) chunk labels, which are described in the following sections.

2.2.3. Knowledge Source Combination

These sources of knowledge can be combined using a log-linear framework, in the following manner:

$$P(e_i|f_j) = \frac{\exp(\sum \lambda_k h_k(e_i, f_j))}{Z}, \qquad (3)$$

where $h_k(e_i, f_j)$ represents a given source of knowledge related to the chunks e_i and f_j, λ_k the associated weight parameter and Z a normalization parameter. The different models are described in more detail below.

2.2.4. Word-to-word probabilities

As a criterion to relate chunks, we use word-to-word probabilities, which are simply extracted from the word alignment module, as described above. Relationships between chunks are then computed thanks to the following model, similar to IBM model 1 [14].

$$h_p(e_i, f_j) = \log \prod_k \sum_l \mathbb{P}(e_{i_l}|f_{j_k}). \qquad (4)$$

This model is often used in SMT as a feature of a log-linear model; in this context, it is called a word-based lexicon model [15].

2.2.5. Cognate identification

It is also possible to take into account a feature based on the identification of cognates. This is especially useful for texts with technical terms, for which it is possible to identify a

significant number of cognates. We use the notation:

$$C(e_{i_l}, f_{j_k}) = \begin{cases} 1 & \text{if there is a cognate between } e_{i_l} \text{ and } f_{j_k}, \\ 0 & \text{otherwise.} \end{cases}$$

We then use the following feature:

$$h_c(e_i, f_j) = \frac{1}{k} \sum_k \max_l C(e_{i_l}, f_{j_k}), \tag{5}$$

which computes the ratio between the number of cognates identified between the source and the target words, and the total number of source words.

2.2.6. *Chunks label*

If a label is assigned to chunks during the chunking process, we can compare the labels in the source and the target and use this information to relate chunks. A chunk label may be NP (for a noun phrase), or DET if we use the marker-based chunker and the first word of the chunk is a determiner. The feature is a simple binary feature:

$$h_l(e_i, f_j) = \begin{cases} 1 & \text{if } e_i \text{ and } f_j \text{ share the same label,} \\ 0 & \text{otherwise.} \end{cases}$$

The weights of the log-linear model are not optimized; we experimented with different sets of parameters and did not find any significant difference as long as the weights stay in the interval $[0.5 - 1.5]$. Outside this interval, the quality of the model decreases.

2.2.7. *Integrating SMT data*

Whilst EBMT has always made use of both lexical and phrasal information [16], it is only recently that SMT has moved towards the use of phrases in their translation models and decoders [7, 17]. It has, therefore, become harder than ever to identify the differences between these two data-driven approaches [10]. However, despite the convergence of the two paradigms, recent research [10, 18] has shown that it is possible to combine elements from EBMT and SMT to create hybrid data-driven systems capable of outperforming the baseline systems from which they are derived. Therefore, SMT phrasal alignments are also added to the aligned chunks extracted by the chunk alignment module, in order to produce higher quality translations. The integration is very easy: the various counts associated with the aligned chunks in the two translation tables are simply added. This integration has two notable effects: firstly, it captures some aligned chunks that may not be extracted if only one of the two strategies is used; secondly, it "boosts" the counts of the aligned chunks that are present in both databases.

2.3. Decoder

The decoding module is capable of retrieving already translated sentences and also provides a wrapper around PHRAMER, a phrase-based SMT decoder. This decoder implements Minimum-Error-Rate Training [19] within a log-linear framework [20]. The BLEU metric [21] is optimized using the provided development set. We use a log-linear combination of several common feature functions: phrase translation probabilities (in both directions), word-based translation probabilities (lexicon model, in both directions), a phrase length penalty and a target language model [22].

The phrase translation probabilities are simply estimated thanks to relative frequencies computed on the aligned dataset of chunks obtained as described above.[4] Word-based translation probabilities are introduced to smooth the phrase translation probabilities, that tend to be over-estimated for phrases that appear only once in the training data [15].

The target (English) language model is a simple 3-gram language model trained on the English portion of the training data, using the SRI Language Modeling Toolkit [23], with modified Kneser-Ney smoothing [24].

3. Experimental results

3.1. Data

The experiments were carried out using the provided datasets, extracted from the Basic Travel Expression Corpus (BTEC) [25]. This multilingual speech corpus contains tourism-related sentences similar to those that are usually found in phrasebooks for tourists going abroad. We participated in the Open Data Track for the following translation directions: Arabic-English and Italian-English, for which we translated both the single-best ASR hypotheses and the text input.

For the supplied data track, 20,000 aligned sentences were provided for training, for both Arabic and Italian. We performed some filtering based on the lengths and the relative lengths of the sentences, ending up with 19,378 aligned sentences for Arabic and 19,599 for Italian. In order to perform Minimum-Error-Rate Training [19], we use the development set number 4, made up of 489 aligned sentences. Note that the system was trained using exclusively the provided datasets.

As a pre-processing step, the English sentences were tokenized using the Maximum-Entropy based tokenizer of the OpenNLP toolkit.[5] This tokenizer was also used for Italian since we found that it was properly dealing with all punctuation marks except apostrophes. For apostrophes, in particular those involved in contractions, we used a set of regular expressions specific to Italian. Additionally, for English and Italian, case information was removed. For Arabic, the tokenization was handled by the ASVM toolkit previously mentioned.

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[4]Note that the various probabilities introduced in Section 2.2 are only used to align the phrases in the first place; once these phrases have been aligned, probabilities are estimated with relative frequencies.

[5]http://opennlp.sourceforge.net/.

		BLEU	NIST	Meteor	WER	PER
ASR (1-best)	Official	0.2598	6.585	0.5497	0.5835	0.4869
	Additional	0.2783	7.228	0.5495	0.5662	0.4498
Text input	Official	0.3126	7.546	0.6246	0.5315	0.4286
	Additional	0.3467	8.358	0.6245	0.4964	0.3744

Table 1: Official results - Italian

		BLEU	NIST	Meteor	WER	PER
ASR (1-best)	Official	0.145	4.531	0.402	0.7027	0.5949
	Additional	0.1391	4.794	0.4	0.7165	0.5870
Text input	Official	0.1624	4.89	0.4336	0.686	0.5678
	Additional	0.1589	5.29	0.432	0.6935	0.5537

Table 2: Official results - Arabic

The official metrics of the evaluation campaign of IWSLT 2006 take case information and punctuation marks into account. Since the input sentences do not contain such information, we need to reintroduce them in the output. In order to do so, we followed the procedure suggested by the organizers. For punctuation restoration, we consider that the punctuation marks are hidden events occurring between words, the most likely hidden tag sequence (consistent with the given word sequence) being found using an n-gram language model trained on a punctuated text. For case restoration, the task is viewed as a disambiguation task in which we have to choose between the (case) variants of each word of a sentence. Again, finding the most likely sequence is done using an n-gram language model trained on a case-sensitive text. These 3-gram language models were trained on the English portion of the training data, again using the SRILM toolkit [23].

Since the datasets do not contain named entities, numbers, or acronyms, as an additional post-processing step we removed the words from the output that were copied by the decoder from the input.

3.2. Results

The system output is evaluated with respect to the following metrics: BLEU, NIST, Meteor, WER, and PER. These metrics are computed thanks to the IWSLT 2006 evaluation server. The results are reported in Tables 1 and 2. Official (resp. additional) results includes (resp. excludes) case and punctuation information.

The results obtained show that our system is competitive with other state-of-the-art systems, which is encouraging for our first participation. Moreover, we successfully adapted our system to Italian-English, a new language pair. As expected, the results obtained on the text input are better than those obtained on the ASR (1-best) output, for almost all of the metrics, the difference ranging from 1.7 (Arabic, Official) to 6.8 (Italian, Additional) BLEU points. With respect to Official vs. Additional, we expected to get better results on the Additional metrics, since it seemed to be an easier task.

This is what we obtained for Italian: 3.41 additional BLEU points on the text input. However, it is less clear for Arabic, for which the Additional scores were better, except for NIST, which conflicts with the other metrics.

4. Conclusion

In this paper, we described MATREX, the hybrid Data-Driven MT system developed at DCU. This system was used for our first participation in the evaluation campaign of IWSLT 2006. This system uses both EBMT and SMT approaches to extract aligned chunk resources. We described several chunking and chunk alignment strategies, integrated within a modular system.

We participated in the Open Data Track for the Arabic to English and Italian to English translation tasks, for which we translated both the single-best ASR hypotheses and the text input. We showed that our system can be easily adapted to new language pairs, and is competitive with other state-of-the-art systems.

We plan to continue our experiments in various directions. First, we will investigate different language pairs, in particular Chinese-English. Then, we will analyze the effects of various chunking strategies on the overall MT system performance; we will also examine how to combine different chunking strategies. We also want to explore the use of other chunk alignment techniques.

5. Acknowledgments

6. References

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