

Results from the ML4HMT-12 Shared Task on Applying Machine Learning Techniques to Optimise the Division of Labour in Hybrid Machine Translation

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Abstract

We describe the second edition of the ML4HMT shared task which challenges participants to create hybrid translations from the translation output of several individual MT systems. We provide an overview of the shared task and the data made available to participants before briefly describing the individual systems. We report on the results using automatic evaluation metrics and conclude with a summary of ML4HMT-12 and an outlook to future work.

Keywords: Machine Translation, System Combination, Machine Learning.

1 Introduction

The ML4HMT-12 workshop and associated shared task are an effort to trigger a systematic investigation on improving state-of-the-art hybrid machine translation, making use of advanced machine-learning (ML) methodologies. The first edition of the workshop (ML4HMT-11) also road-tested a shared task (and associated data set) described and summarised in (Federmann, 2011). The main focus of the ML4HMT-12 (and ML4HMT-11) shared task is to address the question:

Can Hybrid MT and System Combination techniques benefit from extra information (linguistically motivated, decoding, runtime, confidence scores or other meta-data) from the individual MT systems involved?

Participants are invited to build hybrid MT systems and/or system combinations by using the output of several MT systems of different types, as provided by the organisers. While participants are encouraged to explore machine learning techniques to explore the additional meta-data information sources, other approaches aimed at general improvements in hybrid and combination based MT are welcome to participate in the challenge. For systems that exploit additional meta-data information the challenge is that additional meta-data is highly heterogeneous and specific to individual systems.

One of the core objectives of the challenge is to build an MT combination (or more generally a hybrid MT) mechanism, where possible making effective use of the system-specific MT meta-data output produced by the participating individual MT systems as provided by the challenge development set data comprising outputs of four distinct MT systems and various meta-data annotations. The development set provided by the organisers can be used for tuning the combination or hybrid systems during the development phase.

2 Datasets

The organisers of the ML4HMT-12 shared task provide two data sets, one for the language pair Spanish→English (ES-EN), the other for Chinese→English (ZH-EN).

ES-EN Participants are given a development bilingual data set aligned at a sentence level. Each "bilingual sentence" contains:

1. the source sentence;
2. the target (reference) sentence; and
3. the corresponding translations from four individual component MT systems, based on different machine translation paradigms (Apertium (Ramírez-Sánchez et al., 2006); Lucy (Alonso and Thurmair, 2003); two different variants of Moses (Koehn et al., 2007): PB-SMT and HPB-SMT).

The output has been automatically annotated with system-internal meta-data information derived from the translation process of each of the systems.

ZH-EN A corresponding data set for Chinese→English with output translations from three systems (Moses; ICT_Chiero (Mi et al., 2009); Huajian RBMT) was prepared. Again, system output has been automatically annotated with system-internal meta-data information.

In total, with the development data participants received 20,000 translations per system for training and had to translate a test set containing 3,003 sentences ("newstest2011") for Spanish→English, while for the other language pair Chinese→English, a total of 6,752 training sentences per system were available while the test set had a size of 1,357 sentences.

3 Participants

We received six submissions for the Spanish→English translation task and none for Chinese→English. Below, we will briefly describe the participating systems.

3.1 DCU-Alignment

The authors of (Wu et al., 2012) incorporate alignment information as additional meta-data into their system combination module which does not originally utilise any alignment information provided by the individual MT systems producing the candidate translations. The authors add alignment information provided by one of the MT systems, the Lucy RBMT engine, into the internal, monolingual, alignment process. Unfortunately, the extracted alignment is often already a subset of alignments calculated by the monolingual aligner in the system combination and hence the approach does not augment the overall system combination performance as much as expected.

3.2 DCU-QE1

The submission described in (Okita et al., 2012a) incorporates a sentence-level Quality Estimation (QE) score as meta-data into their system combination module. Recently, QE or confidence estimation technology has advanced. It measures the quality of translations without references. The core idea is to incorporate this knowledge into the system combination module through an improved backbone selection.

3.3 DCU-QE2

The work described in (Okita et al., 2012a) also explains how one can incorporate a sentence-level Quality Estimation score to do the data selection process. The authors designed, hence, a method only based on Machine Learning. The translated output tends to preserve the translation quality as is expected, which results in a high Meteor score. The idea in this paper is to select one of the given translation outputs by QE score where a sentence-level QE technology is to measure the confidence estimation for the translation output.

3.4 DCU-DA

The authors of (Okita et al., 2012b) utilised unsupervised topic/genre classification results as meta-data, feeding into their system combination module. Since this module has access to topic/genre information, an MT system can take advantage of this information. MT systems are tuned to particular topic/genre groups and only compute translations for documents in this group, hence the performance of such MT systems may improve.

3.5 DCU-LM

This submission incorporates latent variables as meta-data into the system combination module. Information about those latent variables are supplied by a probabilistic neural language model. This language model can be trained on a huge monolingual corpus, with the disadvantage that the training of such a model takes considerable time. In fact, the LM used for ML4HMT-12 was small due to the huge cost of training, resulting in only small performance gains.

Score	Spanish→English					
	1best	R3	DCU-DA	DCU-LM	DCU-QE1	DFKI
Meteor	0.30692	0.32226	0.32124	0.31684	0.31712	0.32303
NIST	7.4296	7.4291	7.6771	7.5642	7.6481	7.2830
BLEU	0.2614	0.2524	0.2634	0.2562	0.2587	0.2570

Table 1: Translation quality of ML4HMT-12 submissions measured using Meteor, NIST, and BLEU scores for language pair Spanish→English. Best system per metric printed in bold face.

3.6 DFKI

This submission implements a method for system combination based on joint, binarised feature vectors as introduced in (Federmann, 2012b). It can be used to combine several black-box source systems. The authors first define a total order on the given translation output which can be used to partition an n -best list of translations into a set of pairwise system comparisons. Using this data, they train an SVM-based classification model and show how this classifier can be applied to combine translation output on the sentence level.

4 Results

Similar to the first edition of the ML4HMT shared task (ML4HMT-11), we aim to run both an automatic and a manual evaluation campaign. We consider three automatic scoring metrics, namely Meteor (Denkowski and Lavie, 2011), NIST (Dodgington, 2002), and BLEU (Papineni et al., 2002), which are all well-renowned evaluation metrics commonly used for MT evaluation. Manual evaluation is currently being conducted using the Appraise software toolkit as described in (Federmann, 2012a). Table 1 summarises the results for all participating systems.

5 Conclusion

System *DFKI* performed best in terms of Meteor score¹ while system *DCU-DA* achieved best performance for NIST and BLEU scores. It will be interesting to see how these findings correlate with the results from manual evaluation, something we will report on in future work.

If technically feasible, we also intend to apply the algorithms submitted to the Spanish→English portion of the Shared Task to the second language pair, Chinese→English.

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¹Which, in the first edition of the ML4HMT shared task, had shown the best correlation with human judgments. A finding that will be investigated in more detail once results from the manual evaluation of ML4HMT-12 are available.

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