Improving KantanMT Training Efficiency with fast_align

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Abstract

In recent years, statistical machine translation (SMT) has been widely deployed in translators’ workflow with significant improvement of productivity. However, prior to invoking an SMT system to translate an unknown text, an SMT engine needs to be built. As such, building speed of the engine is essential for the translation workflow, i.e., the sooner an engine is built, the sooner it will be exploited.

With the increase of the computational capabilities of recent technology the building time for an SMT engine has decreased substantially. For example, cloud-based SMT providers, such as KantanMT, can built high-quality, ready-to-use, custom SMT engines in less than a couple of days. To speed-up furthermore this process we look into optimizing the word alignment process that takes place during building the SMT engine. Namely, we substitute the word alignment tool used by KantanMT pipeline – Giza++ – with a more efficient one, i.e., fast_align.

In this work we present the design and the implementation of the KantanMT pipeline that uses fast_align in place of Giza++. We also conduct a comparison between the two word alignment tools with industry data and report on our findings. Up to our knowledge, such extensive empirical evaluation of the two tools has not been done before.

1 Introduction

In recent years, statistical machine translation (SMT) systems have been widely deployed in translators’ workflows with significant improvements in productivity. KantanMT is a cloud-based SMT platform that allows its clients to train SMT engines that are customized for their specific translation tasks by using their own data. Many factors contribute to the quality of service provided by KantanMT, e.g. the speed for training an SMT engine with KantanMT is an essential factor as it determines how fast clients can commence translating.1

1To date, SMT engines built using 250 million words of training data can be built with KantanMT in about 3 days.
The KantanMT platform employs a cloud-based architecture that has two main components: (i) an interface component to process, coordinate and distribute job requests and (ii) a collection of processing steps to execute build, translation or analysis jobs. The architecture of KantanMT is based on the Amazon Web Services (AWS)\(^2\). For any job request the interface allocates a machine from the cloud. The machine is set-up to comply with KantanMT requirements and used afterwards to execute the specific job. For a build job, the KantanMT training pipeline is composed of 14 steps.

Crucial for the efficiency of the KantanMT training pipeline is word alignment. Word alignment is the task of identifying word-level translation relations between a source text and its translation. Naturally, to date the KantanMT pipeline has been using Giza++ (Och and Ney (2003)) – the most common word-alignment tool used by the SMT community – for word alignment. An alternative to Giza++ is fast_align (Dyer et al. (2013)), a simple, fast, yet effective tool to perform word alignment. Dyer et al. (2013) show that fast_align is about 10 times faster than IBM Model 4 (Brown et al. (1993)). Moreover, fast_align leads to translation performance comparable to MT engines trained using Giza++ (Dyer et al. (2013)). Accordingly, with the aim of reducing the training time of KantanMT engines, we introduced fast_align into the KantanMT pipeline in place of Giza++. Improved training times would lead to better quality of service as well as reduced resource allocation, an important issue for any cloud-based system.

In this work we present the integration of fast_align into the KantanMT training pipeline. We focus on (i) our collaborative approach to integrating the fast_align tool into a live production system; (ii) the improvements in training time; and (iii) a comparison of the translation quality between MT engines built with Giza++ and with fast_align.\(^3\)

2 Training KantanMT engines with Giza++

2.1 KantanMT training pipeline

Once a building request has been received and a dedicated machine has been allocated, there are 14 processing steps that take place in order to train a KantanMT engine. Each processing step applies on the output from the preceding step and provides input for the next\(^4\). These steps can be divided into 5 major stages:

1. **Instance setup.** Required software is downloaded and installed; bilingual and monolingual data is retrieved and verified.

2. **Data preprocessing.** Once the data is downloaded and verified it is subjected to preprocessing, cleansing and partitioning. The bilingual data is divided into three sets – a training, a tuning and a test set – that are used for training and optimizing the engine.

3. **Building.** Three models are built during this stage: (i) a language model that captures the linguistic aspects of the target language and aims at improving MT output; (ii) a recaser model to set the correct letter casing in the MT output and (iii) a translation model used for decoding unseen text. Monolingual data (in the target language) is often used to improve the quality of the language model. The KantanMT platform employs the open-source toolkit Moses (Koehn et al. (2007)) to train the language, the translation and the recaser models.

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\(^2\)https://aws.amazon.com/

\(^3\)To the best of our knowledge, such an extensive empirical evaluation of these two word-alignment approaches with industry data has not been performed to date.

\(^4\)That is why we refer to the KantanMT architecture as a pipeline architecture.
Figure 1: KantanMT training pipeline.

4. **Engine postprocessing.** After the engine is built it is scored by calculating three evaluation metrics: (i) BLEU score (Papineni et al. (2002)); (ii) F-Measure (van Rijsbergen (1979); Melamed (1995)) and (iii) Translation Error Rate (TER) (Snover et al. (2006)). If required, the engine is also optimized by using the tuning subset from the training data.

5. **Storing.** The models, configuration files and scores are packed and stored for future use.

Word alignment is invoked during building the translation model. To compute the word alignment is one of the computationally most expensive tasks in the building step. Up to date, KantanMT was using Giza++ to perform word alignment during this step.

Figure 1 shows the original (i.e., using the Giza++ word-alignment tool) KantanMT pipeline for training an engine.

2.2 Faster word-alignment for faster end-user delivery

Giza++ implements IBM models 1 to 5 (Brown et al. (1993)) as well as an HMM word alignment model (Och and Ney (2003)). IBM models 1 and 2 are computationally inexpensive, however, higher IBM models increase the complexity of training the models by adding additional components. For example, IBM Model 3 introduces a fertility model which can address the issue of an input word producing multiple target words or zero words.

A software platform oriented to provide MT services to industry, such as KantanMT, needs to meet its clients requirements for quick service delivery. Moreover, there is a twofold gain in improving engine build time: (i) faster delivery to the end-user – the faster MT engines are trained, the sooner the client may start exploiting them; and (ii) optimized resource allocation – allocated hardware is released sooner and can be ready to use for new tasks faster.

A recent project, conducted by the ADAPT centre (Du et al. (2015)), implements an SMT pipeline where Giza++ is substituted by fast_align (Dyer et al. (2013)). Motivated by the results from their experiments and aiming to achieve faster delivery to the end-user as well as improved resource allocation, we integrate the fast_align word alignment tool in the KantanMT platform.

3 KantanMT pipeline with fast_align

In order to integrate fast_align into the KantanMT training pipeline, an absolute prerequisite is that it needs to be 100% compatible with the already used MT pipeline. This has two require-
ments: (i) no task that KantanMT performs should see any degradation in performance; and (ii) the user experience should not be negatively impacted.

3.1 A collaborative approach for industry-standard software development

In order to ensure the aforementioned requirements, we devised a systematic development approach that teamed state-of-the-art academic knowledge and experience with industry-leading software development and quality assessment (QA). We developed our solution following an AGILE-based methodology that involved three main stages:

1. **Design.** During the design stage we first analysed the current KantanMT pipeline and identified the software requirements towards the pipeline for integrating a new word alignment tool. We then identified the software requirements of fast_align. Joining the industry experience and the academic know-how we formulated the system design, i.e., the functional and technical specifications of the modified KantanMT pipeline. Furthermore, we reviewed and accepted any licences of additionally required software.

2. **Implementation.** Upon approval of the system design we implemented the new pipeline according to the steps defined in the technical specification document. As a first part of the quality assessment (QA) strategy we performed a series of tests to verify that each component of the pipeline, including the newly introduced ones, works as designed (i.e., alpha testing).

3. **Quality Assessment.** Our QA strategy involved alpha testing performed in parallel with the initial implementation; beta testing and life testing. While the alpha testing aimed to verify the coherence of the modified pipeline, the latter two parts aimed to ensure that the integrity of the whole system is intact. In addition, during the life testing we focused on the efficiency and user experience of the platform, i.e., empirical evaluation.

The duration of the project for integrating fast_align into the KantanMT training pipeline is 4 weeks plus 2 additional weeks for empirical evaluation.

3.2 System requirements

In order to incorporate fast_align into the KantanMT pipeline we first ensure that all software requirements of fast_align are met (see http://www.cdec-decoder.org/guide/ for details). Next we need to ensure that the input data requirements are met as well. In the original KantanMT pipeline (i.e., using Giza++) we use two files that represent the parallel corpus: one for the source part of the corpus and another for the target part. The fast_align tool uses a different input format. It requires a single file in which each line contains both the source and target parts for one sentence, separated by a triple pipe (|||). Example 3.1 shows such formatting for German source sentences and its English translation.

Example 3.1  

```
doch jetzt ist der Held gefallen . ||| but now the hero has fallen .
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We use the paste_files.pl script from the cdec tool collection to join the two files in one and therefore ensure the correct formatting for fast_align. We invoke paste_files.pl right after the data cleansing (see Figure 1).

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7 [http://agilemethodology.org/](http://agilemethodology.org/)

8 The functional specifications of the pipeline were outlined in a functional specification document; the technical specifications – in a technical specification document.

9 During the data preparation step (see Figure 1) the corpus is encoded in UTF-8.

10 [http://www.cdec-decoder.org/guide/fast_align.html](http://www.cdec-decoder.org/guide/fast_align.html)

11 [http://www.cdec-decoder.org/guide/fast_align.html](http://www.cdec-decoder.org/guide/fast_align.html)

12 [http://www.cdec-decoder.org/](http://www.cdec-decoder.org/)
Figure 2: KantanMT training pipeline modified to invoke fast_align.

We run the fast_align tool in forward (source–target) and reversed (target–source) directions. Each direction generates asymmetric alignments, i.e., by treating either the source or target language in the parallel corpus as primary language being modeled. These two directional fast_align will generate slightly different alignments and need to be then symmetrized. We use the atools script from the cdec collection. The output from atools produces a word alignment in the widely-used $i$–$j$ Pharaoh format (Koehn (2003)). In this format, the pair $i$–$j$ indicates that the $i^{th}$ word (zero-indexed) of the source language is aligned to the $j^{th}$ word of the target language. Example 3.2 shows the word alignment in Pharaoh format for the sentences in Example 3.1.

Example 3.2 0-0 1-1 2-4 3-2 4-3 5-5 6-6

The word alignment in the Pharaoh format is compatible with the steps in the building process that follow the word alignment step.

3.3 System architecture

In order to integrate fast_align we modify the original KantanMT pipeline as follows:

1. Incorporate additional data processing step where we invoke paste_file.pl to join the two files of the parallel corpus in one according to the requirements of fast_align (see Section 3.2).
2. During the build of the translation model we skip Giza++ and invoke fast_align.
3. Invoke atools to symmetrize the output of fast_align.

The rest of the pipeline remains the same. Our modifications are outlined in Figure 2.

The modularity of our pipelines – the original KantanMT training pipeline and the modified one – allow an easy switching between the two, i.e., between training an engine with fast_align and with Giza++. To do so we use a global variable that acts as a switch between fast_align and Giza++. This ensures (i) higher control on the pipeline; (ii) quick and easy rollback in case of unforeseen system issues.

4 Empirical evaluation

In order to determine the effectiveness of the fast_align word alignment tool, a series of experiments were conducted in a closed, controlled system separate from the normal workflow of KantanMT. The goal of running these experiments was to quantify the performance of the KantanMT training pipeline as well as the translation quality of engines trained using fast_align as compared to the original pipeline that uses Giza++.
4.1 Set-up
Our tests involved building 10 engines from 10 different data sets with both Giza++ and fast_align. These data sets are of varying sizes and language pairs. The data is from legal and financial domain; it is part of the KantanLibrary™. At the end of the experiments, speed, performance, accuracy, and stability of each engine were compared to their counterpart for a direct Giza++-to-fast_align assessment. Details about the used data sets are presented in Table 1.

We decided to use small data sets in order to test whether the alignment tool would perform better when given a small data set as compared to larger data sets. The engines built with the larger data sets were used to derive close to realistic estimates on the overall engine performance – i.e., automatic evaluation metrics and building time – when comparing the two alignment tools. Typically, a specialised engine is built on around 10 million words. The language pairs were selected based on the availability of professional linguists, translators or native speakers who can evaluate the quality of translated files.

4.2 Experiments
4.2.1 Experiment 1 – Time consumption
The objective of Experiment 1 is to judge the speed of the KantanMT training pipeline. First we broke down the steps to building an engine from the moment the training data is prepared to when the final package is completed (see Figure 1 and Figure 2). Each step was launched manually, monitored, and timed for all 10 engines for both pipelines – with Giza++ and with fast_align. We then sum the time of each individual step in order to compute the total training time. Table 2 summarises our results from timing each individual step. It shows the time gain ($T^+$) for building an engine with fast_align ($T_{fa}$) as compared to an engine built using Giza++ ($T_{ga}$): $T^+ = \frac{T_{ga} - T_{fa}}{T_{ga}}$.

Table 2 reveals that each engine experienced a decrease in building time when using fast_align, with the time gain being between 48% and 73%. We ought to noted that these times do not account for the initial training data upload time, the instance setup, the data preparation, or the job clean-up which, when dealing with large engines, can add a significant amount of time to a build, i.e., can take around 40 – 60% of the total job time. In order to estimate the impact of the new word alignment tool under life conditions we also measured the time for training an engine launched from the online interface of the platform. Table 2 summerizes our results from timing the engine build including the data upload time, instance setup, etc.

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Table 1: Data sets used in our comparison experiments.

| Language pair      | Relative size | Word count  | Unique word count | Engine reference |
|--------------------|---------------|-------------|-------------------|------------------|
| English-French     | Small         | 781 075     | 42 563            | EN-FR-small      |
| English-French     | Large         | 109 379 800 | 1 008 696         | EN-FR-large      |
| English-German     | Small         | 786 981     | 42 648            | EN-DE-small      |
| English-German     | Large         | 138 119 563 | 1 084 485         | EN-DE-large      |
| English-Spanish    | Small         | 861 557     | 44 375            | EN-ES-small      |
| English-Spanish    | Large         | 154 169 102 | 1 119 475         | EN-ES-large      |
| English-Italian    | Small         | 924 331     | 38 506            | EN-IT-small      |
| English-Italian    | Large         | 104 196 079 | 914 889           | EN-IT-large      |
| English-Chinese    | Small         | 810 134     | 33 281            | EN-ZH-small      |
| English-Chinese    | Large         | 58 274 131  | 550 862           | EN-ZH-large      |

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13KantanLibrary™ is the collection of industry-standard data that KantanMT provides to their clients.
### Specific tasks

| Engine       | Specific tasks | Complete pipeline |
|--------------|----------------|-------------------|
| EN-FR-small  | 00:09:23       | 00:18:00          |
| EN-FR-large  | 10:35:11       | 04:49:00          |
| EN-DE-small  | 00:10:06       | 00:17:00          |
| EN-DE-large  | 15:43:43       | 10:28:00          |
| EN-ES-small  | 00:10:21       | 00:20:00          |
| EN-ES-large  | 14:07:21       | 07:58:00          |
| EN-IT-small  | 00:11:03       | 00:22:00          |
| EN-IT-large  | 11:09:32       | 06:47:00          |
| EN-ZH-small  | 00:10:07       | 00:16:00          |
| EN-ZH-large  | 10:08:16       | 06:55:00          |

| Engine       | Specific tasks | Complete pipeline |
|--------------|----------------|-------------------|
| EN-FR-small  | 00:09:23       | 00:18:00          |
| EN-FR-large  | 10:35:11       | 04:49:00          |
| EN-DE-small  | 00:10:06       | 00:17:00          |
| EN-DE-large  | 15:43:43       | 10:28:00          |
| EN-ES-small  | 00:10:21       | 00:20:00          |
| EN-ES-large  | 14:07:21       | 07:58:00          |
| EN-IT-small  | 00:11:03       | 00:22:00          |
| EN-IT-large  | 11:09:32       | 06:47:00          |
| EN-ZH-small  | 00:10:07       | 00:16:00          |
| EN-ZH-large  | 10:08:16       | 06:55:00          |

**Table 2:** Summary of the results from Experiment 1: time comparison.

![Percentage time breakdown](image.png)

### Figure 3: Percentage time taken to complete each building phase.

These results show a more accurate interpretation as to how long a build job would take for a user. For the smaller engines, the time gain from using fast_align has a smaller impact due to the fact that the setup and shutdown times do not change, taking a larger proportion of the total job time. In Figure 3 we show an time for initialization, training and cleanup for a random small and a large engines.

Table 2 and Figure 3 indicate that the higher the word count of the training data the more influenced the training is by the specific training steps of the pipeline, and in particular by the word alignment. That is why, for larger engines fast_align typically leads to higher time gain.

#### 4.2.2 Experiment 2 – Automatic quality estimation

One of the final step in KantanMT training pipeline is to score the engines (see Figure 1). We compare the F-Measure, BLEU and TER scores computed at that step for each engine in order to determine the relative quality between engines built with Giza++ and engines built with fast_align. We summarize our results in Table 3.

For engines that were built with fast_align we notice maximum score decrease of 4.5 points (in the EN-DE-large engine) and maximum score increase of 2.2 points (in the EN-ES-large engine). The average difference is 1 point in favour of engines built with Giza++.

Regarding, BLEU score, we notice a maximum decrease of 2.8 points (in the EN-DE-small engine) and a maximum increase of 3.6 points (in the EN-DE-large engine). The average
The last three columns in Table 3 refer to the TER score. It shows a maximum increase of 5.9 points (in the EN-DE-large engine) and maximum decrease of 3.8 points (in the EN-DE-small engine). On average there is an increased by 0.83 points for engines built with fast_align.

Although we notice a general tendency of automatic quality measurements to decrease for engines built with fast_align (when compared to Giza++) we outh to point: (i) the fluctuation we observe in Table 3 indicates that there is no sensible change in quality and (ii) the fact that for different language pairs and data set sizes the scores alternate between fast_align and Giza++ indicates that under specific conditions fast_align is better and under other conditions Giza++ is better (the specifics of these conditions are out of the scope of this project and remain a topic for future research).

Experiment 3 In order to be get a more specific estimate of the quality of engines built with fast_align as compared to ones built with Giza++ we involved professional translators and native speakers (members of the KantanMT Professional Services department as well as the ADAPT centre at DCU) for human evaluation. We performed a blind comparison of 4 documents translated by engines built with fast_align and with Giza++ for each of the language pairs and data set sizes. The human evaluators would indicate which of the documents they considered to be better in terms of accuracy, fluency, and overall quality. The objective was to determine which engines translation would read easier when assessed by a person who is fluent in the target language.

For the smaller engines, all of translators independently said that the translation quality from engines built with fast_align is the same as from engines built with Giza++. In practice, due to the quantity of training data used by the smaller engines (being too small to translate to a high standard) the overall quality for all pairs was rather low. Therefore, we consider the results from the larger engines of practical value and focus on their analysis.

The translators had to answer two questions:

1. Which document has higher language quality?
2. Does the quality respond to their requirements as translators/native speakers?

All translators stated that both sets of documents were of a very high quality and that they cannot make a distinctive decision. With one exception: for the EN-FR-large engine, had translators disagreed as to which set of documents were better.
All translators consider both groups of translation documents to match their expectations. They also claimed that there was very little difference between documents, with mainly minor grammatical errors, e.g., two words in a long segment being in the wrong order. The results of the blind test were satisfactory to our requirements for the project.

5 Conclusions

In this work we substituted the word alignment tool used in the KantanMT pipeline – Giza++ – with the more efficient and yet effective fast_align. The latter has already been successfully incorporated in other industrial products and has shown promising results. In our design and implementation strategy we combined industry established software development practices with academic know-how to effectively modify a large-scale online platform such as KantanMT with no downtime or decay in KantanMT services.

To assess the impact of the new word alignment method into the efficiency of the KantanMT pipeline as well as the quality of the built engines we performed a series of tests with industry based data. Our results show an average speed-up of 60% and comparable quality to engines built with Giza++.

Our experiments also show that for languages that differ substantially in the word order (such as English and German) fast_align may lead to a slight decrease in quality (according to automatic measures). In the future, we aim to carry out more investigation on word alignment results from fast_align and examine possible solutions of improving SMT performance.

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