A PARALLEL EVALUATION DATA SET OF SOFTWARE DOCUMENTATION WITH DOCUMENT STRUCTURE ANNOTATION

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ABSTRACT

This paper accompanies the software documentation data set for machine translation, a parallel evaluation data set of data originating from the SAP Help Portal, that we release to the machine translation community for research purposes. It offers the possibility to tune and evaluate machine translation systems in the domain of corporate software documentation and contributes to the availability of a wider range of evaluation scenarios. The data set comprises of the language pairs English to Hindi, Indonesian, Malay and Thai, and thus also increases the test coverage for the many low-resource language pairs. Unlike most evaluation data sets that consist of plain parallel text, the segments in this data set come with additional metadata that describes structural information of the document context. We provide insights into the origin and creation, the particularities and characteristics of the data set.

Keywords Machine translation · Evaluation · Parallel data · Document structure

1 Introduction

The software documentation data set for machine translation is created by SAP as evaluation data for the machine translation (MT) research community. The data originates from the SAP Help Portal that contains documentation for SAP products and user assistance for product-related questions. The current language scope is English (EN) to Hindi (HI), Indonesian (ID), Malay (MS) and Thai (TH). The data has been processed in a way that makes it suitable as development and test data for machine translation purposes. For each language pair about 4k segments are available, split into development and test data. The segments are provided in their document context and are annotated with additional metadata from the document.

The software documentation data set for machine translation as described in this paper is available under the Creative Commons license Attribution-Non Commercial 4.0 International (CC BY-NC 4.0). It is available on Github under https://github.com/SAP/software-documentation-data-set-for-machine-translation. It has been released by SAP for the 7th Workshop on Asian Translation (WAT 2020). We will first provide some context, explaining the role of test data in machine translation and referring to related work (Section 2). We will then describe the origin of the software documentation data set for machine translation in Section 3 including the data preparation and data selection. Section 4 is dedicated to the characteristics of the data set. Section 5 concludes.
2 Context

Test sets are typically used for comparison in MT evaluation campaigns, such as WMT\(^4\) and WAT\(^3\) in which different participants, or rather their systems, compete against each other on specific tasks. Subsequently, those test sets are typically also used in research publications to demonstrate the effectiveness of the approach at hand and to compare to previous results. As such, test sets play a crucial role in showing the progress of machine translation. For many years, test sets have been prevalently drawn from news articles\(^5\). However, to be able to assess machine translation quality in a wider range of usage scenarios, it is important to also evaluate in other domains than news, and thus to create and establish test sets from a wider range of domains. Clearly, specific usage scenarios have other challenges than what is represented in the news domain. Thus, quality results (and claims about human parity) that have been achieved in the news domain can usually not be directly transferred to other domains. Accordingly, data sets and shared tasks have been created for other domains as well, e.g. biomedical\(^6\) and patents\(^6\). With the software documentation data set, we provide the possibility to tune and evaluate MT systems in the domain of corporate software documentation, and thus contribute to a clearer picture of the quality of machine translation across domains. Similarly, the focus of machine translation has often been on high-resource language pairs, such as English-German. With an evaluation data set for four language pairs that are rather on the lower end of availability of resources, we contribute to a better test coverage for the many low-resource language pairs.

With the recent improvements in machine translation quality, up to claims of human parity, flaws in the evaluation setups and interpretation of results have been pointed out (Ioral et al. 2018; Läubli et al. 2018; Bojar et al. 2018). Subsequently, more emphasis has been put on carefully evaluating machine translation, in particular to be able to evaluate segments within their document context, e.g. in Barrault et al. (2019). By creating data sets that consist of documents corresponding to help pages, we contribute to this endeavor. The document structure annotation can also provide additional useful information during human evaluation. Similarly, machine translation approaches have started to look beyond translating independent sentences. Methods for taking more context, e.g. from the document, into account have emerged, with the goal to improve the translation quality (Miculich et al. 2018; Maruf and Haffari 2018; Yu et al. 2020 amongst others). By providing development and test data with document context and metadata, we hope to strengthen such developments.

Data sets that are related to the data set at hand in terms of the covered domain are the data sets from the WMT16 shared task of machine translation of IT domain (Bojar et al. 2016 section 4) and the documentation data set by Salesforce (Hashimoto et al. 2019). The data set from the IT translation shared task consists of answers from a help desk, thus it covers a different text type than software documentation that likely also comes with a different style. Furthermore, the focus of the data set is on European languages, and it does not contain more context than short one-paragraph answers. The data set described and experimented with in Hashimoto et al. (2019) is very similar in nature to ours. Note however that the language scope is different: all language pairs in the data set by Salesforce are rather high-resource.

3 Origin of the data

3.1 Data sources

The contents of the software documentation data set for machine translation originate from the SAP Help Portal that contains SAP product documentation and user assistance for product-related questions. As it describes the use of software, it is rather technical in nature. In contrast to general textual data, it is highly structured, i.e. it contains many tables, lists, links, examples as well as code snippets. The textual presentation and page layout follow a similar structure across documents to obtain a coherent appearance of corporate help pages. This explains some of the particularities of this data set, described in more detail in Section 3.3. Figure 1 shows an example of such a help page.

The content of the help pages is authored by domain experts and then translated by professional translators that are specialized in the translation of SAP content. Hence, the data is of high source and translation quality. Furthermore,
to the best of our knowledge, the translations of the proposed documentation data set were created without machine translation in the loop, so there is no bias to any MT system.

3.2 Data preparation

In this section, we will describe the source format of the data and how we processed it for the software documentation data set for machine translation.

English source texts are edited using DITA™, an XML-based format, well suited for authoring, structuring and publishing content with a high potential of reuse. For translation, SAP uses computer-assisted translation (CAT) tools, such as SDL Trados Studio®, which transform DITA-XML format into XLIFF (XML Localization Interchange File Format) used in translation. As it keeps track of the text structure and inline markup of the source texts, this information can be transferred to the target language after translation. For its use in SDL Trados Studio, SDL developed SDLXLIFF® a special flavor of XLIFF. SDLXLIFF files are highly structured bilingual files that contain both the source document text and its translation.

Figure 2 shows a fragment of an SDLXLIFF document that demonstrates the information used to provide parallel text as well as structural annotation of the document context. Note that typically far more metadata information is contained, but we leave it out here for the sake of simplicity. SDLXLIFF files usually cover one document, the content of which is presented in textual order. A translation unit <trans-unit> is a sequence of consecutive text for the source and the target language, in this case for English and Hindi. It is split into sentences by the Trados sentence segmenter, as shown under <seg-source> and <target> in Figure 2. Segments are enumerated using the mid attribute. We use this information to order the translation pairs consecutively for each document and to count segments that belong to a text unit or paragraph (see description of the document context metadata file further below, columns 2 and 4).

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8 https://en.wikipedia.org/wiki/Darwin_Information_Typing_Architecture
9 https://www.sdl.com/software-and-services/translation-software/sdl-trados-studio/
10 http://xml.coverpages.org/xliff.html
11 http://producthelp.sdl.com/sdl%20trados%20studio/client_en/Edit_View/XLIFF_File_Format.htm
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Figure 2: Example of a translation unit in XLIFF format

<xml>
<trans-unit id="e66c34f4-7383-4ff0-8a68-a3bc3e90c9e0"
>  <source id="11">If you cannot find the course, then your course is an external event. Start over and select External event.</source>
  <mrk mtype="seg" mid="11">If you cannot find the course, then your course is an external event.</mrk>
</trans-unit>
</xml>

Figure 3: Example of a definition of textual elements in an XLIFF file

<cxt-defs xmlns="http://sdl.com/FileTypes/SdlXliff/1.0">
  <cxt-def id="1" type="sdl:title">
    <fmt id="1"/>
  </cxt-def>
  <cxt-def id="2" type="link text" descr="Line of text for a link.">
    <fmt id="2"/>
  </cxt-def>
  <cxt-def id="3" type="section" descr="Organizational division of a topic.">
    <fmt id="4"/>
  </cxt-def>
  <cxt-def id="4" type="unordered list" descr="List of items">
    <fmt id="4"/>
  </cxt-def>
</cxt-defs>

The information about the structural type of a translation unit in the document is conveyed by the <sdl:cxts> context value. Text can be used in a title, a section, a table, an example or an itemized list. In the example in Figure 2, the translation unit occurs in the context <sdl:cxt id="4"/> which corresponds to an unordered list, see Figure 3 for the text element declarations.

Contextual text types are declared for each XLIFF file and vary depending on the document content and its source. To reduce the number of text types that come with naming variants and different levels of granularity, we mapped them to six common and self-explanatory categories for the software documentation data set: title, section, table_element, list_element, example, unspecified.

Parallel segments, positional metadata and text type were extracted from each SDLXLIFF document using the Saxon parser[1] with an XSLT stylesheet. We provide the resulting data in text format, as it is common practice in machine translation, in three sentence-parallel files: source text, target text and document context metadata. The metadata file contains the following five columns:

1. Document ID
2. Segment ID in the document that indicates the contextual order (restarts from 1 in each document)
3. Text Unit ID in the document that indicates segments that occur in consecutive order (starts from 1 in each document). Segments with the same Text Unit ID make up one text block consisting of multiple sentences, for example a paragraph.
4. Segment ID in Text Unit (starts from 1 in each Text Unit)
5. Textual element that describes the structural type of the segment. Values are title, section, table_element, list_element, example, unspecified

[1] http://saxon.sourceforge.net/
The XS Advanced Programming Model  
Writing applications for deployment to SAP HANA XS advanced.
SAP HANA Extended Application Services advanced model (XS advanced) adds an application platform to the SAP HANA in-memory database.
In the Cloud, this platform is provided by Cloud Foundry.
An SAP-developed run-time environment is bundled with SAP HANA on-premise which provides a compatible platform that enables applications to be deployed to both worlds: the Cloud and on-premise.
XS advanced is optimized for simple deployment and the operation of business applications that need to be deployed in both worlds.
For this reason, the XS advanced programming model fully embraces the Cloud Foundry model and leverages its concepts and technologies.
In areas where Cloud Foundry as an intentionally generic platform for distributed Web applications does not address relevant topics or offers choice, the XS advanced programming model provides guidance that is in line with the general Cloud programming model.
In this section, you can find information about the following topics:
Cloud Foundry Concepts
System Architecture
Run-Time Platform
Authentication and Authorization
Component Model
Client User Interface
OData Services
SAP HANA Database

| English source | Metadata |
|---------------|----------|
|               | 1 2 3 4 5 |
| The XS Advanced Programming Model  | 79 1 1 1 title |
| Writing applications for deployment to SAP HANA XS advanced. | 79 2 2 1 section |
| SAP HANA Extended Application Services advanced model (XS advanced) adds an application platform to the SAP HANA in-memory database. | 79 3 3 1 section |
| In the Cloud, this platform is provided by Cloud Foundry. | 79 4 3 2 section |
| An SAP-developed run-time environment is bundled with SAP HANA on-premise which provides a compatible platform that enables applications to be deployed to both worlds: the Cloud and on-premise. | 79 5 3 3 section |
| XS advanced is optimized for simple deployment and the operation of business applications that need to be deployed in both worlds. | 79 6 3 4 section |
| For this reason, the XS advanced programming model fully embraces the Cloud Foundry model and leverages its concepts and technologies. | 79 7 3 5 section |
| In areas where Cloud Foundry as an intentionally generic platform for distributed Web applications does not address relevant topics or offers choice, the XS advanced programming model provides guidance that is in line with the general Cloud programming model. | 79 8 3 6 section |
| In this section, you can find information about the following topics: | 79 9 4 1 section |
| Cloud Foundry Concepts | 79 10 5 1 list_element |
| System Architecture | 79 11 6 1 list_element |
| Run-Time Platform | 79 12 7 1 list_element |
| Authentication and Authorization | 79 13 8 1 list_element |
| Component Model | 79 14 9 1 list_element |
| Client User Interface | 79 15 10 1 list_element |
| OData Services | 79 16 11 1 list_element |
| SAP HANA Database | 79 17 12 1 list_element |

Table 1: Presentation of source segments and text structure annotation

After the XLIFF processing, the contextual annotation of the content of the SAP Help page in Figure 1 would look as shown in Table 1. It is document 79 with 17 segments and 12 text units. There is a paragraph marked as text unit 3 consisting of 6 sentences. Each list element is considered an individual text unit.

3.3 Particularities

As pointed out in Section 3.1 help pages are composed in a way that allows for high reuse of textual content and patterns. For coherent appearance, their structure is intended to be clear and uniform. This has some impact on the kind of text segments we find in software documentation documents.

1. There is a lot of redundancy, i.e. source-target pairs occur several times across documents or even within the same document. This concerns titles, table headers, table values or even complete sentences.
2. As the help pages on the SAP Help Portal contain many tables and list items, many translation segments are short, sometimes consisting of just a number or one word. List and table elements are presented as individual text units which reflects their property of being translated independently (but within their document context obviously).
3. There is a large number of short documents reflecting the segmentation of help page content into reusable units.

These particularities have an impact on the creation of the evaluation data sets, see Section 3.4 and obviously also on the characteristics of the final data set, see Section 4.

The Note displayed on the help page in Figure 1 is not part of the document the data was extracted from. It is inserted at some later stage of the publishing process.
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Figure 4: Redundancy reduction: redundancy in all data vs. the data that was selected for the data set.

3.4 Data selection

Ideally, test and development sets for machine translation meet the requirements of being:

- representative for a given test or usage scenario, in our case for a given domain, covering well its specific terminology, its syntax and style,
- free of duplicates and redundancy,
- balanced, i.e., ideally sampled from a larger set of data, so that the content is spread over various topics.

When building evaluation sets as collections of single sentences (or sentence pairs), it is rather straightforward to adhere to these criteria. However, when creating them for whole documents, the absence of duplicates and redundancy as well as content balance are more challenging. This is particularly true for our help page content that displays similar structuring and repetitions, see Section 3.3. Obviously, duplicate sentence pairs cannot simply be removed if we want to keep the contextual order of segments.

Let us define redundancy as the ratio of all source-target pairs to unique source-target pairs in a data set. Figure 4 shows the redundancy for all data at our disposal (in blue). We see that it differs depending on the language pair. To some extent, this can be explained by the amount of documents used for extraction. While for English to Malay (EN-MS) and to Thai (EN-TH) we had several thousands of original documents at hand, for English to Hindi (EN-HI) and to Indonesian (EN-ID) only a couple of hundred documents were available that had less overlap and thus displayed less repetition.

To meet the requirements of test and development data, we made an effort to reduce this redundancy by selecting documents that are less prone to have content present in other documents. The following indicators were calculated to be used in the selection process:

- Document redundancy ratio: percentage of unique parallel segments to all parallel segments in a document (to flag documents that contain duplicates)
- Number of segments in the document (to flag documents with little content, and hence context)
- Average number of source words per segment (to keep documents with longer segments)
- Cross-document redundancy of a document with respect to all documents (to flag documents that contain a large number of segments that occur in many other documents). We first create a frequency list of source segments of all documents. Then, for each segment of a document, we sum up their overall document frequencies and divide it by the number of segments in the document. This ratio is high if the document contains many segments that occur in many documents.

General guidance for assembling (test) data can be found in Megerdoomian (2003, sec. 1.6.5), Jurafsky and Martin (2008, sec. 4.3), Resnik and Lin (2010, sec. 2.6), amongst others.
Table 2: Statistics on development and test data sets

| Language Pair | # of Documents | # of Parallel Segments | # of Source Words | Data Set Redundancy |
|--------------|----------------|------------------------|-------------------|---------------------|
|              | dev | test | dev | test | dev | test | dev | test |
| EN-HI        | 78  | 76   | 2,016 | 2,073 | 20,662 | 18,128 | 1.33 | 1.14 |
| EN-ID        | 66  | 74   | 2,023 | 2,037 | 21,159 | 18,164 | 1.26 | 1.11 |
| EN-MS        | 210 | 197  | 2,050 | 2,050 | 26,654 | 26,758 | 1.04 | 1.05 |
| EN-TH        | 207 | 205  | 2,048 | 2,050 | 25,759 | 25,426 | 1.03 | 1.05 |

- Document double indicator. It turned out that for EN-MS and EN-TH, many documents were almost identical but for one or two segments. Overall cross-document redundancy does not help in this case, as source-target pairs occur only twice. The document double indicator flags documents that contain a large percentage of source-target pairs that occur exactly twice in the complete data.

For each language pair, we selected a subset of all available documents that contains about 4k sentences that meets the requirements as much as possible by calibrating the indicators. For EN-MS and EN-TH, all five indicators were used to reduce the redundancy as much as possible. For EN-HI and EN-ID, only the document redundancy ratio and the number of segments per document were considered, as there were less documents to choose from and there was less redundancy to start with. With this approach, we successfully obtained a data set with less duplicates across documents, see Figure 4 (in red).

4 Characteristics of the software documentation data set for machine translation

The development and test data sets were drawn from the data set with reduced redundancy, as described in Section 3.4. Table 2 shows more details about their characteristics.

While the number of segments of the development and test sets are in the same range across language pairs, the number of documents and the total amount of words are different for EN-HI and EN-ID compared to the other two language pairs. This difference is also reflected in the distribution of words per segment, see Figure 5. There is a larger number of short segments for EN-HI and EN-ID. For EN-MS and EN-TH, we see a more balanced distribution of short and medium length segments in both, development and test sets.

Now let us take a look at the distribution of textual element annotations in the data sets’ metadata, see Figure 6. They explain, to some extent, the distribution of segment length: We see a larger number of segments labeled as section for EN-MS and EN-TH. Sections usually contain longer segments than table elements.

Finally, we can also look at the redundancy in the released data set, i.e. the number of all source-target pairs related to the number of unique source-target pairs, also shown in Table 2. As expected from Figure 4 there is more redundancy for EN-HI and EN-ID, which ties in with the larger number of shorter segments and table elements. They are more likely to reoccur across documents.

In summary, we can conclude that the data sets for English-Hindi and English-Indonesian are comparable concerning the criteria analyzed in this section. They are different from English-Malay and English-Thai that also have characteristics in common. We would have preferred to provide a more homogeneous data sets. However, given the different sizes and features of the original resources and the constraints imposed by adding contextual metadata, this was not feasible. On the other hand, the charts and graphs in this section indicate that the development and test sets of each language pair share the same characteristics, i.e. their segment length distribution, the types of textual element annotations as well as their word counts are comparable. This makes the development sets well suited to optimize a MT model towards the translation of the corresponding test set.

5 Conclusion

We presented the creation of a domain-specific MT evaluation data set and its particularities. The software documentation data set for machine translation consists of real-world data from the SAP Help Portal. To our knowledge, it is the first data collection with explicit text structure annotation and the first IT-specific evaluation data set for English to Hindi, Indonesian, Malay and Thai. It can be used for automatic quality assessment of context-aware MT systems, giving users the flexibility to consider all or only selected or no text structure metadata. With the release of these data sets, we
strive to support the development and testing of machine translation systems for low-resource language pairs for the translation of software documentation in a corporate context.

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Figure 6: Distribution of textual element annotations

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