JESC: Japanese-English Subtitle Corpus

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Abstract

In this paper we describe the Japanese-English Subtitle Corpus (JESC). JESC is a large Japanese-English parallel corpus covering the underrepresented domain of conversational dialogue. It consists of more than 3.2 million examples, making it the largest freely available dataset of its kind. The corpus was assembled by crawling and aligning subtitles found on the web. The assembly process incorporates a number of novel preprocessing elements to ensure high monolingual fluency and accurate bilingual alignments. We summarize its contents and evaluate its quality using human experts and baseline machine translation (MT) systems.

Keywords: parallel corpus, asian languages, machine translation

1. Introduction

There is a strong need for large parallel corpora from new domains. Modern machine translation (MT) systems are fundamentally constrained by the availability and quantity of parallel corpora. Apart from the exceptions of English-Arabic, English-Chinese, and several European pairs, parallel corpora remain a scarce resource due to the high cost of manual construction (Chu et al., 2014). Furthermore, despite promising work in domain adaptation, MT systems struggle to generalize to new domains that are disparate from their training data (Pryzant et al., 2017).

This need for large, novel-domain data is especially evident in the resource-poor Japanese-English (JA-EN) language pair. Only two large (>1M phrase pairs) and free datasets exist for this language pair (Neubig, 2017; Tiedemann, 2017; Moses, 2017). The first is called ASPEC. It consists of 3M examples and it originates from scientific papers, a highly formalized and written domain (all other JA-EN datasets have similar language) (Nakazawa et al., 2016). The other, OpenSubtitles, is a multi-language dataset of aligned subtitles authored by professional translators; the JA-EN subset of these data contains approximately 1M examples (Lison and Tiedemann, 2016). OpenSubtitles is to the best of these authors knowledge the *only* parallel corpus to cover the unrepresented domains of conversational speech and informal writing. This dearth of large-scale and informal data is especially problematic because colloquial Japanese has significant structural characteristics which can preclude cross-domain translation (Tsujimura, 2013). We hope to alleviate this problem by building off the work of (Lison and Tiedemann, 2016) to construct a larger corpus that incorporates the vast number of unofficial and fan-made subtitles on the web.

Subtitles are an excellent source for alleviating resource scarcity problems. There are a wide and interesting range of linguistic phenomena in subtitles that are poorly represented elsewhere. This includes colloquial exchange, slang, expository discourse, dialect, vernacular, and movie dialog, which is available in great quantities and has been shown to resemble natural conversation (Forchini, 2013). Furthermore, large subtitle databases are freely available on the web, are often crowd-sourced, and the close correspondence between subtitles and their video material renders time-based alignment feasible (Tiedemann, 2008).

We release JESC, a new Japanese-English parallel corpus consisting of 3.2 million pairs of crawled TV and movie subtitles[1]. We also release the tools, crawlers, and parsers used to create it. We provide a comprehensive statistical summary of their contents as well as strong baseline machine translation systems that yield competitive BLEU scores. This is the largest freely available Japanese-English dataset to date and covers the resource-poor domain of conversational or informal speech.

2. Source Data

We crawled four free and open subtitle repositories for Japanese and English subtitles: `kitsunekko.net`, `d-addicts.com`, `opensubtitles.org`, and `subscene.com`. Each subtitle database accepts submissions from the public and disseminates them through a web interface. There is no standard imposed on subtitle submissions, and as such, they exist in a plenitude of file formats, encodings, languages (beyond that being advertised), and content (beyond that being advertised). Though some of these subtitles are indeed the "official" translation, many were translated or transcribed by amateur fans of the video content. Thus, many of our translations are crowd-sourced, and there are no guarantees on the fluency of the participants. Many subtitle files contained grammatical, spelling, optical character recognition (OCR), and a host of other problems that preclude their direct usage for machine translation.

Crawling these online repositories yielded 93,992 subtitle files corresponding to 23,318 individual titles (episodes, etc.), 4,610 grouped titles (shows, etc.), and more than 100 million individual captions corresponding to a broad range of video material (Figure 1). Our objective is to automatically cull a high quality parallel corpus from this unstructured and error-prone data.

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[1]The dataset and code are available at `cs.stanford.edu/~rpryzant/jesc/`
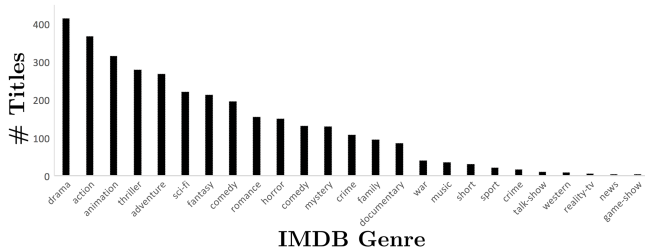
Figure 1: Genre distribution for our crawled titles (obtained via IMDB).

3. Preprocessing

Due to the acute heterogeneity and high error rate of our subtitle files, we underwent a number of preprocessing steps to bring them into a form suitable for alignment. The output of this preprocessing pipeline is a series of documents (one per subtitle file), each structured as a titled list of captions, start times, and end times.

3.1. Document Standardization

First, we converted each subtitle file into a standardized format. We applied the `chardet` library to determine the most likely encoding (Li and Momoi, 2001), and converted this encoding to a `utf-8` standard. We then used the `ffmpeg` library to convert files into a common Sub-Rip (`.srt`) format (Tomar, 2006). Files that `ffmpeg` was unable to convert were interpreted as illegitimate and discarded. Last, we parsed these `.srt` documents into machine-readable YAML[2]. Each resulting document contains a title (obtained from `.srt` metadata) and a list of captions, with each caption consisting of tokenized body text, start time, and end time.

3.2. Text Correction

Next, we preprocessed the English documents by performing syntax correction on each caption. Many fan-made subtitles were created by non-native English speakers and as such contained typographical and spelling mistakes. We developed a laplace-smoothed statistical error model $P(w|w^*)$ that scores the probability of a word w^* being misspelled as w. This model was trained by observing relative misspelling frequencies on the Birkbeck corpus (Mitton, 1985). We then developed two additional laplace-smoothed frequency-based models using unigrams and bigrams from Google's Web 1T N-grams (Islam and Inkpen, 2009). These are language models that score the prior probability of n-gram occurrence, $P(w)$, and the transition probability $P(w_i|w_{i-1})$. We used a smoothing factor of $\alpha = 1$ for all of these models. Next, for each possibly misspelled token t_i of a caption c, we performed depth-4 uniform cost search on the space of edits to produce candidate replacements t_i^*. Armed with the error model $P(t_i|t_i^*)$ and language model $P(t_i^*)P(t_i^*|t_{i-1})$, we scored the probability of each candidate by applying Bayes rule, similar to (Lison and Tiedemann, 2016):

$$P(t_i^*|t_i, t_{i-1}) = P(t_i|t_i^*)P(t_i^*)P(t_i^*|t_{i-1})$$

Note that this checker improves on that of (Lison and Tiedemann, 2016) with the inclusion of a data-driven error model, prior term, and depth-4 uniform cost search (as opposed to making any correction with >50% probability). We also standardized the text of each caption by lowercasing, removing bracketed text, out-of-language subsequences (e.g. encoding errors, OCR errors, machine-readable tags), linguistic queues (i.e. "laughs"), inappropriate punctuation (e.g. leading dashes, trailing commas), and author signatures.

4. Cross-lingual Alignment

Once these subtitle files are brought into a suitable form, they can be aligned to form a parallel corpus. Doing so requires alignment at two levels: the document level, where we group subtitles according to the movie or TV show they correspond too, and the caption level, where we determine which captions are direct translations of one another.

4.1. Document Alignment

In order to align subtitles across distinct languages we must first align the documents themselves, i.e. determine which subtitle documents' captions are worth aligning. This is because (1) multiple subtitle documents may exist for a given movie or TV episode, and (2) subtitles from non-matching movies or TV shows will not be in correspondence.
We generated candidate alignments between Japanese and English documents with a novel technique involving soft matching on file metadata. We first extracted metadata in the form of movie and TV show names as well as episode numbers from each document title. Next, we used the Ratcliff-Obershelp algorithm to determine pairwise title similarities (this algorithm determines similarity via the lengths of matching subsequences), matching two files if their similarity ratio exceeded 90% (Ratcliff and Metzener, 1998). We proceeded to filter out pairs with differing episode numbers.
We refined document alignments with another novel method which considers the temporal sequence of their captions. We created document vectors $D_i = [d_1^i, ..., d_{10,000}^i]$ for each subtitle file i. Each feature d_k^i is a binary indicator that is active when document i has a caption whose closest starting second is k. To account for possible time shift errors, we constructed a multiplicity of vectors for each document, each shifted to a different start time. We then computed the Hamming distance between each Japanese-English document vector and discarded those pairs with a distance greator than 0.04 (chosen based on a bucketed distribution of distances between all pairs).

4.2. Caption Alignment

Now that we have a set of matched English and Japanese subtitle files $\{(\boldsymbol{E}_1, \boldsymbol{J}_1), ..., (\boldsymbol{E}_n, \boldsymbol{J}_n)\}$, we must align the captions of each pair such that captions which are direct translations of each other are selected for extraction.
Let $\boldsymbol{E} = e_1, ..., e_n$ and $\boldsymbol{J} = j_1, ..., j_m$ be a pair of aligned English and Japanese documents that presumably map to
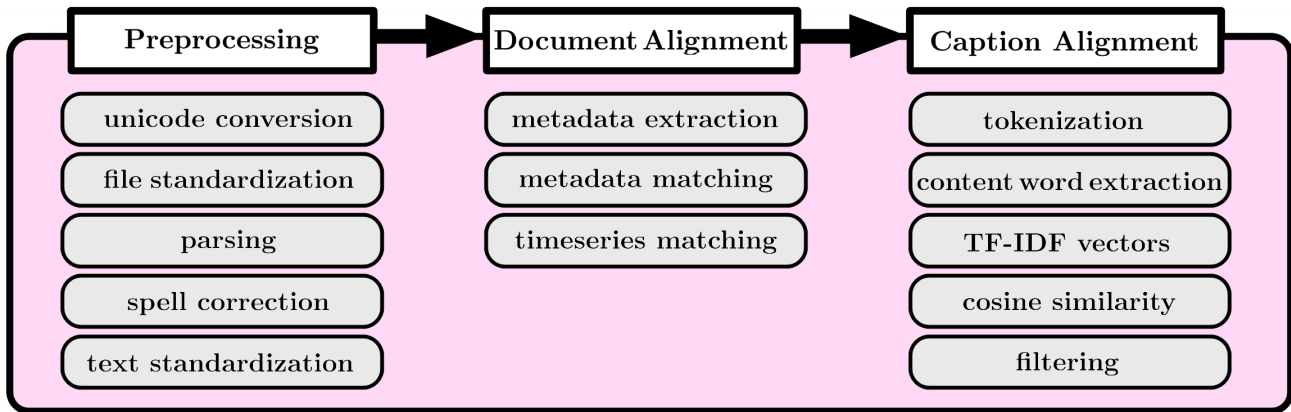
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[2] http://www.yaml.org/

Figure 2: Workflow for the creation of parallel corpora from raw subtitle files.

similar video content. Note that each e_i and j_i are subtitle captions consisting of a start time a_i, end time b_i, and a sequence of text tokens $t_1, ..., t_z$ (in Japanese or English). If E and J were in perfect harmony then we would be able to pair e_1 with j_1, e_2 with j_2 and so on. However, matched documents are rarely in such close correspondence. Optical Character Recognition (OCR) errors, misaligned files, differing start times, speed ratios, framerate, and a host of other problems preclude such a one-to-one correspondence (Tiedemann, 2016).

Due to the severity of the aforementioned problems, especially among documents that have been subtitled by amateur translators, we found existing caption alignment algorithms inadequate for our needs. We developed a novel subtitle alignment algorithm that matches captions based on both timing and content. For each Japanese caption, we search a nearby window (typically 10-15 seconds) of English captions and score their similarity. We then take the highest-scoring match of this window.

We score the quality of an English-Japanese caption pairing by (1) morphologically analyzing Japanese and English captions and discarding all but the content words, then (2) stemming these content words, (3) translating the Japanese to English with simple dictionary lookups, (4) averaging the GLoVE vectors for each caption's words, and (5) computing the cosine similarity between these vector representations. We used the Rakuten and JUMAN morphological analyzers to extract content words from Japanese captions, and the Stanford POS tagger for English (Hagiwara and Sekine, 2014; Manning et al., 2014). We used JUMANPP (Morita et al., 2015) and NLTK to stem these words (Bird, 2006), and JMdict/EDICT to map Japanese words to their English equivalents (Breen, 2004; Matsumoto et al., 1991). Phrases without translations were skipped. Note that our method introduces a bias in the phrase pairs of resultant matches, namely those pairs that would score highly under a lexicon, but we assume that JMdict/EDICT is near-complete with respect to common content words.

4.3. Filtering

The document- and caption-matching procedures outlined above produced 27,716,868 matches between English and
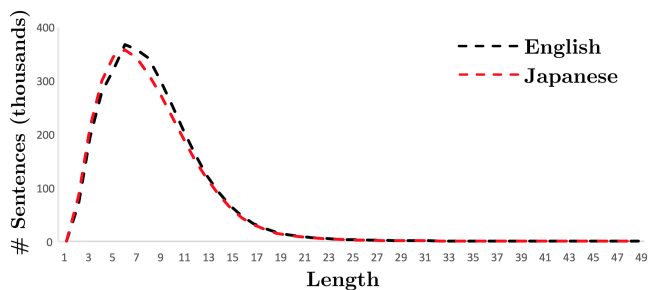

Figure 3: JESC exhibits a right-skewed sentence length distribution. 83 English and 114 Japanese phrases have length > 50.

Japanese captions. We proceeded by filtering out low-quality matches, choosing to retain only the very highest quality matches. We discarded matches whose cosine similarity was below the 84th percentile (assuming a normal distribution), leaving 4,434,699 pairs. This percentile was chosen based on downstream NMT performance. Last, we removed duplicate matches and out-of-language matches (matches where $< 90\%$ of the characters in e or $> 10\%$ of the letters in j are roman), leaving us with a final count of 3,240,661 phrase pairs.

5. Investigation

5.1. Basic statistics

The resulting corpus, which we call JESC, for Japanese English Subtitle Corpus, consists of 29,368 unique English words and 87,833 unique Japanese words. The train/val/test splits are of size 3,236,660 / 2000 / 2001. The lengths of each languages' phases are quite similar (Figure 3). JESC consists mainly of short bursts of conversational dialogue; the average English sentence length is 8.32 words while for Japanese it is 8.11.

JESC also exhibits multiple reference translations for 163,665 and 130,790 Japanese and English phrases, respectively. For example, the English sentence "what?" has translations such as 何だ?/なんだって？/な　なんだよ?/どうしたんですか? due to variations in the Japanese

English	Japanese
look, i don't do that shit anymore.	私は卒業した
thank you! you're so sweet	ありがとう
look, his name is cyrus gold.	いいか 彼の名前はサイラス・ゴールド
is that so? i hate to disappoint you.	そうか それは残念だったな。

Table 1: Samples from JESC.

suffix determined by the circumstances of the speaker and dialogue situation. This feature makes it unique among large parallel corpora and greatly improves its usefulness. While BLEU is designed to benefit from multiple reference translations (Papineni et al., 2002), this is a luxury rarely afforded to the modern system, and both of the major MT workshops use single-reference BLEU to evaluate all their tasks[3][4].

5.2. Evaluation

5.2.1. Alignment evaluation

We checked the validity of bilingual sentence alignments based on the procedure of (Utiyama and Isahara, 2007). A pair of human evaluators (both native Japanese and proficient English speakers) randomly sampled 1000 phrase pairs. On average, 75% of these pairs were perfectly aligned, 13% partially aligned, and 12% misaligned. There was strong agreement between these adjudicators' findings (Cohen's kappa of 0.76) so we may conclude that JESC is noisy but has significant signal that can be useful for downstream applications.

5.2.2. Translation evaluation

In addition to alignment, we evaluated the quality of crowd-sourced translation. Our evaluators used the Japanese Patent Office's adequacy criterion (JPO). The JPO is a 5-point system which provides strong guidelines for scoring the quality of a Japanese-English translation pair (Nakazawa et al., 2016). Again in the style of (Utiyama and Isahara, 2007) we sampled and evaluated 200 phrase pairs from the pool of non-misaligned phrases, observing an average JPO adequacy score of 4.82, implying the amateur and crowd-sourced translations are high quality.

5.2.3. Machine translation performance

We also evaluated JESC with downstream Machine Translation performance, using the TensorFlow and Sequence-to-Sequence frameworks (Abadi et al., 2016; Britz et al., 2017; Lison and Tiedemann, 2016). We used a 4-layer bidirectional LSTM encoder and decoder with 512 units, as well as dot-product attention (Luong et al., 2015). We applied Dropout at a rate of 0.2 to the input of each cell, and optimized using Adam and a learning rate of 0.0001 (Kingma and Ba, 2014). We used a batch size of 128, and train for 10 epochs. For each experiment, we preprocess the data using learned subword units[5] (Sennrich et al., 2015) for a shared vocabulary of 16,000 tokens.

In addition to evaluating JESC, we trained and tested on the ASPEC corpus of (Nakazawa et al., 2016) which consists of scientific abstracts (3M examples), the Kyoto Wiki Corpus (KWC) of (Chu et al., 2014) which consists of translated Wikipedia articles (0.5M examples), and the Open-Subs corpus of (Lison and Tiedemann, 2016) which is the closest analog to JESC and consists of 1M professionally-made and automatically aligned captions.

Train/Test	ASPEC	KWC	OpenSubs	JESC
ASPEC	**36.23**	15.42	3.45	3.81
KWC	5.30	**8.61**	2.31	2.22
OpenSubs	0.2	0.7	**10.01**	6.3
JESC	2.35	3.71	8.8	**14.21**

Table 2: Machine translation results (BLEU).

Even though KWC consists of high quality and human-made translations, we find that it underperforms due to the small size of the dataset (Table 2). Similarly, we find that JESC's large size helps it outperform OpenSubs in both in-domain BLEU and out-of-domain generalization.

6. Conclusion

We introduced JESC, a large-scale parallel corpus for the Japanese-English language pair. JESC is (1) the largest publicly available Japanese-English corpus to date, (2) a corpus that covers the underrepresented domain of conversational speech, and (3) to the extent of these authors knowledge, the only large-scale parallel corpus to support multi-reference BLEU evaluation. Our experimental results suggest that these data are a high quality and novel challenge for today's machine translation systems. By releasing these data to the public, we hope to increase the colloquial abilities of today's MT systems, especially for the Japanese-English language pair.

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[3]http://www.statmt.org/wmt17/
[4]http://lotus.kuee.kyoto-u.ac.jp/WAT/WAT2017/

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[5]https://github.com/google/sentencepiece

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