Massively Multilingual Document Alignment with Cross-lingual Sentence-Mover’s Distance

Ahmed El-Kishky
ahelk@fb.com
Facebook AI
Menlo Park, CA

Francisco Guzmán
fguzman@fb.com
Facebook AI
Menlo Park, CA

ABSTRACT
Cross-lingual document alignment aims to identify pairs of documents in two distinct languages that are of comparable content or translations of each other. Such aligned data can be used for a variety of NLP tasks from training cross-lingual representations to mining parallel bitexts for machine translation training. In this paper, we develop an unsupervised scoring function that leverages cross-lingual sentence embeddings to compute the semantic distance between documents in different languages. These semantic distances are then used to guide a document alignment algorithm to properly pair cross-lingual web documents across a variety of low, mid, and high-resource language pairs. Recognizing that our proposed scoring function and other state-of-the-art methods are computationally intractable for long web documents, we utilize a more tractable greedy algorithm that performs comparably. We experimentally demonstrate that our distance metric performs better alignment than current baselines outperforming them by 7% on high-resource language pairs, 15% on mid-resource language pairs, and 22% on low-resource language pairs.

1 INTRODUCTION
While the World Wide Web provides a large amount of monolingual text, cross-lingual parallel data is more difficult to obtain. Despite its scarcity, parallel cross-lingual data plays a crucial role in a variety of tasks in natural language processing. Traditionally, machine translation approaches have leveraged parallel sentences as training data for use with sequence-to-sequence models. Previous works have also shown that training on sentences extracted from parallel or comparable documents mined from the Web can improve machine translation models [28]. Parallel cross-lingual documents can also be used for learning word-level translation lexicons [14, 34]. Other tasks that leverage these parallel data include cross-lingual information retrieval and document classification. Additionally, cross-lingual data facilitates training multilingual representations such as XLM [24] which can be used as input to many downstream NLP tasks yielding language-agnostic NLP.

Document alignment is a method for obtaining cross-lingual parallel data that seeks to pair documents in different languages such that pairs are translations or near translations of each other. As seen in Figure 1, this involves a one-to-one pairing of documents in a source language with documents in a target language. While it is possible to manually align documents across languages, the process is costly and time consuming due to the quadratic search space for document pairs. Additionally, for low-resource languages, identifying these cross-lingual document pairs is difficult due to their relative scarcity and the scarcity of human annotators familiar with the languages.

2 RELATED WORKS
The concept of crawling and mining the web to identify sources of parallel data has been previously explored [35]. A large body of this work focuses on identifying parallel text from multilingual data obtained from a single source. For example, one parallel corpus was curated from the United Nations General Assembly Resolutions [32, 42]. Another parallel corpus was curated from documents of the European Parliament [21]. Both of these parallel corpora were curated from specific, homogeneous sources by examining the content and deriving domain-specific rules for aligning documents. As such, these techniques do not generalize to arbitrary web-domains obtained from large-scale web scraping efforts.

Other approaches have identified parallel documents in unstructured web corpora by relying on metadata. Some of these methods have focused on publication date and other temporal heuristics to aid in identifying parallel documents [1, 10, 28, 29, 40]. However, temporal features are often sparse, noisy, and unreliable. Another class of alignment methods rely on document structure [7, 36]. Once again these document structure features can be sparse in web-domains and may require hand-crafted rule-sets to fully leverage. These rule-sets may not generalize to new domains.
In the WMT-2016 bilingual document alignment shared task, many techniques were proposed to retrieve, score, and align cross-lingual document pairs [5]. However this shared task only considered English to French – a high-resource direction. The techniques were not evaluated on languages of varying resource availability and the proposed techniques were not readily extendable to application on a massively multilingual scale.

Some of the proposed methods translated the target corpus into the source language, then applied standard retrieval and matching approaches on translated 5-grams to query, retrieve, and align documents [9]. Similar methods for generating candidates by retrieving matches based on the least frequent bi-lingual 5-grams were proposed with the insight that rare snippets are more informative and can better identify cross-lingual pairs [15]. Both of these methods rely on high-quality translation systems to translate either the source or the target, however such models may not exist, especially for low-resource language directions. Additionally, these methods leverage rare n-grams to identify likely candidates. However it is precisely low-frequency words and phrases that are likely to be mistranslated by machine translation systems.

In the shared task, many document similarity measures were investigated for use in aligning English to French web documents. One method utilized a phrase table from a phrase-based statistical machine translation system to compute coverage scores, based on the ratio of phrase pairs covered by a document pair [15]. Other methods utilize the translated content of the target (French) document, and find the source (English) corresponding document based on n-gram matches in conjunction with a heuristic document length ratio [9, 39]. Other methods translate the target documents into the source language and apply cosine similarity between tf/idf weighted vectors on unigrams and n-grams [6, 19, 25]. Finally, several methods were introduced that leverage metadata in each document such as links to documents, URLs, digits, and HTML structure [13, 30].

Recently, the use of neural embedding methods has been explored for bilingual alignment of text at the sentence and document level. One method proposes using hierarchical document embeddings, constructed from sentence embeddings, for bilingual document alignment [17]. Another method leverages a multilingual sentence encoder to embed individual sentences from each document, then performs a simple vector average across all sentence embeddings to form a dense document representation. Cosine similarity is then used to identify document pairs [11].

Word mover’s distance (WMD) has been recently used for document similarity and classification [3, 18, 23]. However these methods have been solely applied in the monolingual space. Other methods have been proposed to leverage EMD for cross-lingual document retrieval [4], however these methods treat individual words as the base semantic unit for comparison. The large number of tokens present in web documents coupled with the cubic complexity of WMD make these approaches intractable for large-scale web-alignment.

Finally, sentence mover’s similarity has been proposed for automatically evaluating machine-generated texts outperforming ROUGE [8]. However the proposed method is purely monolingual and sentence representations are constructed by summing individual word embeddings.

Figure 1: Documents in a source and target language in the same web-domain. Solid lines indicate cross-lingual document pairs.

3 PROBLEM DEFINITION

Given a set of source documents, \(D_s\) and a set of target documents \(D_t\), there exist \(|D_s| \times |D_t|\) potential pairs of documents where each document pair is of the form \((d_s, d_t)\) s.t. \(d_s \in D_s\) and \(d_t \in D_t\) respectively. Let \(\mathcal{P}\) be the set of all candidate pairs \((D_s \times D_t)\). Then cross-lingual document alignment aims to find the largest mapping from source documents to target documents, \(\mathcal{P}' \subset \mathcal{P}\), s.t. given an \(D_s\) and \(D_t\) where, without a loss of generality, \(|D_s| \leq |D_t|\), the largest injective mapping between \(D_s\) and \(D_t\):

\[
\forall a, b \in D_s, (a, c) \in \mathcal{P}' \land (b, c) \in \mathcal{P}' \implies a = b
\]

In other words, each source document and target document can only be used in at most a single pair.

This can be seen in Figure 1 where within the same web-domain, documents can be separated into two disjoint sets: documents in the source language \((D_s)\) and documents in the target language \((D_t)\). The task then becomes to match each source document to a unique target document where possible.

To find the best possible mapping between \(D_s\) and \(D_t\) we require two components: 1) a similarity function \(\phi(d_s, d_t)\) which is used to score a set of candidate document pairs according to their semantic relatedness; and 2) an alignment or matching algorithm which uses the scores for each of the pairs in \(D_s \times D_t\) to produce an alignment of size \(\min(|D_s|, |D_t|)\) representing the best mapping according to \(\phi(d_s, d_t)\).

The remainder of this paper is organized as follows: In Section 4 we introduce our proposed cross-lingual document distance metric and in Section 5 we describe a simple algorithm that leverages this metric to perform cross-lingual document alignment. In Section 6 we evaluate our method end-to-end and conduct ablation studies on different design decisions in Section 7. We conclude in Section 8.

4 CROSS-LINGUAL SENTENCE MOVER’S DISTANCE

WMD extends the notion of earth mover’s distance, a measure of distance between two probability distributions over a metric space, to measure semantic document similarity. This adaptation represents each document as a bag-of-words (BOW) normalized by their relative counts in the document, and measures distances between words using standard word embeddings such as Word2Vec or Glove [26, 31]. The distance can then be formulated as the minimum amount of distance that the embedded words of one document need to “travel” to reach the embedded words of another document.
While demonstrating powerful results in classification and retrieval tasks, WMD fails to generalize to our use case for two reasons: (1) the technique relies on monolingual word representations which fail to capture the semantic distances between documents whose content are in different languages and (2) web documents may be thousands of words long or even how no word boundaries in certain languages. As such, WMD becomes quickly intractable or infeasible on these web-documents.

To address this, we adapt WMD to better measure the similarity between two documents in potentially different languages. We perform this by introducing a distance metric we dub cross-lingual sentence mover’s distance (XLSMD). We show that by representing each document as a bag-of-sentences (BOS) and leveraging recent improvements in cross-lingual sentence representations, XLSMD can better identify cross-lingual document pairs.

4.1 Multilingual Sentence Embeddings

Evaluating the distance between document pairs involves breaking up documents into constituent semantic units such as sentences and measuring the distance between these units. In order to evaluate the distance between documents composed in many different languages, we require a joint embedding scheme for all the considered languages.

Previous approaches have trained bi-lingual embeddings for each and every language pair under consideration [12, 16, 41]. However, training bilingual embedding models for each language pair is difficult to scale beyond a handful of language pairs. Instead, we adopt the massively multilingual sentence representation proposed in the LASER toolkit [2]. Figure 2 demonstrates the training process for learning to encode sentences into a shared multilingual embedding space using a sequence-to-sequence model with a shared BPE vocabulary. This approach simultaneously models 93 languages covering 23 different alphabets into a joint embedding space. LASER accomplishes this by training a sequence-to-sequence model on many language pairs at once using a shared encoder and a shared byte-pair encoding (BPE) vocabulary for all languages. The sentence representation is obtained by max-pooling over all encoder output states [2].

For our XLSMD approach, we leverage these multilingual sentence embeddings to measure euclidean distance between sentences in the source document and target document.

4.2 Cross-Lingual Sentence Mover’s Distance

Our proposed XLSMD solves the same optimization problem as WMD, but utilizes cross-lingual sentence embeddings instead of word embeddings as the base semantic unit of a document. In particular, we utilize LASER sentence representations [2] whereby each sentence is encoded using an LSTM encoder into a fixed-length dense representation as described in Section 4.1.

XLSMD is a distance metric based on the Wasserstein metric also known as the earth mover’s distance (EMD) [38]. In our approach, we adapt the EMD to measure the distance between two documents by comparing the distributions of sentences within each document. This metric can be viewed as the sentence-based adaptation of WMD [23]. More specifically, XLSMD represents each document as a bag-of-sentences (BOS) where each sentence has associated with it some probability mass. Leveraging that distances can be computed between dense sentence embeddings, the overall document distance can then be computed by examining how close the distribution of sentences in the source document is to sentences in the target document. This formulation captures note only item similarity on a BOS histogram representations of the text, but also the multilingual sentence embedding distances. We formulate that the distance an arbitrary pair of documents A and B is the minimum cost of transforming one document into the other.

For our basic formulation of XLSMD, each document is represented by the relative frequencies of sentences, i.e., for the $i_{th}$ sentence in the document,

$$d_{A,i} = \frac{\text{count}(i)}{\sum_{s \in A} \text{count}(s)}$$  \hspace{1cm} (1)

where $\sum_{s \in A} \text{count}(s)$ is the total number of sentence in document A, and $d_{B,j}$ is defined similarly for document B. Under this assumption, each individual sentence in a document is equally important and probability mass is allocated uniformly to each sentence. Later, we will investigate alternative schemes to allocating probability mass to sentences.

Now let the $i_{th}$ sentence be represented by a vector $v_i \in \mathbb{R}^{m}$. This length-m dense embedding representation for each sentence allows us to define distances between the $i_{th}$ and $j_{th}$ sentences. We denote $\Delta(i,j)$ as the distance between the $i_{th}$ and $j_{th}$ sentences and let $V$ denote the vocabulary size where the vocabulary is the unique set of sentences within a document pair. We follow previous works and use the Euclidean distance, $\Delta(i,j) = ||v_i - v_j||$ [23]. The XLSMD between a document pair is then the solution to the linear program:

$$\text{XLSMD}(A,B) = \min_{T \geq 0} \sum_{i=1}^{V} \sum_{j=1}^{V} T_{i,j} \times \Delta(i,j)$$  \hspace{1cm} (2)

subject to:

$$\forall i \sum_{j=1}^{V} T_{i,j} = d_{A,i}$$

$$\forall j \sum_{i=1}^{V} T_{i,j} = d_{B,j}$$

Where $T \in \mathbb{R}^{V \times V}$ is a nonnegative matrix, where each $T_{i,j}$ denotes how much of sentence $i$ in document $A$ is assigned to sentences $j$ in document $B$, and constraints ensure the flow of a given sentence cannot exceed its allocated mass. Specifically, XLSMD ensures the the entire outgoing flow from sentence $i$ equals $d_{A,i}$, i.e. $\sum_{j} T_{i,j} = d_{A,i}$. Additionally, the amount of incoming flow to sentence $j$ must match $d_{B,j}$, i.e., $\sum_{i} T_{i,j} = d_{B,j}$.

As described in Section 5, our competitive matching algorithm for aligning documents relies on a similarity score. As such, before alignment, we transform each XLSMD into a similarity score as follows:

$$\text{XLSMS}(A,B) = e^{-\text{XLSMD}(A,B)}$$  \hspace{1cm} (3)

Whereby two documents are more similar if the distance between them is smaller.
4.3 Alternative Sentence Weighting Schemes

In Equation 1, each document is represented as a normalized bag-of-sentences (nBOS). Under this assumptions, each sentence is considered equally important as a constituent of the document and the overall probability mass allocated to a sentence is proportional to the number of times it appears in a document. However, we posit that some sentences may be more semantically important than others within the same document and should therefore be allocated more mass. We investigate several weighting schemes to reflect these insights and evaluate their efficacy for document alignment in Section 6.2.

**Sentence Length Weighting.** The first insight we investigate is that documents will naturally be segmented into sentences of different lengths based on the choice of sentence segmentation method, the language of the content int the document, and the content of a sentence. While Equation 1, treats each sentence equally, we posit that longer sentences should be assigned larger weighting than shorter sentences.

Under this weighting schema, each document is represented by a bag-of-sentences, but each sentence is weighted by the number of tokens in the sentence relative to the total number of tokens in the entire document, i.e., for the $i_{th}$ sentence in the document $A$, 

$$d_{A,i} = \frac{\text{count}(i) \times |i|}{\sum_{s \in A} \text{count}(s) \times |s|} \tag{4}$$

where $|i|$ and $|s|$ indicate the number of tokens in sentence $i$ and sentence $s$ respectively. As such, longer sentence receive larger probability mass than shorter sentences. Once again, $d_{B,i}$ is computed in the same manner for document $B$.

**IDF Weighting.** The second insight we investigate is that when mining for cross-lingual document pairs from a webdomain corpus, individual crawled documents contain many standard segments of text such as titles, column text, navigation text, etc. We believe that because this content is ubiquitous within the web-domain, it is less semantically informative and should be allocated less weight when computing document distances. Based on this insight, we apply a variant of inverse document frequency (IDF) – a weighting scheme common in the information retrieval space – to individual sentences [37]. Under this scheme, the more common a sentence is within a webdomain, the less mass the sentence will be allocated.

We formalize IDF for a sentence $s$ in a webdomain-specific corpus $D$ as follows:

$$d_{A,i} = 1 + \log \frac{N + 1}{1 + |\{d \in D : s \in d\}|} \tag{5}$$

where $N$ is the total number of web-documents in the web domain $D$, and $|\{d \in D : s \in d\}|$ is the number of documents where the sentence $s$ occurs. Smoothing by $1$ is performed to prevent 0 IDF and division by zero.

As most sentences will occur only once within the web domain, they will have equal IDF weighting. Only repetitive sentences that are occur frequently within the web domain (e.g. boilerplate) will be down weighted.

**SLIDF Weighting.** Finally, we propose combining both sentence length and inverse document frequency into a joint weighting scheme:

$$d_{A,i} = \frac{\text{count}(i) \times |i|}{\sum_{s \in A} \text{count}(s) \times |s|} \times \left(1 + \log \frac{N + 1}{1 + |\{d \in D : s \in d\}|}\right) \tag{6}$$

In this scheme, each sentence is weighted proportionally to the number of tokens it contains as well as by the IDF of the sentence within the domain. This weighting scheme is reminiscent of the use of tf-idf to determine word relevance, but instead sentence length and idf are used to determine sentence importance [33].

4.4 Handling Imbalanced Document Mass

Many different aspects can lead to an unequal mass between source and target documents. One natural scheme considers that many document pairs contain an unequal number of sentences between the source document and target document. With an equal constant mass for each sentence, this naturally leads to unequal mass in the pair. In Section 4.3, alternate weighting schemes such as IDF and SLIDF can introduce unequal total mass between the source document and target document. As such, we must adapt earth mover’s distance to handle computing a distance metric between documents of unequal mass.

As seen in Figure 3, when computing the distance between two documents, the mass in the source document is not equal to the mass in the target document. Normally, EMD operates on a normalized histogram that induce a probability distribution with unit measure of 1. As a result, there is always equal mass in the source document and target document. However, this assumption doesn’t hold in
our investigation because we consider weighting schemes that may place a greater mass on one document than on another.

We propose three ways to address the imbalance between source and target documents that may occur due to the different weighting schemes we propose: (1) a no penalty evaluation (2) normalizing the mass in each document with any weighting scheme to unit measure 1 and (3) imposing an imbalance penalty for any leftover mass after optimal transportation calculation. In Section 7.1, we experimentally evaluate the impact these approaches have on downstream document alignment.

**No Penalty Evaluation.** Under the no penalty evaluation, when the source and target documents have different mass, we allow for a partial matching between the source and target. That is, mass from sentences in the larger document is allocated to sentences in the smaller document. The left over (unmoved) mass from the larger document is then discarded without penalty. One caveat is that without a proper penalty, the imbalance causes this formulation to no longer be a true distance metric.

**Imbalance Penalty Evaluation.** The second proposal allows for leftover sentences to be destroyed from the larger of the two documents. However, there is a cost penalty for any leftover mass from sentences in the larger document. This cost penalty \( \sigma \) signifies the penalty cost of one unit of leftover mass.

For the resulting distance to be a metric, \( \sigma \) should be greater than or equal to half the diameter of the space i.e, the maximum possible distance between any two points. For our use case, we select the distance between the furthest two sentences between the source and target documents ensuring a proper resultant distance metric.

**Document Mass Normalization.** The third option is to ensure that the two documents have the same mass regardless of the weighting scheme used. This can be done through normalizing the mass allocated to each sentence such that the total mass is of unit measure. We compute this normalization as follows:

\[
 d'_{A,i} = \frac{d_{A,i}}{\sum_{s \in A} d_{A,s}}
\]  

(7)

Consequently, by normalizing the mass to unit measure in both the source and target documents, each document has a legitimate distribution and the induced distance metric is valid.

### 4.5 Fast Distance Approximation

Previous works have shown that WMD achieves state-of-the-art results in many retrieval and classification tasks, WMD, and other EMD-based variants have been shown to suffer from high computational complexity \( O(p^3 \log p) \), where \( p \) denotes the number of unique words in the each document pair.

**Relaxed XLSMD.** Given the scalability challenges for computing WMD, simplified version of WMD was proposed that relaxes one of the two constraints in the original formulation [23]. Applying the same principle to XLSMD, we formulate:

\[
\text{XLSMD}(A, B) = \min_{T \geq 0} \sum_{i=1}^{V} \sum_{j=1}^{V} T_{i,j} \times \Delta(i,j)
\]

subject to: \( \forall i \sum_{j=1}^{V} T_{i,j} = d_{A,i} \). Analogous to the relaxed-WMD, this relaxed problem yields a lower-bound to the XLSMD as every XLSMD solution satisfying both constraints remains a feasible solution if one constraint is removed. The optimal solution to this relaxed formulation can be found by simply allocating the mass in each source sentence to the closest sentence in the target document as measured in the Euclidean embedding space.

The same computation can be performed in the reverse direction by removing the second constraint and keeping the first constraint: \( \forall j \sum_{i=1}^{V} T_{i,j} = d_{B,j} \). In this scenario each sentence in the target document has its mass allocated to the closest sentence in the source document. Both these distances can be calculated by computing the distance matrix between all pairs of sentences in \( O(p^3) \) time. For a tighter estimate of distance, the maximum of the two resultant distances achieved from removing each of the constraints independently can be used.

**Greedy Mover’s Distance.** We introduce an alternative to the relaxed-EMD variant wherein we keep both constraints in the transportation problem, but identify an approximate transportation scheme, instead of solving for the optimal transport strategy. This proposed greedy approximation algorithm we dub "greedy mover’s distance" (GMD) finds the two closest sentences and moves as much mass between the two sentences as possible; the algorithm moves to the next two closest pairs until all mass has been moved between the source and target document while maintaining both constraints.

As seen in Algorithm 1, the algorithm takes a source document \( (d_s) \) and a target document \( (d_t) \) as well as the weights for the sentences in each; respectively \( w_s \) and \( w_t \). The algorithm first computes the euclidean distance between each sentence pair from source to target and sorts these pairs in ascending order by their euclidean distance. The algorithm then iteratively chooses the closest sentence pair and moves the mass of the smallest between the two sentences. The remaining (unmoved) mass of each sentence is updated by subtracting the moved mass from the unmoved mass. The total distance is updated by the amount of mass moved between the two sentences over the distance between the sentences. The algorithm terminates when all pairs of sentences have been observed and all moveable
The algorithm terminates when the cost of sorting all candidate pairs is a more tractable decision. Unlike the Hungarian algorithm, the runtime complexity is dominated by the cost of sorting all candidate pairs. Unlike the relaxation approximation, as both constraints must still hold, but the relaxation may not represent the optimal transport, this formulation yields an upper-bound to XLSMD. In the experiments section, we show that this approximation gives comparable distances to the exact EMD and the distances generated provide comparable downstream cross-lingual alignment results.

We experimentally compare the effect of both approximation strategies on downstream document alignment in Section 7.2.

5 DOCUMENT MATCHING ALGORITHM

In addition to a similarity metric (i.e. XLSMS), we need a document matching algorithm to determine the best mapping between documents in two languages. In our case, this works as follows: for any given webdomain, each document in the source document set, $D_s$, is paired with each document in the target set, $D_t$, yielding $|D_s| \times |D_t|$ scored pairs – a fully connected bipartite graph representing all candidate pairings. Similar to previous works, the expected output assumes that each webpage in the non-dominant language has a translated or comparable counterpart [6]. As visualized in Figure 1, this yields a $\min(|D_s|, |D_t|)$ expected number of aligned pairs.

While an optimal matching maximizing scoring can be solved using the Hungarian algorithm [27], the complexity of this algorithm is $O(max(|D_s||D_t|)^3)$ which is intractable to even moderately sized web domains. As such, similar to the work in [6], a one-to-one matching between English and non-English documents is enforced by applying, competitive matching, a greedy bipartite matching algorithm.

In Algorithm 2, the algorithm first scores each candidate document pair using the document similarity scoring function. These candidates are then sorted in order of most similar to least similar using their numerical score. The algorithm then iteratively chooses a document pair with the highest score as long as the $d_s$ and $d_t$ of each pair have not been used in a previous (higher scoring) pair. The algorithm terminates when $\min(|D_s|, |D_t|)$ pairs have been selected. Unlike the Hungarian algorithm, the runtime complexity is a more tractable $O(|D_s||D_t| \times \log(|D_s||D_t|))$ which is dominated by the cost of sorting all candidate pairs.

### 6 EXPERIMENTS AND RESULTS

In this section, we explore the question of whether XLSMS can be used as a similarity metric for the document alignment problem. Moreover, we explore what are the different variants of weightings that yield the best results.

#### 6.1 Experimental Setup

**Dataset.** We evaluate on the test set from the URL-Aligned CommonCrawl dataset [11]. This dataset consists of a massive collection of 54 million web documents in non-English languages aligned with their English translation. The document pairs cover 92 language directions covering languages varying in resource availability, language family, and morphology. 47 language directions across low, mid, and high resource directions were selected for evaluation.

**Baseline Methods.** For comparison, we implemented two existing and intuitive document scoring baselines previously evaluated on this URL-Aligned CommonCrawl dataset [11]. The first method dubbed direct embedding (DE) treats the entire content of a document as a single input and embeds the document into a multilingual space using LASER; documents are then compared by computing cosine similarity between document representations. The second baseline performs document embedding by segmenting each document into smaller sentences, performing embedding at the sentence level, then averaging all sentence embeddings to form a document representation; once again documents are compared by computing cosine similarity between their dense representations. For consistency, all multilingual representations used for this experiment were performed using LASER embeddings.

**XLSMD Weightings.** We investigate variants of our XLSMD using four different weighting schemes: (1) vanilla XLSMS with each sentence equally weighted within each document (2) weighting by sentence length (SL) where XLSMS is computed under a scheme where each sentence is weighted by its length (number of tokens) normalized by the length of the entire document (3) weighting by inverse document frequency (IDF) where XLSMS is computed under a scheme where each sentence is weighted by the idf of the sentence (4) computing XLSMD under a scheme where each sentence is weighted by both sentence length and inverse document frequency (SLIDF).

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**Algorithm 1: Greedy Mover’s Distance**

**Input:** $d_s$, $d_t$, $w_s$, $w_t$

**Output:** $\Delta(d_s, d_t)$

1. $\text{pairs} \leftarrow \{(s_s, s_t) \mid s_s, s_t \in D_s \times D_t\}$ in ascending order by $\|s_s - s_t\|$
2. $\text{distance} \leftarrow 0.0$
3. for $s_s, s_t \in \text{pairs}$ do
   4. $\text{flow} \leftarrow \min(w_s[s_s], w_t[s_t])$
   5. $w_s[s_s] \leftarrow w_s[s_s] - \text{flow}$
   6. $w_t[s_t] \leftarrow w_t[s_t] - \text{flow}$
   7. $\text{distance} \leftarrow \text{distance} + \|s_s - s_t\| \times \text{flow}$
4. return total

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**Algorithm 2: Competitive Matching**

**Input:** $P = \{(d_s, d_t) \mid d_s \in D_s, d_t \in D_t\}$

**Output:** $P' = \{(d_s, d_t)\}$

1. $\text{scored} \leftarrow \{(p, \text{score}(p)) \mid p \in P\}$
2. $\text{sorted} \leftarrow \text{sort(scored)}$ in descending order
3. $\text{aligned} \leftarrow \emptyset$
4. $S_s \leftarrow \emptyset$
5. $S_t \leftarrow \emptyset$
6. for $d_s, d_t \in \text{sorted}$ do
   7. if $d_s \notin S_s \land d_t \notin S_t$ then
      8. $\text{aligned} \leftarrow \text{aligned} \cup \{(d_s, d_t)\}$
      9. $S_s \leftarrow S_s \cup d_s$
     10. $S_t \leftarrow S_t \cup d_t$
11. end
12. return $\text{aligned}$
were trained on parallel sentences and embedding larger documents within the document (SA). This is intuitive as LASER embeddings web-document pairs that are translations or of comparable content, individually embedding sentences and constructing the document representations that were described in Section 4.5.

Directly using LASER results in poorer representations than by first representation severely under-performs compared to individual sentence representations by averaging the individual sentence representations.

In Table 1, we first notice that constructing document representations by averaging the individual sentence representations directly using LASER results in poorer representations than by first embedding smaller sentences and combining them into the final document representation.

Comparing the basic XLSMD to the best performing baseline (SA), we see a 4%, 12%, and 20% improvement across high, mid, and low-resource directions respectively. This improvement suggests that summing sentence embeddings into a single document representation degrades the quality of the resultant document distances over computing document distances by keeping all sentence representations separate and computing distances between individual sentence pairs and combining these distances into a final document distance. This is more pronounced in lower-resource over higher-resource pairs which we theorize is due to the quality of lower-resource embeddings being worse due LASER being trained on fewer low-resource sentence pairs. As such averaging is more destructive to these representations while XLSMD avoids this degradation.

Further analyzing the results by comparing the four variants we proposed for XLSMD, we verify our intuitions that different directions over assigning equal probability mass to each sentence.

### Evaluation Metric for Document Alignment

Because the ground-truth document pairs only reflect a high-precision set of document pairs and combining these distances into a final document distance. This is more pronounced in lower-resource over higher-resource pairs which we theorize is due to the quality of lower-resource embeddings being worse due LASER being trained on fewer low-resource sentence pairs. As such averaging is more destructive to these representations while XLSMD avoids this degradation.

6.2 Results

In Table 1, we first notice that constructing document representations by directly embedding (DE) the entire content of each document and computing document similarity using cosine similarity of the representation severely under-performs compared to individually embedding sentences and constructing the document representations by averaging the individual sentence representations within the document (SA). This is intuitive as LASER embeddings were trained on parallel sentences and embedding larger documents directly using LASER results in poorer representations than by first

### Normalization

For our experiments, we use document mass normalization to deal with imbalanced document mass. In Section 7.1 we present ablation results on different techniques for handling unbalanced document mass.

### Distance approximation

We use the greedy mover’s distance approximation for all variants reported. In Section 7.2 we further explore the performance of the full distance computation and relaxed variants that were described in Section 4.5.

### Table 1: Alignment recall on URL-aligned CommonCrawl dataset.

| Language | DE | SA | XLSMD | SL IDF | SLIDF | Recall |
|----------|----|----|-------|-------|-------|--------|
| French   | 0.39 | 0.84 | 0.81 | 0.84 | 0.83 | 0.85 |
| Spanish  | 0.34 | 0.53 | 0.59 | 0.63 | 0.62 | 0.64 |
| Russian  | 0.06 | 0.64 | 0.69 | 0.69 | 0.70 | 0.71 |
| German   | 0.52 | 0.74 | 0.78 | 0.76 | 0.77 | 0.77 |
| Italian  | 0.22 | 0.47 | 0.55 | 0.56 | 0.56 | 0.59 |
| Portuguese| 0.17 | 0.36 | 0.39 | 0.41 | 0.38 | 0.40 |
| Dutch    | 0.28 | 0.49 | 0.54 | 0.54 | 0.54 | 0.56 |
| Indonesian| 0.11 | 0.47 | 0.49 | 0.52 | 0.51 | 0.53 |
| Polish   | 0.17 | 0.38 | 0.45 | 0.46 | 0.46 | 0.46 |
| Turkish  | 0.12 | 0.38 | 0.52 | 0.56 | 0.57 | 0.59 |
| Swedish  | 0.19 | 0.40 | 0.44 | 0.46 | 0.45 | 0.45 |
| Danish   | 0.27 | 0.62 | 0.63 | 0.69 | 0.65 | 0.69 |
| Czech    | 0.15 | 0.40 | 0.43 | 0.44 | 0.44 | 0.43 |
| Bulgarian| 0.07 | 0.43 | 0.52 | 0.54 | 0.55 | 0.52 |
| Finnish  | 0.06 | 0.47 | 0.51 | 0.51 | 0.54 | 0.52 |
| Norwegian| 0.13 | 0.33 | 0.37 | 0.39 | 0.42 | 0.41 |
| AVG      | 0.20 | 0.50 | 0.54 | 0.56 | 0.56 | 0.57 |

| Language | DE | SA | XLSMD | SL IDF | SLIDF | Recall |
|----------|----|----|-------|-------|-------|--------|
| Romanian | 0.15 | 0.40 | 0.44 | 0.43 | 0.45 | 0.43 |
| Vietnamese| 0.06 | 0.28 | 0.29 | 0.29 | 0.29 | 0.32 |
| Ukrainian| 0.05 | 0.68 | 0.67 | 0.78 | 0.78 | 0.82 |
| Greek    | 0.05 | 0.31 | 0.47 | 0.48 | 0.49 | 0.49 |
| Korean   | 0.06 | 0.34 | 0.60 | 0.54 | 0.61 | 0.60 |
| Arabic   | 0.04 | 0.32 | 0.63 | 0.59 | 0.65 | 0.61 |
| Croatian | 0.16 | 0.37 | 0.40 | 0.40 | 0.41 | 0.41 |
| Slovak   | 0.20 | 0.41 | 0.46 | 0.46 | 0.46 | 0.46 |
| Thai     | 0.02 | 0.19 | 0.41 | 0.33 | 0.47 | 0.41 |
| Hebrew   | 0.05 | 0.18 | 0.39 | 0.43 | 0.41 | 0.41 |
| Hindi    | 0.04 | 0.27 | 0.34 | 0.34 | 0.54 | 0.52 | 0.53 |
| Hungarian| 0.15 | 0.49 | 0.50 | 0.54 | 0.51 | 0.54 |
| Lithuanian| 0.11 | 0.73 | 0.79 | 0.79 | 0.80 | 0.80 |
| Serbian  | 0.06 | 0.32 | 0.56 | 0.57 | 0.57 | 0.57 |
| Baltic   | 0.16 | 0.37 | 0.40 | 0.40 | 0.41 | 0.41 |
| Slovakian| 0.13 | 0.33 | 0.34 | 0.35 | 0.36 | 0.36 |
| Russian  | 0.06 | 0.32 | 0.56 | 0.57 | 0.58 | 0.58 |
| Persian  | 0.06 | 0.32 | 0.56 | 0.57 | 0.58 | 0.58 |
| AVG      | 0.09 | 0.37 | 0.49 | 0.50 | 0.52 | 0.52 |

| Language | DE | SA | XLSMD | SL IDF | SLIDF | Recall |
|----------|----|----|-------|-------|-------|--------|
| Estonian | 0.28 | 0.52 | 0.69 | 0.66 | 0.74 | 0.72 |
| Bengali  | 0.05 | 0.32 | 0.78 | 0.72 | 0.77 | 0.79 |
| Albanian | 0.23 | 0.56 | 0.66 | 0.65 | 0.65 | 0.66 |
| Macedonian| 0.02 | 0.33 | 0.32 | 0.36 | 0.38 | 0.33 |
| Urdu     | 0.06 | 0.22 | 0.60 | 0.60 | 0.49 | 0.56 |
| Serbian  | 0.06 | 0.59 | 0.75 | 0.74 | 0.74 | 0.74 |
| Azerbaijani| 0.08 | 0.34 | 0.74 | 0.75 | 0.75 | 0.74 |
| Armenian | 0.02 | 0.18 | 0.32 | 0.35 | 0.34 | 0.38 |
| Belarusian| 0.07 | 0.47 | 0.67 | 0.69 | 0.73 | 0.71 |
| Georgian | 0.06 | 0.24 | 0.46 | 0.48 | 0.45 | 0.45 |
| Tamil    | 0.02 | 0.20 | 0.51 | 0.45 | 0.51 | 0.53 |
| Marathi  | 0.02 | 0.11 | 0.43 | 0.46 | 0.33 | 0.39 |
| Kazakh   | 0.05 | 0.31 | 0.44 | 0.46 | 0.45 | 0.45 |
| Mongolian| 0.03 | 0.13 | 0.18 | 0.22 | 0.21 | 0.23 |
| Burmese | 0.01 | 0.10 | 0.26 | 0.33 | 0.46 | 0.46 |
| Bosnian | 0.18 | 0.64 | 0.61 | 0.69 | 0.65 | 0.72 |
| AVG      | 0.08 | 0.33 | 0.53 | 0.54 | 0.54 | 0.55 |
content. Finally, we investigate the performance of document alignment after combining both sentence length and inverse document frequency weighting to assign probability mass to each sentence (SLIDF). Falling in line with our intuition, we see a 3%, 3% and 2% absolute improvement in recall for high, mid, and low-resource directions respectively over the approach that equally weights each sentence. Overall, our XLSMD with SLIDF weighting scheme to assigning probability mass to sentences outperforms the sentence averaging baseline by 7% on high-resource directions, 15% on mid-resource directions, and 22% on low-resource directions.

7 DISCUSSION

In this section, we analyze the performance of XLSMD under additional conditions. First we investigate the effects of different approaches to account for imbalanced document sizes. Second, we explore the effect of choosing faster approximation algorithms to speed-up distance computation.

7.1 Document Imbalance Experiments

While most implementations of EMD measure the distance between two distributions, in Section 4.3, we introduce several weighting schemes that do not constitute probability distributions. In Section 4.4, we note that this can lead to document imbalance whereby the source and target documents have unequal total mass and proposed three approaches to addressing unequal mass.

We pick a variant of XLSMD (SLIDF) perform document alignment on a selection of low, mid, and high-resource directions. For each direction, we evaluate the distance with three approaches to handling document mass imbalance (1) no penalty (2) max distance penalty and (3) normalizing weights.

| Approach      | Low  | Mid  | High | All   |
|---------------|------|------|------|-------|
| No Penalty    | 0.44 | 0.37 | 0.44 | 0.40  |
| Penalty       | 0.47 | 0.44 | 0.50 | 0.46  |
| Normalization | 0.55 | 0.52 | 0.57 | 0.54  |

Table 2: Evaluating approaches for handling document-mass imbalance due to alternative sentence weighting.

In Table 2 we report the average document alignment recall for low, mid, and high-resource language pairs for each technique for handling document imbalance. We observe that the worst-performing technique is to calculate the distance without imposing any penalty when imbalance is present. We posit this is because scenarios can arise where a document with a small amount of content can be paired with a document with a large amount of content due to the smaller content having sentences semantically close to many sentences in the larger document. However, such pairings are not necessarily good pairs. Imposing a penalty appears to mitigate this and outperforms no penalty across low, mid, and high-resource language pairs. However, consistently normalizing the unbalanced documents each to unit measure as specified in Equation 7 consistently outperforms both the no-penalty and penalty approaches to handling imbalance.

7.2 Distance Computation Experiments

Although using sentences over words as the base semantic unit drastically reduces the overall cost of computing EMD-based metrics, the cubic computation still prohibits its use as a fast similarity metric for large-scale alignment efforts. As such, in Section 4.5 we described two approximations to EMD computation: (1) a relaxation of constraints and (2) a greedy algorithm for computing EMD. Using these two techniques, we can significantly speed up the distance computations between document pairs. However, the constraint relaxation and greedy algorithm for computing distances represent a lower-bound and upper bound respectively on the true XLSMD.

We first analyze and compare the distances from each approximation scheme to the true XLSMD.

| Method       | Kendall-Tau | Recall | MAE     | Runtime (s) |
|--------------|-------------|--------|---------|-------------|
| Exact-XLSMD  | 1.00        | 0.69   | 0.000   | 0.402       |
| Relaxed-XLSMD| 0.70        | 0.58   | 0.084   | 0.031       |
| Greedy-XLSMD | 0.98        | 0.69   | 0.010   | 0.107       |

Table 3: Comparing exact XLSMD computation to approximation schemes for computing XLSMD on 10 webdomains.

In Figure 5, we see that the distance computations for exact XLSMD and the greedy XLSMD approximation are highly correlated with small variance, while the relaxed approximation is less so with high variance. Additionally, as discussed in Section 4.5, the visualizations verify that our greedy approximation is a fairly tight upper bound while the relaxed approximation is a looser lower bound.

In Table 3, we compare quantitative metrics for the relaxed and greedy approximations to the exact solution of XLSMD on ten webdomains. Our first evaluation investigates how the approximate computation of distances affects the ordering of document pairs. For the ten selected webdomains, we sort the document pairs in order by their computed distances and compare the ordering to the ordering induced by the exact computation of XLSMD. We evaluate the orderings using the Kendall-Tau metric [20]. This correlation coefficient measures the agreement between the two rankings; if the agreement between the two rankings is perfect (i.e., the two rankings are the same) the coefficient has value 1 and if the disagreement between the two rankings is perfect (i.e., one ranking is the reverse of the other) the coefficient has value -1. Intuitively, we would like the distances computed by an approximation to induce a similar ordering to the ordering by the exact distance computation. Comparing the Kendall-Tau for the relaxed and greedy approximations in relation to the exact computation shows that the order induced by the greedy approximation is very similar to the ordering induced by the exact computation while the relaxed approximation varies considerably. Additionally, the relaxed approximation demonstrates fairly high mean absolute error (MAE) and results in lower document alignment recall when compared to the exact computation of XLSMD, while our greedy approximation performs comparably and shows insignificant MAE. Finally, while the runtime of the relaxed computation is the fastest at 13 times faster than the exact computation, our greedy algorithm is approximately 4 times faster while delivering comparable document alignment performance to the exact computation and superior performance to the relaxed computation.
To ensure that the greedy algorithm consistently outperforms the relaxed algorithm on document alignment, we investigate the effect of using each approximation method on the downstream document alignment performance across 47 language pairs of varying resource availability. We do not report results from the exact XLSMD distance as it was not tractable to run on the 47 evaluated language pairs.

| Approximation       | Low  | Mid  | High | All  |
|---------------------|------|------|------|------|
| Relaxed-XLSMD       | 0.44 | 0.43 | 0.50 | 0.46 |
| Greedy-XLSMD        | 0.54 | 0.50 | 0.56 | 0.54 |

Table 4: Document alignment performance of fast methods for approximating the same variant of XLSMD.

As seen in Figure 4, in 45 of the 47 evaluated language pairs, our proposed Greedy Mover’s Distance approximation yielded higher downstream recall in our alignment task over using the relaxed distance proposed for use in WMD [23]. In Table 4, we see a 10%, 7%, and 6% improvement in downstream recall across low, mid, and high-resource directions respectively. These results indicate that relaxing one of the two constraints in EMD is too lax for measuring an accurate distance. We posit this is because there are many sentences that can be considered "hubs" that are semantically close to many other sentences. These sentences can have a lot of probability mass allocated to them, resulting in a lower approximate EMD. Our greedy approximation ensures that both constraints are maintained even if the final result is not the minimum distance between the two.

8 CONCLUSION & FUTURE WORK

In this paper, we introduce XLSMD a cross-lingual sentence mover’s distance metric for automatically assessing the semantic similarity of two documents in different languages. We leverage state-of-the-art multilingual sentence embeddings and apply XLSMD to the task of cross-lingual document alignment. We demonstrate that our new metric outperforms other unsupervised metrics by a margin, especially in medium and low-resourced conditions.

Recognizing that solving for the exact solution of XLSMD becomes computationally intractable for long web-documents and large-scale document alignment, we introduce a fast approximation scheme with comparable performance to exact computation.

One natural extension of this work is to further investigate weighting schemes. As seen in our results, choosing a proper weighting scheme can significantly improve the performance of downstream document alignment. Another area of investigation is in better cross-lingual representations.

Finally, a supervised model might better guide the cross-lingual alignment process than the unsupervised distance metric used here. Several approaches could be investigated to incorporate supervision including metric learning and directly learning document representations to discern cross-lingual documents.

REFERENCES

[1] Sadaf Abdul-Rauf and Holger Schwennen. 2009. On the use of comparable corpora to improve SMIT performance. In Proceedings of the 12th Conference of the European Chapter of the Association for Computational Linguistics. Association for Computational Linguistics, 16–23.

[2] Mikel Artetxe and Holger Schwennen. 2019. Massively multilingual sentence embeddings for zero-shot cross-lingual transfer and beyond. Transactions of the Association for Computational Linguistics 7 (2019), 597–610.

[3] Kubilay Atasu, Thomas Parnell, Celestine Dünner, Manolis Sifalakis, Haralampos Pozidis, Vasileios Vasileiadis, Michalis Vlachos, Cesar Berrospi, and Abdel Labibi. 2017. Linear-complexity relaxed word Mover’s distance with GPU acceleration. In 2017 IEEE International Conference on Big Data (Big Data). IEEE, 889–896.

[4] Georgios Balikas, Charlotte Laclau, Ivgen Redko, and Massih-Reza Amini. 2018. Cross-lingual document retrieval using regularized wasserstein distance. In European Conference on Information Retrieval. Springer, 398–410.

[5] Christian Buck and Philipp Koehn. 2016. Findings of the WMT 2016 bilingual document alignment shared task. In Proceedings of the First Conference on Machine Translation: Volume 2, Shared Task Papers. 554–563.

[6] Christian Buck and Philipp Koehn. 2016. Quick and reliable document alignment via tf-idf-weighted cosine distance. In Proceedings of the First Conference on Machine Translation: Volume 2, Shared Task Papers. 672–678.

[7] Jiaci Chen and Jian-Yun Nie. 2000. Parallel web text mining for cross-language IR. In Content-Based Multimedia Information Access. Volume 1 LE CENTRE DE HAUTES ETUDES INTERNATIONALES D’INFORMATIQUE DOCUMENTAIRE, 62–77.

[8] Elizabeth Clark, Azi Celikyilmaz, and Noah A Smith. 2019. Sentence mover’s similarity. Automatic evaluation for multi-sentence texts. In Proceedings of the
Maurice G Kendall. 1938. A new measure of rank correlation. In Proceedings of the First Conference on Machine Translation: Volume 2, Shared Task Papers, 679–684.

Thu-Ngoc-Diep Do, Viet-Bac Le, Brigitte Bigi, Laurent Besacier, and Eric Castelli. 2009. Mining a comparable text corpus for a Vietnamese-French statistical machine translation system. In Proceedings of the Fourth Workshop on Statistical Machine Translation. Association for Computational Linguistics, 165–172.

Ahmed El-Kishky, Vishrav Chaudhary, Francisco Guzmán, and Philipp Koehn. 2017. A Massive Collection of Cross-Lingual Web-Document Pairs. arXiv preprint arXiv:1711.06154 (2017).

Garrett Goldney and Serge G. Belongie. 2016. A new measure of document alignment. In Proceedings of the First Conference on Machine Translation: Volume 2, Shared Task Papers, 685–691.

Pascale Fung and Lo Yuen Yee. 1998. An IR approach for translating new words from nonparallel, comparable texts. In COLING 1998 Volume 1: The 17th International Conference on Computational Linguistics.

Luis Gomez and Gabriel Perez-Rosas. 2016. First steps towards coverage-based document alignment. In Proceedings of the First Conference on Machine Translation: Volume 2, Shared Task Papers, 697–702.

Mandy Guo, Qinlan Shen, Yinfei Yang, Heming Ge, Daniel Cer, Gustavo Hernandez Abrego, Keith Stevens, Noah Constant, Yun-Hsuan Sung, Brian Strope, et al. 2018. Effective parallel corpus mining using bilingual sentence embeddings. arXiv preprint arXiv:1807.11906 (2018).

Mandy Guo, Yinfei Yang, Keith Stevens, Daniel Cer, Heming Ge, Yun-Hsuan Sung, Brian Strope, and Ray Kurzweil. 2019. Hierarchical Document Encoder for Parallel Corpus Mining. In Proceedings of the Fourth Conference on Machine Translation. Association for Computational Linguistics, Florence, Italy, 64–72.http://www.aclweb.org/anthology/W19-5207

Gao Huang, Chuan Guo, Matt J. Kusner, Yu Sun, Fei Sha, and Kilian Q. Weinberger. 2016. Supervised word mover’s distance. In Advances in Neural Information Processing Systems, 4862–4870.

Laurent Jakubina and Philippe Langlais. 2016. Bad luc@ WMT 2016: a bilingual document alignment based on keywords and statistical translation. In Proceedings of the First Conference on Machine Translation: Volume 2, Shared Task Papers, 728–732.

Miquel Esplà-Gomís, Mikel Forcada, Sergio Ortiz Rojas, and Jorge Ferrández-Tordera. 2016. Bitextor’s participation in WMT’16: shared task on document alignment. In Proceedings of the First Conference on Machine Translation: Volume 2, Shared Task Papers, 685–691.

Reinhard Rapp. 1999. Automatic identification of word translations from un-related English and German corpora. In Proceedings of the 37th annual meeting of the Association for Computational Linguistics. Association for Computational Linguistics, 519–526.

Philip Resnik. 1999. Mining the Web for bilingual text. In Proceedings of the 37th annual meeting of the Association for Computational Linguistics. Association for Computational Linguistics, 527–534.

Philip Resnik and Noah A. Smith. 2003. The web as a parallel corpus. Computational Linguistics 29, 3 (2003), 349–380.

Stephen Robertson. 2004. Understanding inverse document frequency: on theoretical arguments for IDF. Journal of documentation 60, 5 (2004), 503–520.

Yossi Rubner, Carlo Tomasi, and Leonidas J. Guibas. 1998. A metric for distributions with applications to image databases. In Sixth International Conference on Computer Vision (IEEE Cat. No. 98CH36271). IEEE, 59–66.

Vadim Shchukin, Dmitry Khristich, and Irina Galinskaya. 2016. Word clustering approach to bilingual document alignment (wmt 2016 shared task). In Proceedings of the First Conference on Machine Translation: Volume 2, Shared Task Papers, 740–744.

Raghavendra Udupa, K Saravanan, A Kumaran, and Jagadeesh Jagarlamudi. 2009. Mint: A method for effective and scalable mining of named entity transliterations from large comparable corpora. In Proceedings of the 12th Conference of the European Chapter of the Association for Computational Linguistics. Association for Computational Linguistics, 799–807.

Yinfei Yang, Gustavo Hernandez Abrego, Steve Yuan, Mandy Guo, Qinlan Shen, Daniel Cer, Yun-Hsuan Sung, Brian Strope, and Ray Kurzweil. 2019. Improving Multilingual Sentence Embedding using Bi-directional Dual Encoder with Additive Margin Softmax. arXiv preprint arXiv:1902.08564 (2019).

Michal Ziemska, Marcin Junczyk-Downsunt, and Bruno Pouliquen. 2016. The United Nations parallel corpus v1.0. In Proceedings of the Tenth International Conference on Language Resources and Evaluation (LREC 2016). 3530–3534.