DISCOVERING BILINGUAL LEXICONS IN POLYGLOT WORD EMBEDDINGS

Ashiqur R. KhudaBukhsh∗
Carnegie Mellon University
akhudabu@cs.cmu.edu

Shriphani Palakodety∗
Onai
spalakod@onai.com

Tom M. Mitchell
Carnegie Mellon University
tom.mitchell@cs.cmu.edu

September 1, 2020

ABSTRACT

Bilingual lexicons and phrase tables are critical resources for modern Machine Translation systems. Although recent results show that without any seed lexicon or parallel data, highly accurate bilingual lexicons can be learned using unsupervised methods, such methods rely on existence of large, clean monolingual corpora. In this work, we utilize a single Skip-gram model trained on a multilingual corpus yielding polyglot word embeddings, and present a novel finding that a surprisingly simple constrained nearest neighbor sampling technique in this embedding space can retrieve bilingual lexicons, even in harsh social media data sets predominantly written in English and Romanized Hindi and often exhibiting code switching. Our method does not require monolingual corpora, seed lexicons, or any other such resources. Additionally, across three European language pairs, we observe that polyglot word embeddings indeed learn a rich semantic representation of words and substantial bilingual lexicons can be retrieved using our constrained nearest neighbor sampling. We investigate potential reasons and downstream applications in settings spanning both clean texts and noisy social media data sets, and in both resource-rich and under-resourced language pairs.

Keywords Hope Speech Detection · Unsupervised Machine Translation · Polyglot Word Embeddings

1 Introduction

Bilingual lexicons have been a key building block for effective Machine Translation systems for the last few decades [1, 2, 3]. Several prominent recent lines of work on bilingual lexicon induction [4, 5, 6, 7, 8, 2, 3] involve training embeddings on two monolingual corpora and learning a mapping between the two embeddings.

In this widely studied NLP problem, primary focus areas are (1) methods (e.g., joint training [6] versus separate training [2]; incorporating adversarial approaches [10, 11, 3]) (2) performance and (3) alleviating resource requirements (e.g., seed lexicon, parallel data). While recent successes with unsupervised methods demonstrate that effective lexicons can be learned without any seed lexicon or parallel data [3], to the best of our knowledge, no prior work has focused on an extreme condition of learning bilingual lexicons from noisy, multilingual social media data using unsupervised methods. In the context of Romanized Hindi, an expression of Hindi primarily observed in social media, this in fact is a real world challenge. With a combined language base of more than 500 million Hindi speakers in India and Pakistan, and prior studies reporting that more than 90% of Indian language texts found on the web are Romanized [12], rich bilingual lexicons would help in the under-explored task of analyzing Romanized Hindi web content.

In this paper, we describe a surprisingly simple technique to retrieve bilingual lexicons. We find that by (1) training a single Skip-gram model on the whole multilingual corpus, and (2) conducting a constrained nearest neighbor sampling on the resulting polyglot word embedding space for a given source word, we can retrieve substantial bilingual lexicons even in harsh social media multilingual data sets. On two data sets found in the literature [13, 14] and one data set first introduced in this paper, we demonstrate that without any parallel data, monolingual corpora or seed lexicon, our method

* Ashiqur R. KhudaBukhsh and Shriphani Palakodety are equal contribution first authors.
Discovering Bilingual Lexicons in Polyglot Word Embeddings

A Preprint

Figure 1: A t-SNE [16] 2D visualization of Skip-gram polyglot embeddings trained on (a) a data set of 2.04 million YouTube comments relevant to the 2019 India-Pakistan conflict [13] and (b) en-es Europarl corpus [17]. In Figure 1(a) three nearest neighbors (using cosine distance) of the Hindi word "mazhab" "religion" and the English word "religion" are highlighted. In Figure 1(b) three nearest neighbors (using cosine distance) of the Spanish word "lucha" "fight" and the English word "fight" are highlighted. These results indicate that naive nearest neighbor sampling of a word yields other words with similar meaning in the same language.

retrieves substantial lexicons. We then demonstrate practical benefits of our bilingual lexicon through a cross-lingual sampling task defined in [15]. On an important task of detecting peace-seeking, hostility-diffusing user generated web content from heated political discussions between nuclear adversaries, dubbedhope speech detection [13], we present a purely unsupervised cross-lingual sampling method that detects hope speech in Romanized Hindi. Our method obtains a 45% improvement over previously reported results.

While our performance numbers are encouraging, we see our paper primarily as a discovery paper where we are intrigued by the observation that polyglot Skip-gram embeddings trained on a multilingual corpus learn a rich semantic representation that captures word meanings across languages. We devote a considerable part of this paper in understanding the possible reasons and investigating the generality of our approach. Our experiments reveal that our method can retrieve bilingual lexicons even across European language pairs.

Contributions: In this paper, we (1) Construct a simple yet capable method to mine substantial bilingual lexicons from noisy social media corpora. (2) Focus on a poorly resourced but extremely prevalent language pair: English-Romanized Hindi. (3) Release the resulting lexicons of 1,100 word pairs. (4) Provide a purely unsupervised cross-lingual sampling technique for an important humanitarian domain. (5) Provide insights into our finding on polyglot word embeddings with a broad study across several language pairs.

2 Our Approach

The Skip-gram objective predicts an input word’s context [9]. Nearest neighbor sampling in the resulting embedding space yields (syntactically or semantically) similar words; subtle semantic relationships like word-associations (e.g., big:bigger::quick:quicker or France:Paris::Italy:Rome) are also revealed. When two separate Skip-gram models are trained on two monolingual corpora, it is observed that the trained embeddings exhibit isomorphism [4] and using a seed lexicon, a linear projection can be learned to construct a bilingual lexicon.

What happens when we train a single Skip-gram model on a bilingual corpus? Intuitively, sampling a word’s nearest neighbors in a polyglot embedding space trained on a bilingual corpus would still yield semantically similar words in the same language of the probe word. For instance, as presented in Figure 1(b) in Skip-gram polyglot word-embeddings trained on an English-Spanish Europarl data set [17], nearest neighbors of the Spanish (es) word "lucha", are contra, luchar and combatir; the English (en) word "fight" are fighting, combating and combat. Or, in Skip-gram polyglot word-embeddings trained on a noisy social media English-Romanized Hindi corpus of YouTube video comments relevant to the 2019 India-Pakistan conflict [13], we notice that nearest neighbors of a word include spelling variations and incorrect spellings of a word along with words with similar meanings.

Do these polyglot word embeddings capture richer semantic structures that tell us "lucha and fight or religion and mazhab" are related, in fact, synonymous to each other? In this paper, we describe a surprisingly simple constrained nearest neighbor sampling that allows us to retrieve substantial bilingual lexicon that requires (1) no seed lexicon (2) no parallel
data and even (3) no monolingual corpora. Recent analyses of polyglot embedding spaces have shown that tokens and documents are grouped together based on their language - i.e., the monolingual components are grouped together. A resulting algorithm $\hat{L}_{\text{polyglot}}$ exploits this phenomenon to perform document [13] and token [15] level language identification with minimal supervision. Intuitively, the neighborhood of a word in a given language would be other words belonging to the same language, and conducting naive nearest neighbor sampling is unlikely to reveal semantic relationships with words belonging to the other language. In fact, neither lucha nor fight features in each others top 1,000 naively sampled nearest neighbors.

What happens when nearest neighbor searches are restricted to words in the corpus written in a different language than the input word? We discover that this simple constrained nearest neighbor sampling is capable of retrieving substantial bilingual lexicons and this phenomenon is observed in multiple language pairs.

Formally, in a bilingual corpus $D$ of two languages $L_{\text{source}}$ and $L_{\text{target}}$, let $V_{\text{source}}$ and $V_{\text{target}}$ denote the vocabularies of the two languages, respectively. The translation scheme $L_{\text{source}} \rightarrow L_{\text{target}}$ takes a word $w_{\text{source}} \in V_{\text{source}}$ as input and outputs a single word translation, $w_{\text{target}}$, such that $w_{\text{target}} \in V_{\text{target}}$ and $\forall w \in V_{\text{target}}, \text{dist}(w_{\text{source}}, w) \geq \text{dist}(w_{\text{source}}, w_{\text{target}})$. Following [9], we take cosine distance as our distance metric ($\text{dist}(.))$. Since we are operating on a single multilingual, noisy, social media corpus and Romanized Hindi does not have any standard spelling rules (e.g., the word amaan meaning peace in Hindi can be spelled as aman or amun), we need a token-level language identification method to estimate the vocabularies of $L_{\text{source}}$ and $L_{\text{target}}$. For this, we use the minimally supervised algorithm $\hat{L}_{\text{polyglot}}$.

When we perform nearest neighbor sampling with this additional constraint, surprisingly, we find that the nearest neighbor of religion is mazhab and the nearest neighbor of lucha is fight! Note that, our method involves no explicit attempt to achieve alignment; a single Skip-gram model is trained on a bilingual corpus and lexicons are retrieved using this simple constrained nearest neighbor sampling. Further, noisy estimations of vocabularies are obtained using $\hat{L}_{\text{polyglot}}$. Using our technique, we retrieve substantial bilingual lexicons across three different Indian social media corpora, and several (synthetically induced) bilingual corpora of European language pairs.

3 Notation

We denote English, Spanish, German, Romanized Hindi as $en$, $es$, $de$, and $hi_c$, respectively. $L_{\text{source}}$ and $L_{\text{target}}$ indicate the direction of translation. For example, when translating $en \rightarrow es$, $L_{\text{source}}$ is English and $L_{\text{target}}$ is Spanish. The vocabularies of the source and target languages are denoted by $V_{\text{source}}$ and $V_{\text{target}}$, respectively. The ground truth language label of a specific token $w$ or a document $d$ is returned by the function $L(.)$. When we use $\hat{L}_{\text{polyglot}}$ to estimate the language label or vocabulary, we indicate that by $\hat{L}(.).$ In our work, we perform several frequency-based analyses to understand our method’s strengths and weaknesses. We denote the top 5% of words by $V^{0-5}$ and similarly, the top 5-10% by $V^{5-10}$.

4 Related Work

Bilingual lexicon induction has a rich line of prior literature [18, 19, 20, 21, 22, 23, 24, 25] with modern methods [4, 26, 27, 28, 29, 30, 31, 32, 33] leveraging continuous representation of words [9, 34, 35]. While this list is far from exhaustive, several of these focus on alleviating resource requirements like seed lexicon, or parallel data. For example, [30] aligned two monolingual embeddings trained on distinct monolingual corpora using digits to address the requirement of large seed lexicons; [3] aligned monolingual embeddings using a Cross-Domain Local Scaling measure that requires no seed lexicon, or parallel data. The resulting aligned embeddings perform favorably when compared against supervised methods. Our work contrasts with the literature in the following key ways. Unlike previous work, we embrace the challenge of learning bilingual lexicons from harsh, social media data. Our method does not require clean, monolingual corpora; we learn a single Skip-gram embedding on a bilingual corpus and present a novel finding that constrained nearest neighbor sampling can retrieve substantial bilingual lexicons without any explicit attempt to align. Our unsupervised method is particularly well-suited for noisy language expression typical of informal social media settings (e.g., Romanized Hindi) where procuring clean, monolingual (let alone parallel) data could be difficult. Recent work in unsupervised machine translation [36] utilizes monolingual language models and alignment steps to learn a phrase-level translation model. Our work discards the individual monolingual models and the alignment steps instead using just a single polyglot Skip-gram model and a mining step. To reiterate, our motivations are not performance-driven - this paper explores the extent of multilingual information embedded in polyglot Skip-gram models.
Discovering Bilingual Lexicons in Polyglot Word Embeddings

As much as our paper is about bilingual lexicon induction using noisy, social media data, we also highlight the intriguing observation that polyglot embeddings can learn a rich semantic representation that captures word meanings across languages. While polyglot word-embeddings and polyglot training in particular have received attention recently for demonstrating performance improvements across a variety of NLP tasks [37, 38, 39, 13, 15], to the best of our knowledge, no previous work has explored their effectiveness in retrieving bilingual lexicons.

Our work is related to [15] in two key ways: (1) use of $L_{\text{polyglot}}$ to perform token-level language identification and (2) a shared task of cross-lingual sampling in the domain of hope speech. However, unlike [15] who use vocabulary estimates to measure the extent of code mixing, we use the vocabulary estimates for our constrained nearest neighbor sampling. Moreover, our approach to perform cross-lingual sampling is different. We use our bilingual lexicons to construct noisy translations of English hope speech while [15] harness code switching. Finally, we obtain a 45% performance improvement over the best-performing method reported by [15].

| Sampled hope speech | Loose translation |
|---------------------|------------------|
| kaash dono mulko ne dosti ho jaye dono mil kr Europe ke desho ki tra developed ho sakte hai piece love | I wish two countries make friendship and together prosper and develop like European countries: peace, love. |
| kaash dono desho mein shanti k rishte kayam ho sake | I wish both countries can forge a relationship of peace. |
| jung taliti rhe to bahatar he ap or ham sabhi k anagan me shama jalti rhe to bahatr he jung to khud hi ek masla he jung kiya maslo ka hal de gi | It is better if war is avoided. All of us should prosper. War in itself is a problem, how can it be a solution? |

Table 1: Random sample of hope speech obtained through our method.

5 Data Sets

We use three Indian social media data sets. Two of them were introduced in prior literature. In addition, we construct a new data set.

- $D_{\text{hope}}$ consists of 2.04 million comments posted by 791,289 user on 2,890 YouTube videos relevant to the 2019 India-Pakistan conflict [13].
- $D_{\text{election}}$ consists of 6.18 million comments on 130,067 videos by 1,518,077 users posted in a 100 day period leading up to the 2019 Indian General Election [14].
- $D_{\text{covid}}$ consists of 4,511,355 comments by 1,359,638 users on 71,969 videos from fourteen Indian news outlets (see, Appendix for details) posted between 30th January, 2020 and 7th May, 2020.

5.1 Data set challenges

As documented in [13][14][15], typical to most noisy, short social media texts generated in linguistically diverse regions, the data sets we consider exhibit a considerable presence of code mixing, and grammar and spelling disfluencies. On top of these, $D_{\text{hope}}$ and $D_{\text{election}}$ involve two additional challenges. First, due to a strong presence of content contributors who do not speak English as their first language, varying levels of English proficiency in the corpus with a substantial incidence of phonetic spelling errors were reported. For example, 32% of times, the word liar was misspelled as lier [14], or consider the following example comment – [pak pm godblashu my ind pilat thanksh you cantri] that possibly intended to express Pak PM God bless you; my Ind pilot, thank you country. We corroborated this finding on $D_{\text{covid}}$ where 31.8% of the time liar was misspelled as lier. Second, since Romanized Hindi does not have any standard spelling rules [12] (e.g., the word nuksaan meaning damage is spelled in the corpus as nuksaan, nuqsaan and nuksan), a high level of spelling variations added to the challenges.

5.2 Preprocessing

For each of these three data sets as input, we conduct the following preprocessing and output the $en$ and $hi_e$ vocabularies.

- We first clean the multilingual corpus with the same steps (e.g., removing emojis, lower casing words written in Roman script, removing punctuations) described in [14].
- Following [13], we train 100 dimensional FastText embeddings [35] (full training configuration presented in Appendix). Following [15], we construct the $hi_e$ and $en$ vocabularies.

---

2First COVID-19 positive case reported in India.
Discovering Bilingual Lexicons in Polyglot Word Embeddings

Note that, while our constrained nearest neighbor sampling restricts the vocabulary of the target word based on our obtained (noisy) vocabularies from \( \mathcal{L}_{polyglot} \), we perform no explicit monolingual corpus extraction or removal of any other language expressed in Roman script or traditional script (e.g., Hindi in Devanagari constitutes a small fraction of all corpora, see Appendix for visualizations).

6 Results

| Measure | \( D_{\text{hope}} \) | \( D_{\text{election}} \) | \( D_{\text{covid}} \) |
|---------|-----------------|-----------------|-----------------|
| p@1     | 0.18            | 0.21            | 0.24            |
| p@5     | 0.39            | 0.44            | 0.50            |
| p@10    | 0.47            | 0.52            | 0.61            |

Table 2: Word translation performance on social media data. For each training corpus and translation direction, 500 source words are selected from \( \mathcal{V}_{source} \) and are mapped to target words in \( \mathcal{V}_{target} \) that are present in the corpus for at least 100 or more times. p@K indicates top-K accuracy.

6.1 en-hi\(_e\) translation

Table 2 summarizes our performance in extracting bilingual lexicons across three Indian social media data sets. Following standard practice \([2, 3]\), we report p@1, p@5 and p@10 performance. p@K is defined as the top-K accuracy \([4]\), i.e., an accurate translation of the source word is present in the retrieved top K target words. It is common practice to restrict the vocabularies for source words (and target words) based on some prevalence criterion \([3]\). We restrict \( \mathcal{V}_{source} \) to words that have appeared at least 100 times in the corpus (Appendix contains hyperparameter sensitivity analysis).

As shown in Table 2, we observe that substantial bilingual lexicons can be retrieved using our unsupervised method. Even on multilingual, challenging social media data sets, a p@5 performance as high as 0.5 was achieved on multiple occasions. Across the three data sets, we obtain best performance in \( D_{\text{covid}} \). Compared to other two data sets, \( D_{\text{covid}} \) has stronger presence of hi\(_e\). Romanized Hindi does not have standard spelling rules; a larger volume of data could be useful in learning embeddings robust to spelling variations.

The three data sets we looked into have wildly different topical focus: international conflict, general election and a global pandemic. The nature of the successfully retrieved words also reflect this. From \( D_{\text{hope}} \), we obtained translations for several conflict-words (e.g., attack, war, peace, brave, martyred). In contrast, from \( D_{\text{election}} \) we obtained words focusing on national priorities and issues (e.g., corruption, population, unemployment), while our method when applied on \( D_{\text{covid}} \) retrieved words focusing on disease symptoms, preventive measures and treatment terms (e.g., fever, cough, wash, distance, treatment, medicine). Our obtained lexicons had non-overlapping regions which indicate the possibility of growing the lexicon through combining multiple corpora focusing on topics with minimal overlap. We will release this bilingual lexicon (consensus label by two annotators, annotator details are present in the Appendix) of 1,100 unique word pairs as a resource. Table 3 lists a few randomly chosen examples of successfully translated word pairs across our three data sets.

6.1.1 Qualitative Analysis

In our translation scheme, we found that translations for nouns, adjectives and adverbs were successfully discovered (see Table 3). Preserving plurality (hazaron thousands, musalmano muslims, naare slogans) on most occasions, translating

| \( \text{D}_{\text{hope}} \) | \( \text{D}_{\text{election}} \) | \( \text{D}_{\text{covid}} \) |
|----------------|----------------|----------------|
| aatankvadi terrorst | deshblakti patriotism | ilaz treatment |
| bahaduri bravery | turant immediately | joota shoe |
| musalmano muslims | patrakaar journalist | kahani story |
| andha blind | angrezo britishers | jukam cold |
| nuksan damage | berojan unemployment | saf clean |
| faida benefit | ummeed expectation | bhaloo hands |
| aata days | nokri jobs | bachche kids |
| bharosa trust | bikash development | muddle issues |
| tarakki progress | gareebi poverty | munnj patient |
| gayab vanish | shi ryt | sankramit infected |

Table 3: A random sample of word pairs translated by our algorithm. Appendix contains more examples.
numerals (char 4, eik one) were among some surprising observations considering the noisy social media setting. For a
given source word, multiple valid synonymous target words were often among the top translations produced by our
method (e.g., aman and shanti for peace; dharam, mazhab and jaat for religion). Stylistic choices like contraction were
reflected in the translation (e.g., kyki (kyuki) mapped to bcz (because), and shi (sahi) mapped to ryt (right)). Verbs are
conjugated differently in Hindi and English and word-for-word translations don’t typically exist - for instance help him
translates to uska “him” madad “help” karo “do”, thus words like karo were rarely successfully translated.

Polysemy: Our system performs single word translation. During translation, without context, detecting polysemy and
resolving it to the true meaning w.r.t. the context is not possible. However, we were curious to learn if top translation
choices of polysemous source words include valid translations of their different meanings. We notice that this was
the case in a few instances. For example, the word cold can mean both low temperature or a common viral infection.
In $D_{covid}$, both these meanings were captured in the top translations while translations in $D_{hope}$ and $D_{election}$ only
reflected the meaning of low temperature. It is unlikely that cold in the sense of viral infection would be highly discussed
in the latter two corpora, while it is understandable that common cold and associated symptoms would be heavily
discussed in $D_{covid}$.

Nativization of loanwords: Lexical borrowing across language pairs in the context of loanwords (or borrowed words)
has been studied in linguistics [49, 41, 42] and computational linguistics [43, 44]. Borrowed words, also known as
loanwords, are lexical items borrowed from a donor language. For example, the English word avatar or yoga is borrowed
from Hindi, while botal (bottle) and astabal (stable) are Hindi words borrowed from English. We noticed nativized
loanwords, i.e., borrowed words that underwent phonological repairs to adapt to a foreign language, translate back to
their English donor counterpart (e.g., rashan and angrezi translate to donor words ration and English, respectively).

6.1.2 Digging deeper

We conduct a detailed ablation study to understand this phenomenon. In what follows, we summarize our findings (see,
Appendix for details).

- **Disabling numbers**: In prior literature, [30] showed that digits can be used as seed lexicons to align monolingual
embeddings. Although our method doesn’t make any explicit attempt to align, phrases like 2019 election (2019 chunao),
1971 war (1971 jung) can appear in both languages and hence can serve as signals. We replaced all numbers with a
specific randomly chosen string that does not occur in the original corpus and evaluated the retrieval performance of our
previously successful p@1 translations. We observed a performance dip of 28% which indicates that numeric literals
may contribute to this phenomenon.

- **Loanwords**: We observe that in most cases, in successfully translated word pairs (e.g., (madad, help),
 ⟨ilaj, treatment⟩), at least one of the words is borrowed and used in the other language (e.g., humein help chahiye
“We need help”). These loanwords thus result in similar contexts for word pairs from different languages - which are
possibly reflected in the obtained word embeddings facilitating translation.

- **Frequency preserving corpus transformation**: We perform a frequency preserving loanword exchange (see, Ap-
 pendix) to modify the corpus where translated word pairs are interchanged to diminish the extent of borrowing of these
loanwords (e.g., phrases like humein help chahiye is rewritten as humein madad chahiye). We observe that the p@1
performance dipped by 33% after this corpus modification indicating that loanwords are possibly major contributors to
this phenomenon.

6.2 Cross-lingual sampling

In our previous section, we have demonstrated that our unsupervised constrained nearest neighbor sampling method is
able to retrieve substantial bilingual lexicons across three different en-hi_e data sets. We now demonstrate a practical
benefit of our method.

We focus on the task of detecting hostility-diffusing hope speech first introduced in [13]. In a corpus focusing on the
2019 India-Pakistan conflict, the authors advocated the importance of hostility-diffusing hope speech and presented a
hope speech classifier for English content. While the authors present an important study of a modern conflict, much of
the focus was centered around the English sub-corpus. In a recent study, [15] widened the analysis with a cross-lingual
sampling technique to detect hope speech content authored in Romanized Hindi. Using the English hope speech
classifier and leveraging $L_{polyglot}$ to perform token-level language identification, their proposed method first detects
highly code mixed hope speech, then uses it to sample hi_e hope speech using nearest-neighbor sampling (NN-sampling)
in the comment embedding space of the hi_e sub-corpus, $D_{hope}$.

**Baselines**: We include both methods proposed in [15] and their baseline (random sampling) for performance comparison.

**Our approach**: We take a set of English hope speech comments, $A$, as inputs and output a sample of Hindi hope
Discovering Bilingual Lexicons in Polyglot Word Embeddings

**Algorithm 1:** translateEmbedding($S_{source}$)

Input: A document $S_{source}$ denoted by $[w_1, \ldots, w_k]$  
Output: A document embedding of $S_{source}$ translated into $L_{target}$  

Dependency: topTranslations($w_i$, $N_{target}$) returns $N$ nearest neighbors of embedding($w_i$) from $V_{target}$  

Initialization: $E \leftarrow \{ \}$  

Main loop:  
foreach word $w_i \in S_{source}$ do  
if $L_{source}$($w_i$) = $L_{target}$ then  
   $E \leftarrow E \cup \{\text{embedding}(w_i)\}$  
else  
   $T \leftarrow \text{topTranslations}(w_i, N_{target})$  
   $C \leftarrow \{\}$  
   foreach word $w_t \in T$ do  
      if $w_i \in \text{topTranslations}(w_t, N_{source})$ then  
         $C \leftarrow C \cup \{w_t\}$  
      end  
   end  
   if $C \neq \{}$ then  
      randomly select $w$ from $C$  
      $E \leftarrow E \cup \{\text{embedding}(w)\}$  
   end  
end  

Output: Average of $E$

---

speech comments from the Romanized Hindi subset, $D_{hope}^{hi}$. For each English comment in $A$, we compute a document embedding of a noisy translation in Hindi using our method - translateEmbedding described in Algorithm 1. $N$ is set to 10. Once we obtain a set of translated embeddings, $B$, similar to [15], we perform NN-sampling in the comment embedding space of $D_{hope}^{hi}$ (described in the Appendix). For fair comparison, in all our experiments, our parameter configurations are identical to those in [15].

| Method                           | Performance |
|----------------------------------|-------------|
| random-Sample($D_{hope}^{hi}^{1}$) | 1.8%        |
| NN-Sample($D_{hope}^{hi}$) [15]   | 21.88%      |
| NN-Sample($D_{hope}^{hi}$) [15]   | 31.68%      |
| Only top translation choice without back-translation | 23.08% |
| Without back-translation         | 25.36%      |
| Our method                       | 46.04%      |

Table 4: Sampling performance. Percentage of samples output by the algorithm that are judged correct by human. Results marked with symbol † are obtained from [15].

Our translateEmbedding algorithm is inspired by [2] with some modifications. We now describe the intuitions behind our design choices. Performing a naive translation using our translation scheme runs into the well-studied hubness problem observed in high-dimensional spaces [45, 46, 47]. Essentially, the hubness problem arises when a small subset of words are “universal” neighbors and hence attract several many-to-one mappings. Existing strategies like mutual nearest neighbor [45] and a more involved method of Cross-Domain Similarity Local Scaling [3] have been previously proposed to address this issue. We employ a simple mutual nearest neighbor technique, i.e., a source word’s top translations should include only those target words that include the source word when translated back. For an input document, we obtain the noisy word-for-word translation and compute the resulting document’s embedding - the average of the normalized word embeddings.

In our earlier analyses, we noticed that our translation scheme found several synonyms in its top choices (e.g., religion has mazhab, dharam and jaat in its top translated choices). Also, since Romanized Hindi does not have standard spelling rules, the translations often contained prevalent spelling variations of the same word (e.g., aman, amaan, jung, jang). Moreover, our retrieved dictionaries are noisy with substantially better p@10 than p@1 performance. To account for this noise in translation and to induce more diversity, for each word, we randomly sample a mutually nearest neighbor.

Table [compares the performance of our sampling method against existing approaches. In order to shed light into influence of different design choices on performance, we present our main method and ablation studies after disabling random sampling from top choices and back-translation to address the hubness problem. We notice that strictly limiting ourselves to the top translation choice and not accounting for hubness yields substantially worse performance. Allowing more diversity through randomly selecting one of the top translation choices improves performance somewhat, however,
Figure 2: A 2D visualization showing the sampling results against the document embedding space.

| Data set   | Measure | en → es | es → en | en → de | de → en |
|------------|---------|---------|---------|---------|---------|
| Europarl   | p@1     | 0.25    | 0.25    | 0.19    | 0.16    |
|            | p@5     | 0.37    | 0.39    | 0.30    | 0.18    |
|            | p@10    | 0.39    | 0.44    | 0.33    | 0.19    |
| Wikipedia  | p@1     | 0.24    | 0.34    | 0.16    | 0.34    |
|            | p@5     | 0.40    | 0.50    | 0.31    | 0.46    |
|            | p@10    | 0.48    | 0.56    | 0.38    | 0.50    |

Table 5: Performance comparison on Europarl [17] and Wikipedia. \( \hat{V}_{\text{target}} \) is restricted to words that appeared more than 100 times in the corpus.

the hubness problem appears to be the primary performance bottleneck. Our final algorithm as described in Algorithm 1 achieves the best performance. On a highly challenging task of mining rare positives (random sampling only yields 1.8% hope speech), we obtained a 45% improvement over the previously reported best result.

Table 1 lists a random sample of hope speech obtained using our method. We notice that the comments are mostly written in Romanized Hindi. A 2D visualization of the obtained comments indicate (see, Figure 2) that our method retrieved comments reasonably distributed across the Hindi region.

6.3 Analyzing other language pairs

We were curious to learn if our approach works with other language pairs. On two European language pairs, (en, es) and (en, de), we observed that our simple approach of constrained nearest neighbor sampling retrieves reasonable bilingual lexicons even when trained on a single, multilingual corpus (synthetically induced) without any explicit attempt to align. We acknowledge that prior art with supervision and seed lexicon (e.g., [4]) and recent unsupervised approaches (e.g., [3]) achieve considerably better performance on our test data set introduced in [3]. For instance, compared to our p@1 performance on en → es of 0.25, [4] and [3] achieved performance of 0.33, and 0.82 respectively. Our focus is not on competing with the rich research conducted so far, rather, we are interested in reporting the generalizability of our approach.

Data sets: We conduct experiments using Europarl [17] and Wikipedia data sets. We synthetically induce a multilingual corpus by combining two monolingual corpora and then randomly shuffling at the sentence level. Table 5 summarizes our results. We find that our overall performance improved with Wikipedia data especially for de → en and es → en. [3] also reported a performance boost with Wikipedia data.

In addition to an English-Italian translation retrieval task, we present an ablation study in the Appendix. Our primary takeaways are:

• Source word frequency: Our experiments with Indian social media data sets indicate that our method performs better when we restrict ourselves to high-frequency source words. A fine-grained look at the performance based on the frequency of the source word reveals that we perform substantially better on high-frequency words belonging to \( \hat{V}_{\text{source}} \) (e.g., en → es performance jumps from 0.25 to 0.61 when we consider words in \( \hat{V}_{\text{source}} \)).

• Topical cohesion: When we sample the en part of the corpus from Europarl and the es (or de) part from Wikipedia, we remove the topical cohesion between the en and es (de) components. We observe that performance dips slightly.

7 Conclusions and Future Work

In this paper, we explore the word embedding space resulting from training a single Skip-gram model on several bilingual corpora. Our detailed experiments reveal a rich and expressive embedding space across several language pairs that allows simple methods to retrieve substantial bilingual lexicons. In particular, the English-Romanized Hindi setting is a common occurrence in several corpora sourced in the Indian subcontinent. The (relatively) poorly resourced
Romanized Hindi, and consequently the difficulty in obtaining monolingual corpora in this language pair make our observations and methods particularly well-suited for this setting. We explore intuitive but formidable cross-lingual sampling methods, and finally conduct detailed ablation studies for English-German and English-Spanish language pairs on existing data sets. We report that in all cases the rich embedding space is consistently observed and our methods just as applicable. Future directions include exploring the presence of this phenomenon in settings like contextual embeddings, and alternate models such as the highly successful transformer based methods.

References

[1] Reinhard Rapp. Identifying word translations in non-parallel texts. In 33rd Annual Meeting of the Association for Computational Linguistics, pages 320–322, Cambridge, Massachusetts, USA, June 1995. Association for Computational Linguistics.

[2] Samuel L. Smith, David HP Turban, Steven Hamblin, and Nils Y Hammerla. Offline bilingual word vectors, orthogonal transformations and the inverted softmax. arXiv preprint arXiv:1702.03859, 2017.

[3] Alexis Conneau, Guillaume Lample, Marc'Aurelio Ranzato, Ludovic Denoyer, and Hervé Jégou. Word translation without parallel data. arXiv preprint arXiv:1710.04087, 2017.

[4] Tomas Mikolov, Quoc V. Le, and Ilya Sutskever. Exploiting similarities among languages for machine translation. arXiv preprint arXiv:1309.4168, 2013.

[5] Georgiana Dinu and Marco Baroni. How to make words with vectors: Phrase generation in distributional semantics. In Proceedings of the 52nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 624–633, Baltimore, Maryland, June 2014. Association for Computational Linguistics.

[6] Stephan Gouws, Yoshua Bengio, and Greg Corrado. Bilbowa: Fast bilingual distributed representations without word alignments. 2015.

[7] Thang Luong, Hieu Pham, and Christopher D. Manning. Bilingual word representations with monolingual quality in mind. In Proceedings of the 1st Workshop on Vector Space Modeling for Natural Language Processing, pages 151–159, Denver, Colorado, June 2015. Association for Computational Linguistics.

[8] Jocelyn Coulmance, Jean-Marc Marty, Guillaume Wenzek, and Amine Benhaloum. Trans-gram, fast cross-lingual word-embeddings. In Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing, pages 1109–1113, Lisbon, Portugal, September 2015. Association for Computational Linguistics.

[9] Tomas Mikolov, Kai Chen, Greg Corrado, and Jeffrey Dean. Efficient estimation of word representations in vector space. arXiv preprint arXiv:1301.3781, 2013.

[10] Antonio Valerio Miceli Barone. Towards cross-lingual distributed representations without parallel text trained with adversarial autoencoders. In Proceedings of the 1st Workshop on Representation Learning for NLP, pages 121–126, Berlin, Germany, August 2016. Association for Computational Linguistics.

[11] Meng Zhang, Yang Liu, Huanbo Luan, and Maosong Sun. Adversarial training for unsupervised bilingual lexicon induction. In Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 1959–1970, Vancouver, Canada, June 2017. Association for Computational Linguistics.

[12] Spandana Gella, Kalika Bali, and Monojit Choudhury. “ye word kis lang ka hai bhai?” testing the limits of word level language identification. In Proceedings of the 11th International Conference on Natural Language Processing, pages 368–377, 2014.

[13] Shriphani Palakodety, Ashiqur R. KhudaBukhsh, and Jaime G. Carbonell. Hope speech detection: A computational analysis of the voice of peace. In Proceedings of ECAI 2020, page To appear, 2020.

[14] Shriphani Palakodety, Ashiqur R. KhudaBukhsh, and Jaime G. Carbonell. Mining insights from large-scale corpora using fine-tuned language models. In Proceedings of the Twenty-Fourth European Conference on Artificial Intelligence (ECAI-20), page To appear, 2020.

[15] Ashiqur R. KhudaBukhsh, Shriphani Palakodety, and Jaime G. Carbonell. Harnessing code switching to transcend the linguistic barrier. In Proceedings of the International Joint Conference on Artificial Intelligence - Pacific Rim International Conference on Artificial Intelligence (IJCAI-PRICAI), page To appear, 2020.

[16] Laurens van der Maaten and Geoffrey Hinton. Visualizing data using t-SNE. Journal of machine learning research, 9(Nov):2579–2605, 2008.

[17] Philipp Koehn. Europarl: A parallel corpus for statistical machine translation. In MT summit, volume 5, pages 79–86, 2005.
[18] Reinhard Rapp. Automatic identification of word translations from unrelated English and German corpora. In Proceedings of the 37th Annual Meeting of the Association for Computational Linguistics on Computational Linguistics, pages 519–526. Association for Computational Linguistics, 1999.

[19] Philipp Koehn and Kevin Knight. Learning a translation lexicon from monolingual corpora. In Proceedings of the ACL-02 workshop on Unsupervised Lexical Acquisition, pages 9–16, 2002.

[20] Charles Schaffer and David Yarowsky. Inducing translation lexicons via diverse similarity measures and bridge languages. In COLING-02: The 6th Conference on Natural Language Learning 2002 (CoNLL-2002), 2002.

[21] Pascale Fung and Percy Cheung. Mining very-non-parallel corpora: Parallel sentence and lexicon extraction via bootstrapping and e. In Proceedings of the 2004 Conference on Empirical Methods in Natural Language Processing, pages 57–63, Barcelona, Spain, July 2004. Association for Computational Linguistics.

[22] Eric Gaussier, J.M. Renders, I. Matveeva, C. Goutte, and H. Dejean. A geometric view on bilingual lexicon extraction from comparable corpora. In Proceedings of the 42nd Annual Meeting of the Association for Computational Linguistics (ACL-04), pages 526–533, Barcelona, Spain, July 2004.

[23] Aria Haghighi, Percy Liang, Taylor Berg-Kirkpatrick, and Dan Klein. Learning bilingual lexicons from monolingual corpora. In Proceedings of ACL-08: HLT, pages 771–779. Columbus, Ohio, June 2008. Association for Computational Linguistics.

[24] Ivan Vulić and Marie-Francine Moens. Cross-lingual semantic similarity of words as the similarity of their semantic word responses. In Proceedings of the 2013 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (NAACL-HLT 2013), pages 106–116. ACL; East Stroudsburg, PA, 2013.

[25] Ivan Vulić, Wim De Smet, and Marie-Francine Moens. Identifying word translations from comparable corpora using latent topic models. In Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies, pages 479–484, Portland, Oregon, USA, June 2011. Association for Computational Linguistics.

[26] Will Y Zou, Richard Socher, Daniel Cer, and Christopher D Manning. Bilingual word embeddings for phrase-based machine translation. In Proceedings of the 2013 Conference on Empirical Methods in Natural Language Processing, pages 1393–1398, 2013.

[27] Manaal Faruqui and Chris Dyer. Improving vector space word representations using multilingual correlation. In Proceedings of the 14th Conference of the European Chapter of the Association for Computational Linguistics, pages 462–471, 2014.

[28] Chao Xing, Dong Wang, Chao Liu, and Yiye Lin. Normalized word embedding and orthogonal transform for bilingual word translation. In Proceedings of the 2015 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 1006–1011, Denver, Colorado, May–June 2015. Association for Computational Linguistics.

[29] Ziyi Dou, Zhi-Hao Zhou, and Shujian Huang. Unsupervised bilingual lexicon induction via latent variable models. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, pages 2979–2984, Brussels, Belgium, October-November 2018. Association for Computational Linguistics.

[30] Jeffrey Pennington, Richard Socher, and Christopher D Manning. Glove: Global vectors for word representation. In Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 1532–1543, 2014.

[31] Piotr Bojanowski, Edouard Grave, Armand Joulin, and Tomas Mikolov. Enriching word vectors with subword information. Transactions of the Association for Computational Linguistics, 5:135–146, 2017.
[36] Guillaume Lample, Myle Ott, Alexis Conneau, Ludovic Denoyer, and Marc’Aurelio Ranzato. Phrase-based & neural unsupervised machine translation. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, pages 5039–5049, Brussels, Belgium, October-November 2018. Association for Computational Linguistics.

[37] Phoebe Mulcaire, Jungo Kasai, and Noah A. Smith. Polyglot contextual representations improve crosslingual transfer. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pages 3912–3918, Minneapolis, Minnesota, June 2019. Association for Computational Linguistics.

[38] Phoebe Mulcaire, Swabha Swayamdipta, and Noah A. Smith. Polyglot semantic role labeling. In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers), pages 667–672, Melbourne, Australia, July 2018. Association for Computational Linguistics.

[39] Phoebe Mulcaire, Jungo Kasai, and Noah A Smith. Low-resource parsing with crosslingual contextualized representations. In Proceedings of the 23rd Conference on Computational Natural Language Learning (CoNLL), pages 304–315, 2019.

[40] Kyril Holden. Assimilation rates of borrowings and phonological productivity. Language, pages 131–147, 1976.

[41] Andrea Calabrese and Leo Wetzels. Loan phonology. John Benjamins Publishing Company, 2009.

[42] Frans Van Coetsem. Loan phonology and the two transfer types in language contact, volume 27. Walter de Gruyter GmbH & Co KG, 2016.

[43] Yulia Tsvetkov and Chris Dyer. Cross-lingual bridges with models of lexical borrowing. Journal of Artificial Intelligence Research, 55:63–93, 2016.

[44] Jasabanta Patro, Bidisha Samanta, Saurabh Singh, Abhipsa Basu, Prithwish Mukherjee, Monojit Choudhury, and Animesh Mukherjee. All that is English may be Hindi: Enhancing language identification through automatic ranking of the likeliness of word borrowing in social media. In Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing, pages 2264–2274, Copenhagen, Denmark, September 2017. Association for Computational Linguistics.

[45] Georgiana Dinu, Angeliki Lazaridou, and Marco Baroni. Improving zero-shot learning by mitigating the hubness problem. arXiv preprint arXiv:1412.6568, 2014.

[46] Herve Jegou, Cordelia Schmid, Hedi Harzallah, and Jakob Verbeek. Accurate image search using the contextual dissimilarity measure. IEEE Transactions on Pattern Analysis and Machine Intelligence, 32(1):2–11, 2008.

[47] Miloš Radovanović, Alexandros Nanopoulos, and Mirjana Ivanović. Hubs in space: Popular nearest neighbors in high-dimensional data. Journal of Machine Learning Research, 11(Sep):2487–2531, 2010.
8 Appendix

| Measure | $V_{source}$ | $en \rightarrow en_N^{5-10}$ | $en \rightarrow hi_N^{5-10}$ | $hi \rightarrow en_N^{5-10}$ | $hi \rightarrow hi_N^{5-10}$ |
|---------|----------------|-------------------------------|------------------------------|-----------------------------|-------------------------------|
| p@1     | $V_{source}$   | 0.18                          | 0.10                         | 0.21                        | 0.24                         |
|         |                |                               |                              |                             | 0.29                         |
|         |                | 0.11                          | 0.02                         | 0.22                        | 0.19                         |
|         |                |                               |                              |                             | 0.27                         |
|         |                | 0.09                          | 0.02                         | 0.06                        | 0.11                         |
|         |                |                               |                              |                             | 0.07                         |
|         |                | 0.39                          | 0.27                         | 0.44                        | 0.50                         |
|         |                |                               |                              |                             | 0.54                         |
|         |                | 0.26                          | 0.15                         | 0.43                        | 0.33                         |
|         |                |                               |                              |                             | 0.45                         |
|         |                | 0.20                          | 0.07                         | 0.18                        | 0.21                         |
|         |                |                               |                              |                             | 0.23                         |
|         |                | 0.47                          | 0.38                         | 0.52                        | 0.61                         |
|         |                |                               |                              |                             | 0.63                         |
|         |                | 0.35                          | 0.20                         | 0.48                        | 0.46                         |
|         |                |                               |                              |                             | 0.50                         |
|         |                | 0.22                          | 0.10                         | 0.22                        | 0.26                         |
|         |                |                               |                              |                             | 0.26                         |

Table 6: Word translation performance on social media data. Each cell summarizes the $p@K$ performance for a given translation direction on a data set as $a / b / c$, where $a$ (top) is the performance observed when the source vocabulary is restricted to $\hat{V}_{source}^{5-10}$ (color coded with blue); $b$ (middle) is the performance observed when the source vocabulary is restricted to $\hat{V}_{source}^{10-100}$ (color coded with red); $c$ (bottom) is the performance observed when the source vocabulary is restricted to $\hat{V}_{target}$ (color coded with gray). 500 source words are randomly selected from $\hat{V}_{source}^{5-10}$ and $\hat{V}_{source}^{10-100}$, 100 source words are randomly selected. The selected words are mapped to target words in $\hat{V}_{target}$ that are present in the corpus for at least 100 or more times. $p@K$ indicates top-K accuracy.

| Data set | Measure | $en \rightarrow et$ | $es \rightarrow en$ | $en \rightarrow de$ | $de \rightarrow en$ |
|----------|---------|---------------------|---------------------|---------------------|---------------------|
| p@1      | $V_{source}$ | 0.25                | 0.25                | 0.19                | 0.16                |
|          |          | 0.61                | 0.26                | 0.43                | 0.15                |
|          |          | 0.50                | 0.28                | 0.39                | 0.12                |
|          |          | 0.17                | 0.24                | 0.13                | 0.22                |
| Europarl | p@5     | 0.37                | 0.39                | 0.30                | 0.18                |
|          |          | 0.79                | 0.58                | 0.68                | 0.38                |
|          |          | 0.70                | 0.52                | 0.65                | 0.34                |
|          |          | 0.26                | 0.33                | 0.19                | 0.28                |
|          |          | 0.39                | 0.44                | 0.33                | 0.19                |
|          |          | 0.83                | 0.66                | 0.73                | 0.50                |
|          |          | 0.76                | 0.59                | 0.70                | 0.43                |
|          |          | 0.28                | 0.37                | 0.22                | 0.31                |

Table 7: Performance summary of our approach with training data set Europarl [17]: test data set (denoted by $D_{test}$) introduced in [6]. $\hat{V}_{target}$ is restricted to words that appeared more than 100 times in the training data set. Each cell summarizes the $p@K$ performance for a given translation direction as $a / b / c / d$, where $a$ (top) is the overall performance observed on $D_{test}$; $b$ is the performance observed on $\hat{V}_{source}^{5-10} \cap D_{test}$ (color coded with blue); $c$ is the performance observed on $\hat{V}_{source}^{10-100} \cap D_{test}$ (color coded with red); $d$ (bottom) is the performance observed on $\hat{V}_{source}^{5-100} \cap D_{test}$ (color coded with gray).

8.1 $D_{covid}$ data set

We used the publicly available YouTube API to crawl our comments. We focused on the following date range: 30th January, 2020 and 7th May, 2020. Our data set consists of 4,511,355 comments by 1,359,638 users on 71,969 videos from fourteen Indian news outlets listed in Table 9.

Figure 3 presents a 2D visualization of the word embeddings obtained using $\hat{E}_{polyglot}$. The visualization indicates that apart from Romanized Hindi and English, our data set also demonstrates substantial presence of Hindi written in Devanagari script further establishing the challenges associated to our task. The size of the estimated vocabularies is presented in Table 8.

---

5 First COVID-19 positive case reported in India.
Discovering Bilingual Lexicons in Polyglot Word Embeddings

Figure 3: A 2D visualization of $D_{covid}$. Apart from English and Romanized Hindi, Hindi in Devanagari also has substantial presence in the corpus.

| Corpus  | $\hat{V}$ for en | $\hat{V}$ for hi_e | $\hat{V}$ for hi_e |
|---------|------------------|-------------------|-------------------|
| $D_{hope}$ | 38,516           | 71,677            | 23,560            |
| $D_{election}$ | 55,164       | 109,341           | 45,467            |
| $D_{covid}$ | 46,504         | 109,809           | 59,219            |

Table 8: Size of the estimated vocabularies using $\hat{V}_{polyglot}$ on our data sets. Spelling variations in Romanized Hindi possibly contributed to a large size of Romanized Hindi vocabulary.

8.2 Embedding Hyperparameters

All the models discussed in this paper are obtained by training Fasttext Skip-gram models with the following parameters unless stated otherwise:

- Dimension: 100
- Minimum subword unit length: 2
- Maximum subword unit length: 4
- Epochs: 5
- Context window: 5
- Number of negatives sampled: 5

8.3 Hyperparameter sensitivity analysis

Recall that, we restricted $\hat{V}_{source}$ and $\hat{V}_{target}$ to prevalence criteria that (1) $\hat{V}_{source}$ is restricted to $V_{source}^{0−5}$ (2) $\hat{V}_{target}$ contains words that have appeared at least 100 or more times in the corpus. In Table 6, we relax the prevalence criterion on $\hat{V}_{source}$ and observe that as we move towards more infrequent words, the translation performance degrades. The performance drop is more visible with $V_{source}^{10−100}$. Our annotators informed that poor quality of spelling and increased prevalence of contraction made the annotation task particularly challenging for rare words.

We next analyze the effect of the frequency threshold of 100 on $\hat{V}_{target}$. In order to reduce annotation burden, we only focused on the subset of words with perfect translation (i.e., p@1 performance 100%). When we relax the frequency threshold to 10, our p@1, p@5 and p@10 numbers are respectively, 0.38, 0.84, 0.91, respectively. Hence, although for 91% or the source words we found a translation within the top 10 translations, our p@1 performance took a considerable hit. Our annotators reported that with a lowered frequency threshold, the retrieved translations contained higher degree of misspellings. Our conclusion from this experiment is 100 is a reasonable threshold given the noisy nature of our corpora.

We conducted a similar analysis on our word translation tasks using European language pairs. As shown in Table 7 when English is the source language, our translation performance on frequent words is substantially better than rare words. However, when English is the target language, we did not observe any similar trend, the performance was roughly equal across the entire spectrum of words ranked by frequency. With Wikipedia corpus (not shown in the Table), we observed qualitatively similar trends.
8.4 Annotation

We used two annotators fluent in Hindi, Urdu and English. For word translations, consensus labels were used. For hope speech annotation, the minimum Fleiss’ $\kappa$ measure was high (0.88) indicating strong inter-rater agreement. After independent labeling, differences were resolved through discussion.

8.5 Extended examples of lexicons

Table 10 lists an extended bilingual lexicon containing 90 word pairs (30 from each corpus) obtained using our method. We will release the complete lexicon of 1,100 word pairs upon acceptance.

| D$_{hope}$ | D$_{election}$ | D$_{covid}$ |
|------------|----------------|------------|
| adalat | terror | treatment |
| bahaduri  | bravery | tarant | immediately | posta | shoe |
| musalmano | muslims | paarakar | journalist | kaalam | story |
| anak | blind | angrez | britashers | pakam | cold |
| naksan  | damage | berojgari | unemployment | saf | clean |
| tuula  | benefit | ummeed | expectation | batthon | hands |
| dino  | days | norki | jobs | backie | kids |
| haareo | trust | baike | development | musle | issues |
| tarakki | progress | gareels | poverty | mari | patient |
| gayab | vanish | shi | ryi | sankramit | infected |
| kyki | becz | bazar | market | hoshiyar | smart |
| jahannam | hell | masoom | innocent | khubsurat | beautifull |
| jilmi | sanghatan | organization | dange | riots |
| darr | fear | chhavi | image | bikhaki | absolutely |
| halat | condition | mahina | moomth | arakshan | reservation |
| intzaar | wait | qatal | murder | palan | obey |
| sipahi | soldier | hinsak | violent | maka | deal |
| peety | drinking | behot | very | sadaavya | member |
| gau cows | gahten | poors | achatnak | suddenly |
| jawab | answer | bhot | dhabba | dost | friend |
| alig separate | chokkidaar | watchman | hinsa | violence |
| pulse | first | shabed | word | behad | extremely |
| fark | difference | fela | spread | bukhar | fever |
| banana | make | peshba | urine | bikhali | discrimination |
| sahi | right | niyam | regulations | vakeel | lawyer |
| panah | shelter | monka | chance | taqat | strength |
| khan | eat | pahlen | lat | aurat | woman |
| sadak | road | bhaus | debate | unpudit | uneducated |
| shinakar | thanks | aker | fast | sakshic | everything |
| bhyan focus | gotala | scam | sanskrit | culture |

Table 10: A random sample of translated word pairs from our corpora.

8.6 Loanword

We now slightly abuse the definition of a loanword and consider a word is a loanword if it appears in a context of words written in a different language, and define a simple measure to quantify to what extent this occurs in a two-language setting. Let $c$ denote the context (single word left and right) of a word $w$. We first count the instances where the language labels of $c$ and $w$ agree, i.e., $L(w) = L(c)$ (e.g., help is not a loanword in the following phrase: please help us). Let this number be denoted as $N_{\text{not-borrowed}}$. Similarly, we count the instances when $c$ and $w$ have different language labels, i.e., $L(w) \neq L(c)$. This scenario would arise when a word is borrowed from a different language (e.g., help is a loanword in humein help chahiye). In our scheme, the Loan Word Index (LWI) of a word $w$ is defined as $LWI(w) = \frac{N_{\text{borrowed}}}{N_{\text{borrowed}} + N_{\text{not-borrowed}}}$. A high $LWI$ indicates substantial lexical borrowing of the word outside its language.

Since we use $\hat{L}_{\text{polyglot}}$ to estimate language labels, we indicate $LWI(.)$ as $\hat{LWI}(.)$. For a word pair $\langle w_{\text{source}}, w_{\text{target}} \rangle$, we define $LWI(.)$ as the maximum of their individual $LWIs$. For example, if the $LWI$ is high for the pair $\langle \text{help}, \text{madad} \rangle$, it indicates that at least one of these words was substantially borrowed. Our hypothesis is that successfully translated word pairs would have a high $LWI$ indicating at least one of the pair was used as a loanword facilitating translation. The average Loan Word Index of all successfully translated word pairs in our test data sets across all three corpora is 0.15. Compared to this, randomly generated word pairings have an average Loan Word Index of 0.09. We next performed a frequency preserving loan word exchange to modify the corpus where translated word pairs are interchanged to diminish the extent to which words are borrowed (e.g., phrases like humein help chahiye is rewritten as humein madad chahiye). Frequency is preserved by interchanging both words in a successfully translated word pair as many times as
the least borrowed word is borrowed. In our example if madad was borrowed 10 times, and help 15 times, we alter 10 instances where madad is borrowed with help, and 10 instances where help is borrowed with madad. We thus preserve word frequencies while diminishing the loanword phenomenon. We observed that the retrieval performance of our p@1 set dipped by 33\% after this corpus modification indicating that frequent borrowing of words possibly positively contributed to our method’s translation performance.

8.7 NN-sample

Algorithm\[2\] reproduces the NN-Sample (we refer to this as NN-Sampling in our paper) method as presented in [15]. The method takes a seed set of documents $S$ and a pool of documents $U$ as inputs, and outputs $E \subset U$, containing nearest neighbors of $S$ in the comment-embedding space. Initially, $E$ is an empty set and at each step, $E$ is expanded with nearest neighbors that are not present in the expanded set or the seed set. Consistent with [15], the parameter size is set to 5, and $U$ is set to $D_{\text{hope}}$.

8.8 Topical cohesion

We break topical cohesion by sampling en and es (de) from Europarl and Wikipedia respectively. Our results show that bilingual lexicons are still retrieved albeit with marginally lower performance. We conclude that topical cohesion possibly helps but may not be a prerequisite for retrieving a reasonably sized bilingual lexicon.

Table 11: Evaluating the importance of topical cohesion. Blue, red and gray denote Europarl, Wikipedia and a mixed corpus where English is sampled from Europarl and the other language (Spanish or German) is sampled from Wikipedia, respectively. Results indicate that lack of topical cohesion affects performance. However, in spite of reduced topical cohesion, our method still retrieves bilingual lexicons of reasonable size.

8.9 Translation retrieval task

We evaluated our approach on a task of translation retrieval. We followed the same experimental protocol described in [3]. We used 300K English sentences and 300K Italian sentences from the Europarl corpus to learn the bilingual lexicons using our constrained nearest neighbor sampling method. The translation retrieval task involves mapping 2k sentences from a source language to 2k in the target language out of a pool of 200K sentences in the target language. For a sentence in the source language, Method 2 uses the translateEmbeddings algorithm as described in Algorithm[1] and obtains an equivalent (noisy) embedding in the target language. Next, using the obtained embedding, it finds the nearest neighbor(s) in the 200K sentences in target language ranked by cosine distance in the ascending order. In
Table 12: Evaluating translation retrieval performance. We follow the evaluation task as presented in [3]. The translation task involves mapping 2K randomly sampled sentences in a source language to 200K sentences in the target language.

| Methods | en→it | it→en |
|---------|-------|-------|
| [4]     | 0.11  | 0.19  | 0.23 | 0.12 | 0.22 | 0.27 |
| [45]    | 0.45  | 0.72  | 0.81 | 0.49 | 0.71 | 0.78 |
| [2]     | 0.55  | 0.75  | 0.78 | 0.43 | 0.62 | 0.69 |
| [3]     | 0.66  | 0.80  | 0.83 | 0.69 | 0.80 | 0.83 |
| Method 1| 0.16  | 0.27  | 0.32 | 0.03 | 0.06 | 0.08 |
| Method 2| 0.12  | 0.22  | 0.30 | 0.03 | 0.06 | 0.08 |

Method 1, we perform a minor modification in translateEmbeddings. Recall that, in translateEmbeddings, for a given source word, the Algorithm first finds potential translations, and then prunes it to only include translations that include the source word when we translate back; from this pruned set, we randomly pick a target word. Unlike the previous task of detecting hope speech where we intended to retrieve a diverse pool of comments, in this task, we are more interested in finding the exact match of a source sentence in a target language. For this reason, instead of randomly sampling from the pruned list of target word choices for a source word, we always select the top choice.

Our performance is summarized in Table 12. Understandably, our methods are outperformed by existing sophisticated methods that perform explicit alignment. For en → it translation, we obtained slightly better performance than [4]. In contrast with [4], our method conducts no explicit attempt to align and does not require any seed lexicon ([4] requires a lexicon of 5,000 words).