

# Automatically Creating a Large Number of New Bilingual Dictionaries

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## Abstract

This paper proposes approaches to automatically create a large number of new bilingual dictionaries for low-resource languages, especially resource-poor and endangered languages, from a single input bilingual dictionary. Our algorithms produce translations of words in a source language to plentiful target languages using available Wordnets and a machine translator (MT). Since our approaches rely on just one input dictionary, available Wordnets and an MT, they are applicable to any bilingual dictionary as long as one of the two languages is English or has a Wordnet linked to the Princeton Wordnet. Starting with 5 available bilingual dictionaries, we create 48 new bilingual dictionaries. Of these, 30 pairs of languages are not supported by the popular MTs: Google<sup>1</sup> and Bing<sup>2</sup>.

## Introduction

Bilingual dictionaries play a major role in applications such as machine translation, information retrieval, cross lingual document, automatic disambiguation of word sense, computing similarities among documents and increasing translation accuracy (Knight and Luk 1994). Bilingual dictionaries are also useful to general readers, who may need help in translating documents in a given language to their native language or to a language in which they are familiar. Such dictionaries may also be important from an intelligence perspective, especially when they deal with smaller languages from sensitive areas of the world. Creating new bilingual dictionaries is also a purely intellectual and scholarly endeavor important to the humanities and other scholars.

The powerful online MTs developed by Google and Bing provide pairwise translations for 80 and 50 languages, respectively. These machines provide translators for single words and phrases also. In spite of so much information for some “privileged” language pairs, there are many languages for which we are lucky to find a single bilingual dictionary online or in print. For example, we can find an online

Karbi-English dictionary and an English-Vietnamese dictionary, but we can not find a Karbi-Vietnamese<sup>3</sup> dictionary.

The question we address in this paper is the following: Given a language, especially a resource-poor language, with only one available dictionary translating from that language to a resource-rich language, can we construct several good dictionaries translating from the original language to many other languages using publicly available resources such as bilingual dictionaries, MTs and Wordnets? We call a dictionary *good* if each entry in it is of high quality and we have the largest number of entries possible. We must note that these two objectives conflict: Frequently if an algorithm produces a large number of entries, there is a high probability that the entries are of low quality. Restating our goal, with only one input dictionary translating from a source language to a language which is a language with an available Wordnet linked to the Princeton Wordnet (PWN) (Fellbaum 1998), we create a number of good bilingual dictionaries from that source language to all other languages supported by an MT with different levels of accuracy and sophistication.

Our contribution in this work is our reliance on the existence of just one bilingual dictionary between a low-resource language and a resource-rich language, viz., *eng*. This strict constraint on the number of input bilingual dictionaries can be met by even many endangered languages. We consciously decided not to depend on additional bilingual dictionaries or external corpora because such languages usually do not have such resources. The simplicity of our algorithms along with low-resource requirements are our main strengths.

## Related work

Let  $A$ ,  $B$  and  $C$  be three distinct human languages. Given two input dictionaries  $Dict(A, B)$  consisting of entries  $(a_i, b_k)$  and  $Dict(B, C)$  containing entries  $(b_k, c_j)$ , a naïve method to create a new bilingual dictionary  $Dict(A, C)$  may use  $B$  as a pivot: If a word  $a_i$  is translated into a word  $b_k$ , and the word  $b_k$  is translated into a word  $c_j$ , this straightforward approach concludes that the word  $c_j$  is a translation of the word  $a_i$ , and adds the entry  $(a_i, c_j)$  into the dictionary  $Dict(A, C)$ . However, if the word  $b_k$  has more than one sense, being a

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<sup>1</sup><http://translate.google.com/>

<sup>2</sup><http://www.bing.com/translator>

<sup>3</sup>The ISO 639-3 codes of Arabic, Assamese, Dimasa, English, Karbi and Vietnamese are *arb*, *asm*, *dis*, *eng*, *ajz* and *vie*, respectively.

polysemous word, this method might make wrong conclusions. For example, if the word  $b_k$  has two distinct senses which are translated into words  $c_{j1}$  and  $c_{j2}$ , the straightforward method will conclude that the word  $a_i$  is translated into both the word  $c_{j1}$  and the word  $c_{j2}$ , which may be incorrect. This problem is called the ambiguous word sense problem. After obtaining an initial bilingual dictionary, past researchers have used several approaches to mitigate the effect of the ambiguity problem. All the methods used for word sense disambiguation use Wordnet distance between source and target words in some ways, in addition to looking at dictionary entries in forward and backward directions and computing the amount of overlap or match to obtain disambiguation scores (Tanaka and Umemura 1994), (Gollins and Sanderson 2001), (Bond et al. 2001), (Ahn and Framp-ton 2006), (Bond and Ogura 2008), (Mausam et al. 2010), (Lam and Kalita 2013) and (Shaw et al. 2013). The formulas used and the names used for the disambiguation scores by different authors are different. Researchers have also merged information from sources such as parallel corpora or comparable corpora (Nerima and Wehrli 2008), (Otero and Campos 2010) and a Wordnet (Istvan and Shoichi 2009). Some researchers have also extracted bilingual dictionaries from parallel corpora or comparable corpora using statistical methods (Brown 1997), (Haghighi et al. 2008), (Nakov and Ng 2009), (Heja 2010), (Ljubescic and Fiser 2011) and (Bouamor, Semmar, and Zweigenbaum 2013).

The primary similarity among these methods is that they work with languages that already possess several lexical resources or these approaches take advantage of related languages (that have some lexical resources) by using such languages as intermediary. The accuracies of bilingual dictionaries created from available dictionaries and Wordnets are usually high. However, it is expensive to create such original lexical resources and they do not always exist for many languages. For example, such resources do not exist for most major languages of India, some spoken by hundred of millions. The same holds for many other widely spoken languages from around the world. In addition, these methods can only generate one or just a few new bilingual dictionaries using published approaches.

In this paper, we propose methods for creating a significant number of bilingual dictionaries from a single available bilingual dictionary, which translates a source language to a resource-rich language with an available Wordnet. We use publicly available Wordnets in several resource-rich languages and a publicly available MT as well.

## Bilingual dictionary

An entry in a dictionary, called *LexicalEntry*, is a 2-tuple  $\langle \text{LexicalUnit}, \text{Definition} \rangle$ . A *LexicalUnit* is a word or phrase being defined, the so-called *definiendum* (Landau 1984). A list of entries sorted by the *LexicalUnit* is called a *lexicon* or a *dictionary*. Given a *LexicalUnit*, the *Definition* associated with it usually contains its class and pronunciation, its meaning, and possibly additional information. The meaning associated with it can have several *Senses*. A *Sense* is a discrete representation of a single aspect of the meaning of a

word. Entries in the dictionaries we create are of the form  $\langle \text{LexicalUnit}, \text{Sense}_1 \rangle, \langle \text{LexicalUnit}, \text{Sense}_2 \rangle, \dots$

## Proposed approaches

This section describes approaches to create new bilingual dictionaries  $\text{Dict}(S, D)$ , each of which translates a word in language  $S$  to a word or multiword expression in a destination language  $D$ . Our starting point is just one existing bilingual dictionary  $\text{Dict}(S, R)$ , where  $S$  is the source language and  $R$  is an “intermediate helper” language. We require that the language  $R$  has an available Wordnet linked to the PWN. We do not think this is a big imposition since the PWN and other Wordnets are freely available for research purposes.

### Direct translation approach (DT)

We first develop a direct translation method which we call the DT approach (see Algorithm 1). The DT approach uses transitivity to create new bilingual dictionaries from existing dictionaries and an MT. An existing dictionary  $\text{Dict}(S, R)$  contains alphabetically sorted *LexicalUnits* in a source language  $S$  and each has one or more *Senses* in the language  $R$ . We call such a sense  $\text{Sense}_R$ . To create a new bilingual dictionary  $\text{Dict}(S, D)$ , we simply take every pair  $\langle \text{LexicalUnit}, \text{Sense}_R \rangle$  in  $\text{Dict}(S, R)$  and translate  $\text{Sense}_R$  to  $D$  to generate translation candidates *candidateSet* (lines 2-4). When there is no translation of  $\text{Sense}_R$  in  $D$ , we skip that pair  $\langle \text{LexicalUnit}, \text{Sense}_R \rangle$ . Each candidate in *candidateSet* becomes a  $\text{Sense}_D$  in language  $D$  of that *LexicalUnit*. We add the new tuple  $\langle \text{LexicalUnit}, \text{Sense}_D \rangle$  to  $\text{Dict}(S, D)$  (lines 5-7).

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#### Algorithm 1 DT algorithm

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Input:  $\text{Dict}(S, R)$

Output:  $\text{Dict}(S, D)$

```

1:  $\text{Dict}(S, D) := \phi$ 
2: for all  $\text{LexicalEntry} \in \text{Dict}(S, R)$  do
3:   for all  $\text{Sense}_R \in \text{LexicalEntry}$  do
4:      $\text{candidateSet} = \text{translate}(\text{Sense}_R, D)$ 
5:     for all  $\text{candidate} \in \text{candidateSet}$  do
6:        $\text{Sense}_D = \text{candidate}$ 
7:       add tuple  $\langle \text{LexicalUnit}, \text{Sense}_D \rangle$  to  $\text{Dict}(S, D)$ 
8:     end for
9:   end for
10: end for
```

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An example of generating an entry for a  $\text{Dict}(\text{asm}, \text{vie})$  using the DT approach from an input  $\text{Dict}(\text{asm}, \text{eng})$  is presented in Figure 1.

### Using publicly available Wordnets as intermediate resources (IW)

To handle ambiguities in the dictionaries created, we propose the IW approach as in Figure 2 and Algorithm 2.

For each  $\text{Sense}_R$  in every given *LexicalEntry* from  $\text{Dict}(S, R)$ , we find all *Offset-POSS*<sup>4</sup> in the Wordnet of

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<sup>4</sup>Synset is a set of cognitive synonyms. *Offset-POS* refers to the

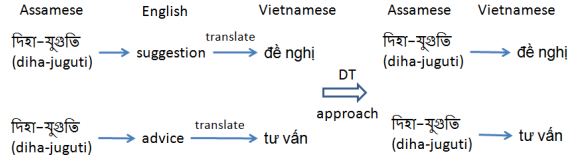


Figure 1: An example of DT approach for generating a new dictionary  $Dict(asm, eng)$ . In  $Dict(asm, eng)$ , the word “diha-juguti” in *asm* has two translations in *eng* “suggestion” and “advice”, which are translated to *vie* as “đề nghị” and “tư vấn”, respectively, using the Bing Translator. Therefore, in the new  $Dict(asm, vie)$ , the word “diha-juguti” has two translations in *vie* which are “đề nghị” and “tư vấn”.

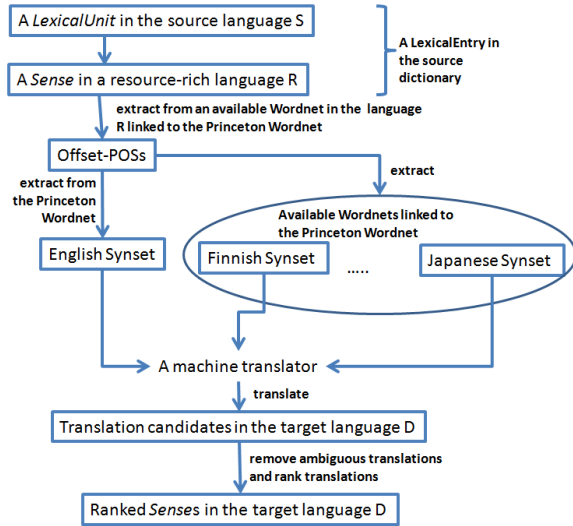


Figure 2: The IW approach for creating a new bilingual dictionary

the language  $R$  to which  $Sense_R$  belongs (Algorithm 2, lines 2-5). Then, we find a candidate set for translations from the *Offset-POSs* and the destination language  $D$  using Algorithm 3. For each *Offset-POS* from the extracted *Offset-POSs*, we obtain each *word* belonging to that *Offset-POS* from different Wordnets (Algorithm 3, lines 2-3) and translate it to  $D$  using a MT to generate translation candidates (Algorithm 3, line 4). We add translation candidates to the *candidateSet* (Algorithm 3, line 6). Each candidate in the *candidateSet* has 2 attributes: a translation of the word *word* in the target language  $D$ , the so-called *candidate.word* and the occurrence count or the rank value of the *candidate.word*, the so-called *candidate.rank*. A candidate with a greater rank value is more likely to become a correct translation. Candidates having the same ranks are treated similarly. Then, we sort all candidates in the *candidateSet* in descending order based on their rank values (Algorithm 2, line 7), and add them into the new dic-

offset for a synset with a particular POS, from the beginning of its data file. Words in a synset have the same sense.

tionary  $Dict(S, D)$  (Algorithm 2, lines 8-10). We can vary the Wordnets and the numbers of Wordnets used during experiments, producing different results.

### Algorithm 2 IW algorithm

Input:  $Dict(S, R)$

Output:  $Dict(S, D)$

```

1:  $Dict(S, D) := \phi$ 
2: for all  $LexicalEntry \in Dict(S, R)$  do
3:   for all  $Sense_R \in LexicalEntry$  do
4:      $candidateSet := \phi$ 
5:     Find all Offset-POSs of synsets containing  $Sense_R$ 
       from the  $R$  Wordnet
6:      $candidateSet = FindCandidateSet(Offset-POSs, D)$ 
7:     sort all candidate in descending order based on
       their rank values
8:     for all  $candidate \in candidateSet$  do
9:        $Sense_D = candidate.word$ 
10:      add tuple  $(LexicalUnit, Sense_D)$  to  $Dict(S, D)$ 
11:    end for
12:  end for
13: end for

```

### Algorithm 3 FindCandidateSet (*Offset-POSs*, $D$ )

Input: *Offset-POSs*,  $D$

Output: *candidateSet*

```

1:  $candidateSet := \phi$ 
2: for all  $Offset-POS \in Offset-POSs$  do
3:   for all word in the Offset-POS extracted from the
       PWN and other available Wordnets linked to the
       PWN do
4:      $candidate.word = translate(word, D)$ 
5:      $candidate.rank++$ 
6:      $candidateSet += candidate$ 
7:   end for
8: end for
9: return candidateSet

```

Figure 3 shows an example of creating entries for  $Dict(asm, arb)$  from  $Dict(asm, eng)$  using the IW approach.

## Experimental results

### Data sets used

Our approach is general, but to demonstrate the effectiveness and usefulness of our algorithms, we have carefully selected a few languages for experimentation. These languages include widely-spoken languages with limited computational resources such as *arb* and *vie*; a language spoken by tens of millions in a specific region within India, viz., *asm* with almost no resources; and a couple of languages in the UNESCO’s list of endangered languages, viz., *dis* and *ajz* both from northeast India, again with almost no resources at all.

We work with 5 existing bilingual dictionaries that translate a given language to a resource-rich language, which happens to be *eng* in our experiments:  $Dict(arb, eng)$



Dict.	Score	Entries	Dict.	Score	Entries
arb-deu	4.29	1,323	arb-spa	3.61	1,709
arb-vie	3.66	2,048	asm-arb	4.18	47,416
asm-spa	4.81	20,678	asm-vie	4.57	42,743
vie-arb	2.67	85,173	vie-spa	3.55	35,004

Table 1: The average score and the number of *LexicalEntries* in the dictionaries created using the DT approach.

Dict. we create		Wordnets used			
		A	B	C	D
arb-vie	Top 1	3.42	3.65	3.33	<b>3.71</b>
	Top 3	3.33	3.58	<b>3.76</b>	3.61
	Top 5	2.99	3.04	3.08	<b>3.31</b>
asm-arb	Top 1	4.51	3.83	<b>4.69</b>	4.67
	Top 3	4.03	3.75	3.80	<b>4.10</b>
	Top 5	3.78	3.85	3.42	<b>4.00</b>
asm-vie	Top 1	4.43	4.31	3.86	<b>4.43</b>
	Top 3	3.93	3.59	3.33	<b>3.94</b>
	Top 5	<b>3.74</b>	3.34	3.4	2.91
vie-arb	Top 1	3.11	2.94	2.78	<b>3.11</b>
	Top 3	2.47	2.72	2.61	<b>3.02</b>
	Top 5	2.54	2.37	2.60	<b>2.73</b>

Table 2: The average score of *LexicalEntries* in the dictionaries we create using the IW approach.

“better” input dictionaries, our results will be commensurately better.

The average scores and the numbers of *LexicalEntries* in the dictionaries created by the IW approach are presented in Table 2 and Table 3, respectively. In these tables, *Top n* means dictionaries created by picking only translations with the top *n* highest ranks for each word, A: dictionaries created using PWN only; B: using PWN and FWN; C: using PWN, FWN and JWN; D: using PWN, FWN, JWN and WWN. The method using all 4 Wordnets produces dictionaries with the highest scores and the highest number of *LexicalEntries* as well.

The number of *LexicalEntries* and the accuracies of the newly created dictionaries definitely depend on the sizes and qualities of the input dictionaries. Therefore, if the sizes and the accuracies of the dictionaries we create are comparable to those of the input dictionaries, we conclude that the new dictionaries are acceptable. Using four Wordnets as intermediate resources to create new bilingual dictionaries increases not only the accuracies but also the number of *LexicalEntries* in the dictionaries created. We also evaluate several bilingual dictionaries we create for a few of the language pairs. Table 4 presents the number of *LexicalEntries* and the average score of some of the bilingual dictionaries generated using the four Wordnets.

The dictionaries created from *arb* to other languages have low accuracies because our algorithms rely on the POS of the *LexicalUnits* to find the *Offset-POSs* and the input *Dict(arb,eng)* does not have POS. We were unable to access a better *Dict(arb,eng)* for free. For *LexicalEntries* without POS, our algorithms choose the best POS of the *eng* word.

Dict. we create		Wordnets used			
		A	B	C	D
arb	Top1	1,786	2,132	2,169	<b>2,200</b>
-	Top3	3,434	4,611	4,908	<b>5,110</b>
vie	Top5	4,123	5,926	6,529	<b>6,853</b>
asm	Top1	27,039	27,336	27,449	<b>27,468</b>
-	Top3	70,940	76,695	78,979	<b>79,585</b>
arb	Top5	104,732	118,261	125,087	<b>126,779</b>
asm	Top1	25,824	26,898	27,064	<b>27,129</b>
-	Top3	64,636	73,652	76,496	<b>77,341</b>
vie	Top5	92,863	111,977	120,090	<b>122,028</b>
vie	Top1	63,792	65,606	<b>66,040</b>	65,862
-	Top3	152,725	177,666	183,098	<b>185,221</b>
arb	Top5	210,220	261,392	278,117	<b>282,398</b>

Table 3: The number of *LexicalEntries* in the dictionaries we create using the IW approach.

Dict. we create	Top 1		Top 3	
	Score	Entries	Score	Entries
arb-deu	4.27	1,717	4.21	3,859
arb-spa	4.54	2,111	4.27	4,673
asm-spa	4.65	26,224	4.40	72,846
vie-spa	3.42	61,477	3.38	159,567

Table 4: The average score of entries and the number of *LexicalEntries* in some other bilingual dictionaries constructed using 4 Wordnets: PWN, FWN, JWN and WWN.

For instance, the word “book” has two POSs, viz., “verb” and “noun”, of which “noun” is more common. Hence, all translations to the word “book” in *Dict(arb,eng)* will have the same POS “noun”. As a result, all *LexicalEntries* translating to the word “book” will be treated as a noun, leading to many wrong translations.

Based on experiments, we conclude that using the four public Wordnets, viz., PWN, FWN, JWN and WWN as intermediate resources, we are able to create good bilingual dictionaries, considering the dual objective of high quality and a large number of entries. In other words, the IW approach using the four intermediate Wordnets is our best approach. We note that if we include only translations with the highest ranks, the resulting dictionaries have accuracies even better than the input dictionaries used. We are in the processes of finding volunteers to evaluate dictionaries translating from *ajz* and *dis* to other languages. Table 5 presents the number of entries of some of dictionaries, we created using the best approach, without human evaluation.

## Comparing with existing approaches

It is difficult to compare approaches because the language involved in different papers are different, the number and quality of input resources vary and the evaluation methods are not standard. However, for the sake of completeness, we make an attempt at comparing our results with (Istvan and Shoichi 2009). The precision of the best dictionary created by (Istvan and Shoichi 2009) is 79.15%. Although our score is not in terms of percentage, we obtain the average score

Dict.	Entries	Dict.	Entries
ajz-arb	4,345	ajz-cht	3,577
ajz-deu	3,856	ajz-mww	4,314
ajz-ind	4,086	ajz-kor	4,312
ajz-zlm	4,312	ajz-spa	3,923
ajz-tha	4,265	ajz-vie	4,344
asm-cht	67,544	asm-deu	71,789
asm-mww	79,381	asm-ind	71,512
asm-kor	79,926	asm-zlm	80,101
asm-tha	78,317	dis-arb	7,651
dis-cht	6,120	dis-deu	6,744
dis-mww	7,552	dis-ind	6,762
dis-kor	7,539	dis-zlm	7,606
dis-spa	6,817	dis-tha	7,348
dis-vie	7,652		

Table 5: The number of *LexicalEntries* in some other the dictionaries, we created using the best approach. *ajz* and *dis* are endangered.

of all dictionaries we created using 4 Wordnets and containing 3-top greatest ranks *LexicalEntries* is 3.87/5.00, with the highest score being 4.10/5.00 which means the entries are very good on average. If we look at the greatest ranks only (Top 1 ranks), the highest score is 4.69/5.00 which is almost excellent. We believe that we can apply these algorithms to create dictionaries where the source is any language, with a bilingual dictionary, to *eng*.

To handle ambiguities, the existing methods need at least two intermediate dictionaries translating from the source language to intermediate languages. For example, to create *Dict(asm,arb)*, (Gollins and Sanderson 2001) and (Mausam et al. 2010) need at least two dictionaries: *Dict(asm,eng)* and *Dict(asm,French)*. For *asm*, the second dictionary simply does not exist to the best of our knowledge. The IW approach requires only one input dictionary. This is a strength of our method, in the context of resources-poor language.

### Comparing with Google Translator

Our purpose of creating dictionaries is to use them for machine learning and machine translation. Therefore, we evaluate the dictionaries we create against a well-known high quality MT: the Google Translator. We do not compare our work against the Microsoft Translator because we use it as an input resource.

We randomly pick 300 *LexicalEntries* from each of our created dictionaries for language pairs supported by the Google Translator. Then, we compute the matching percentages between translations in our dictionaries and translations from the Google Translator. For example, in our created dictionary *Dict(vie,spa)*, “người quảng cáo” in *vie* translates to “anunciante” in *spa* which is as same as the translation given by the Google Translator. As the result, we mark the *LexicalEntry* (“người quảng cáo”, “anunciante”) as “matching”. The matching percentages of our dictionaries *Dict(arb,spa)*, *Dict(arb,vie)*, *Dict(arb,deu)*, *Dict(vie,deu)*, *Dict(vie,spa)* and the Google Translator are 55.56%, 39.16%, 58.17%, 25.71%, and 35.71%, respec-

Dict.	Source word	Meaning of the source word in eng	Our translation	Google Translator
vie-spa	nửa quý	semiprecious	semipreciosas	la mitad de ustedes
	lễ nh kền	bulky	voluminosos	grande Lenh
vie-deu	vừa ở cạn vừa ở nước	amphibians	amphibien	tanto en aguas poco profundas justo en
	trụ sở hội	institute	institut	Kongress-Zentrale
arb-vie	درب الثليقة	galaxy	thiên hà	Milky Way
	ريغا	Riga (the capital of Latvia)	thủ đô của Latvia	Riga
	حرفي	racism	phân biệt chủng tộc	Interracial

Table 6: Some *LexicalEntries* in dictionaries we created are correct but do not match with translations from the Google Translator. According to our evaluators, the translations from the Google Translator of the first four source words are bad.

tively.

The *LexicalEntries* marked as “unmatched” do not mean our translations are incorrect. Table 6 presents some *LexicalEntries* which are correct but are marked as “unmatched”.

### Crowdsourcing for evaluation

To achieve better evaluation, we intend to use crowdsourcing for evaluation. We are in the process of creating a Website where all dictionaries we create will be available, along with a user friendly interface to give feedback on individual entries. Our goal will be to use this feedback to improve the quality of the dictionaries.

### Conclusion

We present two approaches to create a large number of *good* bilingual dictionaries from only one input dictionary, publicly available Wordnets and a machine translator. In particular, we created 48 new bilingual dictionaries from 5 input bilingual dictionaries. We note that 30 dictionaries we created have not supported by any machine translation yet. We believe that our research will help increase significantly the number of resources for machine translators which do not have many existing resources or are not supported by machine translators. This includes languages such as *ajz*, *asm* and *dis*, and tens of similar languages. We use Wordnets as intermediate resources to create new bilingual dictionaries because these Wordnets are available online for unfettered use and they contain information that can be used to remove ambiguities.

### Acknowledgments

We would like to thank the volunteers evaluating the dictionaries we create: Dubari Borah, Francisco Torres Reyes, Conner Clark, and Tri Si Doan. We also thank all friends in the Microsoft, Xobdo and Panlex projects who provided us dictionaries.

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