Known Words Will Do: Unknown Concept Translation via Lexical Relations

Winston Wu
Computer Science and Engineering
University of Michigan
wuws@umich.edu

David Yarowsky
Center for Language and Speech Processing
Johns Hopkins University
yarowsky@jhu.edu

Abstract
Translating into low-resource languages is challenging due to the scarcity of training data. In this paper, we propose a probabilistic lexical translation method that bridges through lexical relations including synonyms, hypernyms, hyponyms, and co-hyponyms. This method, which only requires a dictionary like Wiktionary and a lexical database like WordNet, enables the translation of specialized terms into low-resource languages for which we may only know the translation of a related concept. Experiments on translating a core vocabulary set into 472 languages, most of them low-resource, show the effectiveness of our approach.

1 Introduction
When humans encounter lexical gaps in their speech, they may attempt to “talk around” it — a process known as circumlocution — or use another known, related word such as a synonym. Similarly, in machine translation (MT), one method for resolving out-of-vocabulary words (OOVs) involves replacing them with synonyms from the known lexicon. Synonym replacement is especially useful in a low-resource setting and has been recently investigated, for example in Vietnamese (Ngo et al., 2019) and Japanese (Tanaka and Baldwin, 2003). Some MT evaluation metrics also use synonyms as part of their computation (Banerjee and Lavie, 2005; Liu et al., 2010; He et al., 2010). Other applications of synonyms include improving robustness of MT systems (Cheng et al., 2018), finding translations in comparable corpora (Andrade et al., 2013), and improving information retrieval systems (Collier et al., 1998).

However, synonyms are not the only lexical relation through which translations can be found. For example, the concept of watermelon can be translated in Serbo-Croatian as бостан ‘melon’ (a hypernym) and in Italian as cocomero ‘cucumber’ (a co-hyponym). These lexical relations have not been adequately studied in the literature as sources for translation. Translation via lexical relations are usually studied in the context of constructing multilingual WordNets (Huang et al., 2002, 2005; Nien et al., 2009), where researchers translate the English WordNet in order to bootstrap the construction of a new WordNet in their target language. In contrast, our work investigates the acceptability of a word’s translation in a low-resource language based on lexically-related concepts across multiple languages. Our work is related to the idea of translation bridging (Tanaka and Umemura, 1994; Mann and Yarowsky, 2001; Schafer and Yarowsky, 2002), where a word in the source language is first translated into an intermediate bridge language, then translated into the target language. However, instead of bridging through a third language, we propose bridging through lexically-related words in the same language.

We specifically focus on four types of lexical semantic relations: synonymy, hypernymy, hyponymy, and co-hyponymy. Using the aggregation of these translations across hundreds of languages available in Wiktionary, we develop and analyze a probabilistic model of lexical relation bridging to enable the translation of unknown concepts using existing known words in the target language’s lexicon. Code and data for this paper are available at github.com/wswu/bridging-lexrel.

2 Translation Bridging via Lexical Relations
Suppose we wish to translate into a low-resource language a concept, such as hound, whose translation we do not know in said language. This is quite common in extremely low-resource scenar-
ios, where little to no bitext exists for training machine translation systems, nor is there even any monolingual text for applying unsupervised machine translation methods such as cross-lingual embeddings. This scenario is more common than one might imagine. The world has around 7,000 languages, but roughly 160 of them have readily available bitext or monolingual text, which might be acquired from the web using methods such as ParaCrawl (Bañón et al., 2020) or Common Crawl (Smith et al., 2013). Beyond this range, we enter the territory of low-resource languages, where the only significant source of text is likely to be the Bible, available for roughly 1,600 languages (McCarthy et al., 2020). Beyond this, the best one can hope for is a small bilingual dictionary perhaps manually constructed by a field linguist or a native informant.

What kind of translation is possible with no other bilingual resource but a small dictionary? In English, the word *hound* is usually used to indicate a hunting dog, so one might intuitively talk about their *dog* instead of their *hound*. Although *Dog* may not capture the full semantic nuances of *hound*, it at least conveys the notion that the word it replaces, *hound*, is a four-legged canine. Moreover, it is more likely that the word *dog* exists in any given dictionary than *hound*; *hound* is a more specialized word and thus ranks lower in terms of coreness (see Wu et al. (2020) for one definition of core vocabulary).

Thus we can replace a less core word with a more core word. The replacement word could be a hypernym, such as *dog* for *hound*,1 but could also be a synonym, hyponym, or even a co-hyponym. These four lexical relations are illustrated in the lexical relation graph in Figure 1, using the concept of *hound*.1 Synonyms share the same meaning. Hyperynms and hyponyms comprise the *isa* relation, where the hypernym is the supertype (e.g. *melon*) and the hyponym is the subtype (e.g. *watermelon*). Co-hyponyms are words that share the same hyponym. In order to obtain lexically-related words, we use WordNet 3.0 (Fellbaum, 2010), a freely-available lexical database of English words and their relations. Because these relationships are stored in WordNet at the synset level, rather than at the word level, a pair of words may be linked by more than one relation. For example, *dog* is both a synonym and a hypernym of *hound*.

To develop a model of translations of related

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1In WordNet, *hound* and *dog* are also synonyms. This is because *hound* and *dog* exist in multiple synsets.

2We distinguish between the semantic concept HOUND and the English word *hound*. The lexical relation graph constructed around concepts are valid in any language.
Table 2: Lexical relations extracted from Wiktionary.

| Relation      | Count | %  |
|---------------|-------|----|
| Synonym       | 962K  | 39 |
| Co-Hyponym    | 593K  | 23 |
| Hyponym       | 468K  | 19 |
| Hypernym      | 460K  | 19 |

Table 3: Words lexically related to watermelon, with their translations in various languages.

| Lang | Word | Relation | Related Word |
|------|------|----------|--------------|
| ara  | ﺑﻄﻴﺦ | hyper | melon |
| bul  | дия | hyper | melon |
| haw  | ipu | hyper | melon |
| hbs  | бостан | hyper | melon |
| isl  | vatsmelona | hyper | melon |
| ita  | cocomero | co-hypo | cucumber |
| mkd  | бостан | hyper | melon |
| mri  | merengi | hyper | melon |
| por  | melancia | hyper | melon |
| ron  | repene | co-hypo | cucumber |
| rup  | repene | hyper | melon |
| scn  | miluni | hyper | melon |
| tsn  | lekatane | hyper | melon |
| vie  | dуа háу | hyper | melon |

Table 3: Words lexically related to watermelon, with their translations in various languages.

| Lang | Word | Relation | Related Word |
|------|------|----------|--------------|
| bul  | грізач | syn | gnawer |
| dan  | gnaver | syn | gnawer |
| deu  | Nager  | syn | gnawer |
| fin  | jyrssjia | syn | gnawer |
| hbs  | glodar | syn | gnawer |
| hbs  | глодар | syn | gnawer |
| hil  | balabaw | hypo | mouse |
| hil  | balabaw | hypo | rat |
| msa  | tikus | hypo | mouse |
| msa  | tikus | hypo | rat |
| nld  | knaagdier | syn | gnawer |
| swe  | gnaagare | syn | gnawer |
| zho  | 鼠 | hypo | mouse |
| zho  | 鼠 | hypo | rat |

Table 4: Concepts lexically related to rodent, with their translations in various languages.

In total, this process learns translation distributions for over 42K concepts from 2.4 million relation pairs. As shown in Table 2, we find most of the relations are overwhelmingly synonyms, with the other three relations relatively close in scale. Some example lexical relations are shown for the words watermelon in Table 3 and rodent in Table 4.

3 Experiments

We evaluate our lexical relation translation bridging model on the task of generating translations from English into a foreign language. That is, in the \( e \rightarrow f \) direction, the model translates \( e \rightarrow e_{\text{rel}} \rightarrow f \), where \( p(e_{\text{rel}} \mid e) \) is learned via Wiktionary and WordNet, and \( e_{\text{rel}} \leftrightarrow f \) is a mapping that exists in Wiktionary. We evaluate our translation model on a test set of 1,000 concepts in the core vocabulary (Wu et al., 2020), a set of concepts ranked by their propensity to be included in any dictionary. We examine 472 languages with at least 100 word coverage over this test set. Furthermore, we provide in-depth analysis on for four diverse test languages: Bulgarian, Irish, Galician, and Maltese. These languages are all of different language families and are medium- to low-resource languages based on their number of entries in Wiktionary (recall we assume no other data is available besides what is in Wiktionary). Note that because these are low-resource languages, their dictionaries may not contain all 1,000 test concepts. Ultimately, we can only test on available existing ground truth.

Results on languages with over 100 word coverage of the core vocabulary are presented in Figure 3. Because our translation model provides a probability for each hypothesis, we report 1-best accuracy (is the top hypothesis in the gold translations?) and 10-best accuracy (are any of the top 10
hypotheticals in the gold translations?). In addition, we evaluate groups of languages by their coverage of the core vocabulary to test the effectiveness of lexical relation translations at various levels of language resourceness.

Figure 3 presents a high-level summary of this translation approach’s performance. We find that for 43 high resource languages (with over 900 word coverage of the core vocabulary), a 1-best accuracy of 36% and a 10-best accuracy of 64% shows that almost 2/3 of concepts can be translated using a lexically-related concept. For low-resource languages that cover at least 100 concepts of the core vocabulary, a respectable 1-best accuracy of 19% and a 10-best accuracy of 28% indicates that translation via lexical relations is still viable even when few known translations exist.

4 Analysis

To more deeply understand bridging through lexical relations, we analyze our translation approach in depth, focusing on four test languages, Bulgarian, Irish, Galician, and Maltese. Detailed results on these languages are shown in Table 5. We report 1-best, 10-best, and n-best accuracy (do any of the hypotheses appear in the gold translations?). Results on these languages follow from the overall results presented in Figure 3.

We first explain why one should consider other metrics besides 1-best accuracy. In a low-resource generating-into-a-vacuum scenario, producing good 1-best results is often not a necessity; 10-best or even 100-best hypothesis lists generated by any dictionary induction method can be filtered using a language model once target language data is acquired. Thus, n-best accuracy provides an upper bound on the performance of this approach. We find that our translation model can correctly identify translations of over a third of test concepts as words already in the target language’s translation dictionary. Considering the extremely impoverished size of low-resource languages’ dictionaries, this is quite impressive and useful for low-resource languages and tasks.

One strength of our approach is our use of WordNet as a universal lexical relation database. Our model is language agnostic and does not rely on WordNet in any specific target language. Rather, we assume the relations in WordNet to hold across languages. As future improvements and additions are made to the English WordNet as well as WordNets in other languages, they can be easily incorporated into our model to potentially improve the quality of our translations. At present, we find that the English WordNet only covers roughly half the concepts in our test set. Thus, we also report performance on the subset of test concepts that exist in WordNet in Table 6. In this test scenario, our model achieves 2x improved performance, because all test concepts are guaranteed to occur in WordNet.

We now examine some model predictions in detail. Table 7 shows predictions when translating into Irish. For example, when the Irish words for remedy (leigheas, neart, ioc) were held out,
| Concept | Gold | Hypotheses |
|---------|------|------------|
| single  | aonartha, aonta, singil, aonarach, aonaruil | (syn) unmarried → singil 0.357  
|         |      | (syn) one → aonta 0.310 |
| remedy  | leigheas, neart, íoc | (hyper) medicine → leigheas 0.363  
|         |      | (co) medicine → leigheas 0.363 |
|         |      | (syn) cure → leigheas 0.171 |
|         |      | (syn) cure → íoc 0.171 |
| marsh   | corcach, seascann, riasc, corrach, eanach | (hypo) antidote → leigheas 0.036  
|         |      | (co) swamp → eanach 0.480 |
|         |      | (co) swamp → corcach 0.480 |
|         |      | (syn) fen → eanach 0.085 |

Table 7: Translation hypotheses in Irish from lexical relations.

| Concept | Gold | Hypotheses |
|---------|------|------------|
| she-goat | коза, коза́ | (hyper) goat → коза́ 0.917  
| liberty | свобodá | (hyper) freedom → свобода́ 0.659 |
| cumin   | кимион | (co) caraway → кимион 0.667 |
| gradient | склон, градиент, наклон | (syn) slope → склон 0.353  
|         |      | (co) inclination → склон 0.216  
|         |      | (co) inclination → наклон 0.216 |
|         |      | (hypo) pitch → наклон 0.098 |
|         |      | (hypo) grade → наклон 0.078 |
|         |      | (hypo) rake → наклон 0.059 |

Table 8: Translation hypotheses in Bulgarian from lexical relations.

| Concept | Gold | Hypotheses |
|---------|------|------------|
| liberate | liberar, ceibar | (syn) free → liberar 0.427  
|         |      | (hyper) free → liberar 0.427 |
|         |      | (syn) release → liberar 0.152  
|         |      | (syn) release → ceibar 0.152 |
|         |      | (syn) loose → ceibar 0.026 |
| quarrel | rifar, cotifar | (co) open → ceibar 0.013  
|         |      | (hyper) argue → cotifar 0.093 |
| azure   | blao, azul | (co) open → ceibar 0.013 |
| claw    | garra, уña, cocoa, gadoupa | (co) open → ceibar 0.013 |
|         |      | (hypo) blue → azul 0.514 |
|         |      | (co) nail → уña 0.284 |
|         |      | (co) hoof → уña 0.123 |

Table 9: Translation hypotheses in Galician from lexical relations.

| Concept | Gold | Hypotheses |
|---------|------|------------|
| white   | bojod, bajda, abjad | (co) pale → abjad 0.101  
| stick   | hatar, bastun | (co) pale → abjad 0.101  
|         |      | (co) rod → hatar 0.089 |
|         |      | (hypo) staff → bastun 0.089 |
|         |      | (hypo) club → hatar 0.075 |
| deceive | lagħab, gidem, baram, qarraq | (co)Staff → а́бжад 0.101  
|         |      | (hypo) club → hatar 0.075 |
|         |      | (hypo) cheat → qarraq 0.283 |
|         |      | (hypo) cheat → lagħab 0.283 |

Table 10: Translation hypotheses in Maltese from lexical relations.
Table 11: Irish translations which were correctly predicted when training on all languages, but could not be correctly predicted when training on only related languages.

| Concept          | Gold          | Hypotheses               |
|------------------|---------------|--------------------------|
| die              | éag, faigh bás, básaigh, caill | (co) decay → éag 0.007 |
| moment           | nóiméad       | (syn) minute → nóiméad 0.087 |
| now              | anois, adrásta, anuas | (syn) at present → adrásta 0.150 |
| resin            | bí, roisin    | (syn) rosin → roisin 0.800 |
| empty            | fásach        | (co) desert → fásach 0.015 |
| penance          | aithrí        | (syn) penitence → aithrí 0.233 |
| accumulator      | bailitheoir   | (syn) collector → bailitheoir 0.750 |

the model was able to apply the lexical relations remed → {medicine, cure, antidote}, for which we have known translations, allowing the model to produce an appropriate translation of remedy’s hypernyms, hyponyms, co-hyponyms, and synonyms.

For Bulgarian (Table 8), we see similar model behavior. she-goat is a rather specific term, but since our model has learned that goat is the hypernym of she-goat and is an acceptable translation, and that goat already exists in the dictionary, the model correctly predicts θοσα, the translation of goat, as the translation for she-goat. Caraway translated as cumin is an interesting successful example. Although they are not the same herb, caraway and cumin are visually similar, and Bulgarian uses the same word for both: кимион (kimion). Indeed, caraway is also known as Persian cumin.

Galician (Table 9) also contains several examples of words with subtle meanings that can be expressed with a more general-purpose word. For example, liberate (liberar, ceibar) is adequately translated with free or release. To quarrel is essentially to argue, albeit in a heated manner, and azure is a specific shade of blue. These hypernym translations are successfully found by our model.

Finally, for Maltese (Table 10), the lowest-resourced language in the test set, we find that the translation with lexical relations approach provides the greatest benefits. For the word for stick (hatar, bastun), our model finds that other more specialized sticks (staff, rod, club) are also translated as stick. Similarly, deceive can be translated as cheat or betray, hyponyms of deceive.

In addition to these experiments, we also examined the effects of training on only languages in the same language family as the test language, versus training on the entire test set. We find that performance is worse when trained on all languages, for Bulgarian, Galician, and Maltese. Only for Irish did the performance increase. Table 11 shows some Irish examples in which the model trained on all languages was able to outperform the model trained on only Irish-related languages. Thus, we find that training on more languages on average reduces performance on the translation task. While the reasons for this finding require more investigation, we suspect that training on more languages introduces more noise. For example, in word compounding, often it is not the word itself, but rather the compounding recipe (a calque) that gets borrowed (Wu and Yarowsky, 2018). For example, the English brainwash comes from Chinese 洗脑 ‘wash+brain’, due to contact between different languages and cultures. In contrast, lexically related words are often language specific. Translating watermelon as cucumber is unusual and only occurs in Italian and Romanian; there is little reason to believe that any non-Romance language would share this translation. Indeed, other languages use compounds such as 西瓜 ‘west melon’ (in Chinese) or görögdinnye ‘Greek melon’ (in Hungarian), which is a compositional formation recipe, but not a robust one.

5 Conclusion

Using only the existing lexical resources Wiktionary and WordNet, we develop a probabilistic method for accurately predicting the translation of unknown words by bridging through lexically related hypernyms, hyponyms, co-hyponyms, and synonyms. This simple but effective method that identifies existing known words as valid translations does not require any neural model nor intensive training, and is especially well-suited for extremely low-resource languages for which little resources are available. Future work will augment our lexical resources with other WordNets and dictionaries, and apply our method to complement existing low-resource translation systems.
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