Introducing two Vietnamese Datasets for Evaluating Semantic Models of (Dis-)Similarity and Relatedness

Kim Anh Nguyen and Sabine Schulte im Walde and Ngoc Thang Vu
Institut für Maschinelle Sprachverarbeitung
Universität Stuttgart
Pfaffenwaldring 5B, 70569 Stuttgart, Germany
{nguyenkh,schulte,thangvu}@ims.uni-stuttgart.de

Abstract

We present two novel datasets for the low-resource language Vietnamese to assess models of semantic similarity: ViCon comprises pairs of synonyms and antonyms across word classes, thus offering data to distinguish between similarity and dissimilarity. ViSim-400 provides degrees of similarity across five semantic relations, as rated by human judges. The two datasets are verified through standard co-occurrence and neural network models, showing results comparable to the respective English datasets.

1 Introduction

Computational models that distinguish between semantic similarity and semantic relatedness (Budanitsky and Hirst, 2006) are important for many NLP applications, such as the automatic generation of dictionaries, thesauri, and ontologies (Biemann, 2005; Cimiano et al., 2005; Li et al., 2006), and machine translation (He et al., 2008; Martin et al., 2009). In order to evaluate these models, gold standard resources with word pairs have to be collected (typically across semantic relations such as synonymy, hypernymy, antonymy, co-hyponymy, meronymy, etc.) and annotated for their degree of similarity via human judgements.

The most prominent examples of gold standard similarity resources for English are the Rubenstein & Goodenough (RG) dataset (Rubenstein and Goodenough, 1965), the TOEFL test questions (Landauer and Dumais, 1997), WordSim-353 (Finkelstein et al., 2001), MEN (Bruni et al., 2001; Li et al., 2006), and SimLex-999 (Hill et al., 2015), and the lexical contrast datasets (henceforth Lex-Con), cf. Nguyen et al. (2016a).

2 Related Work

Over the years a number of datasets have been collected for studying and evaluating semantic similarity and semantic relatedness. For English, Rubenstein and Goodenough (1965) presented a small dataset (RG) of 65 noun pairs. For each pair, the degree of similarity in meaning was provided by 15 raters. The RG dataset is assumed to reflect similarity rather than relatedness. Finkelstein et al. (2001) created a set of 353 English noun-noun pairs (WordSim-353)2, where each pair was rated by 16 subjects according to the degree of semantic relatedness on a scale from 0 to 10. Bruni et al. (2012) introduced a large test collec-
tion called MEN\(^3\). Similar to WordSim-353, the authors refer to both similarity and relatedness when describing the MEN dataset, although the annotators were asked to rate the pairs according to relatedness. Unlike the construction of the RG and WordSim-353 datasets, each pair in the MEN dataset was only evaluated by one rater who ranked it for relatedness relative to 50 other pairs in the dataset. Recently, Hill et al. (2015) presented SimLex-999, a gold standard resource for the evaluation of semantic representations containing similarity ratings of word pairs across different part-of-speech categories and concreteness levels. The construction of SimLex-999 was motivated by two factors, (i) to consistently quantify similarity, as distinct from association, and apply it to various concept types, based on minimal intuitive instructions, and (ii) to have room for the improvement of state-of-the-art models which had reached or surpassed the human agreement ceiling on WordSim-353 and MEN, the most popular existing gold standards, as well as on RG. Scheible and Schulte im Walde (2014) presented a collection of semantically related word pairs for German and English,\(^4\) which was compiled via Amazon Mechanical Turk (AMT)\(^5\) human judgement experiments and comprises (i) a selection of targets across word classes balanced for semantic category, polysemy, and corpus frequency, (ii) a set of human-generated semantically related word pairs (synonyms, antonyms, hypernyms) based on the target units, and (iii) a subset of the generated word pairs rated for their relation strength, including positive and negative relation evidence.

For other languages, only a few gold standard sets with scored word pairs exist. Among others, Gurevych (2005) replicated Rubenstein and Goodenough’s experiments after translating the original 65 word pairs into German. In later work, Gurevych (2006) used the same experimental setup to increase the number of word pairs to 350. Leivant and Reichart (2015) translated two prominent evaluation sets, WordSim-353 (association) and SimLex-999 (similarity) from English to Italian, German and Russian, and collected the scores for each dataset from the respective native speakers via crowdflower.\(^6\)

\(^3\) clic.cimec.unitn.it/~elia.bruni/MEN
\(^4\) www.ims.uni-stuttgart.de/data/sem-rel-database/
\(^5\) www.mturk.com
\(^6\) www.crowdflower.com

3 Dataset Design

3.1 Criteria

Semantic similarity is a narrower concept than semantic relatedness and holds between lexical terms with similar meanings. Strong similarity is typically observed for the lexical relations of synonymy and co-hyponymy. For example, in Vietnamese “dội” (team) and “nhóm” (group) represents a synonym pair; “ô tô” (car) and “xe đạp” (bike) is a co-hyponym pair. More specifically, words in the pair “ô tô” (car) and “xe đạp” (bike) share several features such as physical (e.g. bánh xe / wheels) and functional (e.g. vận tải / transport), so that the two Vietnamese words are interchangeable regarding the kinds of transportation. The concept of semantic relatedness is broader and holds for relations such as meronymy, antonymy, functional association, and other “non-classical relations” (Morris and Hirst, 2004). For example, “ô tô” (car) and “xăng dầu” (petrol) represent a meronym pair. In contrast to similarity, this meronym pair expresses a clearly functional relationship; the words are strongly associated with each other but not similar.

Empirical studies have shown that the predictions of distributional models as well as humans are strongly related to the part-of-speech (POS) category of the learned concepts. Among others, Gentner (2006) showed that verb concepts are harder to learn by children than noun concepts.

Distinguishing antonymy from synonymy is one of the most difficult challenges. While antonymy represents words which are strongly associated but highly dissimilar to each other, synonymy refers to words that are highly similar in meaning. However, antonyms and synonyms often occur in similar context, as they are interchangeable in their substitution.

3.2 Resource for Concept Choice: Vietnamese Computational Lexicon

The Vietnamese Computational Lexicon (VCL)\(^7\) (Nguyen et al., 2006) is a common linguistic database which is freely and easily exploitable for automatic processing of the Vietnamese language. VCL contains 35,000 words corresponding to 41,700 concepts, accompanied by morphological, syntactic and semantic information. The morphological information consists of 8 morphemes.

\(^7\) https://vlsp.hpda.vn/demo/?page=vcl
including simple word, compound word, reductive word, multi-word expression, loan word, abbreviation, bound morpheme, and symbol. For example, “hánh” (table) is a simple word with definition “đổ thường làm bằng gỗ, có mất phía và chân đỗ . . .” (pieces of wood, flat and supported by one or more legs . . .). The syntactic information describes part-of-speech, collocations, and subcategorisation frames. The semantic information includes two types of constraints: logical and semantic. The logical constraint provides category meaning, synonyms and antonyms. The semantic constraint provides argument information and semantic roles. For example, “yêu” (love) is a verb with category meaning “emotion” and antonym “ghét” (hate).

VCL is the largest linguistic database of its kind for Vietnamese, and it encodes various types of morphological, syntactic and semantic information, so it presents a suitable starting point for the choice of lexical units for our purpose.

3.3 Choice of Concepts

3.3.1 Concepts in ViCon

The choice of related pairs in this dataset was drawn from VCL in the following way. We extracted all antonym and synonym pairs according to the three part-of-speech categories: noun, verb and adjective. We then randomly selected 600 adjective pairs (300 antonymous pairs and 300 synonymous pairs), 400 noun pairs (200 antonymous pairs and 200 synonymous pairs), and 400 verb pairs (200 antonymous pairs and 200 synonymous pairs). In each part-of-speech category, we balanced the size of morphological classes in VCL, for both antonymous and synonymous pairs.

3.3.2 Concepts in ViSim-400

The choice of related pairs in this dataset was drawn from both the VLC and the Vietnamese WordNet8 (VWN), cf. Nguyen et al. (2016b). We extracted all pairs of the three part-of-speech categories: noun, verb and adjective, according to five semantic relations: synonymy, antonymy, hypernymy, co-hyponymy, and meronymy. We then sampled 400 pairs for the ViSim-400 dataset, accounting for 200 noun pairs, 150 verb pairs and 50 adjective pairs. Regarding noun pairs, we balanced the size of pairs in terms of six relations: the five extracted relations from VCL and VWN, and an “unrelated” relation. For verb pairs, we balanced the number of pairs according to five relations: synonymy, antonymy, hypernymy, co-hyponymy, and unrelated. For adjective pairs, we balanced the size of pairs for three relations: synonymy, antonymy, and unrelated. In order to select the unrelated pairs for each part-of-speech category, we paired the unrelated words from the selected related pairs at random. From these random pairs, we excluded those pairs that appeared in VCL and VWN. Furthermore, we also balanced the number of selected pairs according to the sizes of the morphological classes and the lexical categories.

3.4 Annotation of ViSim-400

For rating ViSim-400, 200 raters who were native Vietnamese speakers were paid to rate the degrees of similarity for all 400 pairs. Each rater was asked to rate 30 pairs on a 0–6 scale; and each pair was rated by 15 raters. Unlike other datasets which performed the annotation via Amazon Mechanical Turk, each rater for ViSim-400 conducted the annotation via a survey which detailed the exact annotation guidelines.

The structure of the questionnaire was motivated by the SimLex-999 dataset: we outlined the notion of similarity via the well-understood idea of the six relations included in the ViSim-400 dataset. Immediately after the guidelines of the questionnaire, a checkpoint question was posed to the participants to test whether the person understood the guidelines: the participant was asked to pick the most similar word pair from three given word pairs, such as kiêu_căng/kiêu_ngạo (arrogant/cocky) vs. trầm/bông (high/low) vs. côleđiển/biểng (classical/lazy). The annotators then labeled the kind of relation and scored the degree of similarity for each word pair in the survey.

3.5 Agreement in ViSim-400

We analysed the ratings of the ViSim-400 annotators with two different inter-annotator agreement (IAA) measures, Krippendorff’s alpha coefficient (Krippendorff, 2004), and the average standard deviation (STD) of all pairs across word classes. The first IAA measure, IAA-pairwise, computes the average pairwise Spearman’s ρ correlation between any two raters. This IAA measure has been a common choice in previous data collections in distributional semantics (Padó et al., 2007; Reisinger and Mooney, 2010; Hill et al., 2015).
Table 1: Inter-annotator agreements measured by Spearman’s $\rho$, Krippendorff’s $\alpha$, and the average standard deviation (STD) of all pairs across word classes.

|                  | All  | Noun | Verb | Adjective |
|------------------|------|------|------|-----------|
| IAA-Mean $\rho$  | 0.86 | 0.86 | 0.86 | 0.78      |
| IAA-Pairwise $\rho$ | 0.79 | 0.76 | 0.78 | 0.75      |
| Krippendorff’s $\alpha$ | 0.78 | 0.76 | 0.78 | 0.86      |
| STD              | 0.87 | 0.87 | 0.90 | 0.82      |

The second IAA measure, IAA-mean, compares the average correlation of the human raters with the average of all other raters. This measure would smooth individual annotator effects, and serve as a more appropriate “upper bound” for the performance of automatic systems than IAA-pairwise (Vulić et al., 2017). Finally, Krippendorff’s $\alpha$ coefficient reflects the disagreement of annotators rather than their agreement, in addition to correcting for agreement by chance.

Table 1 shows the inter-annotator agreement values, Krippendorff’s $\alpha$ coefficient, and the response consistency measured by STD over all pairs and different word classes in ViSim-400. The overall IAA-pairwise of ViSim-400 is $\rho = 0.79$, comparing favourably with the agreement on the SimLex-999 dataset ($\rho = 0.67$ using the same IAA-pairwise measure). Regarding IAA-mean, ViSim-400 also achieves an overall agreement of $\rho = 0.86$, which is similar to the agreement in Vulić et al. (2017), $\rho = 0.86$. For Krippendorff’s $\alpha$ coefficient, the value achieves $\alpha = 0.78$, also reflecting the reliability of the annotated dataset.

Furthermore, the box plots in Figure 1 present the distributions of all rated pairs in terms of the fine-grained semantic relations across word classes. They reveal that –across word classes– synonym pairs are clearly rated as the most similar words. Hypernymy, co-hyponymy and holonymy are in between, but rather similar than dissimilar.

4 Verification of Datasets

In this section, we verify our novel datasets ViCon and ViSim-400 through standard and neural co-occurrence models, in order to show that we obtain a similar behaviour as for the corresponding English datasets.

4.1 Verification of ViSim-400

We adopt a comparison of neural models on SimLex-999 as suggested by Nguyen et al. (2016a). They applied three models, a Skip-gram model with negative sampling SGNS (Mikolov et al., 2013), the dLCE model (Nguyen et al., 2016a), and the mLCM model (Pham et al., 2015). Both the dLCE and the mLCM models integrated lexical contrast information into the basic Skip-gram model to train word embeddings for distinguishing antonyms from synonyms, and for reflecting degrees of similarity.

The three models were trained with 300 dimensions, a window size of 5 words, and 10 negative samples. Regarding the corpora, we relied on Vietnamese corpora with a total of ≈145 million tokens, including the Vietnamese Wikipedia,9 VNESCocorpus and VNTQcorpus,10 and the Leipzig Corpora Collection for Vietnamese11 (Goldhahn et al., 2012). For word segmentation and POS tagging, we used the open-source toolkit UETnlp12 (Nguyen and Le, 2016). The antonym and synonym pairs to train the

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9https://dumps.wikimedia.org/viwiki/latest/
10http://viet.jnlp.org/download-du-lieu-tu-vung-corpus
11http://wortschatz.uni-leipzig.de/en/download
12https://github.com/phongnt570/UEtnlp
dLCE and mLCM models were extracted from VWN consisting of 49,458 antonymous pairs and 338,714 synonymous pairs. All pairs which appeared in ViSim-400 were excluded from this set.

Table 2 shows Spearman’s correlations $\rho$, comparing the scores of the three models with the human judgements for ViSim-400. As also reported for English, the dLCE model produces the best performance, SGNS the worst.

| Model    | Noun Score | Verb Score | Adj Score |
|----------|------------|------------|-----------|
| SGNS     | 0.66       | 0.63       | 0.70      |
| mLCM     | 0.81       | 0.92       | 0.96      |
| dLCE     | 0.92*      | 0.95       | 0.98      |

Table 3: AUC scores for distinguishing antonyms from synonyms in ViSim-400.  

### 4.2 Verification of ViCon

In order to verify ViCon, we applied three co-occurrence models to rank antonymous and synonymous word pairs according to their cosine similarities: two standard co-occurrence models based on positive point-wise mutual information (PPMI) and positive local mutual information (PLMI) (Evert, 2005) as well as an improved feature value representation weight$^{SA}$ as suggested by Nguyen et al. (2016a). For building the vector space co-occurrence models, we relied on the same Vietnamese corpora as in the previous section. For inducing the word vector representations via weight$^{SA}$, we made use of the antonymous and synonymous pairs in VWN, as in the previous section, and then removed all pairs which appeared in ViSim-400. Optionally, we applied singular value decomposition (SVD) to reduce the dimensionalities of the word vector representations.

As in Nguyen et al. (2016a), we computed the cosine similarities between all word pairs, and then sorted the pairs according to their cosine scores. Average Precision (AP) evaluated the three vector space models. Table 4 presents the results of the three vector space models with and without SVD. As for English, the results on the Vietnamese dataset demonstrate significant improvements ($\chi^2 < .001$) of weight$^{SA}$ over PPMI and PLMI, both with and without SVD, and across word classes.

| Metric | Noun Score | Verb Score |
|--------|------------|------------|
| PPMI   | 0.70       | 0.38       |
| PLMI   | 0.59       | 0.44       |

Table 4: AP evaluation of co-occurrence models on ViCon in comparison to LexCon (Nguyen et al., 2016a).
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