SemR-11: A Multi-Lingual Gold-Standard for Semantic Similarity and Relatedness for Eleven Languages

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Abstract
This work describes SemR-11, a multi-lingual dataset for evaluating semantic similarity and relatedness for 11 languages (German, French, Russian, Italian, Dutch, Chinese, Portuguese, Swedish, Spanish, Arabic and Persian). Semantic similarity and relatedness gold standards have been initially used to support the evaluation of semantic distance measures in the context of linguistic and knowledge resources and distributional semantic models. SemR-11 builds upon the English gold-standards of Miller & Charles (MC), Rubenstein & Goodenough (RG), WordSimilarity 353 (WS-353), and Simlex-999, providing a canonical translation for them. The final dataset consists of 15,917 word pairs and can be used to support the construction and evaluation of semantic similarity/relatedness and distributional semantic models. As a case study, the SemR-11 test collections was used to investigate how different distributional semantic models built from corpora in different languages and with different sizes perform in computing semantic relatedness similarity and relatedness tasks.

Keywords: Gold standard, Semantic Similarity, Semantic Relatedness, Multi-linguality, Word-embeddings

1. Motivation
The ability to automatically determine and quantify the degree of semantic similarity and semantic relatedness between pairs of words or expressions is one of the archetypal tasks for assessing the ability of a system to perform semantic interpretation. The ability to quantify semantic relatedness can provide a lightweight semantic interpretation operation which can be applied in different areas of Artificial Intelligence, Natural Language Processing and Information Retrieval. Examples of applications include coping with lexical and semantic gaps in Question Answering Systems (Freitas, 2015) [Freitas and Curry, 2014], using the semantic relatedness score as a ranking function in Information Retrieval systems (Freitas et al., 2012) and serving as a semantic scoping mechanism in deductive/abductive methods (Freitas et al., 2014).

Due to its simplicity in comparison to other tasks such as Question Answering, Text Entailment and Machine Translation, semantic similarity and relatedness gold standards have been initially used to support the evaluation of the interaction between semantic distance measures and of linguistic and knowledge resources [Resnik, 1995] [Lin, 1991] [Wu and Palmer, 1994] [Agirre et al., 2009]. As the conditions to process large-scale corpora emerged, distributional semantic models automatically built from textual corpora were created (Turney and Pantel, 2010a) using, in most cases, a vector space representation of meaning. As distributional semantic models can induce modes with a more comprehensive underlying vocabulary and also capture a broader set of semantic relations, new gold-standards emerged (Finkelstein et al., 2001), evolving from capturing semantic similarity to semantic relatedness behavior. More recently, the creation of neural/predictive word embedding models (Mikolov et al., 2013) [Pennington et al., 2014] pushed semantic similarity and relatedness gold-standards to evolve in the direction of quantifying more fine-grained semantic relations (Hill et al., 2013).

Currently, most of the existing gold-standards for evaluating semantic similarity and relatedness have focused on the English language, with some initiatives providing initial gold-standards for few other languages (Faruqui and Dyer, 2014). This paper describes SemR-11, a multi-lingual gold-standard which aims at generalizing existing semantic similarity and relatedness gold-standards to 11 languages (German, French, Russian, Italian, Dutch, Chinese, Portuguese, Swedish, Spanish, Arabic and Persian). The resource is built using a principled translation method over four reference gold-standards: Miller & Charles (Miller and Charles, 1991), Rubenstein & Goodenough (Rubenstein and Goodenough, 1965), WS-353 (Finkelstein et al., 2001) and Simlex-999 (Leviant and Reichart, 2015). The final resource contains in total 15,917 word pairs.

The resource aims to contribute to research in the following directions:

- Supporting the development of linguistic resources and distributional semantic models for non-English languages.
- Providing a comparative framework for analyzing the impact of language structural features and types (e.g. analytic, isolating and synthetic languages) in the development of semantic relatedness models.
• Evaluating the use of machine translation to support semantic similarity and relatedness (Freitas et al., 2016).

• Creating semantic similarity and relatedness models which work on languages not having a high-volume supporting corpora.

This paper is organized as follows: Section 2 describes the state-of-the-art in existing gold-standards for semantic similarity and relatedness computations as well as their language variants; Section 3 describes the English gold-standards which were used as a reference for the machine translation process; Section 4 describes the SemR-11 gold-standard and its creation process.

2. Related Work

Camacho-Collados et al. (2017) developed a multi-lingual gold-standard which includes 518 word pairs for five languages (English, German, Italian, Spanish and Persian). It is composed of nominal pairs of multi-word expressions, domain-specific terms and named entities that are manually scored between 0 to 4 where 0 indicates that they are completely dissimilar and 4 denotes that the two words are synonymous. This dataset focuses on semantic similarity.

Bruni et al. (2014) introduced a test collection containing 3000 word pairs. The MEN dataset obtained by crowdsourcing using Amazon Mechanical Turk via the CrowdFlower interface. The dataset focuses on semantic relatedness pairs on the English language (similarly to the WS-353 dataset (Finkelstein et al., 2001)). They developed it, specifically to test multimodal models. Compared to WS-353, MEN is sufficiently large, and the human judgments are relative rather than absolute. At (Bruni et al., 2014), each rater chose the word pair that was more similar out of two random pairs of words. They used this technique to have a comparative judgment rather than absolute scores for single pairs, which was used in the WS-353.

Agirre et al. (2009) split the WS-353 into two test collections (WS-Sim and WS-Rel) containing 203 and 252 word pairs on the English language, respectively. WS-Sim focuses on only measuring similarity, and the other one on only relatedness.

3. Reference Gold-standards

SemR-11 consists of the translation of four semantic similarity and relatedness gold-standards: Miller & Charles (MC) (Miller and Charles, 1991), Rubenstein & Goodenough (RG) (Rubenstein and Goodenough, 1965), Wordsimilarity 353 (WS-353) (Finkelstein et al., 2001) and Simlex-999 (Leviant and Reichart, 2015). These four datasets were selected for being consensus gold-standards for the evaluation of semantic similarity and relatedness models.

The problem of measuring the semantic similarity and relatedness of two concepts can be stated as follows: given two concepts A and B, determine a numerical measure f(A, B) which expresses the semantic similarity or relatedness between concepts A and B. The notion of semantic similarity is associated with taxonomic (is-a) relations, while semantic relatedness represents more general relations. Car and train are examples of similar concepts (both share a common taxonomic ancestor, vehicle) while car and wheel are related concepts (a wheel is part of a car).

As a consequence, semantic similarity is considered a particular case of semantic relatedness. Alternatively semantic similarity can also be defined as two concepts sharing a high number of salient features (attributes): synonymy (car/automobile), hyperonymy (car/vehicle), co-hyponymy (car/van/truck), while semantic relatedness can be defined as two words semantically associated without being necessarily similar: function (car/drive), meronymy (car/tyre), location (car/road), attribute (car/fast) (Freitas, 2015).

The gold standards are described below:

• Wordsimilarity 353: WS-353 (Finkelstein et al., 2001) is certainly the most popular evaluation gold standard for distributional semantic models. The dataset is focused on semantic relatedness. The dataset contains two subsets: set 1 (153 word pairs, evaluated by 13 subjects), and set 2 (200 word pairs evaluated by 16 subjects) each one containing pairs from different parts-of-speech, a proper noun and pairs involving subjective bias.

• Rubenstein & Goodenough: RG (Rubenstein and Goodenough, 1965) contains 65 pairs which are often used to evaluate Distributional Semantic Models. RG reflects similarity of words rather than their relatedness. It is build by rating of 15 annotators to score the semantic similarity of each pair.

• Miller & Charles: MC (Miller and Charles, 1991) is a subset of 30 noun pairs from the RG gold standard which are re-annotated following new similarity guidelines. Ten pairs were selected from the highest level (between 3 and 4 on a scale from 0 to 4), ten pairs from the intermediate level (between 1 and 3), and ten pairs from the lowest level (0 to 1) of semantic similarity.

• SIMLEX-999: Simlex-999 (Hill et al., 2016) Leviant and Reichart, 2015) is aimed to measure how well Distributional Semantic Models capture similarity, rather than relatedness. Simlex-999 contains a range of 111 adjective, 666 noun and 222 verb pairs with an independent rating for each pair. It was built by using 500 annotators via Amazon Mechanical Turk.

4. SemR-11

The process of creating SemR-11 (Table 3) consisted in the translation of the three gold-standards WS-353, MC,
| Language | Parameters | MC | RG | WS-353 | SIMLEX-999 |
|----------|------------|----|-----|---------|-------------|
| German   | # of Tokens | 40 | 52  | 431     | 1094        |
|          | Vocabulary Size | 40 | 52  | 431     | 1094        |
| French   | # of Tokens | 37 | 45  | 430     | 1106        |
|          | Vocabulary Size | 37 | 43  | 424     | 1097        |
| Russian  | # of Tokens | 38 | 48  | 435     |             |
|          | Vocabulary Size | 36 | 46  | 426     |             |
| Italian  | # of Tokens | 34 | 43  | 426     | 1051        |
|          | Vocabulary Size | 34 | 43  | 424     | 1051        |
| Dutch    | # of Tokens | 37 | 45  | 426     | 1025        |
|          | Vocabulary Size | 37 | 45  | 426     | 1018        |
| Chinese  | # of Tokens | 37 | 51  | 471     |             |
|          | Vocabulary Size | 37 | 51  | 471     |             |
| Portuguese | # of Tokens | 37 | 46  | 434     | 1149        |
|          | Vocabulary Size | 37 | 46  | 434     | 1141        |
| Swedish  | # of Tokens | 35 | 44  | 430     | 1002        |
|          | Vocabulary Size | 35 | 44  | 430     | 995         |
| Spanish  | # of Tokens | 35 | 44  | 430     | 993         |
|          | Vocabulary Size | 35 | 44  | 437     | 991         |
| Arabic   | # of Tokens | 38 | 54  | 448     |             |
|          | Vocabulary Size | 36 | 49  | 448     |             |
| Persian  | # of Tokens | 34 | 43  | 456     |             |
|          | Vocabulary Size | 34 | 43  | 436     |             |

Table 2: The vocabulary and token distribution for each language of four gold-standards

| Language | SemR-11 | SE17 |
|----------|---------|------|
|          | MC     | RG   | WS 353 | Simlex 999 | T2 |
| German   | ✓      | ✓    | ✓      | ✓          | ✓  |
| French   | ✓      | ✓    | ✓      | ✓          | ✓  |
| Russian  | ✓      | ✓    | ✓      | ✓          | ✓  |
| Italian  | ✓      | ✓    | ✓      | ✓          | ✓  |
| Dutch    | ✓      | ✓    | ✓      | ✓          | ✓  |
| Chinese  | ✓      | ✓    | ✓      | ✓          | ✓  |
| Portuguese | ✓    | ✓    | ✓      | ✓          | ✓  |
| Swedish  | ✓      | ✓    | ✓      | ✓          | ✓  |
| Spanish  | ✓      | ✓    | ✓      | ✓          | ✓  |
| Arabic   | ✓      | ✓    | ✓      | ✓          | ✓  |
| Persian  | ✓      | ✓    | ✓      | ✓          | ✓  |

Table 3: SemR-11 and its relation to existing multi-lingual gold standards.

| Language | English       | Portuguese   |
|----------|---------------|--------------|
|          | hard;difficult;9.69 | difícil;difícil;10 |
|          | apparent;obvious;9.08 | visível;obvio;9.15 |
|          | disease;infection;7.08 | doença;infeção;4.46 |

Table 4: Comparison between English and Portuguese gold standards.

The word pairs were translated by paid professional translators skilled in data localisation tasks.

All translated pairs followed the protocol below:

1. Given a pair of words, translators should assume the most similar senses associated with the pair.
2. Translators should preserve the lexical category of the sense identified for that word.

In the end, 15,917 word pairs were translated to 11 languages. Table 2 quantifies the vocabulary and token distribution for each language. The datasets are available on the Web.

The SemR-11 gold-standard assumes that the translations are preserving the similarity and relatedness scores of their original English human annotation. The target task was described to the human translators, who had access to the word pairs and scores.

3SemEval-2017 Task 2
4Lionbridge Natural Language Solutions
5https://github.com/Lambda-3/Gold-Standards/tree/master/SemR-11
Table 6: Examples with all the languages for each of four datasets

| Language | English | German | French | Russian | Italian | Dutch | Chinese | Portuguese | Swedish | Spanish | Arabic | Persian |
|----------|---------|--------|--------|---------|---------|-------|---------|------------|---------|---------|--------|---------|
| Word-pairs | food;rooster | nahrung;hahn | nourriture;coq | еда;птица | cibo;galo | voedsel;haan | 食物;公鸡 | comida;galo | mat;upp | comida;galo | طعام;ديك | غذا|خورش |
|             | monk;oracle | mönch;orakel | moine;oracle | МОНАХ;ОРАКУЛ | monaco;oracolo | monnik;orakel | 僧侣;甲骨文 | monge;oráculo | munk;orakel | garderob;kläder | راهب;بلايس | راهب;بلايس |
|             | Wandschrank;Kleidung | cabinet;vêtements | Rigistigma;vestiti | СТЕННЫЙ ШКАФ;ОДЕЖДА | ripostigio;vestiti | kast;kleren | 衣服;衣服 | armario;ropa | kläder;förråd | armario;ropa | - | - |
|             | clothes;closet | clothes;closet | cabinet;vêtements | плак;плак | vestiti;armadio | kleding;kast | - | ropa;armario | - | - | - | - |
|             | Simlex-999 | Simlex-999 | Simlex-999 | Simlex-999 | Simlex-999 | Simlex-999 | Simlex-999 | Simlex-999 | Simlex-999 | Simlex-999 | Simlex-999 | Simlex-999 |

Tables 4 and 5 show examples of translated pairs of Simlex-999 test collection (with the associated average similarity score) into Portuguese and French languages, respectively, while Table 6 provides example of word-pairs for each language and dataset.

5. Use Case

Distributional Semantic Models (DSM) are consolidating themselves as fundamental components for supporting automatic semantic interpretation in different application scenarios in natural language processing. From question answering systems, to semantic search and text entailment, distributional semantic models support a scalable approach for representing the meaning of words, which can automatically capture comprehensive associative commonsense information by analysing word-context patterns in large-scale corpora in an unsupervised or semi-supervised fashion (Freitas, 2015; Turney and Pantel, 2010b; Sales et al., 2016).

The SemR-11 test collection was used by Freitas et al. (2016), Sales et al. (2018) and Barzegar et al. (2018) to evaluate how different distributional semantic models built from corpora in different languages and with different sizes, perform in computing semantic relatedness similarity and relatedness tasks. Additionally, SemR-11 was used to analyze the role of machine translation approaches to support the construction of high-quality distributional vectors and computing semantic similarity & relatedness measures for other languages.

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