A Compositional-Distributional Semantic Model for Searching Complex Entity Categories

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Abstract

Users combine attributes and types to describe and classify entities into categories. These categories are fundamental for organising knowledge in a decentralised way acting as tags and predicates. When searching for entities, categories frequently describe the search query. Considering that users do not know in which terms the categories are expressed, they might query the same concept by a paraphrase. While some categories are composed of simple expressions (e.g. Presidents of Ireland), others have more complex compositional patterns (e.g. French Senators Of The Second Empire). This work proposes a hybrid semantic model based on syntactic analysis, distributional semantics and named entity recognition to recognise paraphrases of entity categories. Our results show that the proposed model outperformed the comparative baseline, in terms of recall and mean reciprocal rank, thus being suitable for addressing the vocabulary gap between user queries and entity categories.

1 Introduction

A significant part of search queries on the web target entities (e.g. people, places or events) (Pound et al., 2010). In this context, users frequently use the characteristics of the target entity to describe the search query. For example, to find Barack Obama, it is reasonable that a user types the query Current President of United States.

The combination of attributes and types of an entity in a grammatically correct fashion defines an entity category, which groups a set of entities that share common characteristics. Examples of entity categories are French Female Artistic Gymnasts, Presidents of Ireland and French Senators Of The Second Empire. Considering that users do not know in which terms the categories are expressed, they might query the same concept by a paraphrase, i.e. using synonyms and different syntactic structures.

The flexibility and richness of natural language allow describing Brazilian aerospace conglomerate both as Brazilian Planemaker or as Aircraft manufacturers of Brazil.

In addition to their occurrence in texts, entity categories are also available in the form of structured data. The Yago project (Suchanek et al., 2007) shares unary properties associating hundreds of thousands of descriptive categories manually created by the Wikipedia community to DBpedia entities (Auer et al., 2007). Thus, a mechanism to recognise paraphrases can make a shortcut between a natural language expression and a set of entities. Table 1 shows a list of entity categories and associated paraphrases.

This paper focuses on the recognition of paraphrases of entity categories, which is designed as an information retrieval task. To
deal with this problem, we propose an approach which combines syntactic analysis, distributional semantics and named entity recognition. To support reproducibility and comparability, we provide the test collection and the source code related to this work at [http://bit.ly/cat-test-collection](http://bit.ly/cat-test-collection) and [http://bit.ly/linse-code](http://bit.ly/linse-code).

### 2 Understanding the Structure of an Entity Category

An entity category names and classifies a set of entities. It is composed of a central concept, called core, and its specialisations. For example, the entity category 2008 Film Festivals embraces festivals, which defines the category’s core. More specifically, this category covers those festivals that are related to films and occurred in 2008. In its turn, Populated Coastal Places in South Africa embraces places (the core) that are populated, in the coast (coastal) and within South Africa. While festivals and places act as cores, all other terms work as specialisations, defining characteristics such as temporality (specialisations of time), localization (specialisations of place) and other general characteristics. These three types of terms are respectively classified as temporal named entity, spatial named entity, and general specialisation.

By analysing a large set of entity categories generated in a decentralised setting, Freitas et al. (2014) described them according to a group of recurring features: contains verbs, contains temporal references, contains named entities, contains conjunctions, contains disjunctions and contains operators. These features suggest a syntactic pattern that can be described as a combination of simple relations based on the lexical categories of their constituent terms (Freitas et al., 2014). In this manner, we apply a list of parsing rules to determine the graph structure/hierarchy according to Table 2, which defines the core-oriented segmentation model.

During the parsing process, categories are analysed from left to right. Once a pattern is identified, the core-side attribute specifies the side where the core is located. Both parts are then recursively analysed, where the opposite part is treated as specialisation(s). The order of the rules determines their precedence. To simplify the rule list, some tags are normalised, e.g. POS-tag TO is converted to IN and NNPS is converted to NNP. When no pattern is identified, the last term in the resulting chunk is admitted as the core and all others as specialisations, if any.

Figure 1 shows the graph generated by the core-oriented segmentation method for the entity category Populated Coastal Places in South Africa. The graph root (places) represents the core.

| POS Pattern  | Core-side |
|--------------|-----------|
| [VB, IN]     | left      |
| [NN, VBG]    | left      |
| [IN]         | left      |
| [“”]         | left      |
| [POS]        | right     |
| [CC]         | left      |

Table 2: Rules to construct the graph of an entity category.

| POS Pattern  | Core-side |
|--------------|-----------|
| [VB, IN]     | left      |
| [NN, VBG]    | left      |
| [IN]         | left      |
| [“”]         | left      |
| [POS]        | right     |
| [CC]         | left      |

Table 1: Examples of paraphrases.
3 Semantic Approximation & Compositionality

From a finite set of words, it is possible to express unlimited utterances and ideas. This property is credited to the principle of semantic compositionality (Baroni et al., 2014a).

Distributional semantics is based on the hypothesis that words co-occurring in similar contexts tend to have similar meaning (Harris, 1954; Turney and Pantel, 2010). Distributional semantics supports the automatic construction of semantic models from large-scale unstructured corpora, using vector space models to represent the meaning of a word. The process to construct distributional models ranges from statistical methods to models based on machine learning (Dumais et al., 1988; Mikolov et al., 2013; Jeffrey Pennington, 2014).

Distributional semantics allows measuring the semantic compositionality by combining an appropriate word representation and a suitable method to semantically compose them. Its meaning representation supports the construction of more comprehensive semantic models which have semantic approximation at its centre. We compute the semantic similarity and relatedness between two terms using vector operations in the vector space.

4 Compositional-Distributional Model

This work proposes a hybrid model that combines the core-oriented segmentation model with semantic approximation based on distributional semantics to provide a semantic search approach for entity categories. This approach segments the entity categories and stores their constituent parts according to their type in a graph-based data model.

The graph data model has a signature \( \Sigma = (C, Z, R, S, E) \), where \( C, Z, R \) and \( S \) represent the sets of cores, general specialisations, temporal specialisations and spatial specialisations respectively. \( E \) contains sets of edges, where each set represents a graph. The elements in \( C \) and \( Z \) are natural language terms indexed in distributional semantics spaces. The elements in \( R \) are closed integer intervals representing the temporal expressions in years. The elements in \( S \) are sets of equivalent terms referring to a geographic place and its demonyms. The proposed graph data model is inspired by the \( \tau \)-Space (Freitas et al., 2011), which represents graph knowledge in a distributional space.

Distributional semantics spaces represent terms by distributional vectors. The distributional vectors are generated from a large external corpus to capture the semantic relation in a broader scenario. It allows that even when dealing with a small dataset, the semantic representation is not limited to that context. The distributional space allows searching by measuring the geometric distances or vector angles between the query term and the indexed terms.

Temporal and spatial specialisations do not use the same representation strategy. In the case of spatial named entities, our tests have shown poor performance when using general-purpose distributional semantics models to compare them. The problem resides in the fact that places and demonyms have a high relatedness with common nouns. For example, in one distributional model\(^1\), American has a higher relatedness with war than with Texas. To avoid this kind of misinterpretation, spatial expressions are compared using their names, acronyms, and demonyms.

Because of the numerical and ordered nature of temporal references, temporal specialisations are represented as year intervals. By this representation, two expressions of time are compared by computing the interval intersection. We consider them as semantically related if the intersection is not empty.

4.1 Constructing the Knowledge Representation Model

The first step is to build the data model based on the target set of entity categories. For each entity category in the set, the segmentation model presented in Section 2 generates a graph representation \( G = (V, E) \). The set of vertices \( V \) is the union of the core term \( \bar{c} \), the set of general specialisations (\( Z' \)), the set of temporal specialisations (\( R' \)) and the set of spatial specialisations (\( S' \)), i.e.

\[
V = \{\bar{c}\} \cup Z' \cup R' \cup S'.
\]

Any of these three sets of specialisations can eventually be empty. The process of building the data space from a target set of entity categories \( T \) is described in Algorithm 1.

In line 6, the category \( \bar{c} \) is decomposed by the core-oriented segmentation model. Each term is indexed in their respective index according to their type: the core \( \bar{c} \) in the core space \( C \) and the specialisations in the general specialisation space \( Z' \).

\(^1\)Distributional models used in the context of this work are presented in Section 5.
temporal space ($R$) and spatial space ($S$).

Spatial specialisations are identified by the longest string matching method comparing against a dictionary which contains the name, acronym and demonym of places. Temporal expressions are converted to an interval of years. Terms that are considered neither spatial nor temporal specialisations fall into the general specialisation case.

Navigating over the graph structure, the query (line 4). Considering the graph structure, the query feeds a sub-query in the distributional core space. The alignment is defined by computing the cosine between the query core and the target cores that makes them semantically relevant. In the context of this work, $\eta$ is defined dynamically according to the result set. Let $X$ be the descending-order set of returned cosine scores, $\eta = x_{n} | x_{n} \in X, x_{n+1} \in X, x_{n}/2 > x_{n+1}$. The distributional search returns a set of pairs ($k, h$) where $k$ is a core term and $h$ is the normalised $\text{cosine}(k, c)$. Entity categories containing relevant cores are select for the next search step (lines 6, 7).

The next step deals with the specialisations. Spatial and temporal named entities found in the query are searched in their respective sub-sets, identifying equivalent spatial representations (lines 11-13) and comparing the time intervals (lines 14-20). Temporal expressions out-of-range are penalised by a negative score (line 20). The pairing of general specialisations (lines 22-24) follows the same principle of the core search. When there are two or more general specialisations, the method $\text{maximiseMatching}$ aims to avoid that two terms from one side match to the same term on the other side, selecting the pairs that maximise the final score.

The final score is determined by the composition of all scores proportionally to the number of terms in the categories according to the expressions in the lines 26-29.

In the example of Figure 2, 2008 Movie Celebrations is the query which is segmented in celebration (core), movie (general specialisation) and 2008 (temporal interval). The core term celebrations feeds a sub-query in the distributional core space. The alignment is defined by computing a distributional semantic relatedness function between celebrations and all cores in the core space and by filtering out all the elements which are below the semantic relatedness threshold $\eta$.

Navigating over the graph structure, the query submitted to their respective specific index (representation space).

To illustrate visually, Figure 2 depicts a diagram where the entity categories 2000s Film Festivals and Populated Coastal Places in South Africa are represented within the model. The cores festivals and places are stored in the core distributional space (C: geometric representation). The first category has two specialisations: the time interval 2000-2009, indexed in the temporal space (R: interval representation); and film, indexed in the general specialisation space (Z: also geometric representation). Next, the second category has three specialisations: the spatial named entity South Africa, indexed in the spatial index (S: expanded index); and the general specialisations coastal and populated, indexed in (Z). Dashed lines connecting the cores to their specialisations represent the flattened edges of the graphs, i.e. all specialisations are connected directly to their respective core.

4.2 Searching as Semantic Interpretation

Algorithm 2 describes the interpretation process that receives the query and the graph data model $\Sigma$ as inputs. Queries are paraphrases that follow the same syntactic pattern of entity categories. The process starts by generating the graph of the input query (line 4). Considering the graph structure, each vertex becomes a sub-query to be submitted to their respective specific index (representation space).

The core defines the first sub-query. It needs to be semantically aligned to relevant cores in $\Sigma$. In line 5, $\text{distSearch}(\vec{c}, C)$ searches for cores semantically related to the query core $\vec{c}$. In addition to the simple searching of terms and synonyms, the vector cosine defines how related $\vec{c}$ is to the cores present in $C$. Given a threshold $\eta$, distributional search returns $K = \{(k, h) | k \in C, h = \text{cosine}(k, \vec{c}), h > \eta\}$. The semantic relatedness threshold $\eta$ determines the minimum distance or angle between the query core and the target cores that makes them semantically relevant.

Algorithm 1 Construction

1: input : $T$ : target set of entity categories. 
2: output : $\Sigma$ : a filled graph data model. 
3: 4: $C \leftarrow \emptyset, Z \leftarrow \emptyset, R \leftarrow \emptyset, S \leftarrow \emptyset, E \leftarrow \emptyset$ 
5: for $t \in T$ do 
6: $\vec{c}, Z', R', S', E' \leftarrow \text{graphOf}(t)$ 
7: $C \leftarrow C \cup \{\vec{c}\}$ 
8: $Z \leftarrow Z \cup Z'$ 
9: $R \leftarrow R \cup R'$ 
10: $S \leftarrow S \cup S'$ 
11: $E \leftarrow E \cup \{\text{flat}(E')\}$ 
12: return $\Sigma$
Distributional and Named Entity Spaces
place demonym
South Africa South African
... ...
Spatial SpaceTemporal Space
... ...
DSM
C
R
Z
S
celebrations
movie
α
QUERY: 2008 Movie Celebrations
2008
5 Evaluation
The evaluation focuses on comparing the compositional-distributional model to baseline approaches and assessing the performance of different distributional semantic models in combination with our representation model. The evaluation scenarios are designed to measure the individual contribution of each component.

5.1 Setup
The evaluation has three comparative baselines:
**Bag-of-words search:** Target entity categories are indexed in a state-of-the-art information retrieval system treating each category as a separate document. Additionally, the document is enriched by synonyms obtained from WorNet (Miller, 1995). Lucene\(^5\) 4.10.1 is the information retrieval system used in the experiment.

**Pure core-oriented segmentation:** The core-oriented segmentation model incorporated by this work is applied in an isolated fashion, i.e. without the distributional component but making use of simple string matching, WordNet expansion and temporal and spatial named entity indices.

**Sum-algebraic-based method:** Entity categories are compared by an algebraic operation that sums up component vectors using the resulting vectors to calculate the cosine similarity. This method results in many scenarios, one for each distributional model.

Five different models are analysed in this work: **Latent Semantic Analysis** (Dumais et al., 1988): LSA is a distributional semantic space that extracts statistical relations between words in narrow context windows. It is characterised for executing a costly operation to reduce the space dimensionality.

**Random Indexing (RI)** (Sahlgren, 2005): Random Indexing was proposed to avoid the dimensional reduction. It dynamically accumulates context vectors based on the occurrence of words in contexts to generate the semantic space.

**Explicit Semantic Analysis** (Gabrilovich and Markovitch, 2007): ESA uses entire documents as contexts. It was created under the assumption of concept hypothesis\(^6\) which states that a portion of information such as an article or document is associated with a particular concept, and the space model could take advantage of this information.

**Continuous Skip-gram Model** (W2V) (Mikolov et al., 2013): Skip-gram is a vector space model created by deep learning techniques focused on lo-

\(^5\)http://lucene.apache.org/

\(^6\)Studies contest the existence of this hypothesis (Gottron et al., 2011).
Algorithm 2: Semantic Interpretation Process

1: input: query and $\Sigma = (C, Z, R, S, E)$
2: output: $Z$ : related categories and their score.
3:
4: $\tilde{c}, \tilde{Z}, \tilde{R}, \tilde{S}, \tilde{E} \leftarrow \text{graphOf}(\text{query})$
5: $U \leftarrow \text{distSearch}(\tilde{c}, C)$
6: for $(\tilde{k}, h) \in K$ do
7:     $D \leftarrow \text{selectGraphsByCore}(\tilde{k}, E)$
8:     for all $D' \in D$ do
9:         $\tilde{k}, \tilde{Z}', \tilde{R}', \tilde{S}', \tilde{E}' \leftarrow D'$
10:     $a \leftarrow 0$
11:     for $s \in S'$ do
12:         if $\exists s \in S' | s \equiv s$ then
13:             $a \leftarrow a + 1$
14:     $b \leftarrow 0$
15:     for $r \in R'$ do
16:         if $\exists r \in R' | r \equiv r$ then
17:             $b \leftarrow b + 1$
18:         else
19:             if $R' \neq \emptyset$ then
20:                 $b \leftarrow b - 0.5$
21:     $X \leftarrow \emptyset$
22:     for $\tilde{o} \in O'$ do
23:         $J \leftarrow \text{distSearch}(\tilde{o}, O')$
24:         $X.append(J)$
25:     $Y \leftarrow \text{maximiseMatching}(X)$
26:     $n^q \leftarrow |E^q|$
27:     $n^c \leftarrow |E^c| + 1$
28:     $u \leftarrow h + a + b + \left(\sum_{x=1}^{n} y_x \cdot y_x \in Y\right)$
29:     $U.append(D', u)$
30: return sort($U$)

5.2 Test Collection

The test collection is composed of a knowledge base of more than 350,000 entity categories obtained from the complete set of Wikipedia 2014 categories, but removing those containing non-ASCII characters. Each category has between one to three paraphrases.

The creation of the queries was guided by seed target categories. The use of seed entity categories was deliberately decided to ensure the presence of one paraphrase equivalence for each query.

Queries were generated by asking a group of English-speaking volunteers to paraphrase the subset of 105 categories. They were instructed to describe the same meaning using different words and, if possible, different syntactic structures. After that, we applied a curation process conducted by two researchers to validate the paraphrase’s equivalence intuitively. In the end, we admitted a set of 233 paraphrased pairs.

To create various degrees of difficulty in the topics, we balanced the test collection with categories varying in size (two to ten terms), in the occurrence of places and demonyms references, in the presence of temporal expressions and, in the occurrence of noun phrase components (verbs, adjectives, adverbs).

Test collection files are available at http://bit.ly/cat-test-collection.

5.3 Results and Discussion

We evaluate our approach in three scenarios. The first considers the TOP-10 list of each execution. The second considers the TOP-20 list and the third the TOP-50.

For each query in the test collection, we calculate the recall and mean reciprocal ranking, together with their aggregate measures (Table 3). Figure 3 provides a visual representation of the recall scores. In the experiment, we assumed that only one category corresponded to the correct answer. This assumption makes precision a redundant indicator since it can be derived from recall ($\text{precision} = \text{recall}/\text{range}|\text{range} \in \{10, 20, 50\}$).

The evaluation shows that distributional semantic models address part of the semantic matching tasks since distributional approaches outperform simple stemming string search and WordNet-
| Approaches                          | Recall   |          |          | MRR      |          |          |
|------------------------------------|----------|----------|----------|----------|----------|----------|
|                                    | Top 10   | Top 20   | Top 50   | Top 10   | Top 20   | Top 50   |
| Lucene                             | 0.0904   | 0.1040   | 0.1357   | 0.0410   | 0.0420   | 0.0429   |
| Core-Oriented Segmentation         | 0.0985   | 0.1126   | 0.1361   | 0.0613   | 0.0623   | 0.0630   |
| Sum-algebraic-based method         | -        | -        | -        | -        | -        | -        |
| with LSA                           | 0.1126   | 0.1621   | 0.2117   | 0.0595   | 0.0631   | 0.0645   |
| with RI                            | 0.0630   | 0.0945   | 0.1216   | 0.0348   | 0.0371   | 0.0379   |
| with ESA                           | 0.0540   | 0.0900   | 0.1486   | 0.0271   | 0.0296   | 0.0312   |
| with W2V                           | 0.2657   | 0.3333   | 0.3963   | 0.1356   | 0.1403   | 0.1422   |
| with GloVe                         | 0.2702   | 0.3558   | 0.4324   | 0.1417   | 0.1476   | 0.1501   |
| Our proposed method                | -        | -        | -        | -        | -        | -        |
| with LSA                           | 0.3545   | 0.4000   | 0.4590   | 0.1981   | 0.2013   | 0.2033   |
| with RI                            | 0.3073   | 0.3743   | 0.4078   | 0.1768   | 0.1813   | 0.1823   |
| with ESA                           | 0.2818   | 0.3182   | 0.4000   | 0.1822   | 0.1846   | 0.1872   |
| with W2V                           | **0.3727** | **0.4364** | **0.4909** | **0.2448** | **0.2491** | **0.2510** |
| with GloVe                         | **0.3727** | **0.4090** | **0.4500** | **0.2274** | **0.2300** | **0.2314** |

Table 3: Results for recall and mean reciprocal rank (MRR).

Based query expansion. By applying either sum-algebraic-based method and our proposed method, most of the distributional models present significant performance improvement in comparison to non-distributional methods. It is also important to stress that Word2Vec and GloVe consistently deliver better results for the test collection. Apart the controversies about predictive-based and count-based distributional models (Baroni et al., 2014b; Lebret and Collobert, 2015; Levy and Goldberg, 2014), in the context of this work, these results suggest that predictive-based distributional models outperform count-based methods (despite the proximity of LSA results).

Regarding the compositional method, the results of the core-oriented strategy combined with the named entity recognition exceeded all results delivered by the sum-algebraic-based method when comparing the same distributional model. The performance increases not only in the recall, which represents more entity categories retrieved but also in the mean reciprocal rank, reflecting that the target categories are better positioned in the list. Our proposed method succeed in almost 50% of the test collection when considered the Top-50 scenario.

Sales et al. (2015) shows a prototype demonstration of this work.

### 5.4 Analysing Unsuccessful Cases

The most significant limitation is the restriction of comparing words one-by-one, assuming that each word in a paraphrase is semantically equivalent to only one word in the target categories and vice-versa. For example, the pair (Swedish Metallurgists, Metal Workers from Sweden) is ranked at #1173 when using W2V. It occurs because metallurgists and workers have low relatedness (0.0031). Comparing the relatedness of metallurgists to metal workers would have a higher score.

Concerning named entities, we observed three relevant issues. Our approach uses a simple longest string matching method to identify places. Categories containing terms such as Turkey are always considered a spatial named entity. In the pair (American Turkey Breeds and Chicken Breeds Originating in the US) the terms turkey and chicken would not be semantically compared, since Turkey is always considered a spatial named entity. Secondly, when searching for Water Parks in the USA, all parks at Texas, Tennessee or Pennsylvania are also relevant for the user. Our model does not contain this hierarchical information to provide a geographic match. Finally, expressions such as WWI and USSR should be identified as the paraphrasing of World War I and the Soviet Union or even other variations, what is not available in our model.

### 6 Related Work

Balog and Neumayer (2012) propose the hierarchical target type identification problem which aims to identify the most specific type grounded in a given ontology that covers all entities sought...
by a query. Yao et al. (2013) propose an entity type prediction considering the universal schema. In this work, a predictor is expected to label a given entity with types. This schema is composed of all types from diverse available ontologies. To identify types from texts, they compose named entity recognition with dependency parsing. These works focus on identifying the ontological types that are sought by the query.

Regarding entity similarity, Moreau et al. (2008) propose a method to calculate entity similarity based on Soft-TFIDF. Liu and Birnbaum (2007) propose a method based on the Open Directory Project (ODP) to capture category names in all pages where the named entity appears to generate a vector space. Liu et al. (2008) describe a method that uses the set of URLs in which entities are present to measure similarity. The difference to these works is that they focus on comparing named entities, not based on their description, but based on non-linguistic attributes.

Other related topics are paraphrasing and text entailment. Androutsopoulos and Malakasiotis (2010) present an extension overview of datasets and approaches applied in these fields. Papers in this context deal with the paraphrasing of complete sentences (formed of subject and predicate) which cannot benefit from the core-oriented segmentation model. The different format of their target datasets inhibits a direct comparison, while their lack of association with entities does not create the required bridge between unstructured and structured data.

This work distinguishes mainly from existing approaches by proposing a novel compositional method grounded in syntactic analysis to combine distributional vectors and by using distributional semantics models generated from external resources. The target knowledge base (the dataset of categories) is not part of the data used to produce the distributional models. This isolation supports a more comprehensive semantic matching.

7 Conclusion

This work proposes a compositional-distributional model to recognise paraphrases of entity categories. Distributional semantics in combination with the proposed compositional model supports a search strategy with robust semantic approximation capabilities, largely outperforming string and WordNet-based approaches in recall and mean reciprocal rank. The proposed compositional strategy also outperforms the traditional vector-sum method.

This work also provides additional evidence to reinforce (i) the suitability of distributional models to cross the semantic gap (Freitas et al., 2012; Aletras and Stevenson, 2015; Agirre et al., 2009; Freitas et al., 2015) and (ii) suggest that prediction methods generate better semantic vectors when compared to count-based approaches. Considering the controversies about the comparisons between predictive-based and count-based distributional models (Baroni et al., 2014b; Lebret and Collobert, 2015; Levy and Goldberg, 2014), this evidence is restricted to the distributional models involved in the experiment and cannot be generalised. In the context of our work, we conjecture that the better performance is credited to the fact that our problem comprises much more paradigm-
matic than syntagmatic relations. Additionally, the use of distributional semantic models provides a better base for transporting the solution to multi-lingual scenarios, since it does not depend on manually constructed resources. Future work will focus on the investigation of specialised named entity distributional methods in the context of the semantic search problem.

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