Linked Open Data and Web Corpus Data for noun compound bracketing

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Abstract
This research provides a comparison of a linked open data resource (DBpedia) and web corpus data resources (Google Web Ngrams and Google Books Ngrams) for noun compound bracketing. Large corpus statistical analysis has often been used for noun compound bracketing, and our goal is to introduce a linked open data (LOD) resource for such task. We show its particularities and its performance on the task. Results obtained on resources tested individually are promising, showing a potential for DBpedia to be included in future hybrid systems.

Keywords: noun compound bracketing, linked open data, Google Ngrams

1. Introduction
In the field of computational linguistics, large corpora have been shown to be quite good for the task of noun compound bracketing. Such task consists in determining which nouns within a larger noun compound form subgroups. For example, from [Lauer (1995)], woman aid worker would be bracketed as woman [aid worker], called a right-bracketing, contrarily to copper alloy rod, which would be bracketed as [copper alloy] rod, called a left-bracketing.

In compound bracketing, when only three words are used, n1 n2 n3, the task becomes a binary decision between grouping n1 and n2 or grouping n2 and n3. Two models, described in early work by [Lauer (1995)] and still used in recent work, are the adjacency model and the dependency model. The former compares probabilities (or more loosely strength of association) of two alternative adjacent noun compounds, that of n1 n2 and of n2 n3. The latter compares probabilities of two alternative attachment (modifying) noun relations, that of n1 n3 and of n2 n3.

Most compound bracketing research has focus on three-noun compounds, often using a dataset from [Lauer (1995)]. Some recent work [Pitler et al. (2010), Vadas and Curran (2007b)] looks at larger compounds, using a dataset created by [Vadas and Curran (2007a)] which we will also use in our research. For these larger noun compounds, for example home market stock index futures trading taken from the dataset, the adjacency model alone will not allow longer range dependencies to be taken into account. The bracketing algorithm we present mixes adjacency and dependency models, and looks at the complete expression to make its decisions. It relies on word pair association scores provided by different resources.

Among the resources used are web-corpus resources in the form of pre-processed ngrams. We look at Google ngrams and Google books ngrams (less often seen in use for different tasks). Then, a main contribution of this research is to introduce a linked-open data (LOD) resource and explore ways to use it to provide association scores.

Section 2 presents a short literature review, mostly from the perspective of resources used by different researchers for the task of compound bracketing. Section 3 presents the dataset used in our experiments. Section 4 describes the linked-open data and corpus-based resources we use. Section 5 defines association scores for each resource. Section 6 presents our bracketing method. Section 7 explains our evaluation approach and discusses the results obtained on the dataset. Section 8 concludes and discusses future work.

2. Related work
Noun bracketing has not receive as much attention as many other Natural Language Processing (NLP) task. Nakov and Hearst (2005) calls it an understudied language analysis problem. Nevertheless, a small body of work has emerged in the 1990s taking root and inspiration in earlier linguistic work (Levi, 1978). This body of work is expanding, using empirical methods which rely on the availability of larger and larger corpus.

Noun compound bracketing, sometimes referred to as NP parsing (Pitler et al., 2010), has been studied as a task in itself (e.g. [Lauer (1995), Vadas and Curran (2007a), Nakov and Hearst (2005)]). It is also studied as the first step of semantic analysis of NPs (Girju et al., 2005) where not only subgroups of words are found within the compound, but semantic relations between these groups are looked at (Nastase et al., 2013).

To address the noun compound bracketing task, different authors use different datasets, different views on the problem (adjacency, dependency), different methods of resolution (supervised, unsupervised) and different constraints on the problem (compound seen in isolation or in context). Independently of such differences, all researchers look at different resources and different methods for evaluating word-pair associations, since this is a core component in the problem’s resolution steps.

Before the “Web-as-corpus” era, a first resource used in [Lauer (1994)] was the Grolier’s encyclopedia. Processing of the resource found 35,974 noun sequences of which all but 655 were pairs. All pairs are considered non-ambiguous and could be used as observed data for the model. The au-
From this available file, we could construct the dataset for our experiments. In Vadas and Curran (2007a), some of the NP structures which they modified included determiners, numbers, punctuations or coordinations. We leave those out of our dataset to focus only on modified structures containing basic tags like common nouns (NN, NNS), proper nouns (NNP, NNPS), adverbs (RB, RBR) and adjectives (JJ, JJS). Two words expressions were removed as their bracketing is trivial. The construction method of our dataset starts with the differential file published by Vadas and Curran (2007a) and extracts all expressions starting with the following tags: JJP, NML, NP-SBJ and NP. The expressions are then verified for completeness, so that the opening bracket should be closed within the length of text defined in the differential file. Groups which are not explicitly tagged (called implicit groups in Vadas and Curran, 2007b)) are completed with the missing parentheses to produce the assumed right bracketing. For example, “((NML (NNP Nesbitt) (NNP Thomson) (NNP Deacon))” becomes “((NML (NNP Nesbitt) ((NNP Thomson) (NNP Deacon)))”). Tags and single words enclosing parentheses are then removed from the extracted expression to produce a simplified version of the gold-standard bracketed expression including only the basic text and parentheses (i.e. “(Nesbitt (Thomson Deacon))”)

The extraction produced a total 6,600 examples which we called the raw corpus. From these examples, we calculated duplicates expressions, which yielded a final test corpus of 4,749 unique expressions. Table 1 presents the number of examples in the datasets by length for the raw and unique corpora, and Table 2 gives examples for sizes 3 to 6. In Table 2, we purposely show common nouns and proper nouns to illustrate the existing variation within the current dataset. In later sections, we will discuss the coverage of resources and the relation between named entities and noun compound bracketing.

4. Resource description

In our present research, we investigate three resources for the compound bracketing task, focusing on their usefulness in an unsupervised approach. The first two are frequency-based of web-scale, namely the English Google

Table 1: Number of expressions of different size.

| Length | Raw     | Unique |
|--------|---------|--------|
| Count  | Ratio   | Count  | Ratio   |
| 3      | 4 114   | 2889   | 60.95%  |
| 4      | 1 675   | 1270   | 26.79%  |
| 5      | 547     | 413    | 8.71%   |
| 6      | 225     | 127    | 2.68%   |
| 7      | 36      | 32     | <1%     |
| 8      | 6       | 5      | <1%     |
| 9      | 4       | 4      | <1%     |
| Total  | 6 600   | 4 749  | 100%    |

Our method is published as part of the LREC resources sharing effort as a Java program to replicate our data extraction method. This will allow other researchers in the community to use the same data.

3The 1911 version is freely available online, at the ARTFL project, http://machaut.uchicago.edu/roget's

2The Unified Medical Language System (UMLS) is available at http://www.nlm.nih.gov/research/umls/
4.1. Frequency-based resources

The GWN resource was generated from the set of archived pages used by the Google search engine in July 2009. They tokenized each page and summed up each word, number, punctuation and symbol and filtered any ngrams with a frequency count lesser than 200 occurrences. The GBN was created in the same way but the ngrams were generated from the archived electronic books from the Google Books website. As for the GWN, all character or number groups or single punctuation and symbol were added as a token. All case-aware ngrams were compiled separately and those that fell under the 40 mark were removed. Ngrams of length ranging from 1 to 5 were created for both of these resources.

For our purposes, both GWN and the GBN were filtered to remove entries which included numbers, parenthesis and symbols to be more manageable. As entries from both of these resources included multiple similar entries with different cases (i.e. test, TEST, Test), the interrogation technique was modified to add up all the frequencies from each similar entries. Table 3 shows the approximate count of expressions used in this research for the two frequency-based resource. GBN-A and GBN-R are represented as GBN in the table as they are both taken from this dataset.

| L | Example                                                                 | Resource | 1-gram count   | 2-gram count   |
|---|----------------------------------------------------------------------|----------|----------------|----------------|
| 3 | (a) lung cancer deaths                                               | GWN      | >7.3 millions  | >228.4 millions |
|   | (b) Mary Washington College                                          | GBN      | >7.1 millions  | >105.6 millions |

Table 3: Number of one- and two-words expressions available in the frequency resources.

4.2. Linked open data resource

DBpedia\(^4\) (Hellmann et al., 2009) is built from one of the largest resources on the web, Wikipedia. Many Wikipedia pages contain an Infobox (a small two-column table) to provide structured information about the entity described. All infoboxes are automatically parsed to generate DBpedia. DBpedia follows an RDF (Resource Description Format) representation, which is a W3C (World Wide Web Consortium) standard for the semantic web. DBpedia is growing every year, and the version we use (DBpedia V3.9) describes over 4 millions ’’things’’ for the English dataset, with many properties and links to other entities.

Components within the noun compounds to parse are found as entity names in DBpedia. For example New York Medical School contains two entity names New York and Medical School which exist in DBpedia. This split into components resembles query segmentation, useful in Information Retrieval. Query segmentation is ’’the process of taking a user’s search engine query and dividing the tokens into individual phrases or semantic units’’ (Bergsma and Wang, 2007). Such segmentation reduces the complexity of the task, since in this example, the four word compound is reduced to two entity names New York Medical School, basically solving the bracketing problem.

But that would be too easy. Unfortunately, ambiguity comes into play. For example, Mary Washington College, leads to two competing interpretations, Mary Washington College and Mary Washington College. The complexity is therefore not that much reduced as we now work with competing entity names (rather than competing strings) which furthermore could each lead to multiple entities.

We differentiate entity names from entities. Entity names are surface forms that exists in DBpedia but they can lead to many different entities (word senses or actual named entities). There are usually disambiguation markers (e.g. New York(disambiguation)) to show links between entity names and entities. There are also “redirects” links in DBpedia (and Wikipedia) which can be tricky to use as some of them are true synonyms (e.g. automobile and car) but others are just related items (e.g. video and Audio-visual).

Using a structured linked open data resource brings a completely new dimension, as we now work with entities and entity names instead of surface strings as for the frequency-based resources. Table 4 shows all existing entity names in DBpedia with their number of word senses for the complex compound New York Stock Exchange Composite Trading. Examples of the entities are also shown, to illustrate different relations between entity names and entities. Entity names can be considered abbreviations (New - Net_economic_welfare), shorter forms (Exchange - Heat_exchange), or domain specific terms (Composite -

\(^4\)DBpedia is available at http://www.dbpedia.org
Composite (finance)). We also show some examples of redirects in Table 4 (indicated by "R"). The large number of entities (especially for single words) and the set of possible segmentations make the use of DBpedia for noun bracketing not at all trivial. Furthermore, we wish to make use of its structured data. In DBpedia, entities are linked via predicates, for example Paris would be linked to France using a predicate capital-of, or located-in. Such predicates provide paths between entities which we will use to measure their association scores. Our algorithm, presented in Section 5, will look into both segmentation and paths.

4.3 Resource coverage

Knowing the coverage of each resource provides an upper-bound on its usefulness to compute association measures. Table 5 shows resource coverage for the unigrams extracted from the noun compounds in our dataset. It is interesting to note that the GWN and GBN resources have very similar coverage for the unigrams, a marginal difference of only 0.16%. Datasets GBN-R and GBN-A both have the same coverage, represented as GBN in the table. DBpedia is not far behind, also providing a large coverage of unigrams. Table 6 presents a few examples to illustrate coverage differences between DBpedia and GWN/GBN. Here are a few types of coverage problems:

- Concatenations. For example animal care, and department store, found as written in one-word in GWN/GBN but not as an entity names in DBpedia.
- Tokenization. For example U.S.A. or A.C. will not be found as a unigram in GWN and GBN since the tokenization used in these resources includes punctuations.
- Plurals. Since we did not search for plurals in DBpedia, we lowered their coverage.
- Company names. Counter-intuitively, we assume DBpedia will contain companies, but maybe they are small and do not have their own entry, but they are "talked about" enough to be in GWN.
- People’s names. Some links are not explicit in DBpedia (for Biaggi for example) even if a few people with last name Biaggi are in DBpedia.
- Part-of-speech. Some adjectives or adverbs (extremely, interprovincial, award-winning) will not be in DBpedia. Although, many adjective/adverbs are actually found because they also appear as nouns.

Some of these problems are relatively easy to look into in our future work, but others are not. The tokenization problem in GBN and GWN cannot really be resolved, since it is intrinsic to how the resources were built (e.g. U.S.A.). On the other hand, augmenting DBpedia coverage should be easily possible by searching for plurals, and for entities containing unigrams as part of their names.

4.4 Named entities

Many named entities are found in the Penn Treebank (PTB), like cities, people names, or company names. A manual analysis of our subset of PTB showed that 5,286 out of 6,600 expressions (80.09%) contained at least one named entity. While it is not surprising for texts in the news domain, this proportion of named entities is not representative of texts found in other domains.

For named entities, we would expect an entity-oriented resource such as DBpedia to be useful. Many composite named entities like Los Angeles Mayor Tom Bradley (annotated as a noun compound in the revised PTB) are not found as complete expression but Los Angeles and Tom Bradley are found separately. DBpedia does contain entities of larger sizes, as shown in Table 7. In our bracketing approach, since we try to find dependencies between all word-pairs, we do not use entity names with more than two words.

This issue about named entities and noun compound bracketing is complex. It is discussed a bit in [Vadas and Curran, 2007a], as they used a NE annotator to suggest bracketing to the annotators (who could accept or reject them). The entity types used were the ones defined in [Weischedel and Ada Brunstein, 2005] (e.g. Person, Facility, Organization, Nationality, Product, Event, etc). Named entities could be kept "as is" by the annotators. In our dataset, we trans-

| Resource      | Coverage  |
|---------------|-----------|
| GWN           | 92.70%    |
| GBN           | 92.86%    |
| DBpedia       | 88.78%    |

Table 5: Unigram coverage of our dataset.

| Resource                  | Examples                                |
|---------------------------|-----------------------------------------|
| DBpedia only              | 20th, A.C., B&H, black-and-white, U.S.A.|
| GWN/GBN only              | agreements, animalcare, Biaggi, departmentstore, extremely, Interlogic, Interprovincial |
| neither                   | achievement-test, award-winning,       |

Table 6: Examples of unigrams missing in different resources.

| Size | Examples                                                                                     |
|------|-----------------------------------------------------------------------------------------------|
| 3    | magnetic resonance imaging, nuclear power plant, Vincent van Gogh, International Monetary Fund |
| 4    | The Wall Street Journal, New Jersey Turnpike Authority, Carlos Salinas de Gortari, Ho Chi Minh City |
| 5    | Defense Advanced Research Projects Agency, Pennsylvania State Employees Retirement System, real estate mortgage investment conduit, New York State Supreme Court |
| 6    | Ateliers de Constructions Mecaniques de Vevey, St. Johns River Water Management District       |

Table 7: Examples of larger entities found in DBpedia.
formed those into right bracketed, as we wanted to have all expressions fully bracketed. This will have an impact on our results, and we will revisit this decision in future work, as we study more closely this relation between named entities and compositionality of noun compounds.

5. Association measures

A first step for noun bracketing, as we emphasized in Section 2, is to establish association scores between nouns using different resources and measures. Since we use both web corpus data (unstructured), and a link-open data (structured), we present two different ways of calculating association scores. We also discuss the fact that in DBpedia, we must deal with entities described and not surface forms.

5.1. Frequency-based resources

For our two frequency-based resources, we calculate association strength using the Chi square (used in (Vadas and Curran, 2007b)), the pointwise mutual information (PMI) (used both in Nakov and Hearst (2005) and Piter et al. (2010)), as well as the Dice measure. These statistical measures were used on both the GWN and the GBN (-A and -R) resources. These three measures are defined in Table 8.

The Chi square measure refers to a 2x2 table of bigram occurrences for the four frequencies of bigrams containing both words \((O_{11})\), none of the two words \((O_{22})\), the first word but the second \((O_{21})\) or the second but not the first \((O_{12})\). In this formulae, \(N\) refers to the total number of bigrams in the resource and \(O_{nm}\) refers to the frequency count found in the 2x2 table at the \(N^{th}\) row and the \(M^{th}\) column. The PMI measure applies a binary-based log to the bigram probability divided by the product of its unigrams probabilities. The Dice measure uses twice the raw frequency of the studied bigram divided by the sum of the frequency of its unigrams.

5.2. Linked open data resource

As mentioned in Section 4.2, calculating association scores using DBpedia can take on many forms. For the present exploration, we construct our algorithm to combine two hypotheses. The first one is to minimize the number of entity names found in the expression. The second one is to maximize the number of valid paths among the entities represented by the entity names. As we saw earlier, many entity names (either single or multi-words) are ambiguous and refer to different possible entities (such as in Table 2).

Our definition of a valid path is limited to two possibilities. First, both entities are part of the same triple. Second, both entities are part of different triples sharing a subject or an object. For example, given the two triples (New_York, located_in, United_States) and (Chicago, located_in, United_States), there is a valid path between New_York and United_States (same triple) and also a valid path between New_York and Chicago (shared object). In the present work, the two types of paths are counted equally, but future work could assign different weights to them.

Let us illustrate with an example, in which we will use MaxNbPaths(X,Y) to refer to the number of valid paths between entity names X and Y. Given compound expression "ABCD", let us assume all unigrams "A", "B", "C" and "D" exist as entity names. Let us also assume bigrams "AB" and "CD" also exist as entity names. Then three segmentations (S1, S2, S3) are possible: S1(AB,C,D), S2(A,B,CD) or S3(A,B,C,D). The first two segmentations (S1 and S2) minimize the number of entity names and will be kept for path calculation. For each of S1 and S2, the association strength between each pair of entity names will be given by the maximum number of paths among any two of their entities. In Figure 1, we illustrate a possible case for S1, assuming AB links to a single entity, C links to 3 entities, and D links to 2 entities. We calculate MaxNbPaths(AB,C) + MaxNbPaths(AB,D) + MaxNbPaths(C,D) to obtain a score of S1. The same will be performed for segmentation S2, and we keep the segmentation with the highest score. This best segmentation moves to the second step of actual bracketing, explained in Section 6, providing its MaxNbPaths as association scores to the bracketing algorithm.
6. Bracketing method

As in the work of Pitler et al. (2010), our bracketing algorithm looks at the whole expression for its evaluation. This is different from the algorithm suggested in Barker (1998) and used in Vadas and Curran (2007b) which only uses local information (three-words at a time, in a right-to-left moving window).

Our algorithm consists in creating a list (L1) containing every word pair that can be generated from an expression. L1 is then sorted in decreasing order of association scores. The score of each pair is provided either from GBN-A, GBN-R, GWN or Dbpedia and is calculated using one of the methods detailed in Section 5. In our algorithm, association scores are considered as dependency scores, that is modifier/head scores. For example, an expression “1 2 3 4 5” would generate a list L1 containing {(1,2), (1,3), (1,4), (1,5), (2,3), (2,4), (2,5), (3,4), (3,5), (4,5)} and each possible modifier/head pair would be scored using a specific association measure and ordered into L1 in a descending order.

From there, we construct the final list of dependencies (L2), which will define the complete bracketing of the expression. This is done by selecting in order each word pair (A, B) from L1 and adding it to L2 only if both (a) the modifier has not already been used, and (b) the new pair does not create a crossing of modifier/head pairs in the expression (e.g. if L2 already contains (12)(345), then (24) would create an invalid crossing and is not accepted). The selection of pairs from L1 is ended when all words are used as modifiers in L2, except for the right-most one in the expression.

Our algorithm is greedy as only the best score (enabling a valid integration of the word pair into L2) is chosen at every step without consideration for the actual distance between the two words in the source expression. This helps linking far reaching dependencies in noun compounds, but it might also force some strong association between two distant words without regard to the soundness of using nearer words.

7. Evaluation

Two methods are used to evaluate the bracketing algorithm against the gold standard. The first method is a strict match, like the exact evaluation method used in Vadas and Curran (2007b). It requires a complete and exact match for all the groups found in the reference expression without considering the tags. The final score is thus the number of correctly bracketed expressions divided by the number of inspected expressions.

The second method, called lenient, checks for each parenthesis group of an expression and compares it to the gold standard. For example, a six word long candidate “(((A B) C) D) E)” would generate a list L1 containing {AB, AB, ABC, ABDE, ABCDE} compared to a gold standard “(((A B) C) D) E)” which only uses local information (three-words at a time, in a right-to-left moving window).

Our suggested lenient evaluation is different, and more severe, than looking at word relations in a binary tree. Using the previous example, the gold expression would give A-B, B-C, C-D, D-E and E-F which would score a recall of 3/4 = 75% as three groups are correct compared to the four in the gold. As both the gold and test expressions (of length N) are fully bracketed, the number of groups (N-1 excluding the top level group) are always the same in both expressions and thus, precision and recall will be the same as the F-measure.

Table 9: Comparing strict and lenient evaluation results.

| Resource  | Algorithm | Strict | Lenient |
|-----------|-----------|--------|---------|
| Baseline  | Right     | 13.74% | 24.12%  |
|           | Left      | 52.06% | 66.23%  |
| DBpedia   | Path      | 54.08% | 64.60%  |
| GBN-A     | chi       | 60.18% | 72.33%  |
| GBN-R     | pmi       | 61.04% | 73.20%  |
| GWN       | dice      | 59.87% | 72.11%  |
|           | chi       | 54.43% | 66.63%  |

We first show, in Table 9, the comparative results from the three resources, for a strict or lenient evaluation. Two baselines were also calculated, with a default right and left bracketing. Following the findings by Lauer (1995), the left-bracketing is much more common in our dataset. Compared to the left-bracketing baseline, all methods score a bit over for the strict evaluation, and all but DBpedia score again over in the lenient evaluation.

The closest research providing comparable results on longer compounds are Vadas and Curran (2007b) and Pitler et al. (2010), although both focus on supervised approaches, and furthermore, Vadas and Curran (2007b) uses contextual features, assuming the noun compounds are to be bracketed in context. Still, we can compare to the results for unsupervised given in Vadas and Curran (2007b). They report exact match for complex NPs to be 54.66 for Base-
Table 10: Strict evaluation results, per expression size.

| L   | Rand. | BL  | DBpedia | GWN pmi | GBN-A pmi | GBN-R pmi |
|-----|-------|-----|---------|---------|-----------|-----------|
| 3   | 50%   | 79.2% | 69.86% | 80.08%  | 81.23%    | 81.47%    |
| 4   | 20%   | 12.67% | 37.67% | 36.76%  | 37.70%    | 37.23%    |
| 5   | 7.1%  | 0.73%  | 15.46% | 13.53%  | 13.77%    | 13.53%    |
| 6   | 2.4%  | 0.0%   | 0.75%  | 6.06%   | 6.06%     | 6.06%     |
| 7   | 0.8%  | 0.0%   | 3.13%  | 3.13%   | 6.25%     | 6.25%     |
| 8   | 0.2%  | 0.0%   | 0.0%   | 0.0%    | 0.0%      | 0.0%      |
| 9   | <0.1% | 0.0%   | 0.0%   | 0.0%    | 0.0%      | 0.0%      |
| All | 36.88% | 52.06% | 54.08% | 60.41%  | 61.04%    | 61.04%    |

As mentioned in Pitler et al. (2010), the number of possible binary trees (possible bracketing) increases with the Catalan number\(^5\) meaning random results as shown in the second column (named “Rand.”) of Table 10. Results by noun compound length is shown for the left bracketing (BL), DBpedia, as well as the best measure for GWN (pmi) and GBN (chi square). Results were good for the baseline on 3 words expressions but degraded very quickly for longer expressions. All methods did better than random and baseline of lengths from 4 to 7 for the strict evaluation. The top row of Table 10 shows results above 80% obtained (for GBN and GWN) on the 3-word compounds. This is comparable to results in Vadas and Curran (2007b) of around 80% with voters (dependency and adjacency). DBpedia does not perform as well on 3-word compounds, but does on the larger ones, probably showing the usefulness of detecting entity names within the expression.

To get a better sense of the results achieved using each resource, we show in Table 11 the bracketed outputs for the examples previously given in Table 2.

8. Discussion and Conclusion

Even if bracketing of three-word expressions have been performed quite successfully using supervised approaches using web-corpus resources (Nakov and Hearst, 2005), (Vadas and Curran, 2007b), compound bracketing of large expressions remains a challenge. The top row of Table 10 shows results above 80% obtained (for GBN and GWN) on the 3-word compounds. This is comparable to results in Vadas and Curran (2007b) of around 80% with voters (dependency and adjacency). DBpedia does not perform as well on 3-word compounds, but does on the larger ones, probably showing the usefulness of detecting entity names within the expression.

To get a better sense of the results achieved using each resource, we show in Table 11 the bracketed outputs for the examples previously given in Table 2.

We measured that out of 6600 queries, DBPedia found at least one entity name of two words in 65% of them. It found sometimes 2 entity names, for a total of 5800. We have started a discussion on the relation between named entities and bracketing issues, but we hope to further investigate this issue, and the related issue of determining compounds on which DBPedia does well compared to GWN/GBN (and vice-versa). DBpedia, built from Wikipedia, has grown large enough to allow coverage near the one of GWN/GBN. Eventually, we believe an hybrid model, built after a good understanding of the strength and weaknesses of each resource, will provide a good solution to the noun compound bracketing problem. Within that hybrid model, individual models should also take further advantage of the individual resources. For the frequency-based resource, different searches (as suggested in Vadas and Curran (2007b)) such as simple paraphrases, could be tested. For DBpedia, our simple valid path count algorithm should be revisited to make better use of different path lengths and path types.

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\(^5\) see http://en.wikipedia.org/wiki/Catalan_number
| L. | Resource | Example |
|---|---|---|
| 3 | Gold | (lung cancer) deaths |
|     | GWN | (lung cancer) deaths |
|     | GBN | (lung cancer) deaths |
|     | DBpedia | (lung cancer) deaths |
|     | Gold | (Mary Washington) College |
|     | GWN | (Mary Washington) College |
|     | GBN | Mary (Washington College) |
|     | DBpedia | (Mary Washington) College |
| 4 | Gold | ((standardized (achievement test)) scores) |
|     | GWN | ((standardized (achievement test)) scores) |
|     | GBN | ((standardized (achievement test)) scores) |
|     | DBpedia | (standardized (achievement test scores)) |
|     | Gold | ((Fujitsu President) (Takuma Yamamoto)) |
|     | GWN | ((Fujitsu President) (Takuma Yamamoto)) |
|     | GBN | ((Fujitsu President) (Takuma Yamamoto)) |
|     | DBpedia | (Fujitsu (President (Takuma Yamamoto))) |
| 5 | Gold | (annual ((gross (domestic product)) growth)) |
|     | GWN | (annual ((gross (domestic product)) growth)) |
|     | GBN | (annual ((gross (domestic product)) growth)) |
|     | DBpedia | (annual gross ((domestic product Growth))) |
|     | Gold | (((New York) (Stock Exchange)) issues) |
|     | GWN | (((New York) (Stock Exchange)) issues) |
|     | GBN | (((New York) (Stock Exchange)) issues) |
|     | DBpedia | ((New York) (Stock Exchange) issues) |
| 6 | Gold | ((general obligation) ((distributable ((state aid) bonds)))) |
|     | GWN | ((general obligation) ((distributable ((state aid) bonds)))) |
|     | GBN | ((general obligation) ((distributable ((state aid) bonds)))) |
|     | DBpedia | (General Obligation Distributable ((State Aid) Bonds)) |
|     | Gold | ((Japanese (auto maker)) ((Mazda Motor) Corp)) |
|     | GWN | (((Japanese (auto maker)) (Mazda Motor) Corp)) |
|     | GBN | (((Japanese (auto maker)) (Mazda Motor) Corp)) |
|     | DBpedia | (Japanese (((auto maker) (Mazda Motor)) Corp)) |

Table 11: Examples of bracketed expressions using different resources

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