Evaluation Techniques for Automatic Semantic Extraction: Comparing Syntactic and Window Based Approaches

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Abstract
As large on-line corpora become more prevalent, a number of attempts have been made to automatically extract thesaurus-like relations directly from text using knowledge-poor methods. In the absence of any specific application, comparing the results of these attempts is difficult. Here we propose an evaluation method using gold standards, i.e., pre-existing hand-compiled resources, as a means of comparing extraction techniques. Using this evaluation method, we compare two semantic extraction techniques which produce similar word lists, one using syntactic context of words, and the other using windows of heuristically tagged words. The two techniques are very similar except that in one case selective natural language processing, a partial syntactic analysis, is performed. On a 4 megabyte corpus, syntactic contexts produce significantly better results against the gold standards for the most characteristic words in the corpus, while windows produce better results for rare words.

1 Introduction

As more text becomes available electronically, it is tempting to imagine the development of automatic filters able to screen these tremendous flows of text extracting useful bits of information. In order to properly filter, it is useful to know when two words are similar in a corpus. Knowing this would alleviate part of the term variability problem of natural language discussed in Furnas et al. [1987]. Individuals will choose a variety of words to name the same object or operation, with little overlap between people's choices. This variability in naming was cited as the principal reason for large numbers of missed citations in a large-scale evaluation of an information retrieval system [Blair and Maron, 1985]. A proper filter must be able to access information in the text using any word of a set of similar words. A number of knowledge-rich [Jacobs and Rau, 1990, Calzolari and Bindi, 1990, Mauldin, 1991] and knowledge-poor [Brown et al., 1992, Hindle, 1990, Ruge, 1991, Grefenstette, 1992] methods have been proposed for recognizing when words are similar.
The knowledge-rich approaches require either a conceptual dependency representation, or semantic tagging of the words, while the knowledge-poor approaches require no previously encoded semantic information, and depend on frequency of co-occurrence of word contexts to determine similarity. Evaluations of results produced by the above systems are often limited to visual verification by a human subject or left to the human reader.

In this chapter, we propose gold standard evaluation techniques, allowing us to objectively evaluate and to compare two knowledge-poor approaches for extracting word similarity relations from large text corpora. In order to evaluate the relations extracted, we measure the overlap of the results of each technique against existing hand-created repositories of semantic information such as thesauri and dictionaries. We describe below how such resources can be used as evaluation tools, and apply them to two knowledge-poor approaches.

One of the semantic extraction approaches tested here uses selective natural language processing, in this case the lexical-syntactic relations that can be extracted for each word in a corpus by robust parsers [Hindle, 1983, Grefenstette, 1994a]. The other approach uses a variation on a classic windowing technique around each word such as was used in [Phillips, 1985]. Both techniques are applied to the same 4 megabyte corpus. We evaluate the results of both techniques using our gold standard evaluations over thesauri and dictionaries and compare the results obtained by the syntactic based method to those obtained by the windowing method. The syntax-based method provides a better overlap with the manually defined thesaurus classes for the 600 most frequently appearing words in the corpus, while for rare words the windowing method performs slightly better for rare words.

\section{Gold Standards Evaluation}

\subsection{Thesauri}

Roget’s Thesaurus is readily available via anonymous ftp\textsuperscript{1}. In it are collected more than 30,000 unique words arranged in a shallow hierarchy under 1000 topic numbers such as Existence (Topic Number 1), Inexistence (2), Substantiality (3), Unsubstantiality (4), \ldots, Rite (998), Canonicals (999), and Temple (1000). Although this is far from the total number of semantic axes of which one could think, it does provide a wide swath of commonly accepted associations of English language words. We would expect that any system claiming to extract semantics from text should find some of the relations contained in this resource.

By transforming the online source of such a thesaurus, we use it as a gold standard by which to measure the results of different similarity extraction techniques. This measurement is done by checking whether the ‘similar words’ discovered by each technique are placed under the same heading in this thesaurus.

In order to create this evaluation tool, we extracted a list consisting of all single-word entries from our thesauri with their topic number or numbers. A portion of the extracted Roget list in Figure 1 shows that abatement appears under two topics: Nonincrease (36) and Discount (813). Abbe and abbess both belong under the same topic heading 996 (Clergy). The extracted Roget’s list has 60,071 words (an average of 60 words for each

\footnote{For example, in March 1993 it was available via anonymous ftp at the Internet site world.std.com in the directory /obi/obi2/Gutenberg/text91, as well as at over 30 other sites.}
### Table 1: Samples from One Word Entries in Both Thesauri

| Roget's | Macquarie |
|---------|-----------|
| Entry   | Topic     | Entry               | Subheading |
| abatement | 36         | disesteem           | 036406     |
| abatement | 813        | disesteem           | 063701     |
| abatis   | 717         | disesteem           | 022701     |
| abatjour | 260         | disfavour           | 003901     |
| abattis  | 717         | disfavour           | 056601     |
| abatjour | 361         | disfavour           | 063701     |
| abba     | 166         | disfeature          | 018212     |
| abbacy   | 995         | disfeaturement      | 018210     |
| abbatial | 995         | disfigure           | 006804     |
| abbatical| 995         | disfigure           | 018212     |
| abbatis  | 717         | disfigure           | 020103     |
| abbe     | 996         | disfigured          | 006803     |
| abbess   | 996         | disfigured          | 020102     |

*Figure 1: Samples from One Word Entries in Both Thesauri*

of the 1000 topics). Of these 32,000 are unique (an average of two occurrence for each word). If we assume for simplicity that each word appears under exactly 2 of the 1000 topics, and that the words are uniformly distributed, the chance that two words $w_1$ and $w_2$ occur under the same topic is

$$P_{\text{Roget}} = 1 - \left(\frac{998}{1000}\right)^2,$$

since $w_1$ is under 2 topic headings and since the chance that $w_2$ is under any specific topic heading is 2/1000. The probability of finding two randomly chosen words together under the same heading, then, is about 0.4%.

Our measurement of a similarity extraction technique using this gold standard is performed as follows:

Given a corpus, use the similarity extraction method to derive similarity judgments between the words appearing in the corpus. For each word, take the word appearing as most similar. Examine the human compiled thesaurus to see if that pair of words appears under the same topic number. If it does, count this as a hit.

This procedure was followed on the 4 megabyte corpus described below to test two semantic extraction techniques, one using syntactically derived contexts to judge similarity and one using window-based contexts. The results of these evaluations are also given below.

### 2.2 Dictionary

We also use an online dictionary as a gold standard following a slightly different procedure. Many researchers have drawn on online dictionaries in attempts to do semantic discovery [Sparck Jones, 1986, Vossen et al., 1989, Wilks et al., 1989], whereas we use it here only as a tool for evaluating extraction techniques from unstructured text. We have an online
ad-min-is-tra-tion n. 1. the act or process of administering 2. performance of executive duties :: <MANAGEMENT> 3. the execution of public affairs as distinguished from policy making 4. a) a body of persons who administer b) i<cap> :: a group constituting the political executive in a presidential government c) a governmental agency or board 5. the term of office of an administrative officer. or body.

administer, administering, administrative, affairs, agency, board, constituting, distinguished, duties, execution, executive, government, governmental, making, management, office, officer, performance, persons, policy, political, presidential, public, term

Figure 2: Webster definition of “administration,” and resulting definition list after filtering through stoplist.

version of Webster’s 7th available, and we use it in evaluating discovered similarity pairs. This evaluation is based on the assumption that similar words will share some overlap in their dictionary definitions. In order to determine overlap, each the entire literal definition is broken into a list of individual words. This list of tokens contains all the words in the dictionary entry, including dictionary-related markings and abbreviations. In order to clean this list of non-information-bearing words, we automatically removed any word or token

1. of fewer than 4 characters,
2. among the most common 50 words of 4 or more letters in the Brown corpus,
3. among the most common 50 words of 4 or more letters appearing in the definitions of Webster’s 7th,
4. listed as a preposition, quantifier, or determiner in our lexicon,
5. of 4 or more letters from a common information retrieval stoplist,
6. among the dictionary-related set: slang, attrib, kind, word, brit, ness, tion, ment.

These conditions generated a list of 434 stopwords of 4 or more characters which are retracted from any dictionary definition. The remaining words are sorted into a list. For example, the list produced for the definition of the word administration is given in Figure 2. For simplicity no morphological analysis or any other modifications were performed on the tokens in these lists.

To compare two words using these lists, the intersection of each word’s filtered definition list is performed. For example, the intersection between the lists derived from the dictionary entries of diamond and ruby is (precious, stone); between right and freedom it is (acting, condition, political, power, privilege, right). In order to use these dictionary-derived lists as an evaluation tool, we perform the following experiment on a corpus.

**Given a corpus, take the similarity pairs derived by the semantic extraction technique in order of decreasing frequency of the first term. Perform the intersection of their respective two dictionary definitions as described above. If this intersection contains two or more elements, count this as a hit.**

This evaluation method was also performed on the results of both semantic extraction techniques applied to the corpus described in the next section.
3 Corpus

The corpus used for evaluating the two techniques was extracted from Größer's Encyclopedia for other experiments in semantic extraction. In order to generate a relatively coherent corpus, the corpus was created by extracting only those sentences which contained the word *Harvard* or one of the thirty hyponyms found under the word *institution* in WordNet\(^2\) [Miller et al., 1990], viz. *institution, establishment, charity, religion, . . . , settlement*. This produced a corpus of 3.9 megabytes of text.

4 Semantic Extraction Techniques

We will use these gold standard evaluation techniques to compare two techniques for extracting similarity lists from raw text.

The first technique described in [Grefenstette, 1994b] extracts the syntactic context of each word throughout the corpus. The corpus is divided into lexical units via a regular grammar, each lexical unit is assigned a list of context-free syntactic categories, and a normalized form. Then a time linear stochastic grammar similar to the one described in [de Marcken, 1990] selects a most probable category for each word. A syntactic analyzer based on work done by [Debili, 1982] chunks nouns and verb phrases and create relations within chunks and between chunks. A noun's context becomes all the other adjectives, nouns, and verbs that enter into syntactic relations with it.

As a second technique, more similar to classical knowledge-poor techniques [Phillips, 1985] for judging word similarity, we do not perform syntactic disambiguation and analysis, but simply consider some window of words around a given word as forming the context of that word. We suppose that we have a lexicon, which we do, that gives all the possible parts of speech for a word. Each word in the corpus is looked up in this lexicon as in the first technique, in order to normalize the word and know its possible parts of speech [Evans et al., 1991]. A noun's context will be all the words that can be nouns, adjectives, or verbs within a certain window around the noun. The window that was used was all nouns, adjectives, or verbs on either side of the noun within ten and within the same sentence.

In both cases we will compare nouns to each other, using their contexts. In the first case, the disambiguator determines whether a given ambiguous word is a noun or not. In the second case, we will simply decide that if a word can be at once a noun or verb, or a noun or adjective, that it is a noun. This distinction between the two techniques of using a cursory syntactic analysis or not allows us to evaluate what is gained by the addition of this processing step.

Figure 3 below shows the types of contexts extracted by the selective syntactic technique and by the windowing technique for a sentence from the corpus.

Once context is extracted for each noun, the contexts are compared for similarity using a weighted Jaccard measure\(^3\) [Grefenstette, 1994b]. In order to reduce run time for the

\(^2\)WordNet was not used itself as a gold standard since its hierarchy is very deep and its inherent notion of semantic classes is not as clearly defined as in Roget.

\(^3\)The Jaccard measure is defined as the number of attributes shared by two objects divided by the total number of unique attributes possessed by both objects. If \(A\) is the number of attributes shared by two objects, and \(B\) is the number of attributes only appearing with the first object, and \(C\) is the number of attributes appearing only with the second object, then the Jaccard measure of similarity between the two objects is \(A/(A + B + C)\). This similarity measure yields a value between 0 and 1. The attributes
With the arrival of Europeans in 1788, many Aboriginal societies, caught within the coils of expanding white settlement, were gradually destroyed.

Some contexts extracted with 10 full-word window

arrival aboriginal arrival society arrival catch
arrival coil arrival expand arrival white
arrival settlement arrival destroy arrival european
European aboriginal European society european catch
European coil European expand European white
European settlement European destroy society arrival
Society european society aboriginal society catch
Society coil society expand society white
Society settlement society destroy ...

Figure 3: Comparison of Extracted Contexts using Syntactic and Non-Syntactic Techniques

similarity comparison, only those nouns appearing more than 10 times in the corpus were retained. 2661 unique nouns appear 10 times or more. For the windowing technique 33,283 unique attributes with which to judge the words are extracted. The similarity judging run takes 4 full days on a DEC 5000, compared to 3 and 1/2 hours for the similarity calculation using data from the syntactic technique, due to greatly increased number of attributes for each word. For each noun, we retain the noun rated as most similar by the Jaccard similarity measure. Figure 4 shows some examples of words found most similar by both techniques.

5 Results

The first table, in Figure 5, compares the hits produced by the two techniques over Roget's and over another online thesaurus, Macquarie's, that we had available in the Laboratory for Computational Linguistics at Carnegie Mellon University. This table compares the results obtained from the windowing technique described in preceding paragraphs to those obtained from the syntactic technique, retaining only words for which similarity judgements were made by both techniques.

It can be seen in Figure 5 that simple technique of moving a window over a large corpus, counting co-occurrences of words, and eliminating empty words, provides a good hit ratio for frequently appearing words, since about 1 out of 5 of the 100 most frequent words are found similar to words appearing in the same heading in a hand-built thesaurus.

are weighted by taking the log of the attribute frequency with the object multiplied by an inverse entropy measure of the attribute over the corpus. For example, common adjectives have a high entropy and thus lower weights. See [Grefenstette, 1994b]. Here the objects being compared are two nouns, and their attributes are the words found in lexical-syntactic relations to these nouns.
| Corpus word | Technique used |
|-------------|----------------|
| formation   | creation       |
| work        | school         |
| foundation  | institution    |
| government  | constitution   |
| education   | training       |
| religious   | religion       |
| university  | institution    |
| group       | institution    |
| establishment | creation    |
| power       | authority      |
| creation    | establishment  |
| state       | law            |
| program     | institution    |
| law         | constitution   |
| year        | century        |
| center      | development    |
| art         | architecture   |
| form        | life           |
| century     | year           |
| member      | group          |
| part        | center         |
|             | government     |
|             | government     |
|             | government     |
|             | government     |
|             | public         |
|             | city           |
|             | science        |
|             | life           |
|             | religious      |
|             | group          |
|             | group          |

Figure 4: Sample of words found to be most similar, by the syntactic based technique, and by the window technique, to some frequently occurring words in the corpus

| RANK | WINDOW | SYNTAX | WINDOW | SYNTAX | WINDOW | SYNTAX |
|------|--------|--------|--------|--------|--------|--------|
| 1-20 | 25%    | 30%    | 15%    | 40%    | 55%    | 30%    |
| 21-40| 10%    | 30%    | 20%    | 45%    | 40%    | 60%    |
| 41-60| 25%    | 30%    | 30%    | 35%    | 55%    | 70%    |
| 61-80| 15%    | 40%    | 20%    | 30%    | 45%    | 65%    |
| 81-100| 15%    | 40%    | 15%    | 35%    | 35%    | 55%    |
| 101-200| 14%    | 31%    | 15%    | 34%    | 34%    | 55%    |
| 201-300| 21%    | 29%    | 20%    | 30%    | 26%    | 34%    |
| 301-400| 13%    | 17%    | 12%    | 18%    | 25%    | 29%    |
| 401-500| 15%    | 16%    | 12%    | 13%    | 24%    | 26%    |
| 501-600| 13%    | 11%    | 10%    | 15%    | 18%    | 16%    |
| 601-700| 8%     | 11%    | 11%    | 14%    | 20%    | 14%    |
| 701-800| 11%    | 9%     | 6%     | 9%     | 17%    | 17%    |
| 801-900| 17%    | 6%     | 13%    | 7%     | 25%    | 12%    |
| 901-1000| 8%     | 10%    | 6%     | 9%     | 20%    | 12%    |
| 1001-2000| 10.2%  | 4.9%   | 11.8%  | 5.3%   | 19.2%  | 6.9%   |
| 2001-3000| 7.9%   | 2.4%   | 7.9%   | 2.1%   | 15.2%  | 5.2%   |

Figure 5: Windowing vs Syntactic Percentage of Hits for words from most frequent to least
Figure 6: Comparison of hit percentage in Roget's using simple 10-word windowing technique (clear) vs syntactic technique (black). The y-axis gives the percentage of hits for each group of frequency-ranked terms.

Figure 7: Comparison of hits in Macquarie's using simple 10-word windowing technique (clear) vs syntactic technique (black). The y-axis gives the percentage of hits for each group of frequency-ranked terms.
Figure 8: Comparison of hit percentage in Webster’s using simple 10-word windowing technique (hashed bars) vs syntactic technique (solid bars). The y-axis gives the percentage of hits for each group of frequency-ranked terms.

|               | Syntactic |               | Syntactic |
|---------------|-----------|---------------|-----------|
|               | hits      | miss          | hits      | miss      |
| Window        |           |               |           |           |
| Hits          | 48        | 60            | 42        | 54        |
| Miss          | 91        | 401           | 103       | 401       |

$\chi^2 = 6.4$

$p < .025$

$\chi^2 = 15.3$

$p < .005$

Figure 9: $\chi^2$ results comparing Syntactic and windowing hits in man-made thesauri
It can also be seen that the performance of the partial syntactic analysis based technique is better for the 600 most frequently appearing nouns, which may be considered as the characteristic vocabulary of the corpus. The difference in performance between the two techniques is statistically significant ($p < 0.05$). The results of a $\chi^2$ test are given in Figure 9. Figures 6 and 7 show the same results as histograms. In these histograms it becomes more evident that the window co-occurrence techniques give more hits for less frequently occurring words, after the 600th most frequent word. One reason for this can be seen by examining the 900th most frequent word, employment. Since the windowing technique extracts up to 20 non-stopwords from either side, there are still 537 context words attached to this word, while the syntactically-based technique, which examines finer-grained contexts, only provides 32 attributes.

Figure 8 shows the results of applying the less focused dictionary gold standard experiment to the similarities obtained from the corpus by each technique. For this experiment, both techniques provide about the same overlap for frequent words, and the same significantly stronger showing for the rare words for the windowing technique.

6 Conclusion

In this chapter we presented a general method for comparing the results of two similarity extraction techniques via gold standards. This method can be used when no application-specific evaluation technique exists and provides a relative measurement of techniques against human-generated standard semantic resources. We showed how these gold standards could be processed to produce a tool for measuring overlap between their contents and the results of a semantic extraction method. We applied these gold standard evaluations to two different semantic extraction techniques passed over the same 4 megabyte corpus. The syntax-based technique produced greater overlap with the gold standards derived from thesauri for the characteristic vocabulary of the corpus, while the window-based technique provided relatively better results for rare words.

This dichotomous result suggests that no one statistical technique is adapted to all ranges of frequencies of words from a corpus. Everyday experience suggests that frequently occurring events can be more finely analyzed than rarer ones. In the domain of corpus linguistics, the same reasoning can be applied. For frequent words, finer-grained context such as that provided by even rough syntactic analysis, is rich enough to judge similarity. For less frequent words, reaping more though less exact information such as that given by windows of $N$ words provides more information about each word. For rare words, the context may have to be extended beyond a window, to the paragraph, or section, or entire document level, as Crouch [1990] did for rarely appearing words.

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