Low-Complexity Heuristics for Deriving Fine-Grained Classes of Named Entities from Web Textual Data

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Abstract
We introduce a low-complexity method for acquiring fine-grained classes of named entities from the Web. The method exploits the large amounts of textual data available on the Web, while avoiding the use of any expensive text processing techniques or tools. The quality of the extracted classes is encouraging with respect to both the precision of the sets of named entities acquired within various classes, and the labels assigned to the sets of named entities.

1. Introduction
Class instances of various types constitute a large fraction of the search queries submitted most frequently by Web users. Class instances also occur often in Web documents, confirming the special role that they play in natural language, as they are used to refer to objects and concepts of common interest. Although work on named entity recognition traditionally focuses on the acquisition and identification of instances within a small set of coarse-grained classes, the distribution of instances within query logs indicates that Web search users are interested in a finer-grained set of classes. Depending on prior knowledge, personal interests and immediate needs, users may submit queries in the medical domain, inquiring about the symptoms of leptospirosis or the treatment of monkeypox, both of which are instances of zoonotic diseases, or the risks and benefits of surgical procedures such as prk and angioplasty. Other users may be more interested in geography, through queries referring to uganda and angola, which are african countries, or active volcanoes like etna and kilauea. The wide variation of the domains of interest to Web users illustrates the potential impact that the availability of a large set of fine-grained classes of instances may have in Web search. A variety of text processing tasks, including coreference resolution (McCarthy and Lehnert, 1995), named entity recognition (Stevenson and Gaizauskas, 2000) and seed-based information extraction (Riloff and Jones, 1999), can also directly take advantage of the extracted sets of classes of instances. Starting from a few Is-A extraction patterns widely used in information extraction literature (Hearst, 1992), this paper introduces a few precision-enhancing heuristics that take advantage of textual data available on the Web, by mining a collection of Web search queries and a collection of Web documents to acquire a large number of open-domain classes in the form of instance sets (e.g., \{leptospirosis, brucellosis, lyme disease, monkeypox, psittacosis,...\}) associated with class labels (e.g., zoonotic diseases). By exploiting the contents of query logs during the extraction of labeled classes of instances from Web documents, we acquire thousands of classes covering a wide range of topics and domains. The extraction of classes requires a small amount of supervision, in the form of a few Is-A extraction patterns.

2. Extraction of Fine-Grained Classes

2.1. Document Pre-Processing
The contents of the Web documents, from which the labeled classes of instances are extracted, is converted to text by filtering out Html tags. The documents are split into sentences, tokenized and part-of-speech tagged using the TnT tagger (Brants, 2000).

2.2. Pattern-Based Extraction
In order to acquire pairs of an instance and an associated class label from text, we apply a small set of manually-created extraction patterns. The patterns were introduced in (Hearst, 1992) and successfully used in a large body of previous work on extracting Is-A pairs from text. For simplicity and robustness when applied to large amounts of Web text, the number of extraction patterns is limited to a very small set, namely \(\{C [\text{such as} I]\}\) and \(\{C [\text{including} I]\}\). As such, the patterns represent a low-complexity solution to the problem of extracting candidate pairs of an instance \(I\) (e.g., brucellosis) and an associated class label \(C\) (e.g., zoonotic diseases) from noisy text. For each match within a sentence, the patterns determine the right boundary of the class label, and the left boundary of the class instance respectively. The left boundary of the class label is identified through shallow analysis of the part-of-speech tags of the sentence words situated immediately to the left of the pattern match. If the sequence of tags corresponds to a base (i.e., non-recursive) noun phrase whose last component is a plural-form noun, then the beginning of the noun phrase is the left boundary of the class label. Otherwise, the pattern match is discarded. In comparison, the part-of-speech tags of the sentence words cannot be used reliably to identify the right boundary of the class instance. Indeed, instances of arbitrary classes exhibit significant variation in form, from simpler-to-identify sequences of capitalized, proper nouns (e.g., Mauna Loa and...
2.3. Precision-Oriented Filters

The pairs of a class instance and an associated class label extracted from text via pattern matching are further refined through three precision-oriented heuristics. The first heuristic aims at discarding pairs containing spurious class instances that were extracted due to an undesirable pattern match:

Heuristic 1: Discard pairs of a class label and a class instance, if the class instance is not frequently submitted as a full-length Web search query.

The rationale behind the first heuristic is that, sooner or later, users interested in a particular class instance will inquire about that instance. The inquiries will take many forms, including submissions to a Web search engine of full-length queries containing only the class instance. Whenever a class instance does not occur as an entire, case-insensitive query in query logs, the class instance and its associated class labels are discarded from the pairs extracted via pattern matching. To further trade off recall for higher precision, a second heuristic is applied:

Heuristic 2: Discard pairs of a class label and a class instance, if the head of the class label is not the one that is the most frequently associated with the class instance in the extracted pairs.

The second heuristic analyzes the head nouns of all class labels \( C \) collected via pattern matching for a given instance \( I \). The heuristic identifies which head noun occurs most frequently across the potential class labels of the instance, then discards the labels whose head nouns are not the most frequent head noun. For example, the most frequent head of the labels associated with \textit{brucellosis} is \textit{diseases}. Therefore, class labels such as \textit{zoonotic diseases} and \textit{communicable diseases} are retained, whereas \textit{dangerous bacteria} and \textit{tests} are discarded, thus promoting precision of the class labels at the expense of lower recall.

After filtering, the resulting pairs are arranged into sets of class instances, as shown in Figure 1. After discarding classes with fewer than 25 instances, the top 100 instances are retained for each class.

3. Evaluation

3.1. Experimental Setting

The acquisition of labeled classes of instances relies on unstructured text available within a combination of Web documents maintained by, and search queries submitted to the Google search engine. The collection of Web search queries is a random sample of fully-anonymized queries in English submitted by Web users in 2006. The sample contains approximately 50 million unique queries. Each query is accompanied by its frequency of occurrence in the logs.

The document collection consists of approximately 100 million Web documents in English, as available in a Web repository snapshot from 2006.

3.2. Quantitative Results

The extracted data consists of pairs of an instance and a class label, such that each class label is associated with 25 to 100 instances. Table 1 illustrates the extracted classes ranked according to their popularity within query logs, measured by the frequencies of the class labels as full queries (e.g., \textit{games} or \textit{arcade games}) within query logs. Thanks to the open-domain nature of the precision-oriented filters, the extracted classes are not restricted to any single domain of interest. Instead, the classes cover a wide range of topics and domains, including medicine (e.g., \textit{genetic disorders} at rank 175 and \textit{personality disorders} at rank 255 in Table 1), finance (e.g., \textit{mutual funds} at rank 191), geology (\textit{sedimentary rocks} at rank 245) and entertainment (e.g., \textit{games} at rank 1).

3.3. Qualitative Results

The coverage of the extracted instances is measured against one of the popular lexical resources in natural language applications, namely the WordNet lexical database (Fellbaum, 1998). WordNet encodes English concepts in the form of sets of synonyms, or synsets (e.g., \{\textit{port of entry}, \textit{point of entry}\}), associated with a common definition (e.g., “\textit{a port in the United States where customs officials are stationed to oversee the entry and exit of people and merchandise\}”). WordNet synsets are organized hierarchically, such that more specific concepts, or hyponyms, are located under more general concepts, or hypernyms. Recent versions of WordNet also provide explicit Has-Instance relations, which correspond to Instance-Of relations between a class (e.g., \textit{painter}) and one of its instances (e.g., \textit{Amedeo Modigliano}).
### Table 1: Popularity of the extracted labeled classes, measured by the frequency of occurrence of the class labels as full, case-insensitive queries in query logs

| Rank | Class Label | Rank | Class Label | Rank | Class Label |
|------|-------------|------|-------------|------|-------------|
| 1    | games       | 75   | plants      | 151  | gadgets      |
| 5    | poems       | 81   | bacteria    | 155  | enzymes      |
| 11   | cars        | 85   | spiders     | 161  | magazines    |
| 15   | airlines    | 91   | whole foods | 165  | universities |
| 21   | holidays    | 95   | java games  | 171  | batteries    |
| 25   | horses      | 101  | castles     | 175  | genetic disorders |
| 31   | arcade games| 105  | spells      | 181  | tests        |
| 35   | cartoons    | 111  | addresses   | 185  | mammals      |
| 41   | books       | 115  | classic cars| 191  | mutual funds |
| 45   | fun games   | 121  | video games | 195  | shapes       |
| 51   | flags       | 125  | party games | 201  | satellites   |
| 55   | careers     | 131  | famous people| 205  | symptoms    |
| 61   | cards       | 135  | kids        | 211  | surnames    |
| 65   | fairy tales | 141  | candles     | 215  | codes        |
| 71   | watches     | 145  | robots      | 221  | paintings   |

Table 2: Coverage of extracted instances, measured by the percentage of instances encoded under various WordNet hypernyms via Has-Instance relations that occur among the extracted instances (Cvg=coverage)

| Hypernym                  | Instances | Count |
|---------------------------|-----------|-------|
| Australian state          | Synset    | 6     |
| existentialist            | Definition| 8     |
| government building       | Example   | 4     |
| search engine             | Count     | 3     |
| port of entry             | Count     | 25    |
| possession                | Count     | 13    |
| university                | Count     | 44    |
| couturier                 | Count     | 13    |
| fictional animal          | Count     | 6     |
| memorial                  | Count     | 6     |
| painter                   | Count     | 218   |
| continent                 | Count     | 13    |
| educator                  | Count     | 54    |
| eon                       | Count     | 24    |
| anarchist                 | Count     | 14    |
| microscopist              | Count     | 6     |
| national anthem           | Count     | 6     |
| rebellion                 | Count     | 2     |
| soil horizon              | Count     | 6     |

Average (over 945 hypernyms) - 18.71 0.39

Table 3: Hypernyms and synonyms of the class labels

| Hypernym                  | Examples             | Count | Cvg  |
|---------------------------|----------------------|-------|------|
| Australian state          | New South Wales, Queens            |
| existentialist            | Albert Camus, Beauvoir, Camus, Heidegger, Jean-Paul Sartre |
| government building       | Capitol, Capitol Building, Pentagon, White House |
| search engine             | Ask Jeeves, Google, Yahoo |
| port of entry             | Aberdeen, Bellingham, Brownsville, Greater New York |
| possession                | American Virgin Islands, Faroese, Faeroe Islands, Faeroes, Macau |
| university                | Brown, Brown University, Carnegie Mellon University |
| couturier                 | Balenciaga, Calvin Klein, Calvin Richard Klein, Dior |
| fictional animal          | Donald Duck, Easter bunny, Mickey Mouse, Mighty Mouse |
| memorial                  | Great Pyramid, Lincoln Memorial, Pyramids of Egypt |
| painter                   | Amedeo Modigliano, Andy Warhol, Anna Mary Robertson Moses |
| continent                 | Africa, Antarctic continent, Europe, Eurasia, Gondwanaland, Laurasia |
| educator                  | Abbott Lawrence Lowell, Bethune, Booker T. Washington, Carl Orff |
| eon                       | Archaeozoic, Archaeozoic aeon, Archean aeon, Archean eon |
| anarchist                 | Bakunin, Bartolomeo Vanzetti, Prince Peter Kropotkin |
| microscopist              | Anton van Leeuwenhoek, Anton van Leuwenhoek, Swammerdam |
| national anthem           | The Star-Spangled Banner |
| rebellion                 | Great Revolt, Indian Mutiny, Peasant’s Revolt, Sepoy Mutiny |
| soil horizon              | A horizon, A-horizon, B horizon, B-horizon, C horizon, C-horizon |

Average (over 945 hypernyms) - 18.71 0.39
The instances available within WordNet via Has-Instance relations constitute a benchmark against which the coverage of the instances extracted from text can be automatically computed. To this effect, each component phrase of a synset encoded via a Has-Instance relation under a hyponym synset in WordNet is collected as a benchmark instance of that synset. For instance, the synset corresponding to soil horizon, defined as “a layer in soil profile”, has three Has-Instance synsets in WordNet, each of which contains two synonyms: {A-horizon, A horizon}, {B-horizon, B horizon} and {C-horizon, C horizon}. Therefore the synset soil horizon has 6 instances in the benchmark. As shown in the first four columns of Table 2, the resulting benchmark consists of a total of 945 hyponym synsets, with an average of 18 instances per synset in WordNet.

In order to receive full credit for a WordNet synset in terms of coverage, all its WordNet instances of the synset must occur among the extracted instances as full-length, case-insensitive matches. Any variations due to alternative spelling (e.g., Faeroes vs. faroes) or level of specificity (e.g., Abbott Lawrence Lowell vs. abbott lowell) result in failed comparisons, and therefore a lack of any credit towards the computed coverage scores. The last column in Table 2 shows that the coverage varies significantly across the WordNet synsets. For some of the synsets (e.g., anarchist and soil horizon) the WordNet instances occur among the instances extracted from Web text. At the bottom end of the coverage score spectrum, none of the instances available in WordNet for anarchist and soil horizon are found among the extracted instances.

Table 3 summarizes the precision of the extracted data, which is computed by manually inspecting the instances extracted for a sample of eight labeled classes. The lowest precision score, 0.66, is obtained for the class label african countries. Most of the errors within this class are due to the incorrect extraction of non-African countries as part of the same instance set. The precision-oriented heuristics contribute to a precision score of 0.88, as an average over the instance sets associated to the eight sample classes.

4. Conclusion

This paper introduces a few simple, lightweight precision-oriented heuristics for compiling sets of class instances from unstructured text, as an alternative to iterative extraction starting from a few seeds (Riloff and Jones, 1999). When applied to a large repository of Web documents, the heuristics contribute to the acquisition of a large number of accurate sets of labeled classes.

5. References

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