LLNL-CONF-499791

The C-Cat Wordnet Package: An Open Source Package for modifying andapplying Wordnet

K. Stevens, T. Huang, D. Buttler

September 20, 2011

Global Wordnet Conference 2012
Matsue, Japan
January 9, 2012 through January 13, 2012

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Keith Stevens and Terry Huang
Department of Computer Science
University of California, Los Angeles, 90095
{kstevens,thuang513}@cs.ucla.edu

David Buttler
Center for Applied Scientific Computing
LLNL, Livermore 94550
buttler1@llnl.gov

Abstract

We present the C-Cat Wordnet package, an open source library for using and modifying Wordnet. The package includes four key features: an API for modifying Synsets; implementations of standard similarity metrics, implementations of well-known Word Sense Disambiguation algorithms, and an implementation of the Castanet algorithm. The library is easily extendible and usable in many runtime environments. We demonstrate it's use on two standard Word Sense Disambiguation tasks and apply the Castanet algorithm to a corpus.

1 Introduction

Wordnet (Fellbaum, 1998) is a hierarchical lexical database that provides a fine grained semantic interpretation of a word. Wordnet forms a diverse semantic network by first collecting similar words into synonym sets (*Synset*), for example “drink” and “imbibe” are connected under the verb *Synset* defined as “take in liquids.” Then, *Synsets* are connected by relational links, with the IS-A link being the most well known.

Applications typically access Wordnet through one or more libraries. Every popular programming language has at least one library: the original for C++, JWNL [1] for Java, and WordNet::QueryData [2] for Perl are just a few examples. While these libraries are robust and provide many features, they cannot be easily applied to two new use cases: direct modification and serialization of the database and use in a parallel processing framework, such the Hadoop [3] framework. The first has become a popular research topic in recent years, with Snow et al. (2006) providing a well known method for adding new lexical mappings to Wordnet, and the second will increasingly become important as Wordnet applications are applied to massive web-scale datasets.

We developed the C-Cat Wordnet package to address these use cases as part of a larger information extraction and retrieval system that requires word sense information for new, domain specific terms and novel composite senses on web-scale corpora. One example includes adding new lexical mappings harvested from New York Times articles. Without support for saving additions to Wordnet and parallel processing, we would be unable to leverage existing valuable sense information. Our package solves these issues with a new API focused on modifying the database and by storing the entire Wordnet database in memory.

We designed the package to be a flexible library for any Wordnet application. It is written in Java and defines a standard Java interface for core data structures and algorithms. All code has been heavily documented with details on performance trade-offs and unit tested to ensure reliable behavior. While other Wordnet libraries exist, we hope that the release of ours facilitates the development of new, customized Wordnets and the use of Wordnet in large highly parallelized systems. The toolkit is available at `http://github.com/fozziethebeat/C-Cat`, which include a wiki detailing the structure of the package, javadocs, and a mailing list.

2 The C-Cat Wordnet Framework

Fundamentally, Wordnet acts as a mapping from word forms to possible word senses. Terms with similar senses are collapsed into a single *Synset*. The *Synset* network is then formed by linking a *Synset* to others via semantic links such as IS-A, PART-OF, and SIMILAR-TO. Our package makes two significant contributions: a collection

[1]http://sourceforge.net/projects/jwordnet/
[2]http://people.csail.mit.edu/jrennie/WordNet/
[3]http://hadoop.apache.org/

a standardized reference implementations of well known algorithms and a new API for directly modifying and serializing the *Synset* network. Furthermore, it stores the hierarchy in memory, separating lexical queries from disc access and allows for serialization of modified hierarchies. Lastly, it provides features found in comparable libraries such as JWNL.

The C-Cat library is split up into four packages:

1. The Core API contains data format readers, writers, and *Synsets*;
2. Similarity Metrics;
3. Word Sense Disambiguation algorithms;
4. and Castanet (Stoica and Hearst, 2007), a method for automatically learning document facets using Wordnet.

2.1 Core API

The core API is centered around two interfaces: an *OntologyReader* and a *Synset*. The *OntologyReader* is responsible for parsing a Wordnet file format, building a linked *Synset* network, and returning *Synsets* based on query terms and parts of speech. The *Synset* maintains all of the information for a particular word sense, such as it's definitions, examples, and links to other *Synsets*. Both interfaces provide mechanisms for modifying the sense information, *Synset* links, and lexical mappings. We store this entire structure in memory due to the minimal size of Wordnet, for example, version 3.0 is only 37 Megabytes on disk, and so that users can use Wordnet on novel distributed file systems, such as Hadoop, that do not use standard file system APIs.

Synsets are defined by three sets of values: word forms, links to other *Synsets*, and a part of speech. Each *Synset* may have multiple word forms and multiple links, but only one part of speech. We use both standard Wordnet relations and arbitrary relations to label a directed link between two *Synsets*, with the relation being stored in only the source *Synset*. We provide several methods for accessing relations and related *Synsets*: $getKnownRelationTypes()$, $allRelations()$, and $getRelations()$. In addition, each *Synset* can have a set of example sentences and a definition. To modify each *Synset*, the interface includes additive methods for relations, word forms, and examples. Furthermore, we provide a $merge()$ method that takes all information from one *Synset* and adds it to another

```
OntologyReader reader = ...
Synset cat = reader.getSynset("cat.n.1");
for (Synset rel : cat.allRelations())
  cat.merge(rel);
System.out.println(cat);
```

Figure 1: A simple merge example using the *OntologyReader* and *Synset* interfaces.

Synset. Figure 1 provides a simple example using this merge API; after the code has been run, "cat.n.1" will contain all of the information from it's related *Synsets*. Lastly, the interface also permits arbitrary objects, such as ranking values, feature vectors, or additional meta data, to be attached to any *Synset* as an *Attribute*. Any *Attributes* are also merged on a call to *merge*.

OntologyReader defines an interface that maps word forms to *Synset*s. Implementations are designed to be initialized once and then used ubiquitously throughout an application. The interface provides methods for getting all *Synset*s for a word or a specific sense, for example, the query "cat.n.1" in figure 1 retrieves the first noun *Synset* for the term "cat". To modify the sense network, we provide two key methods: $addSynset(new)$ and $removeSynset(old)$. $addSynset(new)$ adds a mapping from each of *new*'s word forms to *new*. $removeSynset(old)$ removes all mappings from *old*'s word forms to *old*, thus removing it from the lexical mapping completely.

2.2 Similarity Metrics

While the semantic network of Wordnet is interesting on it's own, many applications require sense similarity measures. As such, we provide the *SynsetSimilarity* interface that returns a similarity score between two *Sysnet*s. This is, in short, a Java based implementation of the Wordnet::Similarity package (Pedersen et al., 2004), which is in Perl. Figure 2 provides a naive, but short, code sample of our API that computes the similarity between all noun *Synset*s using multiple metrics.

Below, we briefly summarize the measures from (Pedersen et al., 2004) that we implemented. Several measures utilize the Lowest Common Subsumer (LCS), i.e. the deepest parent common to two *Synset*s using IS-A relations. Each measure takes in two *Synset*s, A and B, as arguments and returns a double value, typically between 0 and 1.

```
OntologyReader reader = WordNetCorpusReader.initialize(...);
Set<Sysnet> nouns = reader.allSynsets(PartsOfSpeech.NOUN);
SynsetSimilarity sims[] = {new PathSimilarity(), new LeskSimilarity(), ...};
for (Synset s1 : nouns)
  for (Synset s2 : nouns)
    for (SynsetSimilarity sim : sims)
      System.out.printf("%s %s %f\n", s1, s2, sim.similarity(s1, s2));
```

Figure 2: Code for computing the pairwise similarity over every noun $Synset$ using multiple metrics

Path Based Methods measure the similarity based on a path connecting A and B. $Path$ simply returns the inverse length of the shortest path between A and B. $Leacock\&Chodorow$ (Leacock and Chodorow, 1998) returns the length of the shortest path scaled by the deepest depth in the hierarchy. $Wu\&Palmer$ (Wu and Palmer, 1994) returns the depth of the LCS scaled by the cumulative depth of A and B. $Hirst\&St.Onge$ (Hirst and St-Onge, 1997) uses all links in the hierarchy and measures the length of the path that is both short and has very few link types.

Lexical methods measure the amount of lexical overlap between A and B. $Lesk$ (Lesk, 1986) returns the number of words overlapping in A and B's glosses. $ExtendedLesk$ (Banerjee and Pedersen, 2003) extends Lesk by also comparing the glosses between any $Synset$s related to A or B.

Information based Methods utilize the Information Content (IC) of a $Synset$, which measures the specificity of the terms in a $Synset$ as measured in a sense tagged corpus. $Resnick$ (Resnik, 1995) returns the IC of the LCS. $Jiang\&Conrath$ (Jiang and Conrath, 1997) returns the inverse difference between the total IC of A and B and the IC of their LCS. Lin (Lin, 1998) returns the IC of the LCS scaled by the total IC of A and B.

In addition to the raw similarity metrics, we provide a utility classes that return meta information about a pair of $Sysnets$ such as their shortest path, their LCS, and several other helpful methods.

2.3 Word Sense Disambiguation

Word Sense Disambiguation is perhaps the most standard application of Wordnet. Disambiguation models attempt to select a $Synset$ for a given word that best matches a given context. For example, an algorithm might select the river bank $Synset$ of "bank" for the context "he sat on the bank of the river" rather than the financial institution $Synset$. We provide a $WordSenseDisambiguation$ interface that applies word sense labels to tokenized sentences. Currently, we only provide a small number of unsupervised algorithms, but plan on adding more. Below, we briefly describe each algorithm.

Lexical Methods rely on lexical information in Wordnet to disambiguate words. $Lesk$ (Lesk, 1986) selects the $Synset$ that has the highest total Lesk similarity to the $Synset$s for other context words. $ExtendedLesk$ (Banerjee and Pedersen, 2003) extends Lesk by using the Extended Lesk similarity metric for all comparisons. $MostFrequentSense$ selects the first $Synset$ returned by Wordnet for a given term. This serves as a canonical baseline which is often challenging to outperform.

Graphical Methods treat the network as a graph and disambiguate using a number of measurements. $PersonalizedPageRank$ (Agirre and Soroa, 2009) (PPR) runs the PageRank algorithm over an undirected graph composed from the entire Wordnet network. Words needing disambiguation are given "artificial" nodes that link to their possible $Synset$s. For each ambiguous word, the algorithm selects the highest ranking $Synset$. $DegreeCentrality$ (Navigli and Lapata, 2010) (DC) forms a subgraph from the Wordnet network composed of ambiguous content words in a sentence and the $Synset$s that connect their possible $Synset$s. It assigns to each word the target $Synset$ with the highest degree in the subgraph. $PageRankCentrality$ (Navigli and Lapata, 2010) (PRC) composes the same subgraph as $DegreeCentrality$, but performs PageRank on this subgraph and selects the $Synset$ with the highest rank for each ambiguous word.

2.4 Castanet

Amazon.com and other online retailers often display manually crafted facets, or categories, for product navigation. A customer can start browsing from the Book category and dive down into more specific categories such as Fiction, Entertainment, or Politics. These facets form a hierarchy of categories and each category is subdivided until a narrow set of interesting items are found. Unfortunately, not all datasets have well structured meta data. The Castanet algorithm automatically learns this hierarchical faceted meta data (HFC) for a set of documents by using discriminative keywords (Stoica and Hearst, 2007), making structured navigation possible for arbitrary document sets.

Castanet takes advantage of Wordnets IS-A hierarchy to automatically create HFC. Castanet first extracts keywords from the set of documents (we use term-frequency inverse document frequency, TF-IDF, by default, but our API allows for other methods). For each extracted keyword, Castanet then creates a chain of words that lead from the root of the hierarchy to the keyword's $Synsets$. Each keyword chain is then merged together to form a "backbone" tree which is later reduced by eliminating redundant or non-discriminative nodes, such as those with one child.

Our Castanet API is both simple and flexible. To create a Castanet tree, one calls $Castanet.buildTree()$ with a directory path to a set of text documents. Our implementation will automatically extract keywords, extract the backbone tree, and finally index each document under it's learned facets. The returned result allows users to fully navigate the documents via the learned facets. We also provide an example Java web service for exploring the hierarchy in a browser.

3 Benchmark

To evaluate our library, we apply our six WSD implementations against two standard evaluations: the all words disambiguation tasks from SenseEval 3 (Snyder and Palmer, 2004) and SemEval 2007 (Pradhan et al., 2007), these use Wordnet version 1.7.1 and 2.1 respectively. We answer all test instances except those that do not have any mapping in Wordnet. Before processing, we apply part of speech tags to each token using the Open NLP MaxEnt Tagger ver 1.5.0[4]. We use the original databases as a baseline, called Base, in our experiments and test our modification API by adding the eXtended Wordnet (XWN) relations (Mihalcea and Moldovan, 2001) to each database and disambiguate using these extended Wordnets[5].

Model	Ver	SenseEval-3	SemEval-07
MFS	Base	59.8	49.4
Lesk	Base	35.2	27.7
E-Lesk	Base	47.8	**37.6**
PPR	Base	42.9	32.8
DC	Base	43.2	33.3
PRC	Base	31.7	22.7
Lesk	XWN	35.2	27.7
E-Lesk	XWN	39.9	33.9
PPR	XWN	**50.3**	36.7
DC	XWN	47.3	37.1
PRC	XWN	33.0	24.0

Table 1: F1 Word Sense Disambiguation scores on the two test sets

Table 1 presents the F1 score for each algorithm using the original and extended databases. As expected, the MFS baseline outperforms each unsupervised algorithm. Although our scores do not match exactly with previous publications of these algorithms, we still see similar trends and the expected gains from adding new relations to the hierarchy. For $DegreeCentrality$ and $PageRankCentrality$, our different results are likely due to a implementation difference: when extracting a subgraph from Wordnet, we only use directed links as opposed to undirected links for computational efficiency. Other variations are possibly due to different methods of handling multiword expressions and our part of speech tags. Still, DC gains about 4% points with WXN relations and PPR gains about 7% points on Senseval-3. Unexpectedly, $ExtendedLesk$ actually does worse with the additional relations.

We also performed a visual test of our Castanet implementation. We ran the algorithm over 1,021 articles extracted from the BBC World News using Wordnet 3.0. The articles came from a diverse set of categories including world, business, technology, and environmental news. Figures 3 and 4 show snapshots of our Castanet web application. Figure 3 displays the top level facets displayed to a new user. The top bar of this screen can break down the facets alphabetically to facilitate facet selection. Figure 4 shows a snapshot of several documents found after selecting several facets. It displays the selected facets, document titles, document text, and interesting key words. While this is only a simple interface, it provides an example of what our implementation can accomplish and how

[4]http://opennlp.sourceforge.net/models-1.5/

[5]Note that we added XWN 1.7 relations to Wordnet 1.7.1 and XWN 2.0 relations to Wordnet 2.1, some links were discarded due to updates in Wordnet.

to use our API.

4 Future Work and Conclusion

We have presented our Java Wordnet library that provides two new key features: maintenance of an in memory database and an API centered around modifying the network directly. Additionally, we've provided implementations of several well known similarity metrics, disambiguation algorithms, and the Castanet information retrieval algorithm. All code is unit tested, heavily documented, and released under the GPL Version 2 license. We are currently working to extend our newest APIs, such as those for WSD and Castanet, to handle more interesting use cases. In the future work we hope to expand this library with an evaluation framework for customized Wordnets, such as those generated by (Snow et al., 2006).

Acknowledgements This work was performed under the auspices of the U.S. Department of Energy by Lawrence Livermore National Laboratory under Contract DE-AC52-07NA27344 (LLNL-CONF-499791).

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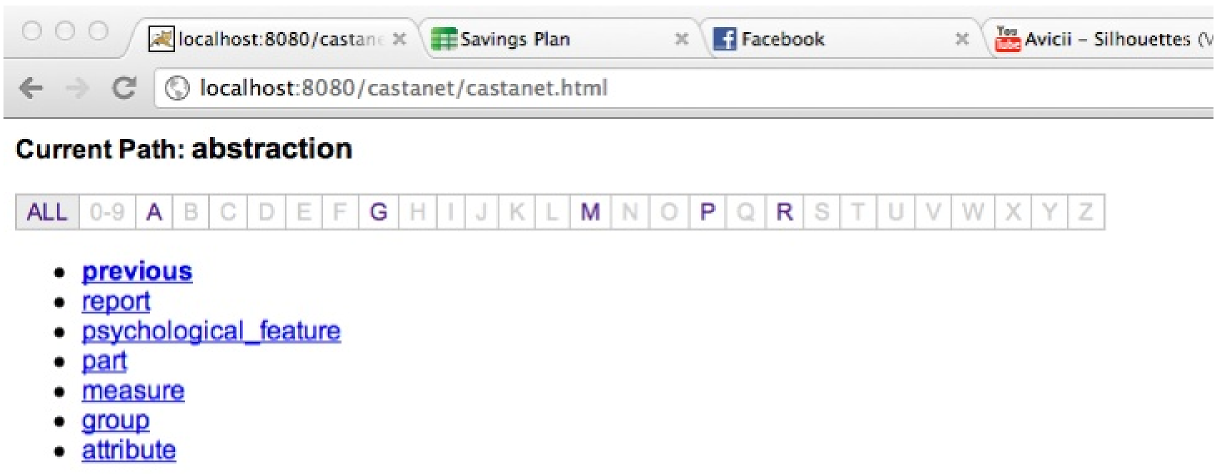
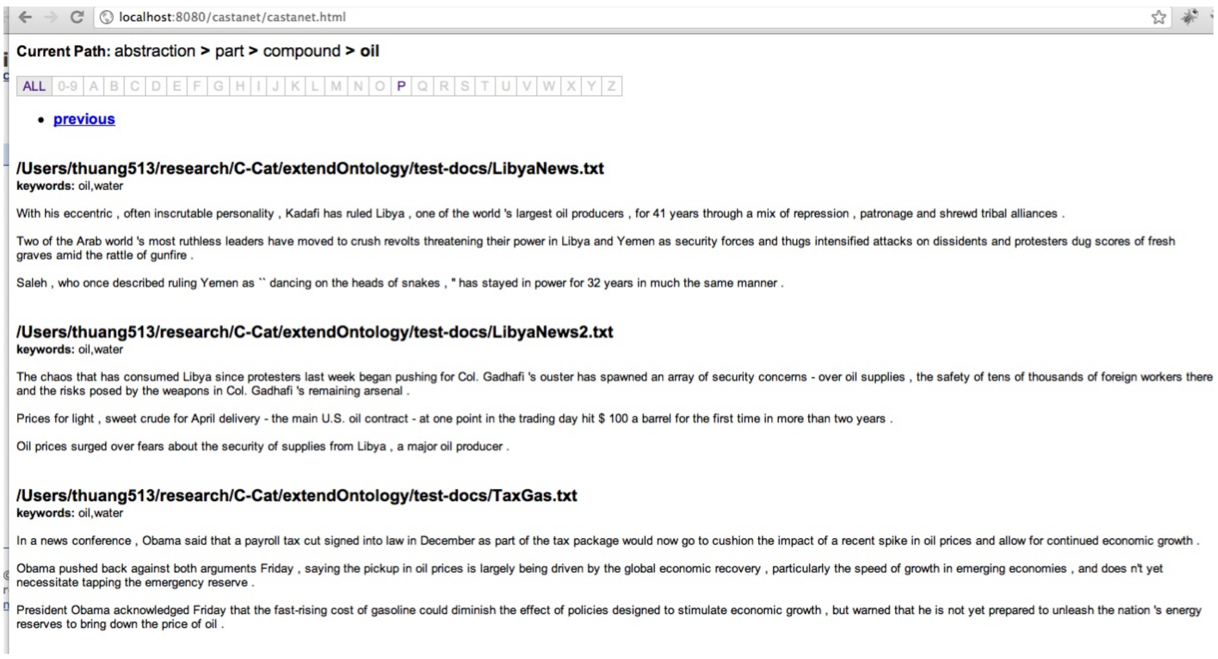


Current Path: abstraction

ALL | 0-9 | A | B | C | D | E | F | G | H | I | J | K | L | M | N | O | P | Q | R | S | T | U | V | W | X | Y | Z

- previous
- report
- psychological_feature
- part
- measure
- group
- attribute

Figure 3: A sample view of learned Castanet facets for the BBC Word News data set



Current Path: abstraction **>** part **>** compound **> oil**

ALL | 0-9 | A | B | C | D | E | F | G | H | I | J | K | L | M | N | O | P | Q | R | S | T | U | V | W | X | Y | Z

- **previous**

/Users/thuang513/research/C-Cat/extendOntology/test-docs/LibyaNews.txt
keywords: oil,water

With his eccentric , often inscrutable personality , Kadafi has ruled Libya , one of the world 's largest oil producers , for 41 years through a mix of repression , patronage and shrewd tribal alliances .

Two of the Arab world 's most ruthless leaders have moved to crush revolts threatening their power in Libya and Yemen as security forces and thugs intensified attacks on dissidents and protesters dug scores of fresh graves amid the rattle of gunfire .

Saleh , who once described ruling Yemen as `` dancing on the heads of snakes , " has stayed in power for 32 years in much the same manner .

/Users/thuang513/research/C-Cat/extendOntology/test-docs/LibyaNews2.txt
keywords: oil,water

The chaos that has consumed Libya since protesters last week began pushing for Col. Gadhafi 's ouster has spawned an array of security concerns - over oil supplies , the safety of tens of thousands of foreign workers there and the risks posed by the weapons in Col. Gadhafi 's remaining arsenal .

Prices for light , sweet crude for April delivery - the main U.S. oil contract - at one point in the trading day hit $ 100 a barrel for the first time in more than two years .

Oil prices surged over fears about the security of supplies from Libya , a major oil producer .

/Users/thuang513/research/C-Cat/extendOntology/test-docs/TaxGas.txt
keywords: oil,water

In a news conference , Obama said that a payroll tax cut signed into law in December as part of the tax package would now go to cushion the impact of a recent spike in oil prices and allow for continued economic growth .

Obama pushed back against both arguments Friday , saying the pickup in oil prices is largely being driven by the global economic recovery , particularly the speed of growth in emerging economies , and does n't yet necessitate tapping the emergency reserve .

President Obama acknowledged Friday that the fast-rising cost of gasoline could diminish the effect of policies designed to stimulate economic growth , but warned that he is not yet prepared to unleash the nation 's energy reserves to bring down the price of oil .

Figure 4: A sample view of a discovered document after navigating the Castanet facets