



NRC Publications Archive (NPArc) Archives des publications du CNRC (NPArc)

A Uniform Approach to Analogies, Synonyms, Antonyms, and Associations

Turney, Peter

Web page / page Web

<http://nparc.cisti-icist.nrc-cnrc.gc.ca/npsi/ctrl?action=rtdoc&an=5764174&lang=en>
<http://nparc.cisti-icist.nrc-cnrc.gc.ca/npsi/ctrl?action=rtdoc&an=5764174&lang=fr>

Access and use of this website and the material on it are subject to the Terms and Conditions set forth at

http://nparc.cisti-icist.nrc-cnrc.gc.ca/npsi/jsp/nparc_cp.jsp?lang=en

READ THESE TERMS AND CONDITIONS CAREFULLY BEFORE USING THIS WEBSITE.

L'accès à ce site Web et l'utilisation de son contenu sont assujettis aux conditions présentées dans le site

http://nparc.cisti-icist.nrc-cnrc.gc.ca/npsi/jsp/nparc_cp.jsp?lang=fr

LISEZ CES CONDITIONS ATTENTIVEMENT AVANT D'UTILISER CE SITE WEB.

Contact us / Contactez nous: nparc.cisti@nrc-cnrc.gc.ca.



National Research
Council Canada

Conseil national
de recherches Canada

Canada



National Research
Council Canada

Institute for
Information Technology

Conseil national
de recherches Canada

Institut de technologie
de l'information

NRC - CNRC

A Uniform Approach to Analogies, Synonyms, Antonyms and Associations.*

Turney, P.D.
August 2008

* Published in the Proceedings of the 22nd International Conference on Computational Linguistics (Coling 2008). Pages 905-912.

Copyright 2008 by
National Research Council of Canada

Permission is granted to quote short excerpts and to reproduce figures and tables from this report, provided that the source of such material is fully acknowledged.

A Uniform Approach to Analogies, Synonyms, Antonyms, and Associations

Peter D. Turney

National Research Council of Canada

Institute for Information Technology

M50 Montreal Road

Ottawa, Ontario, Canada

K1A 0R6

`peter.turney@nrc-cnrc.gc.ca`

Abstract

Recognizing analogies, synonyms, antonyms, and associations appear to be four distinct tasks, requiring distinct NLP algorithms. In the past, the four tasks have been treated independently, using a wide variety of algorithms. These four semantic classes, however, are a tiny sample of the full range of semantic phenomena, and we cannot afford to create ad hoc algorithms for each semantic phenomenon; we need to seek a unified approach. We propose to subsume a broad range of phenomena under analogies. To limit the scope of this paper, we restrict our attention to the subsumption of synonyms, antonyms, and associations. We introduce a supervised corpus-based machine learning algorithm for classifying analogous word pairs, and we show that it can solve multiple-choice SAT analogy questions, TOEFL synonym questions, ESL synonym-antonym questions, and similar-associated-both questions from cognitive psychology.

1 Introduction

A pair of words (petrify:stone) is *analogous* to another pair (vaporize:gas) when the semantic relations between the words in the first pair are highly similar to the relations in the second pair. Two words (levied and imposed) are *synonymous* in a context (levied a tax) when they can be interchanged (imposed a tax), they are *antonymous* when they have opposite meanings (black

and white), and they are *associated* when they tend to co-occur (doctor and hospital).

On the surface, it appears that these are four distinct semantic classes, requiring distinct NLP algorithms, but we propose a uniform approach to all four. We subsume synonyms, antonyms, and associations under analogies. In essence, we say that X and Y are antonyms when the pair $X:Y$ is analogous to the pair black:white, X and Y are synonyms when they are analogous to the pair levied:imposed, and X and Y are associated when they are analogous to the pair doctor:hospital.

There is past work on recognizing analogies (Reitman, 1965), synonyms (Landauer and Dumais, 1997), antonyms (Lin et al., 2003), and associations (Lesk, 1969), but each of these four tasks has been examined separately, in isolation from the others. As far as we know, the algorithm proposed here is the first attempt to deal with all four tasks using a uniform approach. We believe that it is important to seek NLP algorithms that can handle a broad range of semantic phenomena, because developing a specialized algorithm for each phenomenon is a very inefficient research strategy.

It might seem that a lexicon, such as WordNet (Fellbaum, 1998), contains all the information we need to handle these four tasks. However, we prefer to take a corpus-based approach to semantics. Veale (2004) used WordNet to answer 374 multiple-choice SAT analogy questions, achieving an accuracy of 43%, but the best corpus-based approach attains an accuracy of 56% (Turney, 2006). Another reason to prefer a corpus-based approach to a lexicon-based approach is that the former requires less human labour, and thus it is easier to extend to other languages.

In Section 2, we describe our algorithm for recognizing analogies. We use a standard supervised

machine learning approach, with feature vectors based on the frequencies of patterns in a large corpus. We use a support vector machine (SVM) to learn how to classify the feature vectors (Platt, 1998; Witten and Frank, 1999).

Section 3 presents four sets of experiments. We apply our algorithm for recognizing analogies to multiple-choice analogy questions from the SAT college entrance test, multiple-choice synonym questions from the TOEFL (test of English as a foreign language), ESL (English as a second language) practice questions for distinguishing synonyms and antonyms, and a set of word pairs that are labeled *similar*, *associated*, and *both*, developed for experiments in cognitive psychology.

We discuss the results of the experiments in Section 4. The accuracy of the algorithm is competitive with other systems, but the strength of the algorithm is that it is able to handle all four tasks, with no tuning of the learning parameters to the particular task. It performs well, although it is competing against specialized algorithms, developed for single tasks.

Related work is examined in Section 5 and limitations and future work are considered in Section 6. We conclude in Section 7.

2 Classifying Analogous Word Pairs

An analogy, $A:B::C:D$, asserts that A is to B as C is to D ; for example, $\text{traffic:street}::\text{water:riverbed}$ asserts that traffic is to street as water is to riverbed; that is, the semantic relations between traffic and street are highly similar to the semantic relations between water and riverbed. We may view the task of recognizing word analogies as a problem of classifying word pairs (see Table 1).

Word pair	Class label
carpenter:wood	artisan:material
mason:stone	artisan:material
potter:clay	artisan:material
glassblower:glass	artisan:material
traffic:street	entity:carrier
water:riverbed	entity:carrier
packets:network	entity:carrier
gossip:grapevine	entity:carrier

Table 1: Examples of how the task of recognizing word analogies may be viewed as a problem of classifying word pairs.

We approach this as a standard classification problem for supervised machine learning. The al-

gorithm takes as input a training set of word pairs with class labels and a testing set of word pairs without labels. Each word pair is represented as a vector in a feature space and a supervised learning algorithm is used to classify the feature vectors. The elements in the feature vectors are based on the frequencies of automatically defined patterns in a large corpus. The output of the algorithm is an assignment of labels to the word pairs in the testing set. For some of the experiments, we select a unique label for each word pair; for other experiments, we assign probabilities to each possible label for each word pair.

For a given word pair, such as mason:stone , the first step is to generate morphological variations, such as masons:stones . In the following experiments, we use *morpha* (morphological analyzer) and *morphg* (morphological generator) for morphological processing (Minnen et al., 2001).¹

The second step is to search in a large corpus for all phrases of the following form:

“[0 to 1 words] X [0 to 3 words] Y [0 to 1 words]”

In this template, $X:Y$ consists of morphological variations of the given word pair, in either order; for example, mason:stone , stone:mason , masons:stones , and so on. A typical phrase for mason:stone would be “the mason cut the stone with”. We then normalize all of the phrases that are found, by using *morpha* to remove suffixes.

The template we use here is similar to Turney (2006), but we have added extra context words before the X and after the Y . Our morphological processing also differs from Turney (2006). In the following experiments, we search in a corpus of 5×10^{10} words (about 280 GB of plain text), consisting of web pages gathered by a web crawler.² To retrieve phrases from the corpus, we use Wumpus (Büttcher and Clarke, 2005), an efficient search engine for passage retrieval from large corpora.³

The next step is to generate patterns from all of the phrases that were found for all of the input word pairs (from both the training and testing sets). To generate patterns from a phrase, we replace the given word pairs with variables, X and Y , and we replace the remaining words with a wild card symbol (an asterisk) or leave them as they are.

¹<http://www.informatics.susx.ac.uk/research/groups/nlp/carroll/morph.html>.

²The corpus was collected by Charles Clarke, University of Waterloo. We can provide copies on request.

³<http://www.wumpus-search.org/>.

For example, the phrase “the mason cut the stone with” yields the patterns “the X cut * Y with”, “* X * the Y *”, and so on. If a phrase contains n words, then it yields $2^{(n-2)}$ patterns.

Each pattern corresponds to a feature in the feature vectors that we will generate. Since a typical input set of word pairs yields millions of patterns, we need to use feature selection, to reduce the number of patterns to a manageable quantity. For each pattern, we count the number of input word pairs that generated the pattern. For example, “* X cut * Y *” is generated by both mason:stone and carpenter:wood. We then sort the patterns in descending order of the number of word pairs that generated them. If there are N input word pairs (and thus N feature vectors, including both the training and testing sets), then we select the top kN patterns and drop the remainder. In the following experiments, k is set to 20. The algorithm is not sensitive to the precise value of k .

The reasoning behind the feature selection algorithm is that shared patterns make more useful features than rare patterns. The number of features (kN) depends on the number of word pairs (N), because, if we have more feature vectors, then we need more features to distinguish them. Turney (2006) also selects patterns based on the number of pairs that generate them, but the number of selected patterns is a constant (8000), independent of the number of input word pairs.

The next step is to generate feature vectors, one vector for each input word pair. Each of the N feature vectors has kN elements, one element for each selected pattern. The value of an element in a vector is given by the logarithm of the frequency in the corpus of the corresponding pattern for the given word pair. For example, suppose the given pair is mason:stone and the pattern is “* X cut * Y *”. We look at the normalized phrases that we collected for mason:stone and we count how many match this pattern. If f phrases match the pattern, then the value of this element in the feature vector is $\log(f + 1)$ (we add 1 because $\log(0)$ is undefined). Each feature vector is then normalized to unit length. The normalization ensures that features in vectors for high-frequency word pairs (traffic:street) are comparable to features in vectors for low-frequency word pairs (water:riverbed).

Now that we have a feature vector for each input word pair, we can apply a standard supervised learning algorithm. In the following experiments,

we use a sequential minimal optimization (SMO) support vector machine (SVM) with a radial basis function (RBF) kernel (Platt, 1998), as implemented in Weka (Waikato Environment for Knowledge Analysis) (Witten and Frank, 1999).⁴ The algorithm generates probability estimates for each class by fitting logistic regression models to the outputs of the SVM. We disable the normalization option in Weka, since the vectors are already normalized to unit length. We chose the SMO RBF algorithm because it is fast, robust, and it easily handles large numbers of features.

For convenience, we will refer to the above algorithm as PairClass. In the following experiments, PairClass is applied to each of the four problems with no adjustments or tuning to the specific problems. Some work is required to fit each problem into the general framework of PairClass (supervised classification of word pairs) but the core algorithm is the same in each case.

3 Experiments

This section presents four sets of experiments, with analogies, synonyms, antonyms, and associations. We explain how each task is treated as a problem of classifying analogous word pairs, we give the experimental results, and we discuss past work on each of the four tasks.

3.1 SAT Analogies

In this section, we apply PairClass to the task of recognizing analogies. To evaluate the performance, we use a set of 374 multiple-choice questions from the SAT college entrance exam. Table 2 shows a typical question. The target pair is called the *stem*. The task is to select the choice pair that is most analogous to the stem pair.

Stem:	mason:stone
Choices:	(a) teacher:chalk
	(b) carpenter:wood
	(c) soldier:gun
	(d) photograph:camera
	(e) book:word
Solution:	(b) carpenter:wood

Table 2: An example of a question from the 374 SAT analogy questions.

The problem of recognizing word analogies was first attempted with a system called Argus (Reit-

⁴<http://www.cs.waikato.ac.nz/ml/weka/>.

man, 1965), using a small hand-built semantic network with a spreading activation algorithm. Turney et al. (2003) used a combination of 13 independent modules. Veale (2004) used a spreading activation algorithm with WordNet (in effect, treating WordNet as a semantic network). Turney (2006) used a corpus-based algorithm.

We may view Table 2 as a binary classification problem, in which mason:stone and carpenter:wood are positive examples and the remaining word pairs are negative examples. The difficulty is that the labels of the choice pairs must be hidden from the learning algorithm. That is, the training set consists of one positive example (the stem pair) and the testing set consists of five unlabeled examples (the five choice pairs). To make this task more tractable, we randomly choose a stem pair from one of the 373 other SAT analogy questions, and we assume that this new stem pair is a negative example, as shown in Table 3.

Word pair	Train or test	Class label
mason:stone	train	positive
tutor:pupil	train	negative
teacher:chalk	test	hidden
carpenter:wood	test	hidden
soldier:gun	test	hidden
photograph:camera	test	hidden
book:word	test	hidden

Table 3: How to fit a SAT analogy question into the framework of supervised pair classification.

To answer the SAT question, we use PairClass to estimate the probability that each testing example is positive, and we guess the testing example with the highest probability. Learning from a training set with only one positive example and one negative example is difficult, since the learned model can be highly unstable. To increase the stability, we repeat the learning process 10 times, using a different randomly chosen negative training example each time. For each testing word pair, the 10 probability estimates are averaged together. This is a form of bagging (Breiman, 1996).

PairClass attains an accuracy of 52.1%. For comparison, the ACL Wiki lists 12 previously published results with the 374 SAT analogy questions.⁵ Only 2 of the 12 algorithms have higher accuracy. The best previous result is an accuracy of 56.1% (Turney, 2006). Random guessing would

⁵For more information, see *SAT Analogy Questions (State of the art)* at <http://aclweb.org/aclwiki/>.

yield an accuracy of 20%. The average senior high school student achieves 57% correct (Turney, 2006).

3.2 TOEFL Synonyms

Now we apply PairClass to the task of recognizing synonyms, using a set of 80 multiple-choice synonym questions from the TOEFL (test of English as a foreign language). A sample question is shown in Table 4. The task is to select the choice word that is most similar in meaning to the stem word.

Stem:		levied
Choices:	(a)	imposed
	(b)	believed
	(c)	requested
	(d)	correlated
Solution:	(a)	imposed

Table 4: An example of a question from the 80 TOEFL questions.

Synonymy can be viewed as a high degree of semantic similarity. The most common way to measure semantic similarity is to measure the distance between words in WordNet (Resnik, 1995; Jiang and Conrath, 1997; Hirst and St-Onge, 1998). Corpus-based measures of word similarity are also common (Lesk, 1969; Landauer and Dumais, 1997; Turney, 2001).

We may view Table 4 as a binary classification problem, in which the pair levied:imposed is a positive example of the class *synonymous* and the other possible pairings are negative examples, as shown in Table 5.

Word pair	Class label
levied:imposed	positive
levied:believed	negative
levied:requested	negative
levied:correlated	negative

Table 5: How to fit a TOEFL question into the framework of supervised pair classification.

The 80 TOEFL questions yield 320 (80×4) word pairs, 80 labeled positive and 240 labeled negative. We apply PairClass to the word pairs using ten-fold cross-validation. In each random fold, 90% of the pairs are used for training and 10% are used for testing. For each fold, the model that is learned from the training set is used to assign probabilities to the pairs in the testing set. With

ten separate folds, the ten non-overlapping testing sets cover the whole dataset. Our guess for each TOEFL question is the choice with the highest probability of being positive, when paired with the corresponding stem.

PairClass attains an accuracy of 76.2%. For comparison, the ACL Wiki lists 15 previously published results with the 80 TOEFL synonym questions.⁶ Of the 15 algorithms, 8 have higher accuracy and 7 have lower. The best previous result is an accuracy of 97.5% (Turney et al., 2003), obtained using a hybrid of four different algorithms. Random guessing would yield an accuracy of 25%. The average foreign applicant to a US university achieves 64.5% correct (Landauer and Dumais, 1997).

3.3 Synonyms and Antonyms

The task of classifying word pairs as either synonyms or antonyms readily fits into the framework of supervised classification of word pairs. Table 6 shows some examples from a set of 136 ESL (English as a second language) practice questions that we collected from various ESL websites.

Word pair	Class label
galling:irksome	synonyms
yield:bend	synonyms
naive:callow	synonyms
advise:suggest	synonyms
dissimilarity:resemblance	antonyms
commend:denounce	antonyms
expose:camouflage	antonyms
unveil:veil	antonyms

Table 6: Examples of synonyms and antonyms from 136 ESL practice questions.

Lin et al. (2003) distinguish synonyms from antonyms using two patterns, “from X to Y ” and “either X or Y ”. When X and Y are antonyms, they occasionally appear in a large corpus in one of these two patterns, but it is very rare for synonyms to appear in these patterns. Our approach is similar to Lin et al. (2003), but we do not rely on hand-coded patterns; instead, PairClass patterns are generated automatically.

Using ten-fold cross-validation, PairClass attains an accuracy of 75.0%. Always guessing the majority class would result in an accuracy of 65.4%. The average human score is unknown and

there are no previous results for comparison.

3.4 Similar, Associated, and Both

A common criticism of corpus-based measures of word similarity (as opposed to lexicon-based measures) is that they are merely detecting associations (co-occurrences), rather than actual semantic similarity (Lund et al., 1995). To address this criticism, Lund et al. (1995) evaluated their algorithm for measuring word similarity with word pairs that were labeled *similar*, *associated*, or *both*. These labeled pairs were originally created for cognitive psychology experiments with human subjects (Chiarello et al., 1990). Table 7 shows some examples from this collection of 144 word pairs (48 pairs in each of the three classes).

Word pair	Class label
table:bed	similar
music:art	similar
hair:fur	similar
house:cabin	similar
cradle:baby	associated
mug:beer	associated
camel:hump	associated
cheese:mouse	associated
ale:beer	both
uncle:aunt	both
pepper:salt	both
frown:smile	both

Table 7: Examples of word pairs labeled *similar*, *associated*, or *both*.

Lund et al. (1995) did not measure the accuracy of their algorithm on this three-class classification problem. Instead, following standard practice in cognitive psychology, they showed that their algorithm’s similarity scores for the 144 word pairs were correlated with the response times of human subjects in priming tests. In a typical priming test, a human subject reads a *priming* word (*cradle*) and is then asked to complete a partial word (complete *bab* as *baby*). The time required to perform the task is taken to indicate the strength of the cognitive link between the two words (*cradle* and *baby*).

Using ten-fold cross-validation, PairClass attains an accuracy of 77.1% on the 144 word pairs. Since the three classes are of equal size, guessing the majority class and random guessing both yield an accuracy of 33.3%. The average human score is unknown and there are no previous results for comparison.

⁶For more information, see *TOEFL Synonym Questions (State of the art)* at <http://aclweb.org/aclwiki/>.

4 Discussion

The four experiments are summarized in Tables 8 and 9. For the first two experiments, where there are previous results, PairClass is not the best, but it performs competitively. For the second two experiments, PairClass performs significantly above the baselines. However, the strength of this approach is not its performance on any one task, but the range of tasks it can handle.

As far as we know, this is the first time a standard supervised learning algorithm has been applied to any of these four problems. The advantage of being able to cast these problems in the framework of standard supervised learning problems is that we can now exploit the huge literature on supervised learning. Past work on these problems has required implicitly coding our knowledge of the nature of the task into the structure of the algorithm. For example, the structure of the algorithm for latent semantic analysis (LSA) implicitly contains a theory of synonymy (Landauer and Dumais, 1997). The problem with this approach is that it can be very difficult to work out how to modify the algorithm if it does not behave the way we want. On the other hand, with a supervised learning algorithm, we can put our knowledge into the labeling of the feature vectors, instead of putting it directly into the algorithm. This makes it easier to guide the system to the desired behaviour.

With our approach to the SAT analogy questions, we are blurring the line between supervised and unsupervised learning, since the training set for a given SAT question consists of a single real positive example (and a single “virtual” or “simulated” negative example). In effect, a single example (mason:stone) becomes a *sui generis*; it constitutes a class of its own. It may be possible to apply the machinery of supervised learning to other problems that apparently call for unsupervised learning (for example, clustering or measuring similarity), by using this *sui generis* device.

5 Related Work

One of the first papers using supervised machine learning to classify word pairs was Rosario and Hearst’s (2001) paper on classifying noun-modifier pairs in the medical domain. For example, the noun-modifier expression *brain biopsy* was classified as *Procedure*. Rosario and Hearst (2001) constructed feature vectors for each noun-modifier pair using MeSH (Medical Subject Head-

ings) and UMLS (Unified Medical Language System) as lexical resources. They then trained a neural network to distinguish 13 classes of semantic relations, such as *Cause*, *Location*, *Measure*, and *Instrument*. Nastase and Szpakowicz (2003) explored a similar approach to classifying general-domain noun-modifier pairs, using WordNet and Roget’s Thesaurus as lexical resources.

Turney and Littman (2005) used corpus-based features for classifying noun-modifier pairs. Their features were based on 128 hand-coded patterns. They used a nearest-neighbour learning algorithm to classify general-domain noun-modifier pairs into 30 different classes of semantic relations. Turney (2006) later addressed the same problem using 8000 automatically generated patterns.

One of the tasks in SemEval 2007 was the classification of semantic relations between nominals (Girju et al., 2007). The problem is to classify semantic relations between nouns and noun compounds in the context of a sentence. The task attracted 14 teams who created 15 systems, all of which used supervised machine learning with features that were lexicon-based, corpus-based, or both.

PairClass is most similar to the algorithm of Turney (2006), but it differs in the following ways:

- PairClass does not use a lexicon to find synonyms for the input word pairs. One of our goals in this paper is to show that a pure corpus-based algorithm can handle synonyms without a lexicon. This considerably simplifies the algorithm.
- PairClass uses a support vector machine (SVM) instead of a nearest neighbour (NN) learning algorithm.
- PairClass does not use the singular value decomposition (SVD) to smooth the feature vectors. It has been our experience that SVD is not necessary with SVMs.
- PairClass generates probability estimates, whereas Turney (2006) uses a cosine measure of similarity. Probability estimates can be readily used in further downstream processing, but cosines are less useful.
- The automatically generated patterns in PairClass are slightly more general than the patterns of Turney (2006).
- The morphological processing in PairClass (Minnen et al., 2001) is more sophisticated than in Turney (2006).

Experiment	Number of vectors		Number of features		Number of classes
SAT Analogies	2,244	(374×6)	44,880	$(2,244 \times 20)$	374
TOEFL Synonyms	320	(80×4)	6,400	(320×20)	2
Synonyms and Antonyms	136		2,720	(136×20)	2
Similar, Associated, and Both	144		2,880	(144×20)	3

Table 8: Summary of the four tasks. See Section 3 for explanations.

Experiment	Accuracy	Best previous	Human	Baseline	Rank
SAT Analogies	52.1%	56.1%	57.0%	20.0%	2 higher out of 12
TOEFL Synonyms	76.2%	97.5%	64.5%	25.0%	8 higher out of 15
Synonyms and Antonyms	75.0%	none	unknown	65.4%	none
Similar, Associated, and Both	77.1%	none	unknown	33.3%	none

Table 9: Summary of experimental results. See Section 3 for explanations.

However, we believe that the main contribution of this paper is not PairClass itself, but the extension of supervised word pair classification beyond the classification of noun-modifier pairs and semantic relations between nominals, to analogies, synonyms, antonyms, and associations. As far as we know, this has not been done before.

6 Limitations and Future Work

The main limitation of PairClass is the need for a large corpus. Phrases that contain a pair of words tend to be more rare than phrases that contain either of the members of the pair, thus a large corpus is needed to ensure that sufficient numbers of phrases are found for each input word pair. The size of the corpus has a cost in terms of disk space and processing time. In the future, as hardware improves, this will become less of an issue, but there may be ways to improve the algorithm, so that a smaller corpus is sufficient.

Another area for future work is to apply PairClass to more tasks. WordNet includes more than a dozen semantic relations (e.g., synonyms, hyponyms, hypernyms, meronyms, holonyms, and antonyms). PairClass should be applicable to all of these relations. Other potential applications include any task that involves semantic relations, such as word sense disambiguation, information retrieval, information extraction, and metaphor interpretation.

7 Conclusion

In this paper, we have described a uniform approach to analogies, synonyms, antonyms, and associations, in which all of these phenomena are subsumed by analogies. We view the problem of recognizing analogies as the classification of semantic relations between words.

We believe that most of our lexical knowledge is relational, not attributional. That is, meaning is largely about relations among words, rather than properties of individual words, considered in isolation. For example, consider the knowledge encoded in WordNet: much of the knowledge in WordNet is embedded in the graph structure that connects words.

Analogies of the form $A:B::C:D$ are called *proportional analogies*. These types of lower-level analogies may be contrasted with higher-level analogies, such as the analogy between the solar system and Rutherford’s model of the atom (Falkenhainer et al., 1989), which are sometimes called *conceptual analogies*. We believe that the difference between these two types is largely a matter of complexity. A higher-level analogy is composed of many lower-level analogies. Progress with algorithms for processing lower-level analogies will eventually contribute to algorithms for higher-level analogies.

The idea of subsuming a broad range of semantic phenomena under analogies has been suggested by many researchers. Minsky (1986) wrote, “How do we ever understand anything? Almost always, I think, by using one or another kind of analogy.” Hofstadter (2007) claimed, “all meaning comes from analogies.” In NLP, analogical algorithms have been applied to machine translation (Lepage and Denoual, 2005), morphology (Lepage, 1998), and semantic relations (Turney and Littman, 2005). Analogy provides a framework that has the potential to unify the field of semantics. This paper is a small step towards that goal.

Acknowledgements

Thanks to Joel Martin and the anonymous reviewers of Coling 2008 for their helpful comments.

References

- Breiman, Leo. 1996. Bagging predictors. *Machine Learning*, 24(2):123–140.
- Büttcher, Stefan and Charles Clarke. 2005. Efficiency vs. effectiveness in terabyte-scale information retrieval. In *Proceedings of the 14th Text REtrieval Conference (TREC 2005)*, Gaithersburg, MD.
- Chiarello, Christine, Curt Burgess, Lorie Richards, and Alma Pollock. 1990. Semantic and associative priming in the cerebral hemispheres: Some words do, some words don't ... sometimes, some places. *Brain and Language*, 38:75–104.
- Falkenhainer, Brian, Kenneth D. Forbus, and Dedre Gentner. 1989. The structure-mapping engine: Algorithm and examples. *Artificial Intelligence*, 41(1):1–63.
- Fellbaum, Christiane, editor. 1998. *WordNet: An Electronic Lexical Database*. MIT Press.
- Girju, Roxana, Preslav Nakov, Vivi Nastase, Stan Szpakowicz, Peter Turney, and Deniz Yuret. 2007. Semeval-2007 task 04: Classification of semantic relations between nominals. In *SemEval 2007*, pages 13–18, Prague, Czech Republic.
- Hirst, Graeme and David St-Onge. 1998. Lexical chains as representations of context for the detection and correction of malapropisms. In Fellbaum, Christiane, editor, *WordNet: An Electronic Lexical Database*, pages 305–332. MIT Press.
- Hofstadter, Douglas. 2007. *I Am a Strange Loop*. Basic Books.
- Jiang, Jay J. and David W. Conrath. 1997. Semantic similarity based on corpus statistics and lexical taxonomy. In *ROCLING X*, pages 19–33, Tapei, Taiwan.
- Landauer, Thomas K. and Susan T. Dumais. 1997. A solution to Plato's problem: The latent semantic analysis theory of the acquisition, induction, and representation of knowledge. *Psychological Review*, 104(2):211–240.
- Lepage, Yves and Etienne Denoual. 2005. Purest ever example-based machine translation: Detailed presentation and assessment. *Machine Translation*, 19(3):251–282.
- Lepage, Yves. 1998. Solving analogies on words: An algorithm. In *Proceedings of the 36th Annual Conference of the Association for Computational Linguistics*, pages 728–735.
- Lesk, Michael E. 1969. Word-word associations in document retrieval systems. *American Documentation*, 20(1):27–38.
- Lin, Dekang, Shaojun Zhao, Lijuan Qin, and Ming Zhou. 2003. Identifying synonyms among distributionally similar words. In *IJCAI-03*, pages 1492–1493.
- Lund, Kevin, Curt Burgess, and Ruth Ann Atchley. 1995. Semantic and associative priming in high-dimensional semantic space. In *Proceedings of the 17th Annual Conference of the Cognitive Science Society*, pages 660–665.
- Minnen, Guido, John Carroll, and Darren Pearce. 2001. Applied morphological processing of English. *Natural Language Engineering*, 7(3):207–223.
- Minsky, Marvin. 1986. *The Society of Mind*. Simon & Schuster, New York, NY.
- Nastase, Vivi and Stan Szpakowicz. 2003. Exploring noun-modifier semantic relations. In *Fifth International Workshop on Computational Semantics (IWCS-5)*, pages 285–301, Tilburg, The Netherlands.
- Platt, John C. 1998. Fast training of support vector machines using sequential minimal optimization. In *Advances in Kernel Methods: Support Vector Learning*, pages 185–208. MIT Press Cambridge, MA, USA.
- Reitman, Walter R. 1965. *Cognition and Thought: An Information Processing Approach*. John Wiley and Sons, New York, NY.
- Resnik, Philip. 1995. Using information content to evaluate semantic similarity in a taxonomy. In *IJCAI-95*, pages 448–453, San Mateo, CA. Morgan Kaufmann.
- Rosario, Barbara and Marti Hearst. 2001. Classifying the semantic relations in noun-compounds via a domain-specific lexical hierarchy. In *EMNLP-01*, pages 82–90.
- Turney, Peter D. and Michael L. Littman. 2005. Corpus-based learning of analogies and semantic relations. *Machine Learning*, 60(1–3):251–278.
- Turney, Peter D., Michael L. Littman, Jeffrey Bigham, and Victor Shnayder. 2003. Combining independent modules to solve multiple-choice synonym and analogy problems. In *RANLP-03*, pages 482–489, Borovets, Bulgaria.
- Turney, Peter D. 2001. Mining the Web for synonyms: PMI-IR versus LSA on TOEFL. In *Proceedings of the Twelfth European Conference on Machine Learning*, pages 491–502, Berlin. Springer.
- Turney, Peter D. 2006. Similarity of semantic relations. *Computational Linguistics*, 32(3):379–416.
- Veale, Tony. 2004. WordNet sits the SAT: A knowledge-based approach to lexical analogy. In *Proceedings of the 16th European Conference on Artificial Intelligence (ECAI 2004)*, pages 606–612, Valencia, Spain.
- Witten, Ian H. and Eibe Frank. 1999. *Data Mining: Practical Machine Learning Tools and Techniques with Java Implementations*. Morgan Kaufmann, San Francisco.