Robust Photo Retrieval Using World Semantics

Hugo Liu*, Henry Lieberman*

* MIT Media Laboratory
Software Agents Group
20 Ames St., E15-320G
Cambridge, MA 02139, USA
{hugo, lieber}@media.mit.edu

Abstract

Photos annotated with textual keywords can be thought of as resembling documents, and querying for photos by keywords is akin to the information retrieval done by search engines. A common approach to making IR more robust involves query expansion using a thesaurus or other lexical resource. The chief limitation is that keyword expansions tend to operate on a word level, and expanded keywords are generally lexically motivated rather than conceptually motivated. In our photo domain, we propose a mechanism for robust retrieval by expanding the *concepts* depicted in the photos, thus going beyond lexical-based expansion. Because photos often depict places, situations and events in everyday life, concepts depicted in photos such as place, event, and activity can be expanded based on our "common sense" notions of how concepts relate to each other in the real world. For example, given the concept "surfer" and our common sense knowledge that surfers can be found at the beach, we might provide the additional concepts: "beach", "waves", "ocean", and "surfboard". This paper presents a mechanism for robust photo retrieval by expanding annotations using a world semantic resource. The resource is automatically constructed from a large-scale freely available corpus of commonsense knowledge. We discuss the challenges of building a semantic resource from a noisy corpus and applying the resource appropriately to the task.

1. Introduction

The task described in this paper is the robust retrieval of annotated photos by a keyword query. By "annotated photos," we mean a photo accompanied by some metadata about the photo, such as keywords and phrases describing people, things, places, and activities depicted in the photo. By "robust retrieval," we mean that photos should be retrievable not just by the explicit keywords in the annotation, but also by other implicit keywords conceptually related to the event depicted in the photo.

In the retrieval sense, annotated photos behave similarly to documents because both contain text, which can be exploited by conventional IR techniques. In fact, the common query enrichment techniques such as thesaurus-based keyword expansion developed for document retrieval may be applied to the photo retrieval domain without modification.

However, keyword expansion using thesauri is limited in its usefulness because keywords expanded by their synonyms can still only retrieve documents directly related to the original keyword. Furthermore, naïve synonym expansion may actually contribute more noise to the query and negate what little benefit keyword expansion may add to the query, namely, if keywords cannot have their word sense disambiguated, then synonyms for all the word senses of a particular word may be used in the expansion, and this has the potential to retrieve many irrelevant documents.

1.1. Relevant Work

Attempting to overcome the limited usefulness of keyword expansion by synonyms, various researchers have tried to use slightly more sophisticated resources for query expansion. These include dictionary-like resources such as lexical semantic relations (Voorhees, 1994), and keyword co-occurrence statistics (Peat and Willet, 1991; Lin, 1998), as well as resources generated dynamically through relevance feedback, like global document analysis (Xu and Croft, 1996), and collaborative concept-based expansion (Klink, 2001).

Although some of these approaches are promising, they share some of the same problems as naïve synonym expansion. Dictionary-like resources such as WordNet (Fellbaum, 1998) and co-occurrence frequencies, although more sophisticated that just synonyms, still operate mostly on the word-level and suggest expansions that are lexically motivated rather than conceptually motivated. In the case of WordNet, lexical items are related through a very limited set of nymic relations. Relevance feedback, though somewhat more successful than dictionary approaches, requires additional iterations of user action and we cannot consider it fully automated retrieval, which makes it an inappropriate candidate for our task.

1.2. Photos vs. Documents

With regard to our domain of photo retrieval, we make a key observation about the difference between photos and documents, and we exploit this difference to make photo retrieval more robust. We make the observation that photos taken by an ordinary person has more structure and is more predictable than the average document on the web, even though that structure may not be immediately evident. The contents of a typical document such as a web page are hard to predict, because there are too many types and genres of web pages and the content does not predictably follow a stereotyped structure. However, with typical photos, such as one found in your photo album, there is more predictable structure. That is, the intended subject of photos often includes people and things in common social situations. Many of these situations depicted, such as weddings, vacations, sporting events, sightseeing, etc. are common to human experience, and therefore have a high level of predictability.

Take for example, a picture annotated with the keyword *"bride"*. Even without looking at the photo, a person may be able to successfully guess who else is in the photo, and what situation is being depicted. Common sense would lead a person to reason that brides are usually found at weddings, that people found around her may be the groom, the father of the bride, bridesmaids, that weddings may take place in a chapel or church, that there may be a wedding cake, walking down the aisle, and a wedding reception. Of course, common sense cannot be used to predict the structure of specialty photos such as artistic or highly specialized photos; this paper only considers photos in the realm of consumer photography.

1.2.1. A Caveat

Before we proceed, it is important to point out that any semantic resource that attempts to encapsulate common knowledge about the everyday world is going to be somewhat culturally specific. The previous example of brides, churches and weddings illustrates an important point: knowledge that is *obvious* and *common* to one group of people (in this case, middle-class USA) may not be so obvious or common to other groups. With that in mind, we go on to define the properties of this semantic resource.

1.3. World Semantics

Knowledge about the spatial, temporal, and social relations of the everyday world is part of commonsense knowledge. We also call this *world semantics*, referring to the meaning of everyday concepts and how these concepts relate to each other in the world.

The mechanism we propose for robust photo retrieval uses a world semantic resource in order to expand concepts in existing photo annotations with concepts that are, *inter alia,* spatially, temporally, and socially related. More specifically, we automatically constructed our resource from a corpus of English sentences about commonsense by first extracting predicate argument structures, and then compiling those structures into a Concept Node Graph, where the nodes are commonsense concepts, and the weighted edges represent commonsense relations. The graph is structured much like MindNet (Richardson et al., 1998). Performing concept expansion using the graph is modeled as spreading activation (Salton and Buckley, 1988). The relevance of a concept is measured as the semantic proximity between nodes on the graph, and is affected by the strength of the links between nodes.

This paper is structured as follows: First, we discuss the source and nature of the corpus of commonsense knowledge used by our mechanism. Second, a discussion follows regarding how our world semantic resource was automatically constructed from the corpus. Third, we show the spreading activation strategy for robust photo retrieval, and give heuristics for coping with the noise and ambiguity of the knowledge. The paper concludes with a discussion of the larger system to which this mechanism belongs, potential application of this type of resource in other domains, and plans for future work.

2. OMCS: A Corpus of Common Sense

The source of the world semantic knowledge used by our mechanism is the Open Mind Common Sense Knowledge Base (OMCS) (Singh, 2002) - an endeavor at the MIT Media Laboratory that aims to allow a web-community of teachers to collaboratively build a database of "common sense" knowledge.

It is hard to define what actually constitutes common sense, but in general, one can think of it as knowledge about the everyday world that most people within some population consider to be "obvious." As stated earlier, common sense is somewhat culturally specific. Although many thousands of people from around the world collaboratively contribute to Open Mind Common Sense, the majority of the knowledge in the corpus reflects the cultural bias of middle-class USA. In the future, it may make sense to tag knowledge by their cultural specification.

OMCS contains over 400,000 semi-structured English sentences about commonsense, organized into an ontology of commonsense relations such as the following:

- A is a B
- You are likely to find A in/at B
- A is used for B

By semi-structured English, we mean that many of the sentences loosely follow one of 20 or so sentence patterns in the ontology. However, the words and phrases represented by A and B (see above) are not restricted. Some examples of sentences in the knowledge base are:

- Something you find in (a restaurant) is (a waiter)
- The last thing you do when (getting ready for bed) is (turning off the lights)
- While (acting in a play) you might (forget your lines)

The parentheses above denote the part of the sentence pattern that is unrestricted. While English sentence patterns has the advantage of making knowledge easy to gather from ordinary people, there are also problems associated with this. The major limitations of OMCS are four-fold. First, there is ambiguity resulting from the lack of disambiguated word senses, and from the inherent nature of natural languages. Second, many of the sentences are unusable because they may be too complex to fully parse with current parser technology. Third, because there is currently no truth maintenance mechanism or filtering strategy for the knowledge gathered (and such a mechanism is completely nontrivial to build), some of the knowledge may be anomalous, i.e. not common sense, or may plainly contradict other knowledge in the corpus. Fourth, in the acquisition process, there is no mechanism to ensure a broad coverage over many different topics and concepts, so some concepts may be more developed than others.

The Open Mind Commonsense Knowledge Base is often compared with its more famous counterpart, the CYC Knowledge Base (Lenat, 1998). CYC contains over 1,000,000 hand-entered rules that constitute "common sense". Unlike OMCS, CYC represents knowledge using formal logic, and ambiguity is minimized. In fact, it does not share any of the limitations mentioned for OMCS. Of course, the tradeoff is that whereas a community of non-experts contributes to OMCS, CYC needs to be somewhat carefully engineered. Unfortunately, the CYC corpus is not publicly available at this time, whereas OMCS *is* freely available and downloadable via the website (www.openmind.org/commonsense).

Even though OMCS is a more noisy and ambiguous corpus, we find that it is still suitable to our task. By normalizing the concepts, we can filter out some possibly unusable knowledge (Section 3.2). The impact of ambiguity and noise can be minimized using heuristics (Section 4.1). Even with these precautionary efforts, some anomalous or bad knowledge will still exist, and can lead to seemingly semantically irrelevant concept expansions. In this case, we rely on the fail-soft nature of the application that uses this semantic resource to handle noise gracefully.

3. Constructing a World Semantic Resource

In this section, we describe how a usable subset of the knowledge in OMCS is extracted and structured specifically for the photo retrieval task. First, we apply sentence pattern rules to the raw OMCS corpus and extract crude predicate argument structures, where predicates represent commonsense relations and arguments represent commonsense concepts. Second, concepts are normalized using natural language techniques, and unusable sentences are discarded. Third, the predicate argument structures are read into a Concept Node Graph, where nodes represent concepts, and edges represent predicate relationships. Edges are weighted to indicate the strength of the semantic connectedness between two concept nodes.

3.1. Extracting Predicate Argument Structures

The first step in extracting predicate argument structures is to apply a fixed number of mapping rules to the sentences in OMCS. Each mapping rule captures a different commonsense relation. Commonsense relations, insofar as what interests us for constructing our world semantic resource for photos, fall under the following general categories of knowledge:

1. Classification: A dog is a pet
2. Spatial: San Francisco is part of California
3. Scene: Things often found together are: restaurant, food, waiters, tables, seats
4. Purpose: A vacation is for relaxation; Pets are for companionship
5. Causality: After the wedding ceremony comes the wedding reception.
6. Emotion: A pet makes you feel happy; Rollercoasters make you feel excited and scared.

In our extraction system, mapping rules can be found under all of these categories. To explain mapping rules, we give an example of knowledge from the aforementioned Scene category:

```
somewhere THING1 can be is PLACE1
somewherecanbe
THING1, PLACE1
0.5, 0.1
```

Mapping rules can be thought of as the grammar in a shallow sentence pattern matching parser. The first line in each mapping rule is a sentence pattern. THING1 and PLACE1 are variables that approximately bind to a word or phrase, which is later mapped to a set of canonical commonsense concepts. Line 2 specifies the name of this predicate relation. Line 3 specifies the arguments to the predicate, and corresponds to the variable names in line 1. The pair of numbers on the last line represents the confidence weights given to forward relation (left to right), and backward relation (right to left), respectively, for this predicate relation. This also corresponds to the weights associated with the directed edges between the nodes, THING1 and PLACE1 in the graph representation.

It is important to distinguish the value of the forward relation on a particular rule, as compared to a backward relation. For example, let us consider the commonsense fact, *"somewhere a bride can be is at a wedding."* Given the annotation *"bride,"* it may be very useful to return *"wedding."* However, given the annotation *"wedding,"* it seems to be less useful to return *"bride," "groom," "wedding cake," "priest,"* and all the other things found in a wedding. For our problem domain, we will generally penalize the direction in a relation that returns hyponymic concepts as opposed to hypernymic ones. The weights for the forward and backward directions were manually assigned based on a cursory examination of instances of that relation in the OMCS corpus.

Approximately 20 mapping rules are applied to all the sentences (400,000+) in the OMCS corpus. From this, a crude set of predicate argument relations are extracted. At this time, the text blob bound to each of the arguments needs to be normalized into concepts.

3.2. Normalizing Concepts

Because any arbitrary text blob can bind to a variable in a mapping rule, these blobs need to be normalized into concepts before they can be useful. There are three categories of concepts that can accommodate the vast majority of the parseable commonsense knowledge in OMCS: Noun Phrases (things, places, people), Attributes (adjectives), and Activity Phrases (e.g.: *"walk the dog," "buy groceries."*), which are verb actions that take either no argument, a direct object, or indirect object.

To normalize a text blob into a Noun Phrase, Attribute or Activity Phrase, we tag the text blob with part of speech information, and use these tags filter the blob through a miniature grammar. If the blob does not fit the grammar, it is massaged until it does or it is rejected altogether. Sentences, which contain text blobs that cannot be normalized, are discarded at this point. The final step involves normalizing the verb tenses and the number of the nouns. Only after this is done can our predicate argument structure be added to our repository.

The aforementioned noun phrase, and activity phrase grammar is shown below in a simplified view. Attributes are simply singular adjectives.

```
NOUN PHRASE:
(PREP) (DET|POSS-PRON) NOUN
(PREP) (DET|POSS-PRON) NOUN NOUN
(PREP) NOUN POSS-MARKER (ADJ) NOUN
(PREP) (DET|POSS-PRON) NOUN NOUN NOUN
(PREP) (DET|POSS-PRON) (ADJ) NOUN PREP NOUN

ACTIVITY PHRASE:
(PREP) (ADV) VERB (ADV)
(PREP) (ADV) VERB (ADV) (DET|POSS-PRON) (ADJ) NOUN
(PREP) (ADV) VERB (ADV) (DET|POSS-PRON) (ADJ) NOUN NOUN
(PREP) (ADV) VERB (ADV) PREP (DET|POSS-PRON) (ADJ) NOUN
```

The grammar is used as a filter. If the input to a grammar rule matches any optional tokens, which are in parentheses, then this is still considered a match, but the output will filter out any optional fields. For example, the phrase, *"in your playground"* will match the first rule and the phrase will stripped to just *"playground."*

3.3. Concept Node Graph

To model concept expansion as a spreading activation task, we convert the predicate argument structures gathered previously into a Concept Node Graph by mapping arguments to concept nodes, and predicate relations to edges connecting nodes. Forward and backward edge weights come from the mapping rule associated with each predicate relation. A segment of the graph is shown in Figure 1.

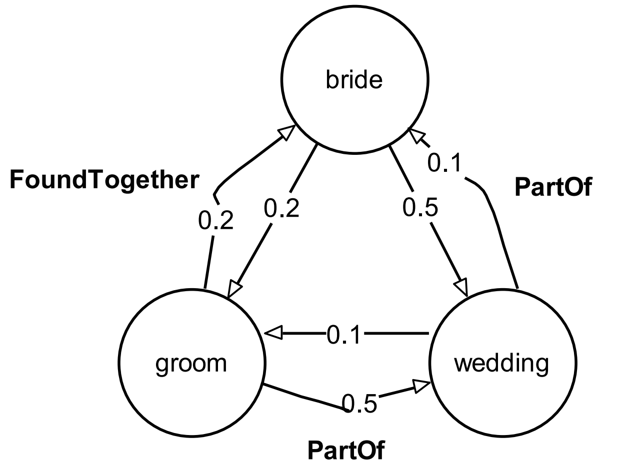

Figure 1. A portion of the Concept Node Graph. Nodes are concepts, and edges correspond to predicate relations.

The following statistics were compiled on the automatically constructed resource:

- 400,000+ sentences in OMCS corpus
- 50,000 predicate argument structures extracted
- 20 predicates in mapping rules
- 30,000 concept nodes
- 160,000 edges
- average branching factor of 5

4. Concept Expansion Using Spreading Activation

In this section, we explain how concept expansion is modeled as spreading activation. We propose two heuristics for re-weighting the graph to improve relevance. Examples of the spreading activation are then given.

In spreading activation, the origin node is the concept we wish to expand (i.e. the annotation) and it is the first node to be activated. Next, nodes one hop away from the origin node are activated, then two levels away, and so on. A node will only be activated if its activation score (AS) meets the activation threshold, which is a tolerance level between 0 (irrelevant) and 1.0 (most relevant). The origin node has a score of 1.0. Given two nodes A and B, where A has 1 edge pointing to B, the activation score of B is given in equation (1).

$$AS(B) = AS(A) * weight(edge(A,B)) \qquad \textbf{(1)}$$

When no more nodes are activated, we have found all the concepts that expand the input concept up to our set threshold.

4.1. Heuristics to Improve Relevance

One problem that can arise with spreading activation is that nodes that are activated two or more hops away from the origin node may quickly lose relevance, causing the search to lose focus. One reason for this is noise. Because concept nodes do not make distinctions between different word senses (an aforementioned problem with OMCS), it is possible that a node represents many different word senses. Therefore, activating more than one hop away risks exposure to noise. Although associating weights with the edges provides some measure of relevance, these weights form a homogenous class for all edges of a common predicate (recall that the weights came from mapping rules).

We identify two opportunities to re-weight the graph to improve relevance: reinforcement and popularity. Both of these heuristics are known techniques associated with spreading activation networks (Salton and Buckley, 1988). We motivate their use here with observations about our particular corpus, OMCS.

4.1.1. Reinforcement

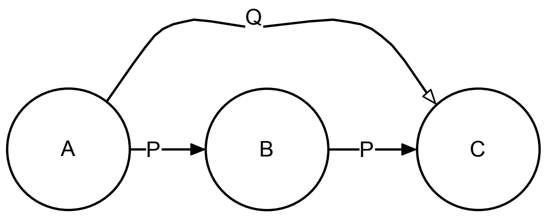

Figure 2. An example of reinforcement

As illustrated in Figure 2, we make the observation that if node C is connected to node A through both paths P and Q, then C would be more relevant to A than had either path P or Q been removed. We call this *reinforcement* and define it as two or more corroborating pieces of evidence, represented by paths, that two nodes are semantically related. The stronger the reinforcement, the higher the potential relevance.

Looking at this in another way, if three or more nodes are mutually connected, they form a cluster. Examples of clusters in our corpus are higher-level concepts like weddings, sporting events, parties, etc., that each have many inter-related concepts associated with them. Within each such cluster, any two nodes have enhanced relevance because the other nodes provide additional paths for reinforcement. Applying this, we re-weight the graph by detecting clusters and increasing the weight on edges within the cluster.

4.1.2. Popularity

The second observation we make is that if an origin node A has a path through node B, and node B has 100 children, then each of node B's children are less likely to be relevant to node A than if node B had had 10 children.

We refer to nodes with a large branching factor as being popular. It happens that popular nodes in our graph tend to either correspond to very common concepts in commonsense, or tend to have many different word senses, or word contexts. This causes its children to have in general, a lower expectation of relevance.

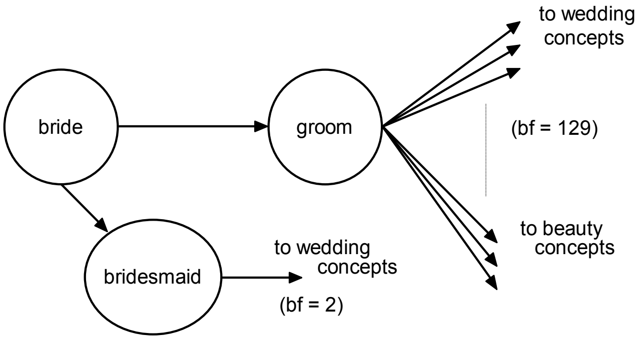

Figure 3. Illustrating the negative effects of popularity

As illustrated in Figure 3, the concept *bride* may lead to *bridesmaid* and *groom*. Whereas *bridesmaid* is a more specific concept, not appearing in many contexts, *groom* is a less specific concept. In fact, different senses and contexts of the word can mean "the groom at a wedding," or "grooming a horse" or "he is well-groomed." This causes *groom* to have a much larger branching factor.

It seems that even though our knowledge is common sense, there is more value associated with more specific concepts than general ones. To apply this principle, we visit each node and discount the weights on each of its edges based on the metric in equation (2). (α and β are constants):

$$newWeight = oldWeight * discount$$
$$discount = \frac{1}{\log(\alpha * branchingFactor + \beta)} \quad \textbf{(2)}$$

4.2. Examples

Below are actual runs of the concept expansion program using an activation threshold of 0.1. They were selected to illustrate what can be commonly expected from the expansions, including limitations posed by the knowledge.

```
>>> expand("bride")
('love', '0.632'), ('wedding', '0.5011')
('groom', '0.19'), ('marry', '0.1732')
('church', '0.1602'), ('marriage', '0.1602')
('flower girl', '0.131') ('happy', '0.131')
('flower', '0.131') ('lake', '0.131')
('cake decoration', '0.131') ('grass', '0.131')
('priest', '0.131') ('tender moment', '0.131')
('veil', '0.131') ('wife', '0.131')
('wedding dress', '0.131') ('sky', '0.131')
('hair', '0.1286') ('wedding bouquet', '0.1286')
('snow covered mountain', '0.1286')

>>> expand('london')
('england', '0.9618') ('ontario', '0.6108')
('europe', '0.4799') ('california', '0.3622')
('united kingdom', '0.2644') ('forest', '0.2644')
('earth', '0.1244')

>>> expand("symphony")
('concert', '0.5') ('music', '0.4')
('theatre', '0.2469')
('conductor', '0.2244')
('concert hall', '0.2244')
('xylophone', '0.1') ('harp', '0.1')
('viola', '0.1') ('cello', '0.1')
('wind instrument', '0.1') ('bassoon', '0.1')
('violin', '0.1')

>>> expand("listen to music")
('relax', '0.4816') ('be entertained', '0.4816')
('have fun', '0.4') ('relaxation', '0.4')
('happy', '0.4') ('hang', '0.4')
('hear music', '0.4') ('dorm room', '0.4')
('understand', '0.4') ('mother', '0.2')
('happy', '0.136')
('get away', '0.136') ('listen', '0.136')
('change psyche', '0.136') ('show', '0.1354')
('dance club', '0.1295') ('frisbee', '0.1295')
('scenery', '0.124') ('garden', '0.124')
('spa', '0.124') ('bean bag chair', '0.124')
```

The expansion of *"bride"* shows the diversity of relations found in the semantic resource. *"Love"* is some emotion that is implicitly linked to brides, weddings, and marriage. Expansions like *"priest", "flower girl,"* and *"groom"* are connected through social relations. *"Wife"* seems to be temporally connected. To *"marry"* indicates the function of a wedding.

However, there are also expansions whose connections are not as obvious, such as *"hair,"* and *"lake."* There are also other expansions that may be anomalies in the OMCS corpus, such as *"tender moment"* and *"snow covered mountain."* These examples point to the need for some type of statistical filtering of the knowledge in the corpus, which is not currently done.

In the last expansion example, the concept of "listen to music" is arguably more abstract than the wedding concept, and so the expansions may seem somewhat arbitrary. This illustrates one of the limitations of any common sense acquisition effort: deciding upon which topics or concepts to cover, how well they are covered, and to what granularity they are covered.

5. Conclusion

In this paper, we presented a mechanism for robust photo retrieval: using a world semantic resource to expand a photo's annotations. The resource was automatically constructed from the publicly available Open Mind Common Sense corpus. Sentence patterns were applied to the corpus, and simple predicate argument structures were extracted. After normalizing arguments into syntactically neat concepts, a weighted concept node graph was constructed. Concept expansion is modeled as spreading activation over the graph. To improve relevance in spreading activation, the graph was re-weighted using heuristics for reinforcement and popularity.

This work has not yet been formally evaluated. Any evaluation will likely take place in the context of the larger system that this mechanism is used in, called (A)nnotation and (R)etrieval (I)ntegration (A)gent (Lieberman et al., 2001) ARIA is an assistive software agent which automatically learns annotations for photos by observing how users place photos in emails and web pages. It also monitors the user as s/he types an email and finds opportunities to suggest relevant photos. The idea of using world semantics to make the retrieval process more robust comes from the observation that concepts depicted in photos are often spatially, temporally, and socially related in a commonsensical way. While the knowledge extracted from OMCS does not give very complete coverage of many different concepts, we believe that what concept expansions *are* done have added to the robustness of the retrieval process. Sometimes the concept expansions are irrelevant, but because ARIA engages in opportunistic retrieval that does not obstruct the user's task of writing the email, the user does not suffer as a result. We sometimes refer to ARIA as being "fail-soft" because good photo suggestions can help the task, but the user can ignore bad photo suggestions.

Robust photo retrieval is not the only IR task in which semantic resources extracted from OMCS have been successfully applied. (Liu et al., 2002) used OMCS to perform inference to generate effective search queries by analyzing the user's search goals. (Liu and Singh, 2002) uses the subset of causal knowledge in OMCS to generate crude story scripts.

In general, the granularity of the knowledge in OMCS can benefit any program that deals with higher-level social concepts of the everyday world. However, because of limitations associated with this corpus such as noise, ambiguity, and coverage, OMCS is likely to be only useful at a very shallow level, such as providing an associative mechanism between everyday concepts or performing first-order inference.

Future work is planned to improve the performance of the mechanism presented in this paper. One major limitation that we have encountered is noise, stemming from ambiguous word senses and contexts. To overcome this, we hope to apply known word sense disambiguation techniques to the concepts and the query, using word sense co-occurrence statistics, WordNet, or LDOCE. A similar approach could be taken to disambiguate meaning contexts, but it is less clear how to proceed.

Another point of future work is the migration from the sentence pattern parser to a broad coverage parser so that we can extract more kinds of commonsense relations from the corpus, and make more sentences "usable."

6. Acknowledgements

We thank our colleagues Push Singh, and Kim Waters at the MIT Media Lab, Tim Chklovski at the MIT AI Lab, and Erik Mueller at IBM, who are also working on the problem of commonsense, for their contributions to our collective understanding of the issues. We would especially like to thank Push for directing OMCS and for his advocacy of commonsense.

7. References

Fellbaum, C. (ed.), 1998. *WordNet: An Electronic Lexical Database.* MIT Press, Cambridge, MA.

Klink, S., 2001. Query reformulation with collaborative concept-based expansion. *Proceedings of the First International Workshop on Web Document Analysis*, Seattle, WA.

Lenat, D., 1998. *The dimensions of context-space*, Cycorp technical report, www.cyc.com.

Lieberman, H., Rosenzweig E., Singh, P., 2001. Aria: An Agent For Annotating And Retrieving Images, *IEEE Computer*, July 2001, pp. 57-61.

Lin, D., 1998. Using collocation statistics in information extraction. *Proceedings of the Seventh Message Understanding Conference (MUC-7)*, San Francisco, CA, http://www.muc.saic.com.

Liu, H., Lieberman, H., Selker, T., 2002. GOOSE: A Goal-Oriented Search Engine With Commonsense. *Proceedings of the 2002 International Conference on Adaptive Hypermedia and Adaptive Web Based Systems*, Malaga, Spain.

Liu, H., Singh, P., 2002. MAKEBELIEVE: Using Commonsense to Generate Stories. *Proceedings of the 20th National Conference on Artificial Intelligence (AAAI-02)* -- Student Abstract. Seattle, WA.

Open Mind Common Sense Website and Corpus. Available at: www.openmind.org/commonsense.

Peat, H.J. and Willett, P., 1991. The limitations of term co-occurrence data for query expansion in document retrieval systems. *Journal of the ASIS*, 42(5), 378-383.

Richardson, S.D., Dolan, W.B., Vanderwende, L., 1998. MindNet: Acquiring and Structuring Semantic Information from Text. *Proceedings of the joint ACL and COLING conference*, 1098-1102, Montreal.

Salton, G., and Buckley, C., 1988. On the Use of Spreading Activation Methods in Automatic Information Retrieval. *Proceedings of the 11th Ann. Int. ACM SIGIR Conf. on R&D in Information Retrieval (ACM),* 147-160.

Singh, P., 2002. The public acquisition of commonsense knowledge. *Proceedings of AAAI Spring Symposium: Acquiring (and Using) Linguistic (and World) Knowledge for Information Access.* Palo Alto, CA, AAAI.

Voorhees, E., 1994. Query expansion using lexical-semantic relations. *Proceedings of ACM SIGIR Intl. Conf. on Research and Development in Information Retrieval*, pages 61—69.

Xu, J., and Croft, W.B., 1996. Query Expansion Using Local and Global Document Analysis. Proceedings of the Nineteenth Annual International ACM SIGIR Conference on Research and Development in Information Retrieval, pp. 4—11.