Commonsense Knowledge Acquisition Using Compositional Relational Semantics

Hakki C. Cankaya
Dept. of Computer Engineering
Izmir Univ. of Economics, Izmir, Turkey
Email: hakki.cankaya@ieu.edu.tr

Eduardo Blanco and Dan Moldovan
Dept. of Computer Science
Univ. of Texas at Dallas, Richardson, Texas
Email: {eduardo, moldovan}@hlt.utdallas.edu

***Abstract*—A method for the acquisition of commonsense knowledge based on instantiations of metarules is presented. The metarules refer to some properties and objects that have those properties. Metarules are instantiated by automatically identifying objects that have those properties. In order to increase the applicability of a commonsense property to objects, composition of semantic relations is used. The method has been implemented and tested over WordNet. Results show that a commonsense metarule can produce many knowledge base axioms.**

***Keywords*-knowledge acquisition; commonsense knowledge; semantics.**

I. Introduction

Commonsense knowledge encompasses information people use everyday and it is assumed known by an average person; thus, it is not communicated most of the time. This makes more difficult to automate the acquisition of commonsense knowledge. To alleviate the problem of automatically extracting commonsense knowledge, semiautomatic approaches have been studied, where the system is given some seed information and is expected to generate more knowledge. There have been proposals to acquire commonsense knowledge from different sources by using different techniques. Some used collaborative efforts of experts and general public over the Web [1], [2]. There are other similar distributed human projects to collect commonsense knowledge [3]. Some proposals link the information obtained by the collaborative effort to known ontologies to expand and structure the commonsense knowledge [4], [5]. Some other proposals used text and World Wide Web as the source for commonsense knowledge acquisition [6], [7]. Despite these and other attempts, there is still a need for developing robust methods for automatic commonsense knowledge acquisition. In this paper, we introduce a new method for extracting commonsense knowledge by using metarules that contain user given commonsense rules and semantic relations.

II. Approach

The approach for extracting commonsense knowledge is based on metarules that contain commonsense rules provided by the user. These are then instantiated on a lexical knowledge base to identify large number of objects to which a high level commonsense rule applies. Commonsense rules refer to some common properties well known by average people. For example one can *see-thru* objects that have the *transparency* property.

To infer more commonsense knowledge of this type, the method automatically identifies in WordNet, or any other lexical source, the objects that have a property by searching for certain semantic relations. For example the object *glass* has the transparency property encoded by semantic relations in a lexical database. The inference mechanism used in the method concludes that one can see-thru glass since it has the transparency property. These instantiations of commonsense rules generate commonsense knowledge axioms.

The proposed method can accommodate potential restrictions and exceptions of a given commonsense rule. For example, some types of glass, like opaque glass, have to be excluded from the commonsense rule as they may not be *see-thru*. In order to find more objects that display a property the method searches for hyponyms of the objects that possess a given property since these also inherit that property, unless there is an exception. For example, the method extracts *round glass* as an object one can *see-thru*.

The mechanism for linking an object with other objects that have the same property relies on composition of semantic relations. The same mechanism is used to expand commonsense rules by cause and goal semantic relations. For example, *see-thru* causes more objects to be visible.

The method offers different metarules, because there are cases where semantic gaps cannot be bridged by the composition of semantic relations. For example, cars have *windshields* that are *transparent*. Even though cars are not *transparent*, one can *see-thru* a car. So, some objects don't inherit the property from their parts by using a Part-Whole relation in composition of semantic relations; however they inherit the rule and generate commonsense knowledge of the same type. The method can simply bridge those semantic gaps by using different metarules.

III. Semantic Relations and Compositional Relational Semantics

A. Semantic Relations

Semantic relations are the underlying relations between concepts expressed by words. They are implicit associations between chunks of text. Formally, a semantic relation is

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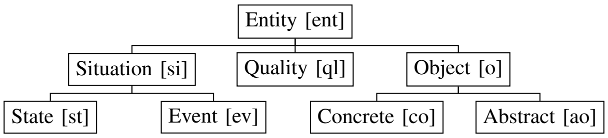

Figure 1. The ontology of sorts used to define DOMAIN(R) and RANGE(R).

represented as R(x, y), where R is the relation type, x the first argument and y the second. R(x, y) should be read as x *is* R *of* y, e.g., ISA(*gas guzzler*, *car*) should be read *gas guzzler* ISA *car*. The inverse of the relation is defined by R^{-1}(x, y), which is equal to R(y, x). Given R, we can define DOMAIN(R) and RANGE(R) as the set of sorts of concepts that can be part of the first and second argument, respectively. R(x, y) is formally defined by stating: *a*) relation type R, *b*) DOMAIN(R); and *c*) RANGE(R).

In order to define DOMAIN(R) and RANGE(R), we use the ontology depicted in Figure 1, which is a reduced version of [8]. The root corresponds to `entities`, which refer to all things about which something can be said. `Situation` is anything that happens at a time and place. Simply put, if one can think of the time and location of an entity, it is a `situation`. If they change the status of other entities, they are called `events` (e.g. *mix*, *grow*), otherwise `states` (e.g. *be standing next to the door*, *account for 10% of the sales*). `Objects` can be either `concrete` or `abstract`. The former occupy space, are touchable, tangible (e.g. *John*, *car*). The later are intangible, they are somehow product of human reasoning (*thought*, *music*). `Qualities` represent characteristics that can be assigned to entities, e.g., *tall*, *heavy*.

In this work, we use a particular set of five relations that are useful for commonsense extraction. This set, depicted in Table I, does not encode all the semantics in a text by any means. However, these relations help inferring commonsense knowledge as shown in the next section.

REASON(x, y) [REA] is defined as a broad relation in which x has a direct impact on y[1], eg, *[They don't smoke]$_y$ because [it is forbidden]$_x$*. GOAL(x, y) [GOA] encodes intentions, purposes, plans and intended consequences, e.g. *[Half of the garage]$_y$ is used for [storage]$_x$*. [PRO] captures the fact that x is a characteristic, property or value for y, eg, PRO(*tall*, *John*). PART-WHOLE(x, y) [PW] encodes the meronymy relation, i.e., x is a constituent part or a member of y. For example, PW(*engine*, *car*). ISA(x, y) [ISA] encodes x is a specialization of y, e.g., ISA(*adult*, *human*).

B. Commonsense Rules as Pseudo Relations

Sometimes it is useful to define and treat a particular connection between two entities like a semantic relation even though it is not one in the pure sense. By doing so we can use the formal framework of Compositional Relational Semantics and combine it with any other given semantic relations. We call this kind of connection *pseudo relation*, since they are not pure relations but are treated as such.

In this work, we define the pseudo relation COMMONSENSE_RULE (CS_R). CS_R(r, p) defines a connection between a situation r that applies given a certain property p. The connection has to have a commonsense nature, meaning that it is rarely explicitly stated. The complete definition is DOMAIN(CS_R) = [si], RANGE(CS_R) = [ql].

[1] It includes relations usually named CAUSE and INFLUENCE.

Table I
THE SET OF SEMANTIC RELATIONS USED IN THIS PAPER

Relation	Abbr.	DOMAIN × RANGE
REASON	REA	[si]×[si]
GOAL	GOA	[si ∪ ao]×[si ∪ o]
PROPERTY	PRO	[ql]×[o]
PART-WHOLE	PW	[o]×[o]
ISA	ISA	[o]×[o]

C. Compositional Relational Semantics (CRS)

The goal of composing, or linking semantic relations is to acquire new semantic relations by applying inference rules over already identified relations. An inference rule takes as input a set of semantic relations, called premises, and yields a conclusion. We define an inference rule by using the composition operator ($\circ$). Formally, $\text{R}_1(x, y) \circ \text{R}_2(y, z) \rightarrow \text{R}_3(x, z)$, where R_1 and R_2 are the premises and R_3 is the conclusion.

In order to apply the composition operator over R_1 and R_2 they must fulfill the following necessary conditions: (a) R_1 and R_2 must be compatible; and (b) the second argument of R_1 and the first of R_2 must be the same concept, y.

a) Two relations R_1 and R_2 are compatible iff $\text{RANGE}(\text{R}_1) \cap \text{DOMAIN}(\text{R}_2) \neq \emptyset$. Say, we have an inference rule, PRO(p, x) $\circ\text{ISA}^{-1}$(x, y) $\rightarrow$ PRO(p, y), which means that if p is a property of x and x is the hypernym of y, then y inherits the property p. This inference rule actually holds because PRO and ISA^{-1} are compatible in this case, RANGE(PRO) $\cap$ DOMAIN(ISA^{-1}) = [o].

b) In an instance of the inference rule above, PRO(*sharpness*, *knife*) $\circ\text{ISA}^{-1}$(*knife*, *butcher-knife*) $\rightarrow$ PRO(*sharpness*, *butcher-knife*), there is a common concept *knife* that links the premises of the inference rule, which fulfills the second requirement of the compositional relational semantics. The conclusion is if *knife* has property *sharpness*, then any hyponym of *knife*, like *butcher-knife* inherits the property unless stated otherwise.

IV. METHOD

The proposed method for commonsense extraction follows a semiautomatic approach. Given a commonsense rule that applies to a certain property, the method uses metarules in order to extract commonsense knowledge. The method exploits properties of objects, the rules that apply to them

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and how they can be transferred thru a chain of semantic relations. Extensions to the method have been studied to automatically infer more properties and commonsense rules, significantly increasing the amount of knowledge extracted. All the inferences are performed within the framework of Compositional Relational Semantics.

A. Metarules

Two main metarules are used to obtain commonsense knowledge.

1) Metarule 1: $\text{CS\_R}(r, p) \circ \text{PRO}(p, x) \rightarrow \text{CS}(r, x)$.

Rationale: *rule r applies to property p; p is a property of x; therefore, r applies to x.*

Example: Given the commonsense rule *you cannot check in for flight sharp objects*, CS_R(*cannot check in for flight*, *sharp*), and the fact that knifes are sharp, PRO(*sharp*, *knife*), we obtain the commonsense knowledge that knifes cannot be checked in for flight, CS(*cannot check in for flight*, *knife*). Formally, $\text{CS\_R}(\textit{cannot check in for flight}, \textit{sharp}) \circ \text{PRO}(\textit{sharp}, \textit{knife}) \rightarrow \text{CS}(\textit{cannot check in for flight}, \textit{knife})$.

The columns *rule(r), property (p), and concepts (x)* in Table II shows examples of knowledge extracted using this metarule.

Some objects x are parts or members of larger objects y. Metarule 1 can be expanded by adding a part-whole relation to the premise, resulting in a new metarule, Metarule 2.

2) Metarule 2: $\text{CS\_R}(r, p) \circ \text{PRO}(p, x) \circ \text{PW}(x, y) \rightarrow \text{CS}(r, y)$

Rationale: *rule r applies to property p; p is a property of x; x is a part of y; therefore, r applies to y.*

Example: Given the commonsense rule *electric objects need power to operate*, CS_R(*need power*, *electric*), electric is a property of electric motors PRO(*electric*, *motor*), the fact that electric motors are components of electric fans, PW(*motor*, *fan*), we obtain CS(*need power*, *fan*), i.e., the commonsense knowledge that fans need power to operate. Formally, $\text{CS\_R}(\textit{need power}, \textit{electric}) \circ \text{PRO}(\textit{electric}, \textit{motor}) \circ \text{PW}(\textit{motor}, \textit{fan}) \rightarrow \text{CS}(\textit{need power}, \textit{fan})$.

B. Restrictions and Exceptions

The metarules introduced so far do not have any restrictions on the kind of concepts they link. However, a closer inspection leads to the conclusion that sometimes restrictions and exceptions have to be imposed in order to guarantee a high accuracy in the inferences performed. Restrictions and exceptions are indicated between brackets and added at the end of the premises with an & operator. Formally, we denote restrictions for an axiom as $\text{R}_1(x, y) \circ \text{R}_2(y, z) \& [\textit{restrictions}] \rightarrow \text{R}_3(x, z)$. An axiom performs an inference only if all the restrictions are fulfilled.

For example, something portable can be carried, but constraints on the weight and the person carrying the object are necessary. A child can carry a *watch*, but will have trouble carrying a *portable television set*. Consider the commonsense rule *eating sweets excessively results in weight gain*. An exception to this rule is *saccharin* which is sweet but *calorie-free*. Thus, an exception is attached to the rule.

The Metarule 2 makes the wholes inherit the rules that apply to the properties of its parts. Several restrictions should be placed in order to avoid invalid inferences.

First, *r* should not describe any physical property such as weight or size. One can *lift light objects*, and *car seat cushions* are *light* and part of *cars*, and yet one cannot lift cars. In other words, rules that state physical properties of parts do not transfer to their wholes.

Second, *r* should not encode an `event` (`ev`). Following Table II, only the rules encoding a `state` (`st`) can be used with Metarule 2. For example, *one can not see alive animals that are extinct* CS_R(*[cannot see alive]$_{st}$*, *extinct.j.1*). Since it encodes a state, the wholes inherit the rule: if *y* has a part *x* which is extinct, one cannot see *y* alive. On the other hand, consider CS_R(*[will roll on inclined path]$_{ev}$*, *round.j.1*). Just because *y* (mouse.n.2) has a round part *x* (ball.n.3), *y* will not roll on an inclined path. Similarly, a *removable cup holder* (*x*) is *portable* (*p*) and part of a *car* (*y*), and one *[can carry]$_{ev}$* (*r*) portable objects. Because *r* is an `event`, we cannot instantiate Metarule 2 and infer CS(*can carry with you*, *car*).

Formally, the final definition of both metarules are:

- $\text{CS\_R}(x, y) \circ \text{PRO}(y, z) \& [\textit{rest(x)}] \rightarrow \text{CS}(x, z)$
- $\text{CS\_R}(r, p) \circ \text{PRO}(p, x) \circ \text{PW}(x, y) \& [\textit{r is a st, no physical properties}] \rightarrow \text{CS\_R}(r, y)$.

C. Extensions using Compositional Relational Semantics

In this section, we aim to automatically extend the commonsense rules (CS_R) and object properties (PRO) by chaining semantic relations. The result is more inferences performed by both metarules and therefore more commonsense knowledge is extracted. We do so by combining CS_R and PRO with semantic relations and the rules of compositional semantics.

1) Rule Extension: Given a rule *r* that applies to a certain property *p*, one can also infer that *a*) actions whose goal is to achieve *p*; and *b*) the goals and effects of *r* also apply to *p*. Formally $\text{CS\_R}(x, y) \circ \text{GOA}(y, z) \rightarrow \text{CS\_R}(x, z)$, $\text{CS\_R}(x, y) \circ \text{GOA}^{-1}(y, z) \rightarrow \text{CS\_R}(x, z)$ and $\text{REA}^{-1}(x, y) \circ \text{CS\_R}(y, z) \rightarrow \text{CS\_R}(x, z)$.

For example, given CS_R(*can-be-seen*, *visible*), and knowing that one foregrounds (foregrd) in order to make visible (GOA(*visible*, *foregrd*)), we obtain CS_R(*can-be-seen*, *foregrd*). Formally, $\text{CS\_R}(\textit{can-be-seen}, \textit{visible}) \circ \text{GOA}(\textit{visible}, \textit{foregrd}) \rightarrow \text{CS\_R}(\textit{can-be-seen}, \textit{foregrd})$. Similarly, as seen in Table II given CS_R(*spills if not in container*, *liquid.j.1*), and knowing that something flows if spilled, REA^{-1}(*flow*, *spill*), we obtain CS_R(*flow if not in container*, *liquid.j.1*).

Table II
EXAMPLES OF KNOWLEDGE EXTRACTED USING THE METARULE 1, $\text{CS\_R}(r, p) \circ \text{PRO}(p, x) \rightarrow \text{CS}(r, x)$ AND EXTENSIONS.

sort	*rule extension*	*rule (r)*	*property (p)*	*concept (x)*	*property extension*
st	cannot be blind	can see thru	transparent.j.1	window.n.1, lens.n.1	rear_window.n.1, quarterlight.n.1, contact_lens.n.1, condenser.n.4
	-	cannot check in for flight	sharp.j.1	knife.n.1, parer.n.2	slicer.n.3, carving_knife.n.1
	-	cannot see alive	extinct.j.1	dinosaur.n.1, moa.n.1	trachodon.n.1, ornithomimid.n.1, anomalopteryx.n.1
	-	cannot touch	imaginary.j.1	bogeyman.n.1, equator.n.1	-
	-	not likable	annoying.j.1	pest.n.1, trial.n.6	nudnik.n.1
ev	-	excess results in weight gain	sweet.j.1	jimmies.n.1, muffin.n.1	popover.n.1, corn_muffin.n.1
	-	you can carry with you	portable.j.1	watch.n.1, flashlight.n.1	pocket_watch.n.1, digital_watch.n.1, penlight.n.1
	will move on inclined path	will roll on inclined path	round.j.1	ball.n.1	golf_ball.n.1, polo_ball.n.1
	flows if not in a container	spills if not in container	liquid.j.1	beverage.n.1, soup.n.1, draft.n.8	softdrink.n.1, coke.n.1, potage.n.1, gazpacho.n.1, vichyssoise.n.1
	can cater, can cook	can eat / consume	edible.j.1	potato.n.1, radish.n.1	french_fires.n.1, mashed_potato.n.1

2) Property Extension: Given the fact that a certain p is a property of x, one can also infer that all hyponyms (ISA^{-1}) of x have that property. Formally, $\text{PRO}(x, y) \circ \text{ISA}^{-1}(y, z) \rightarrow \text{PRO}(x, z)$. For example, in Table II given PRO(*liquid.j.1*, *beverage.n.1*), and knowing that ISA^{-1}(*beverage.n.1*, *soft drink.n.1*) and ISA^{-1}(*beverage.n.1*, *coke.n.1*), we obtain PRO(*liquid.j.1*, *soft drink.n.1*) and PRO(*liquid.j.1*, *coke.n.1*).

One might be tempted to follow the intuition that wholes inherit the properties of its parts. However, closer inspection reveals that this plausible axiom does not hold: cars have as parts windows, windows are transparent, and yet cars are not transparent.

V. IMPLEMENTATION AND RESULTS

In order to automatically instantiate the metarules to identify objects x that have properties p and benefit from the power of the method described in Section 4, it is necessary to have semantic relations readily available. In our experiments, the commonsense rules were provided by humans, including corresponding restrictions and exceptions. For the semantic relations that are necessary for instantiations and extensions, we used an annotated resource called eXtended WordNet-Knowledge Base (XWN-KB).

A. eXtended WordNet Knowledge Base (XWN-KB)

The XWN-KB is an upper ontology built as an extension to eXtended WordNet (XWN) which is derived from WordNet (WN) [9]. The novelty that XWN-KB offers is that the glosses of synsets have been transformed into semantic relations by using a reliable semantic parser and partly verified by human annotators. The result is a knowledge base that is highly interconnected. Unlike a domain specific ontology that is narrow, the XWN-KB uses definitional glosses of WordNet synsets which are regarded as universal knowledge. WordNet and its extensions offer a large and reliable world knowledge source for extracting commonsense knowledge by applying metarules.

Table III
XWN-KB REPRESENTATION OF A CONCEPT

Knife#2: a weapon with a handle and blade with a sharp point	
ISA(*knife, weapon*)	PW(*handle, knife*)
PW(*blade, knife*)	PRO(*sharp, knife*)

For example, the WordNet concept *knife* in sense #2 has the following gloss: *a weapon with a handle and blade with a sharp point*. In XWN-KB this text definition has been transformed into a set of semantic relations as shown in Table III. For us important are PRO(*sharp*, *knife*), PW(*handle*, *knife*), and ISA(*knife*, *weapon*). When CS-R(cannot check in for flight, sharp) is given, the method searches for a property relation and this instantiates the concept *knife#2* by locating its PRO(*sharp*, *knife*) relation. For extensions, it uses the mechanism of composition of semantic relations over the annotated semantic relations provided by the XWN-KB.

B. Implementation

The implementation is coded by perl and python scripts that interface with XWN and WN. The set of commonsense rules are given to the code. The code applies metarules to the given commonsense rules following the procedure below.

Input: A set of commonsense rules.

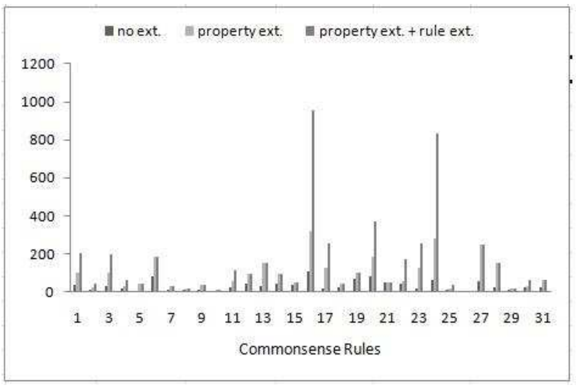

Figure 2. Results for Metarule1

Output: Collection of commonsense axioms for all given rules: $S_x[] + S_y[]$.

Main-Procedure: For each commonsense rule, repeat the steps below:

1. Apply Metarule 1 to the commonsense rule. Instantiate all concepts $c_x[]$ that have the property given in the commonsense rule.

1.1. For each concept in $c_x[]$, process the property extension and find all hyponyms, $h_x[]$. Accumulate all $h_x[]$,

$H_x[] \leftarrow H_x[] + h_x[]$

1.2. Process rule extension for the commonsense rule and calculate all other rules, $k_x[]$. Apply the new rules to all concepts and store the final commonsense axioms,

$S_x[] \leftarrow S_x[] + \{H_x[] + c_x[]\} \times k_x[]$

2. Apply Metarule 2 to all $c_x[]$. Instantiate all concepts $c_y[]$ that inherit the rule.

2.1. Apply Metarule 2 to all $H_x[]$ (calculated previously) and find all concepts $h_y[]$ that inherit the rule. Accumulate all $h_y[]$,

$H_y[] \leftarrow H_y[] + h_y[]$

2.2. Process the rule extension and calculate all other rules $k_y[]$ for Metarule 2. Apply the new rules to all concepts and store the final commonsense axioms,

$S_y[] \leftarrow S_y[] + \{H_y[] + c_y[]\} \times k_y[]$

C. Results on XWN-KB

Following the procedure, a set of 32 commonsense rules was provided as input to the implementation. Metarule 1 has instantiated 1015 commonsense axioms for the given set without any extensions (see Table IV). Then, the property extension was performed by using composition of semantic relations and 2833 axioms were generated this way. Human validation was performed and only 46 generated axioms were tagged as incorrect yielding a precision of 0.984. As explained in earlier sections, the rule extension augments the commonsense rule that applies to the property. All new rules that are generated by the rule extension can also apply to all property inheriting objects including those that are generated by the property extension. Therefore, the cardinality of this rule augmentation becomes a multiplying factor. For example, for a commonsense rule i, CS-$R_i(p_i,r_i)$, the number of concepts that are instantiated and applied to the rule is S_i and the number of extra objects that are found by the property extension is L_i. If the number of new rules that are generated by the rule extension is R_i, the total number of generated axioms is $T = \sum_i (S_i+L_i)*R_i$. Therefore, the rule extension is a rather powerful factor. In the implementation, for Metarule 1, the total number of axioms is 4938 (see Table IV). Figure 2 plots for all rules S_i (no ext.), S_i+L_i (property ext.), and T_i (property ext. + rule ext.) values. The observation of the results reveals that there is quite some variation among the commonsense rules in terms of their S_i, S_i+ L_i, and T_i values. The variation in S_i is caused by the frequency of the property and is related with the number of concepts in the knowledge base that in fact has the property in its gloss and semantic relations. The L_i depends on the hyponmym connectivity of the concept that has the property. Basically more hyponyms result in larger L_i value for rule i.

We also looked at precision values for all 32 commonsense rules and compared them in Figure 3 with and without extensions for Metarule 1. In the experiment, while extensions increased the generated commonsense axioms significantly, the precision did not deteriorate. However, this purely depends on the resource used. And the propagation of errors depends on the hyponym connectivity of the concepts. For example, if the incorrect concepts that are initiated by the metarule have high hyponym connectivity, then the chances are high for obtaining a poor precision, since the error has the ripple effect. So, the authors' suggestion for potential implementations of the method is to introduce an annotation step between the metarule instantiations and the extensions, so that incorrect concepts are weeded out before they ripple and adversely affect the performance.

Experiments showed that with the given set of commonsense rules, Metarules work differently. Even though there were some instantiations where rule applied to the concept without inheriting the property. However, those few results were augmented by the rule extension, increasing the final count for the commonsense knowledge.

The results of the numerical study seems promissing. Starting with 32 commonsense rules provided by the user, the method generated 4950 commonsense axioms, more than two orders of magnitude increase.

VI. Applications

Commonsense knowledge can be used in many applications that require some form of reasoning. It is used to bridge knowledge gaps and leads to solutions which may not be possible otherwise. Such applications are question answering (Q/A), text entailment systems (RTE), search engines, multi agent systems, etc. In question answering systems, the commonsense knowledge can play a significant role in answering questions that seem trivial for humans but are nearly impossible for machines. Below is an example

Table IV
NUMERICAL RESULTS

	No Extension		Extension 1		Extension 2		Extension 1 & 2	
	Conclusion	Precision	Conclusion	Precision	Conclusion	Precision	Conclusion	Precision
Metarule 1	1015	0.974	2833	0.984	1696	0.972	4938	0.985
Metarule 2	7	0.714	7	0.714	12	0.666	12	0.666
Total	1022	0.972	2840	0.983	1708	0.970	4950	0.984

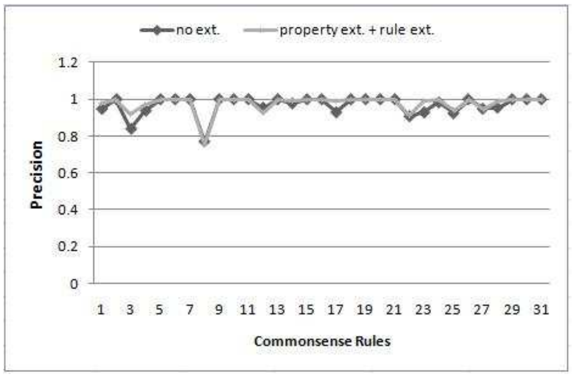

Figure 3. Precision for Metarule 1

from TREC2007. Even though the system used was a high performance system, it could not compute an answer for the question:

Question, Q2.21600004: (Paul Krugman) What is Krugman's academic specialty?

Answer: Economics

Text in BLOG06-20051213-068-0019517474: "..Paul Krugman is Professor of Economics at Princeton University,....."

To answer this question a connection has to be made between *academic* and *economics*. This cannot be done using basic lexical chains in WordNet alone. An axiom establishing this connection was generated by using the proposed method. We run the program of the proposed method with a rule that has *academic* as the property and received a list of concepts that have this property in XWN-KB. One of the concepts in the list is *economics-department* which claimed *academic* as an inherited property. This easily bridges the semantic gap to reach the answer stating that *Krugman is Professor of Economics in Princeton.*

VII. CONCLUSIONS

The resource used in this paper is eXtended WordNet Knowledge Base, simply because it has already synset glosses transformed into semantic relations and it contains information that is widely applicable. Any corpora, including the Internet, that is semantically parsed and transformed into semantic relations can be used in our method. The accuracy of the results is highly correlated to the accuracy of the semantic relations extracted from text.

The method presented here has the disadvantage that users need to provide commonsense rules that are then automatically instantiated to a large number of objects. We found that an average person can come up rather quickly with many commonsense rules but it is nearly impossible for humans to quickly think of many possible instantiations of these rules. In this sense the method introduced here automates the most difficult part of commonsense knowledge acquisition. The method proposes entensions of metarules that rely on compositional relational semantics a powerful technique to increase its generative power.

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