Building a Commonsense Ontology through Children’s Stories

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ABSTRACT
Ontologies allow machines to convey understanding over the data that they process. There are already many research conducted that aim to use ontologies on software applications. Some of the applications include photo annotation, refined search engines, word completion, video annotations and affective classification of text. The problem now lies in being able to capture massive amounts of information and define it in an ontology.

As it is too costly to hire expert engineers to manually build ontologies, crowd sourcing has become a popular approach in building ontologies. Though much research has already been done in probing adults to help build ontologies, children at their young age can become good contributors as well. This is because they are in their early stages of mental development. What may seem obvious to an adult may not be clear to a child. This research proposes to probe children as contributors to creating commonsense ontologies. Seeing as stories are part of our daily lives, they are very familiar to children. This research proposes to use stories that have blanks to be filled up by children in order to gather commonsense.

Keywords
Ontology, commonsense, story generation, knowledge acquisition, knowledge representation, crowd-sourcing

1. INTRODUCTION
In today’s digital age, information coming from text is becoming more prevalent. One contributing factor is the rapid growth of the Internet. There is a flood of online documents such as news articles, blogs, e-mails and instant messaging. People rely on keyword-based approaches to retrieve information; however, this approach is limited as the machine does not “understand” the information being retrieved. Machines cannot process information like humans. Information is not fully understood by the machine and is therefore not fully utilized [7].

One of the ways to address the lack of understanding of machines is through the use of ontologies. An ontology is a collection of concepts that are connected to each other through relationships. This allows commonsense to be defined in the form of binary concepts. This enables the machine to give meaning to the data retrieved and make inferences that will enable software applications to offer more functionality.

1.1 Commonsense
As part of the human experience and everyday living, commonsense knowledge is acquired by everyone without them even knowing it. It includes the physical, social, temporal, psychological and spatial experiences of people. For example, a lemon is sour. To open a door, you must turn the doorknob first. A person needs sleep in order to rest. Of course there are exceptions in which commonsense knowledge does not always hold such as getting fired from work would not always give a negative feeling as the person may have wanted to look for another job all along [7].

Commonsense is a field of great scale, hence, capturing it for computational use still poses a lot of unsolved problems [11]. Commonsense is no longer defined or talked about as it is the most basic or most widely known type of knowledge. Humans learn this over the course of their lifetime and take it for granted once learned [1]. This leaves experts with the difficulty of having a knowledge base filled with commonsense knowledge. People may also disagree in what is commonsense and what is not. This leads to the problem of machines lacking a commonsense understanding. Even if experts start working on a commonsense knowledge base, building it would prove to be too costly and too time- consuming as it requires a massive amount of work.

In order to capture or define commonsense, there is a need to somehow explicate that commonsense. This would serve as the first step in allowing machines to possess commonsense [1]. Over the years, a few million commonsense facts have already been collected, however, in order for truly intelligent machines to come into being, the estimated target of required commonsense facts reaches over hundreds of millions [13].

1.2 Motivation
Giving machines the ability to reason about everyday life has been the goal of much research. Though the idea of machines having commonsense is still far from being practical, the possible applications that it will allow are already known. Machines possessing commonsense would only become possible if experts fully understand the mechanics of commonsense reasoning and contain it in a repository that will be accessible and usable by machines [7].

Significant progress has been made in terms of building commonsense ontologies however, as these were put to use, it was found out that the knowledge coming from them are lacking. Relative to the amount of commonsense found in humans, the ontologies proved to have a sparse coverage and
really could not keep up with the level of reasoning that humans have [7].

A possible reason to the gap in information in the ontology is that the contributors are generally themselves again and again. People are unique and possess their own set of knowledge, namely, commonsense. However, the amount of knowledge covered from one human to another is different. If only a set of people are used to supply the commonsense in the ontologies, chances are there will really be gaps in terms of the knowledge supplied by them. Also, new knowledge acquired goes down when a question is asked to the same set of people [2].

Commonsense is the most basic type of knowledge that everyone develops as part of their life experiences [6]. From the results of the studies made in [2] and [7], it can be seen that a set of people giving all the answers for a commonsense repository will not work. There is a need to explore and gather knowledge from different sets of people. This research is geared towards harnessing the stage of mental development in children by making them contributors to the commonsense ontology.

1.3 Knowledge Bases

ConceptNet [6] is a large-scale knowledge base that possesses commonsense knowledge. Users contribute commonsense knowledge by going to their website and answering questions that pertain to commonsense knowledge. WordNet [10] and Cyc [5] are similar and notable knowledge bases which give semantic meaning to information. However, they are different in terms of their goal in the type of machine understanding that they want to achieve. WordNet is envisioned for lexical categorization and word-similarity while Cyc is envisioned for formalized logical reasoning. ConceptNet on the other hand, having possessed commonsense knowledge, is envisioned for making practical reasoning over real-world contexts.

1.4 Crowd-sourcing

Having understood the potential of using ontologies, there is still the problem of creating an ontology as it requires a lot of effort and work. Because of this, crowd-sourcing has become a popular choice among different researches on knowledge acquisition. Crowd-sourcing is where the community is the one supplying the information as opposed to it being manually encoded by experts or knowledgeable people. ConceptNet has followed this methodology of letting the community contribute information but there is still the problem of defining a framework for letting the community contribute information that may be defined into a knowledge base. Aside from this, there is also the problem of getting the participation of the community in contributing information.

An idea first proposed by Von Ahn and Dabbish [12] is called Games-With-A-Purpose (GWAPs). Many systems turn to GWAPs because it allows the users to contribute information and give them the feeling that they are simply playing a game. It conveys entertainment and fun that gives incentives to the user and encourages them to actually participate.

Much research has already been done on probing adults as the contributors to the resulting commonsense ontology and children are being taken for granted as prime contributors of the knowledge base. First, children between ten to twelve years of age are explicitly expanding their mental capacities as well as their commonsense which make them valuable to the commonsense ontology approach. Children show the eagerness to learn as they possess innate curiosity on things that may seem obvious to adults [1].

1.5 Stories

Storytelling is a common way for people to share experiences and beliefs along with their insights and ideas. It is also a way to convey information among people. People tell stories all the time for different reasons. A teacher tells stories to emphasize a point. A mother tells a bedtime story to her children to help them sleep. A writer creates stories to entertain or to portray society to raise social awareness. Storytelling has become very common such that it is a trivial part of our everyday living [7].

People are able to interpret stories because they embody commonsense knowledge and can reason with this knowledge. Without such knowledge, machines have no mechanism for understanding the human world that will enable them to interpret and to generate stories.

2. CURRENT WORKS

A system that probes children into contributing commonsense knowledge is an experimental system by Bosch and his colleagues [1]. The system is able to get information from children who are ten to twelve years old. The knowledge acquisition process proceeds in two phases, namely, the assertion phase and the validation phase, with knowledge gathered during the first phase is verified in the second phase.

BagPack [2] is a system that applies the GWAP paradigm. It is integrated into Facebook and allows users to validate concept relations in a slot-machine-like game. Results are not yet reliable as the system has yet to be evaluated on an uncontrolled audience. Initial results were done only on eighteen people that were known to the proponents but initial results were positive as the system was able to mine 21% of new concepts with respect to ConceptNet.

Verbosity [13] is also a GWAP system. It is meant to be played by two players with one acting as a narrator and the other acting as a guesser. The narrator is given a word and he needs to make the guesser be able to guess this word by giving clues. Clues are enforced in a sentence format, e.g., it contains a keyboard or it is found at home. If the guesser is able to guess the word given the clues then the given sentence clues are assumed to be factual by the system.

Given the systems such as BagPack [2], Verbosity [13] and the Turing Game [9] that aim to have the online community help in building the ontology, there is still a lack of approaches that harness children as contributors to the knowledge base. The experimental system by Bosch et al provided good results but the system receives much criticism due to its limited relations. The system only covers six of the frequently occurring relations in ConceptNet.

3. Suggested Approach

In line with the vision of AI to embody machines with the ability to reason like a human being, there is a need to look into different ways of gathering commonsense knowledge and representing the collected information into a repository that machines can utilize. As there are already much research that have adults as the contributors, the research work presented in this paper looks into enabling children to contribute commonsense information as well.

As presented in Section 1.5, stories are very common even to young children. Integrating stories into the process of
contributing commonsense knowledge to be stored in the ontology makes the whole process less intimidating especially for children. Given this, this research looks into presenting stories with blanks to be filled up by children. This gives the children the impression that they are simply providing key concepts to complete a story but are abstracted from the engineering process of constructing a commonsense ontology.

3.1 Architecture

The architecture is presented in Figure 1. The system starts with a fixed set of children’s story templates to serve as the initial seed for acquiring knowledge. Succeeding stories are generated by determining the knowledge already stored in the ontology, which includes an initial set of basic knowledge as well as any newly acquired knowledge. A story is comprised of a set of relation extraction templates with blanks to be filled by the children. Filled templates represent the new commonsense knowledge to be stored in the ontology.

![Figure 1. Architecture](image)

The Story Generator interacts with a Surface Realizer to produce a surface text of the story that is then presented to the user. Users provide inputs by filling in concepts onto the blanks to complete a story. These concepts are forwarded to a Lemmatizer so that the words that will be stored into the ontology are in their base or lemma form to prevent duplicate entries in the ontology.

A validation process is included wherein users are presented with previously learned assertions. They can specify if they agree, disagree, or not knowledgeable with the assertion. The user response is used to provide assertion ratings that are used by the Story Generator to come up with meaningful stories as the system acquires more assertions.

3.2 Relation Extraction Templates

A collection of predefined relation extraction templates is defined to collect assertions for the commonsense ontology. These extraction templates, represented in a sentential structure, and have the following format:

\(<\text{Concept A}> \text{<Relation> <Concept B>}\)

Table 1 shows example relations and their corresponding relation extraction. Notice that each relation can have several extraction templates.

### Table 1. Relation Extraction Templates

<table>
<thead>
<tr>
<th>Relations</th>
<th>Meaning</th>
<th>Extraction Template</th>
</tr>
</thead>
<tbody>
<tr>
<td>IsA</td>
<td>What kind of thing is it?</td>
<td>__ is a __</td>
</tr>
<tr>
<td>AtLocation</td>
<td>Where would you find it?</td>
<td>You will likely find a __ in a __.</td>
</tr>
<tr>
<td>UsedFor</td>
<td>What do you use it for?</td>
<td>You can use __ to __.</td>
</tr>
<tr>
<td>MadeOf</td>
<td>What is it made of?</td>
<td>You need __ to make __.</td>
</tr>
<tr>
<td>HasPrerequisite</td>
<td>What do you need to do first?</td>
<td>__ is needed in order to __.</td>
</tr>
</tbody>
</table>

3.3 Story Templates and Preconditions

A collection of story templates is also defined to generate seed stories for collecting knowledge from users. Preconditions are in place to generate variations of stories to enforce the users to input new commonsense knowledge that would go with the story.

A story template is comprised of relation extraction templates. This allows the story to have blanks and should be the medium by which children would contribute commonsense knowledge. Seeing as the stories should be made in such a way that assertions can be learned, the quality and variety of the story is not expected to be as good as those of popular story generation systems.

Two basic types of stories are supported, namely descriptive stories and event-based stories. In a descriptive story, the subject of the story will be described throughout the story through factual knowledge. An example descriptive story template is shown below:

**Good Day! Today we will talk about animals. A Pig is an animal. You will typically see a pig in a farm. A pig can eat. It likes to eat leftovers and it has a snout. A pig is capable of running. It is also capable of lying down. When you think of a pig, the first thing that comes into mind is pork chops.**

In an events-based story, the causal chain of events in a given setting comprises the story. Descriptive statements that will describe the subject or objects in the story can be included but are not necessary. An example events-based story template is shown below. This story was derived from a sample story generated by Picture Books [3].

**ROY THE CHICKEN LEARNS TO TAKE BATH**

The evening was chilly. Roy the chicken was in the bedroom. He played with a ball. Daddy Sam told Roy to take a bath.

Roy did not want to take a bath. He continued to play. Roy did not take the bath. He became dirty.


Roy felt hurt. He cried. Daddy Sam saw Roy was crying. Daddy Sam asked Roy if everything was okay.

He told him to take a bath. Roy wanted to take a bath. He took the bath with a yellow rubber ducky. Roy removed dirt.

Taking bath results to smelling nice. It was fun. Roy was merry. From then on he always took the bath.
4. EVALUATION
There are numerous aspects of the system that need to be evaluated. The first is the commonsense ontology that has been populated with assertions from inputs of the users. Aside from the output of the system, the story templates that will be used for the system are appropriate for children. A child educator or a literary writer could also check if the story templates are appropriate for creating stories. Lastly, the relation extraction templates need to be checked whether it is safe to make assumptions based on the concepts entered into the blanks of the sentence templates. This is an important aspect of evaluation as faulty relation extraction templates will dramatically affect the validity of the resulting commonsense ontology.

5. FURTHER WORK
This paper has presented an initial approach to collecting commonsense knowledge from the community. The study focuses on using children’s stories as a means for young children to provide valuable contributions to this endeavor. Children already develop everyday reasoning at a very young age and upon learning this type of knowledge, it quickly becomes trivial and taken for granted. Various issues remain to be addressed, specifically on validating the content of the resulting ontology to generate more story variants that can further acquire new knowledge as well as sustain the interest of the children. The story templates must be validated by child educators to determine their appropriateness for the target audience. They must also be evaluated to determine their relevance in acquiring a specific class of assertions. Lastly, the relation extraction templates need to be checked as faulty relation extraction templates will dramatically affect the validity of the resulting commonsense ontology.

6. REFERENCES