On the role of Commonsense in concept formation and explanation

Introduction

The number of words in English has grown from 50,000 in Old English to about a million today, largely through a combination of the English language adopting foreign words and the boom in science and technology. How does a culture decide between inventing a new word to explain a concept, or compounding two words to approximate it? The former risks vocabulary proliferation and the latter, a poor approximation to the original concept. On a more micro level, how does an individual come up with similes and analogies in the process of both learning and teaching?

Quoting Marvin Minsky from Chapter 6 of the Emotion Machine, 'we use common sense for things that we expect other people to know and regard as obvious'. Minsky notes that one of the greatest failures of modern artificial intelligence is the inability of machines and 'expert systems' to replicate tasks that most humans deem as basic, but that are extremely difficult for machines to replicate because of the lack of their commonsense thinking. In our efforts to understand and recreate artificial intelligence, Minsky further notes the four levels of thinking: reactive, deliberative, reflective and self-reflective. An artificially intelligent machine can never learn enough specific If-Then rules, and there is a need for abstractions, as was argued in a 1959 essay by John McCarthy in an essay called *Programs with Common Sense*. He proposes a construction of the 'Advice Taker' using predicates and rules to guide decision-making. The Open Mind Common Sense (OMCS) project is an artificial intelligence initiative started at the Media Lab in 1999. The goal of this project is to build and utilize a large commonsense knowledge base from the contributions of many thousands of people across the Web.

Data Set

The dataset used for this project is called ConceptNet, a semantic network based on the information in the OCMS database. ConceptNet is expressed as a directed graph whose nodes are concepts, and whose edges are assertions of common sense about these concepts. Concepts represent sets of closely related natural language phrases, which could be noun phrases, verb phrases, adjective phrases, or clauses. ConceptNet is created from the natural-language assertions in OMCS by matching them against patterns using a shallow parser. Assertions are expressed as relations between two concepts, selected from a limited set of possible relations. The various relations represent common sentence patterns found in the OMCS corpus, and in particular, every "fill-in-the-blanks" template used on the knowledge-collection Web site is associated with a particular relation.

Vision

The main goals of my project were:

1. Identify common sense relations between:
    a. near miss concepts
    b. English proverbs
    c. Scientific analogies
2. Study compound word formation in foreign languages (Chinese and Finnish) as an indicator of common sense knowledge.

Steps

To achieve this, I first set up ConceptNet 5 by running my own copy using Solr and Python. The ConceptNet 5 server comes in three pieces: the main index in Apache Solr, a REST API that's served from Python, and a Web interface on top of that API. I wrote a BFS procedure that took two concepts as an input, searched through the ConceptNet 5 database for the closest relation between the first and second concept, and outputs both the actual relation itself connected through a list of assertions between intermediate concepts and the number of hops taken from one step to another. The node expansion paradigm was to use both forward and backward assertions, in a specific effort to move away from the tendency towards hierarchical relations that most systems fall into.

Analysis

Part 1

To fulfill part 1 a), I used the furniture example of difference-networks in Chapter 6 of the Emotion Machine.

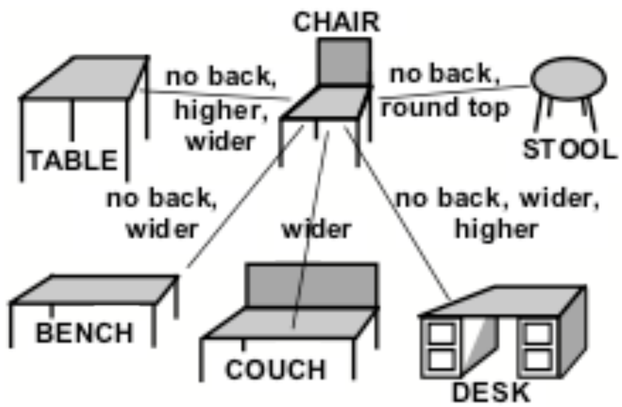

Figure 1 shows the difference network around a Chair concept

Upon running the BFS algorithm, I obtained the following results:

Concept	Intermediate Assertions	Length of shortest path
Couch	HasProperty(chair,	2

	comfortable), HasProperty(couch, comfortable)	
Stool	UsedFor(chair, sit), UsedFor(bar stool, sit)	2
Desk	AtLocation(chair, desk)	1
Bench	UsedFor(chair, seat), UsedFor(bench, seat)	2
Table	MadeOf(chair, wood), MadeOf(table, wood),	2

Table 1: BFS on concept Chair showing intermediate assertions and path length

The average path length between Chair and every other node on this near-miss or difference network was 1.833. It is important to note that ConceptNet connects different concepts based on their similarity, not their differences. One way of reconstructing a difference network from this information is to perform a Lowest Common Ancestor analysis, navigate to that node, and then determine what is different about the two concepts being related. The essence of difference networks lies in the ability to make side-ways connections, and this approach, if carefully constructed, can generate such difference networks given commonsense knowledge as defined in ConceptNet. For example, a Table and Chair both have the property of being made out of Wood, according to Table 1. It is also possible to extract independent qualities out of the object itself, such as a UsedFor() assertion to give UsedFor(table, work) and UsedFor(chair,sit). Thus the difference relation could be 'A Table is like a Chair, except a Table is used to Work and a Chair is used to Sit; both are made of Wood'. There is additional work to be done in determining the right differentiating factor, but ideally it would be an assertion of the same type (ex. UsedFor()) with the most semantic difference in values (ex. Work and Sit would be preferred over Work and Rest). The similarity index of two concepts can be determined using ConceptNet as well. This also makes intuitive sense to a human observing the learning of the difference network.

For part 1 b), I picked a random set of 'Clever Analogies' from http://cleveranalogies.tumblr.com/page/5, and extracted the two concepts being compared manually. I ran the same BFS algorithm to determine how far apart in commonsense terms the two analogous concepts were, and Table 2 encapsulates the results:

Phrase	**Concept 1**	**Concept 2**	**Intermediate Assertions**
Lying is like acting, except during acting you believe in what you are saying.	Lying	Acting	HasSubevent(pretend, lie), HasPrerequisite(act play, pretend)
Bagels are like donuts without the exterior pretense of being sweet. Be like a bagel, not fake like a donut.	Bagel	Donut	IsA(Bagel, Donut)
Sleep is like alcohol - you need just the	Sleep	Alcohol	CausesDesire(alco

right amount. Too little, and you feel no different. Too much, and you end up regretting it.			hol, sleep)
Procrastination is like a fine wine. It gets better with time.	Procrastin-ation	Fine wine	UsedFor(wine, cocktail party), CausesDesire(procrastination, party)

Table 2: BFS on 'Clever Analogies' showing commonsense relation between the two concepts

As we can see, all these concepts are very closely related, at an average distance of 1.5. However, a closer analysis of the assertions themselves seems to indicate that there is very little to no similarity in the meaning of the assertion and the text of the analogy phrase. Only Lying and Acting have the common concept of pretense. The concept of Pretense nicely summarizes the absence or presence of belief in your own speech, which the phrase claims to be the distinguishing factor between Lying and Acting. Information is lost when only concepts are extracted, and hence for Procrastination and Fine Wine, there exists the common link of a Party. This is not the original intention of the text, but the reasoning is still analogy-based. Of course, there is also the node that illustrates that the commonsense system can have a totally different, much shorter link than anticipated. For Sleep and Alcohol, since we find the shortest path, we have a direct CausesDesire() assertion.

In this case, it seems that commonsense systems are weaker at coming up with multiple different and unique, also humorous, relations between related concepts, but will usually find a short link between the two. The commonsense approach will take the most direct route between concepts, but the subtlety of humor is in the exaggerated stretch of assertions.

For part 1 c), I fished for common scientific analogies used by science teachers in elementary and middle school as a way of imparting new knowledge to children as an analogy to what they already know. I then ran the same BFS algorithm to determine how quickly the commonsense system could identify the link, in Table 3:

Concept to be explained	**Concept known**	**Intermediate Assertion**
Eye	Camera	IsA(camera, eye)
Heart	Pump	UsedFor(heart, pump)
Universe	Balloon	HasProperty(universe, expand), CapableOf(gas, expand), HasA(balloon, gas)
Cell	Factory	> 3
DNA	Ladder	> 3

Table 3: BFS to determine commonsense in explanation of scientific concepts through analogy

It can be seen that less of scientific analogies, even some of the most basic ones, can be determined by this system as compared to the other commonsense knowledge explored so far. This might be because scientific terms are typically ill-explained in commonsense knowledge, and the quality of the assertions, where present, is low. Furthermore, the concepts also tend to self-reference themselves, further reducing the number of outgoing connections. The Eye and Heart examples had direct connections, but the Universe example did not. However, it seems like the commonsense network was able to generate a strong and fairly accurate relation.

Thus, we can see that for part 1, the commonsense network tries to approximate three cases: near-misses, 'clever analogies' and scientific analogies; and using the BFS approach it is able to use common properties to generate the near-miss connection, although the organization of the data sometimes makes it hard to.

For 'clever analogies', commonsense networks were found to make the connection, sometimes in more humorous ways than original (Procrastination is like Wine, both promote parties), sometimes in less humorous ways by making the most direct connection (Alcohol causes Sleep).

Commonsense data was the least developed for scientific analogies, although due to the factual nature of the network, in case a link was found, it was generally extremely accurate.

Part 2

For part 2 of the project, I wished to extend the reasoning of explaining new concepts in terms of what we already know to the formation of compound words in foreign languages. The languages chosen were Mandarin Chinese and Finnish.

English	**Chinese (Pinyin)**	**Chinese (translated)**	**Assertions**
Volcano	Huo shan	Fire mountain	IsA(volcano, mountain), HasProperty(volcano, crater fire)
Computer	Dian nao	Electric brain	IsA(human brain, computer), IsA(computer, electronic device)
Insurance	Bao xian	Protect risk	IsA(insurance, protection), HasProperty(insurance, risk),
Telephone	Dian hua	Electric voice	AtLocation(voice, telephone), IsA(telephone, electronic device)
Tip	Xiao fei	Small money	HasProperty(tip, extra money)

Table 4: Formation of Chinese compound words using commonsense data

English	**Finnish**	**Finnish (translated)**	**Assertions**
Dictionary	Sanakirja	Word book	AtLocation(word, dictionary)
Computer	Tietokone	Knowledge machine	UsedFor(computer, knowledge), IsA(computer, machine)
Wednesday	Keskiviikko	Middle week	DefinedAs(Wednesday, third day business week)

Railway	Rautatie	Iron road	ConceptuallyRelatedTo(railway, train), IsA(train, call iron horse)[sometimes],
Umbrella	Sateenvarjo	Shade rain	UsedFor(umbrella, rain), UsedFor(umbrella, shade)

Table 5: Formation of Finnish compound words using commonsense data

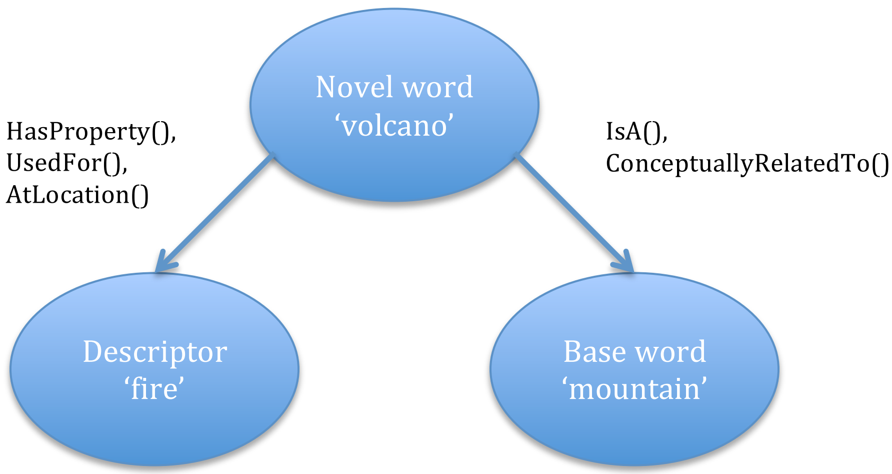

Figure 2: Showing construction of novel word through compounding

As can be seen from the tables above, the structure of these compound words seems to have two fundamental components. The first component includes a base word that indicates what the object is fundamentally, making a direct sideways connection typically in the form of a IsA() or ConceptuallyRelatedTo() assertion. The second component includes a descriptor word that qualifies the transition from the base word to the new word, almost like a function. It can be seen that these transitions can be written as fire(mountain) → volcano; much like f(x) → y.

From an artificial intelligence standpoint, this makes sense since the language first searches for a similar concept in the commonsense space to form the base word and then applies the transformation needed to get to the novel word, the label of the transformation becoming the descriptor word. In fact, this deconstruction is instructive in understanding the real meaning of the word itself. One concern that might arise from this approach is that when one tries to backtrack, i.e. generate Volcano from Fire and Mountain, there might be more than one possible match. I used the ConceptNet 5 Web API to investigate this concept for a few choices, and it turns out that in most cases including the Volcano example, the commonsense network returns the same word, and in some others it returns a less common, but related word as in Electric(Brain) = Android, Mainframe. Thus, this system of compound word formation is quite robust, as the reverse transformation almost unambiguously defines the original novel word.

Conclusion

It seems that although commonsense networks are a good approximation to an artificial intelligent system's understanding of everyday concepts, they are susceptible to incompleteness, wrong or misrepresented information, duplicity of nodes and slow calculations at the human, more practical level. On a deeper level, commonsense networks on the one hand can explore the BFS tree in a systematic way to generate robust outcomes, but falter where the human mind seems to excel: random connections. It must also be noted that commonsense networks only deal with one or two representations of knowledge (linguist and/ or conceptualist), whereas human beings have the added advantage of understanding the same concept through multiple representations, as Minsky points out in Chapter 6.7 about the example debate between the mathematician, linguist, connectionist, conceptualist and statistician.

Commonsense networks seem to have greater explanatory power than the associative power seen in part 1. It can be seen that commonsense networks are a reasonable approximation to understanding real world lexicon, which directly influences our perception of the concepts in the world. It is no surprise that Email in Chinese is 'Diànyóu', which means 'Electric Postal'. This indicates to us that new concepts are learned by applying a familiar transformation to a familiar old concept, thus there is a potential for learning an exponential number of concepts in this manner.