Semantic Networks for Human Brain Modeling

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Abstract

This paper will explore the properties and applications of semantic network models with modeling human brain cognition. Starting with an introduction to semantic networks and cognition modeling, to considering two recent experiments which use them, concluding with how this field will continue to develop.

1 Introduction

There are thousands upon thousands of concepts in the world, with millions of relationships between them. As children we begin to learn these relationships through basic association. They see forks and spoons on their dinner table, grouping them together as 'cutlery', they see their cat playing with a yarn ball and associate them together stronger than a cat and cutlery. In school we learn relationships between groups of people in history, chemical groups in chemistry, and devise experiments to find previously unknown relationships. This increasingly large map of concepts build up a person's understanding of the world. While it is difficult to probe the brain directly to understand how we organize these concepts, it can be effectively modeled using semantic networks.

Semantic network models are computational representations of concepts into a huge graph, where each node is concept label, connected by edges, which could represent IS-A, super/subordinate, and other relationships. These graphs can be traversed to find clusters of similar concepts and allows us to compute a rough 'semantic distance' between concepts. These properties and functionalities have been found useful in approximating how humans process and organize facts.

2 Semantic Networking

The first implementation of a semantic network on a computer was done by Richard H. Richens of the Cambridge Language Research Unit in 1956 (Lehmann and Rodin, 1992). He was exploring ways to improving machine translation, and since concepts have the same relationship regardless of the language they are express in, by incorporating semantic networks as a 'lingua franca' between languages.

The most basic way to build a semantic network is to examine the co-occurrences of words or small permutations of words from a large corpus. With the assumption that terms that occur near and often of each other must somehow be conceptually related, these co-occurrences can be tallied to draw edges between common concept nodes. A more through processing of the source corpus can be done to determine the inheritance relationships or whatever other relationships you wish to capture.

The most well known modern semantic network is WordNet (Miller, 1995) which encodes the hypernyms, hyponyms, antonyms, etc for over 117,000 concepts. This network has proven useful for natural language processing tasks such as word-sense disambiguation and information retrieval, with similar models seeing increased used in cognitive psychology.

3 Human Cognition

Semantic networks are able to map onto human cognition somewhat roughly, but intuitively. Every person is able to group together ideas through some learned relationships. It would be incorrect to assume that the brain truly uses a graph with discrete nodes for different 'ideas', all of us group together ideas differently along various fuzzy continuums with many overlapping concepts. These models simply have properties reflecting people's behavior with language, an input 'What is a cat most like?' would produce similar output with people and models. It it has been shown how humans have an understanding of ’semantic distance’ through experiments showing how semantically near terms can be primed for faster word recognition (Yee and Sedivy, 2006). While the brain’s processing cannot be directly probed like WordNet can, we can plot the activations of various regions in the brain in reaction to meaningful terms to converge on a more refined model of our black-box.

4 Predicting human brain activity with Nouns

Researchers at Carnegie Mellon University (Mitchell et al., 2008) had a hypotheses that when recognizing concrete nouns regions of the brain corresponding the noun’s sensory-motor features would activate, a guess that we recognize objects by their physical properties and motor actions associated with that object. Learning these regions of activations should allow to prediction of what a person is perceiving with only a brain scan. They first built a model from a trillion word corpus that counted the co-occurrences of 60 concrete nouns with 25 sensory words, tallying how often the noun ’glass’ occurred near ’smell’, ’move’, ’break’ and more sensory-motor descriptors. Each noun in the model is represented as a linear combination of these 25 features.

Next they captured the brain activity of subject’s observing 58 of the nouns in an fMRI machine. They observed semantically near terms activated similar regions in the brain, like how semantic models represent semantically near terms with similar feature weights. They were able to correctly predict when subject’s were observing the 2 left out nouns, namely ’celery’ and ’airplane’, just from their brain activity.

These results are promising in showing how the brain seems to organize information. fMRI data of this sort is difficult to collect and the predictive powers of these models are limited by lack of training data. While this experiment was able to show patterns of behavior in our brains, we cannot say for certain which physical features of an object the brain uses for object recognition. While the features of the 60 nouns were gathered from a very large corpus, it is another data limitation, different features gathered from a different trillion word corpus may have been more accurate by chance. These studies are also constrained by their focus on nouns. While we might model the perception of verbs such as a person running through a sensory-motor means, recognizing things such as movement and panting, these relationships are much more difficult to capture than the concrete properties of nouns. Objects can be recorded as a static set of properties once, but actions with temporal aspects must be continuously measured introducing complexities of dynamic state and timing to the semantic model. Measuring the perception of a single, unmoving object is significantly easier and more accurate than verbs (Moseley and Pulvermüller, 2014).

The paper also noted how they mapped activation regions predominantly in the sensor-motor cortex which has been extensively studied and mapped. There was much activity in the frontal lobe, the ’higher thinking’ part of the brain, whose activation patterns remains a mystery.

5 Disentangling narrow and coarse semantic networks in the brain

Researchers at Pennsylvania State University (Schloss and Li, 2017) expanded upon the previous study with more refined semantic models and examining differences between the brains’ left and right hemispheres.

Using a similar method of mapping features of concrete nouns to regions of brain activity, they built various models to measure their predictive power. This experiment used ”Latent semantic analysis” (LSA) and ”hyperspace analogue to language” (HAL) models, where the meaning of a word is represented as a high dimensional vector with each dimension denoting either a word (word-to-word matrix) or a document (word-to-document matrix) co-occurrences respectively. Previous experiments have shown how the LSA model reflects the speed with which children learn words while reading (Landauer and Dumais, 1997), and HAL models simulate childrens semantic representations from their parent’s speech (Li et al., 2000). Schloss and Li found that these two models had different accuracies in various object recognition tasks.

They also applied some data reduction principles to the Mitchell et al. (2008) model and found that only 13 principle features were needed for accurate results. Reduction to dimensionality are always welcome and seem to reflect how the brain optimizes its use of input signals.

The current researchers also explored the differences of semantic organization in the right and left hemispheres. Previous experiments have shown how left brain seems to recognize ’close’ semantic relationships faster, while the right brain instead recognizes ’distance’ relationships quicker. An included example is that the left hemisphere would recognize ”gold” and ”money” as semantically near terms much quicker than the right. The right instead would recognize coarse relationships such as ”gold” and ”pan”, as in ”panning for gold” quicker. Various models were operationalized for different measures of ’semantic density’, but found minimal difference between the hemispheres.

This more in depth exploration of semantic network modeling reflects the improve techniques and methods of more refined NLP modeling. This direction may come with problems of its own, in how the understanding of the brain is limited by the understanding of the models and the scope of information which they cover. While patterns of brain activations can be found, adhering to quickly to these patterns as how the brain actually works may overlook some critical findings. These experiment continue with acknowledging the still unknown patterns of activation in the frontal lobe.

6 Using semantic networks for mental aid

Researchers at Clinical Neuropsychology Working Group of the University Medical Center Hamburg-Eppendorf have found applications of semantic network in designing better treatments for obsessive-compulsive disorder (OCD) (Jelinek et al., 2018). They postulated that OCD patients had hyperactive associations between mundane concepts, such as ’red’, and their OCD-related fears, such as seeing blood. These problematic obsession associations are only reenforce with compulsive behavior, such as excessive cleaning. To help patients with OCD remove or replace these disruptive associations they are develop an Association Splitting (AS) therapy program. Assuming there is a limited amount of activation the brain can distribute among it’s semantic model, the therapy consists of repeatedly training patients to re-associate their obsessions with different, healthier concepts. In combination with more traditional therapies they found that patients treated with AS saw improved results, with less patients reverting back to their compulsions less often, in treating their OCD.

7 Conclusion

Through the sheer statistical force of semantic network models we are able to mimic the meaningful relationships that the human brain seems to make. There are many more ways to ’learn’ a semantic network with many different organizations and properties that can reflect complex patterns of perception. Computational linguistics continues to make advances with more refined formulas and more accurate predictions.

While we can model the brain’s sensory-motor abilities of seeing, touching, moving objects, breaking them, etc..., with increasing accuracy, the frontal lobe’s functions of memory and higher thinking are still a complete unknown to us. Not everybody responds to the same stimulus exactly the same and surely we use our memories to assist in perceiving the world correctly. In the future once these semantic networks can behave and react to new information at the level of the human brain, they can be used to process the every increasing amount of data in the world and discover relationships we ourselves never could.

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