Discover SCIENCE FOR THE CURIOUS

From the Brain to the Machine: Natural Language Processing

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Human brain structure may reveal how our computers are able to understand us.

Language is a fundamental part of the human experience; most of us could hardly imagine a world in which we had no means of communicating with others in the world around us. Because of how central language is to our daily activities, it only follows that as technology has become so prominent in our lives, we want to be able to use the languages we know to communicate with that technology. The convenience of dictating a text to your friend by simply speaking to your phone or searching the internet for something with your voice is undeniably appealing. However, even though humans are generally quite adept at picking up languages, at least when we are young, the same cannot be said for computers. Researchers have been pouring resources into this problem: allowing computers to process natural language.

The history of natural language processing is the history of machine translation, first suggested by Descartes in the seventeenth century when he wrote of a theoretical code or device that could translate between any two natural languages. Until the 1930s, however, no patents were submitted for machine translation. The first patent submitted was for a primitive translation dictionary that used punched paper tape. The broader idea of machine translation remained pure theory, as no capable machines existed at the time. The computational power required for such large scale task as comprehending and translating language would not be readily available until years later. Theorists initially focused on the notion of simple language-to-language translations, which would soon evolve into more complicated grammatical language translations. It wasn't until 1954 that these theories began to become reality when a software was developed to translate between a few Russian and English phrases, and the field has only grown from there.

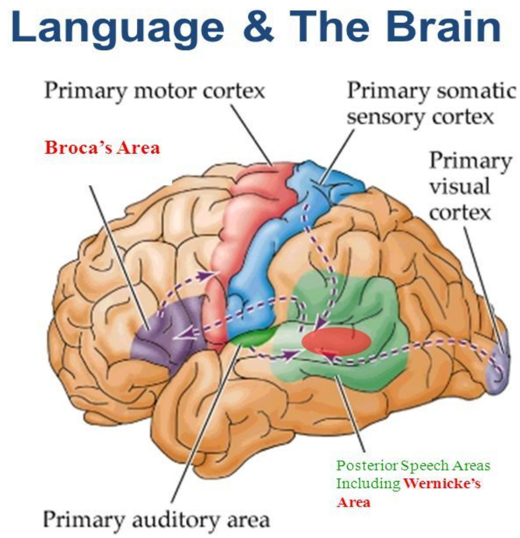
Natural language processing software is meant to approximate how the brain processes language. What the brain receives as sensory input, the computer receives as data that can be processed within its own circuitry. As a result, computer systems like Apple's Siri, Amazon's Alexa, and Microsoft and Google translation services can hear your voice, take a picture of text, and process, translate, and respond to it. Though there is still a long way to go, the technology has developed so far from where it was in the 1950s. In order to understand how exactly such natural language processing technology works, we must first understand how the brain processes language. By modelling our own language processing systems, we can see how software developers attempt to recreate similar functionality in machines.

How is Language Processed in the Brain?

Brain Plasticity

A critical component of neurological development to understand in relation to language is brain plasticity. As infants, we are born with many more neurons than we will ever need; to be exact, we are born with more than 100 times the number of neurons and synapses we will ever use. During the first few years of life, our brains go through a rapid reorganization in which many neurons are eliminated and synapses are pruned. This reorganization allows for a child's brain to be incredibly plastic; it has the ability to reorganize and rewire itself. This fact explains why children have the capacity to acquire information and learn at such a deep level — most people have heard at some point that it is much easier to acquire a language as a child than as an adult. It also accounts for a child's capacity to completely reacquire a function after an accident, something that the adult brain is almost incapable of. In the first few years of life, a child must learn so many skills and facts about the world around them, including how to understand and produce language.

Speech in the Brain: Broca's Area



Scientists who work within the field of neuroscience typically discover how the brain works by studying people who have deficits and working backwards from there. The same goes for recognizing how we produce language. In 1861, Paul Broca first identified the part of the brain responsible for language production by studying individuals with damage in that region. He encountered two patients, both with damage to similar areas of their brain, who had lost the ability to speak. This deficit would later be coined Broca's aphasia or non-fluent aphasia (Dronkers, Plaisant, Iba-Zizen, & Cabanis, 2007). *Aphasia*, an impairment of language making, makes it difficult to both produce or comprehend speech. But aphasia also can involve difficulties in producing language fluently, difficulties in finding words, and or a complete loss of speech as well as a variety of other speech impairment symptoms.

Broca's area is located in the *frontal lobe* of the brain, adjacent to the motor cortex, seen in the picture above. It has been thought that a large portion of the deficits associated with damage to this area occur because of its location in the frontal lobe, which is thought to be the main decision center for the brain. Thus, when damage occurs close to Broca's area, a difficulty to produce language arises. It has also been hypothesized that due to its location, next to the motor cortex, that the deficits of non-fluent aphasia arise due to the proximity of Broca's area to the motor cortex. Damage in this part of the brain the issue could cause an inability to properly produce the motor movements of the mouth that are associated with language. Many of us take for granted our ability to properly move our mouths in the very complex movements required to properly produce language, but it is certainly is not guaranteed, as indicated by the aphasia that certain individuals experience.

Language Comprehension in the Brain: Wernicke's Area

Language use and comprehension is a complex ability set that incorporates a variety of different parts of the brain. The ability to produce speech, for one, is controlled by Broca’s area, but it was found that even when patients experienced deficits in this area, they were still able to understand language. This phenomenon occurs due to the fact that these two different facets of language are processed by different areas of the brain. While producing speech is controlled by Broca’s area, understanding language is controlled by Wernicke's area.

In 1871, some 10 years after the discovery of Broca’s area, neurologist Carl Wernicke was faced with patients who had no problem producing language who but produced words that were not linked together in any way (Cherry, 2018). This condition would later become known as Wernicke’s aphasia, otherwise known as “word salad.” It was as if these patients took words that seemingly have no connection to one another, and then tossed them in a salad bowl, mixing them up before speaking. The result is a sentence with even less meaning. By studying these patients, Wernicke realized that the area that decodes the meaning of words and the area that produces them out loud were clearly different. If you spoke to these patients, they would have trouble understanding what you said and would answer you with complete nonsense, but they would produce this nonsense sentence with complete ease. Unlike those with Broca’s aphasia, where the sentences produced were choppy, people with Wernicke’s aphasia can produce a smooth sentence, even if it is meaningless. Wernicke’s aphasia has since become known as fluent aphasia due to the fact that although the sentences produced may not make any coherent sense, they are produced with ease.

Wernicke’s area, unlike Broca’s area, lies primarily by the brain's biggest association area: the *parietal lobe*, which can be seen in the picture above. This area is split by the Sylvian fissure, one of the largest involutions in the brain, between the parietal lobe and the *temporal lobe*. The parietal lobe and temporal lobe are highly associated when it comes to language processing. The main role of the temporal lobe is involved with hearing, which is clearly a key component for the proper comprehension and production of language. If damage occurs in this area, then there will be deficits in a person's ability to hear and, as a result, their ability to produce appropriate language in response to what they heard. As previously mentioned, the parietal lobe is one of the brain's largest association areas, which means that many different facets of sensory stimuli — in our case language — are sent here and assimilated before being passed onto other areas of the brain for further processing. Input signals are passed through many different parts of the brain to create meaning, and the same applies to linguistic input.

Spoken language is first processed by the sensory receptors in the ear, which is then carried by the auditory nerve to a part of the brain called the thalamus. From there, the information is then passed to the *primary auditory cortex* on the opposite side of the brain. Here, the information will be decoded so you can really “hear” what the person said, before being passed even further on to Wernicke's area, where the words that were heard and the meanings of those words are integrated together to produce understanding. Once the brain understands what was heard, it has to decide how to respond with its own speech. It does this by once again gathering the information from the primary auditory cortex and Wernicke’s area and sending this information to Broca’s area to determine the desired response and produce the necessary speech. There are clearly quite a few steps involved in understanding and producing language, but when we are holding a conversation with someone, all of this happens so quickly we can’t perceive of how it happens. So how does our brain pull it off?

Neural Networks: How the Brain Communicates With Itself at Lightning Speed

How Do Neurons "Communicate"?

Neurons communicate through 3 major parts: the *dendrites,* which take in incoming information; the *axon,* where information is transported from the dendrites to the axon terminals; and the *axon terminals,* which transmit chemical information to other neurons. When one neuron is stimulated, the stimulation is converted into a sort of language that neurons can understand and passed on. This process is known as *firing,* and it is said that the neuron is sending an *action potential*. Through this stimulation and subsequent firing, the neuron is able to communicate some important piece of information to the next neuron in the chain, and so on.

Neural Networks in the Brain

The vital parts of the brain that we have discussed can connect and send information so quickly because of structures called *neural networks*. Neural networks can be thought of in two ways: structural connectivity, in which different parts of the brain are physically connected through axons, and the connectome, which is all of the structural connections that make up the human brain. The strength of these connections between parts of the brain is dependent on the thickness of the *myelin* surrounding the axons and the number of axons going between the connected areas.

When neurons repeatedly fire together, it becomes increasingly easy for these neurons to communicate with each other. After all, if neurons work together often, it is beneficial to have quick signal movement between them. This communicative ease comes about through a variety of different ways, such as a neuron increasing the amount of myelin surrounding its axon. Myelin is a fatty type of protein that surrounds the axon of a neuron and that acts like a sort of insulation for the neuron. This keeps the action potential from degrading on its way through many many neurons; it is important for a signal to remain intact throughout its transmission. It also increases the speed at which the signal is able to travel through the specific set of neurons. The most used neuronal fiber tracts will be the most myelinated tracts. This is a primary example of structural connectivity in the brain forming a neural network.

The brain is one of the most intricate and efficient processing systems that we know of. This brief overview of brain function only begins to scratch the surface of everything that the brain does to function, even just to process language. There are many complex mechanisms that our brains have evolved to use effectively, and the real challenge begins when we try to make computers mimic this functionality. However, computer scientists have been able to take our understand of the brain and use it to develop artificial intelligence (AI) systems for natural language processing.

The AI of Natural Language Processing

Speech to Text to Numbers

The Problem of Input

Before a computer can make sense of language, it must first be able to receive linguistic input and represent it in an understandable format. After all, at the end of the day computers really understand only the 1s and 0s corresponding to electric switches being on or off. For text-based tasks, this translation is rather trivial; there are straightforward ways of representing strings of text in numerical formats that computers can eventually process for meaning. But what about speech? One of the most recognizable applications of natural language processing is speech recognition and production. We now know a bit about how humans do it, so how can a computer take the sound of speech and translate it into machine speak?

Transforming Waveforms and Beyond

When a computer records a sound, the raw data comes in the shape of a *waveform*: a graphical representation of sound waves themselves. The question is then how we can turn these waveforms into a digital representation of the words being said. Like a child would, the computer has to be taught the connection between different sounds and their corresponding letters, words, and phrases.

At the most basic level, programmers use a mathematical tool called the *Fourier transform* to turn the analog data of a sound wave into digital, binary data that a computer can process (Robertson, 2016). But linguistic features like allophones (a single understood sound may be pronounced in many different ways; consider the /t/ in <take> versus <kitten>), homophones (how does a computer know when you are saying “meet” versus “meat”?), differing inflection between speakers and between different interpretations of a phrase (“*I* didn’t steal it” versus “I didn’t *steal* it”), speakers with accents (think of the Bostonian *cah* for *car*, or Brooklyn’s *cawfee*-type vowels), and many more factors complicate matters greatly. If each of these different cases were to be considered individually, here would be quite a lot of rules for someone to program into a computer in order for if to be able to parse out language. When you consider the number of languages and language varieties in the world, this problem grows exponentially. Computer programmers developing speech recognition technology need a method of computation that will allow a computer to recognize and produce the correct sounds in each possible case without hand-coding every single one.

Seeing Text: Optical Character Recognition

Beyond speech, another major source of linguistic data that would need to be translated into a computerized format is written text, be that handwriting, scanned documents, or even pictures of signs. For this task, computer programmers can make use of a technique called *optical character recognition* to extract text elements from visual input (Ng, 2017). Optical character recognition relates to computer vision and image analysis, areas of computing that involve allowing computers to “see” pictures or videos in a meaningful way. This kind of task, though it seems so trivial for humans, is incredibly difficult for computers. A computer sees images as simple matrices of colored pixels, so how can it tell what objects — or in this case, letters — are represented in that image? The answer, as it turns out, is similar to how computers can make sense of language through audio signals: a program that can be given a massive collection of linguistic instances, each connected to its proper meaning, and learn the rules of spoken language or images of text by itself, without being explicitly programmed.

Machine Learning for Natural Language Processing

What Is Machine Learning?

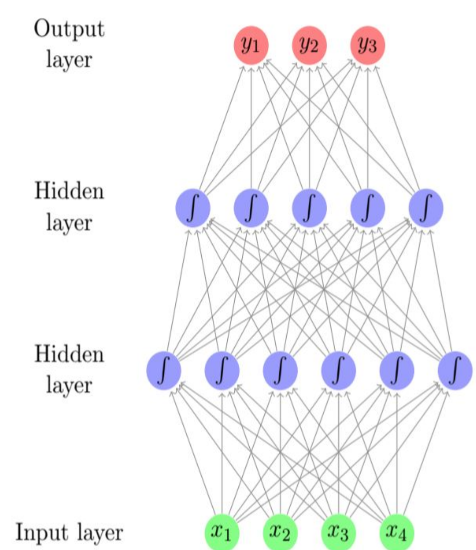
If you don’t want to have to program all of the many different rules of language into a computer by hand, you can instead program the computer to figure out many of those rules on its own. This is called *machine learning*; a computational technique that involves feeding a computer algorithm a large amount of data in order to complete a given task, and letting the computer find patterns in the data that will help it complete that task (Ng, 2016a). Machine learning is a subcategory of artificial intelligence that is particularly data-driven, and there is plenty of data out there of written and spoken language. In the problem of natural language processing, that might involve giving a system a large number of audio recordings with proper translations, or a series of images with text transcriptions and letting the computer figure out how to properly go from one to the other. However, this is, of course, a simplification of how the entire process would actually work.

The Hot Topic in Tech: Artificial Neural Networks

Within machine learning, a number of different algorithms can be used to get the machine to learn depending on the kind of data you have or the kind of problem you are trying to solve. One of the hottest buzzwords of recent years has been *artificial neural networks*, a kind of algorithm that originally appeared in the 1980s but has seen a resurgence in popularity since 2015, when deep learning neural networks came to the forefront of AI research (Ng, 2016b).

Neural networks, in theory, are algorithms inspired by how the brain learns and the structure of the neurons in the human brain — these are the neural networks explained previously, though in computer science, the term “neural network” refers exclusively to the artificial algorithms developed for machine learning. The notion behind neural networks is the “one algorithm hypothesis” which suggests that the brain learns everything it knows with a single learning algorithm, rather than using different methods for different tasks (Ng, 2016b). In computing, this would mean that a single program can learn many different features of a piece of data rather than needing to develop a multitude of programs for each individual feature.

At its most basic level, a neural network consists of a set of a multilayered set of nodes (or “neurons”), each of which is responsible for learning something slightly different about input data and transforming it into a meaningful output. The figure to the right illustrates the structure of a basic neural network, which may also be called a feed-forward neural network because of how each node propagates information forward into the next later (Goldberg, 2016).



The first layer of a neural network is called the *input layer*, and each neuron in that layer corresponds to a different given feature of an example from your data set. For example, a sentence may have features such as subject, verb tense, point of view, or some mathematically determined feature that is less intelligible to us but that helps a computer comprehend the sentence, and each of these features is sent as input to a neuron in the input layer.

From the input layer, data is then sent through the (potentially numerous) *hidden layers* of the neural network, so named because for the most part, human programmers do not really see or care to see what is going on in these layers. Each neuron in the hidden layers is associated with a "weight" value that is used to transform a numerical input into output that will be passed along to the next node(s) in the network (Goldberg, 2016). These weights are what the algorithm learns over time. The hidden neurons each use a non-trivial mathematical function to learn something new about the data, such as a new feature that was not explicitly given in the data set, or perhaps a mathematical combination of multiple features together. The learned weights make each of these neuron features impact the output more or less based on how much each piece helps the computer correctly classify the input.

The last layer of a neural network is the *output layer*, which is the end result of the neural network's learning. For a simple classification system, this output may be the probability that the given data example belongs to a given class of things (Ng, 2016c). To relate this to language, consider a network that wants to classify words by parts of speech; the output later would contain a node each for noun, verb, adjective, et cetera. However, for the more interesting and pressing problems of natural language processing, such a simple neural network architecture may not be sufficient. Many developers in this age turn to more the advanced kinds of neural networks of *deep learning*, which may allow more complex information to be learned from data.

Deep Learning Neural Networks

Deep Learning versus Machine Learning

Deep learning can be considered a subfield of machine learning, or perhaps an extension of the notion of artificial neural networks in machine learning (Mulkar-Mehta, 2016). At the simplest level, deep learning — and particularly deep neural networks — refers to a neural network having many hidden layers in its architecture. A neural network may have as little as a single hidden layer (called a "shallow" network), but deep neural networks have many more, which makes them more computationally intensive and capable of doing more advanced math with data — more layers of neurons means more opportunities to transform and combine simple data features in to ever more complex ones ("Artificial Intelligence (AI) vs. Machine Learning vs. Deep Learning," n.d.).

This is not to suggest, however, that deep learning is simply normal machine learning with neural networks, just with more of the same math on top. Computer and data scientists have developed a number of different models and architectures to create more advanced deep networks, some of which are particularly useful for NLP.

Dynamic Memory Networks

In 2015, researchers at Salesforce in California introduced a neural network architecture called a *dynamic memory network*, or DMN, that "processes input sequences and questions, forms episodic memories, and generates relevant answers" (Kumar et al., 2015). The network consists of four modules, one each for input, questions, episodic memory, and answers. Both the input and question modules take natural language texts and turn them into mathematical representations that are then loaded into the memory module. The episodic memory module uses "attention mechanisms" to determine what inputs to focus on. When a question is asked, the network can refer to the “memories” stored in this module and give them to the answer module, which then produces output (Kumar et al., 2015).

With this architecture, the DMN is able to keep track of and remember a set of input statements and answer questions about the text it was given. The figure to the right illustrates an example of this concept, with I corresponding to input, Q to questions asked of the computer, and A being the machine’s response (Kumar et al., 2015). Here, the algorithm is able to accomplish three important tasks within natural language processing: given a sequence of sentences, use the combination of information provided from each phrase to answer a question; determine the sentiment, either positive or negative, of a complex sentence; and flag the parts of speech present in a given clause.

I:	Jane went to the hallway.
I:	Mary walked to the bathroom.
I:	Sandra went to the garden.
I:	Daniel went back to the garden.
I:	Sandra took the milk there.
Q:	Where is the milk?
A:	garden
I:	It started boring, but then it got interesting.
Q:	What’s the sentiment?
A:	positive
Q:	POS tags?
A:	PRP VBD JJ , CC RB PRP VBD JJ .

Convolutional Neural Networks

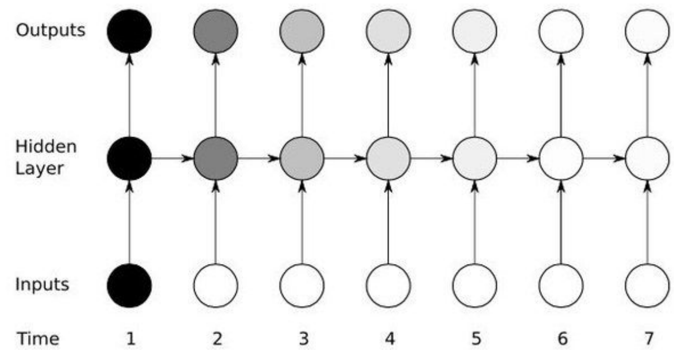
Another kind of neural network that has been used in NLP is called a *convolutional neural network* (CNN), a kind of feed-forward neural network. CNNs are primarily used in image processing, wherein they “take in an input image, assign importance … to various aspects/objects in the image and … differentiate one from the other” (Saha, 2018). However, CNNs can also be used in natural language processing for semantic parsing — determining meaning from chunks of text — and classifying sentences into various categories (Kim, 2014). These networks use a variety of filters in so-called “convolutional layers” and “pooling layers” (recall how our simple neural networks were arranged in layers) to quantify relationships between sister items in the dataset (Saha, 2018).

With images, CNNs are good at handling complex interactions between pixels, so it follows that such networks would also be able to handle complex sentences, using a similar algorithm with words instead of pixels to determine how those words fit together to form a sentence with meaning. On an even larger scale, convolutional networks can be useful if you want the machine to learn a particular phrase or clause that is indicative of the topic of an entire document. CNNs are good at picking out clusters from data and using them to classify the particular input (in this example, the document) in some regard.

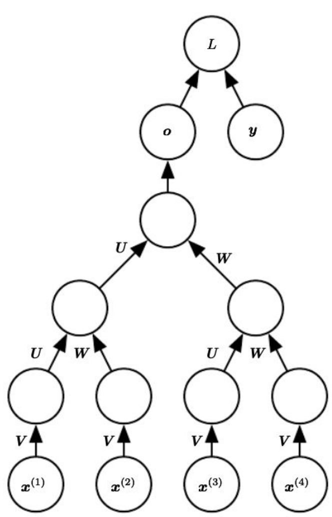
Recurrent and Recursive Neural Networks

Though DMNs and CNNs are quite useful, some of the most popular and powerful deep learning architectures in natural language processing today are recurrent and recursive neural networks (both confusingly abbreviated as RNN). The two networks are similar in certain respects (recursive networks are sometimes considered a generalization of recurrent networks), but the underlying data structure is different between the two, with the former being a sequence while the latter is a hierarchy (Goodfellow, Benigo, & Courville, 2016). In contrast to the convolutional networks of the previous section, these networks are useful because they retain the structure of the linguistic input data, while CNNs sacrifice much of that structure in favor of compressing the data into only its most important components (Goldberg, 2016).

Recurrent networks must consider the temporal sequence of input, meaning that input values are taken over time or in some sort of ordered sequence (Goodfellow et al., 2016). Because of this, the hidden nodes associated with each input node can take not only values from the corresponding input node, but also from the previous hidden node in the sequence, and use both sources to generate outputs. In this way, information flows through the network in two directions, both through the layers from input to output as in the feed-forward network, and from one side to the other over the variable to time. This concept is illustrated in the diagram to the right (Shivkumar, 2016). The network can be visualized as a sort of collection of chains linked together. This kind of network makes sense to apply to language given how we speak; in a given text or dialogue, certain words or phrases must come before others.



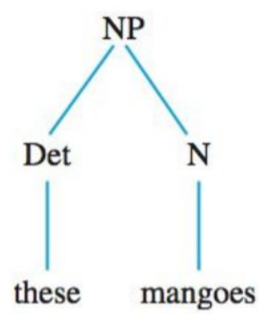
In contrast, recursive networks take the shape of trees rather than chains. In computer science, trees grow from the root node on the top and branch downward, so it will look more like an upside-down tree to the average observer. Trees in this sense are like hierarchies, which becomes important when considering the tree structure of recursive networks. A recursive network is visualized in the diagram below (Goodfellow et al., 2016). A study out of the University of Amsterdam published in 2018 showed that recursive networks (or TreeRNNs as the researchers called them) were particularly adept at processing hierarchical structures, using the simple example of nested arithmetic expressions such as (8 - ((5 - 7) - 2)). Though natural language is considerably more complicated, with a larger vocabulary and more complex and possibly ambiguous syntax, learning hierarchical representations is an incredibly useful technology for natural language processing. Hierarchical representations are especially important when you factor in how linguists posit that language is represented in the human brain when people think about and break down language into its component pieces.

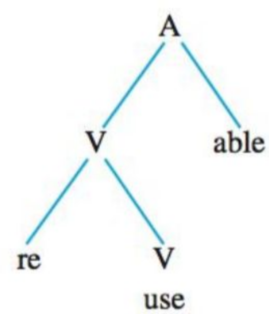


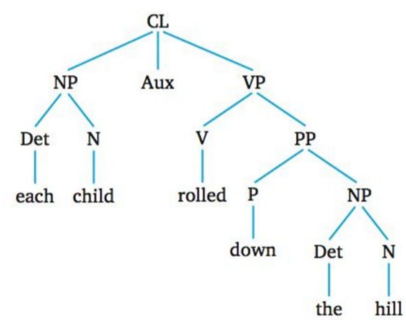
Artificial Neural Networks vs Human Brains

Hierarchical Representations of Language

As mentioned when introducing neural networks, the inspiration for the technology was the human brain itself. Certainly, there are caveats to this metaphor, but it is, in many ways, a useful connection to consider when looking at how artificial neural networks are constructed. Linguists Kristin Denham and Anne Lobeck argue that we understand language as being composed of hierarchical structures. Words, phrases, and entire clauses can be represented in hierarchical or tree form, as illustrated in the figures seen below (Denham & Lobeck, 2012).







Neural networks, particularly recursive networks, are particularly conducive to replicating this structural abstraction for computers to understand and replicate. In this case, we see that in addition to the biological structures of the brain, our mental representations of language influence how computers may be trained in natural language processing.

Similarities and Differences in Function

Artificial neural networks seem to match up with brain function on an abstract level, as both are a network of neurons (though each kind of neuron is structured very differently) that receive input, process it in some way, and produce output. The particular structure of the neurons and means of processing information clearly differ on any technical level, but the high-level, abstracted algorithm is similar between the two. Further, the section above illustrates the capabilities of computers to potentially represent information in a manner not too unlike how humans think about things like language. It is clear that artificial neural networks are an incredible simplification of what the brain does, but they illustrate the direction in which artificial intelligence and machine learning are developing.

Many people, scientists and citizens alike, have pondered the question of whether or not computers will ever fully be able to mimic the mental function of humans, and the differences in function and capabilities that distinguish human and machine may provide insight as to whether or not our computers can (or ever will be able to) think like we do. While the answers to such a question is relatively far off, computer scientists have made incredible advancements in technologies involving natural language processing. Let us examine some of the many applications of natural language processing that are being explored by developers today.

The Present and Future of Language Technologies

Unless you're a neuroscientist or computer scientist, the main reason why all these theories and explanations matter to you is in the way that they can be, or are already being, applied. It may not be as dramatic as airplanes or submarines, but natural language processing has certainly had transformative effects on how people live their lives.

Current Applications

Natural language processing already defines many small, easily missed portions of your life. It is used extensively in accessibility programs that are capable of detecting human speech and deriving written words from it or that can take a piece of written text and read it to you. It is used in predictive text programs, from the ones that write entire machine-written chapters from imaginary books to the ones that fill in the ends of your text messages. It is used in chatbots, fake customer service representatives, and AI assistants like Alexa or Siri. Ofcourse, these few examples do not capture full extent of the technology.

Natural language processing is not limited to working with the spoken word, however; programs can also start with images of text and deconstruct them to discover what they're saying. Such applications are already taking state — for instance, programs exist to translate scanned documents into text files, and Google translate has added an application that allows you to translate text taken from photos of signs.

One field that can benefit greatly from natural language processing is that of information storage. Natural language processing makes it easier for a machine to detect what you want or what you're looking for. Computers that can process language can generate metadata describing data files in more useful ways to aid in search functions, reducing the need to hand-label data. Using this new technology, you can access files from large databases and cross-reference them with others with ever-greater accuracy without ever involving a human accountant. In combination with other language based technologies like speech recognition, this can be incredibly powerful. In the future, calculating quarterly expenses for a business might be as easy as asking, "Siri, what're our expenses?"

Theoretical Applications

If these advancements seem simple, it's only because the technology remains in its very early stages. The "understanding" that computers have of language is currently incredibly limited compared to humans. However, the future of natural language processing promises to bring out continuous changes, large and small, that make it important to understand what this technology is and where it's coming from. This is an area of study which, despite its long history, has only just begun in earnest, and its most transformative effects have yet to be felt.

Translation

One of the most obvious, and most positive, applications is translation. After all, natural language processing is already based around translating between human and computer languages, and after that, translating between different human languages seems relatively easy, even for languages such as sign language. The process of breaking language down into its fundamental building blocks, analyzing those components, and building them back up in a comprehensible manner is identical. Natural language processing will make translating easier, faster, and more accurate, while reducing the need for dedicated translators in intercultural communication. Real-time translation devices may allow speakers of different languages to communicate face to face with minimal delay. With better text translation comes easier access to magazines, technical manuals, and even scientific studies published in other languages, allowing more people to benefit from the world's knowledge. In time, you might have a universal translator app on your computer, obviating the need for translators for print media altogether.

Analyzing Meaning

This is to say nothing of translating and discerning meaning within a particular language. Already, efforts are ongoing to write AIs that can read articles and derive from them the intended tone, sentiment, and biases. Imagine if you could run an article through a filter that would tell you what it would look like with a more optimistic tone, or from another point of view.

Though it may seem incredible, this technology is not without risks. Human translators have their biases, but so do human programmers, and those biases may show up in how the technology they develop behaves. If you allow too much of the content you're exposed to be filtered through a specific technological product, you'd better be sure you trust that product to not be lying to you. It doesn't even have to be a product of malice; if an early version of this technology reads an article, comes to a conclusion about what the article is saying, and is wrong, you'll only be reading express-printed misinformation.

Here's an example. Humans love taking photos of giraffes. Tens of thousands of photos of giraffes are floating about the internet. Those images are often used as part of galleries to train bots to detect certain elements in images, and those bots come to the conclusion that the world is far more filled with giraffes than it actually is. Consequently, any photo featuring a tall, tan-to-brown object will probably be labelled as a picture of a giraffe. A similar event could occur with examinations of articles. Your translator software might read an article about political unrest, hone in on a mention of a hospital, and decide it's an article about cancer research, restructuring the information accordingly. You have to be careful, especially with technology in as early a stage as this. It is easy to think of computers as more rational and objective than their human counterparts, but in reality, this is not necessarily the case.

Search Engines and More

Despite its flaws and limits, however, natural language processing has brought a computational understanding of writing not possible to earlier forms of computing. This understanding has its own interesting implications. As research progresses, many new technologies may become possible. Search engines will become more intuitive and more responsive, without users having to worry about keywords and the like. Applets will exist that allow you to feed in articles and webpages and return a generated summary. Blind users will be able to generate a caption for any image they might come across. Again, this is not something that is entirely without concern. In this scenario, you're allowing machines to decide a great deal of what you read and, in the later case, how you interpret the world. That's not necessarily a bad thing, but those machines had better be terrifyingly reliable.

User Interfaces

A more interesting — and less worrying — application of this technology comes in the form of natural UI, also called invisible UI. Modern *user interfaces*, the manner in which you indicate your intentions to a machine, are comparatively crude. A natural UI would allow you to communicate with your machine with no effort on your part. You wouldn't have to figure out what sequence of buttons to push or the exact order of words and lines you need to type — you could just tell your computer what you want and it would understand and respond seamlessly. Siri is an excellent example of an invisible UI that already exists. If you want a pizza, you don't need to hunt through an owner's manual for how to buy things, and you don't need to go hunting on online forums for how to figure out the pizza protocol. You just have to ask for it.

Final Thoughts

Natural language processing is essentially the process of teaching computers to read and write, to the extent that their readings and their writing may one day become indistinguishable from how a human would read or write. Such a development in computational linguistic capability would make information more accessible, reduce barriers to human communication, and greatly improve our ability to interact with machines. It would, however, also open up new ways to scam and misinform people.

Imagine a program that could take your name, search for your social media, pour over your photos to discern your location, and use all this information to design a scam letter hand-crafted to target you. Anyone could do this already, but it's just not practical. All natural language processing does is make it easier.

This isn't even getting into the philosophical implications. As the difference between human-written and computer-generated content disappears, we need to think about how we label that content, and how we can continue to tell the two apart, as well as what it means for the careers of the people interested in writing. Moreover, such advanced technology would mean that you're going to be a lot less certain of the veracity of anything you don't see with your own eyes. If a computer can print any picture, write any story, conjure any quote, and do it in a convincing way, the trustworthiness of anything you access online could be entirely destroyed.

Fortunately for the people of the present day, computers are still bad enough at analyzing text and images and producing language that with a little critical analysis, we cannot be fooled all that easily. Language, how it is understood, and how it works in the brain is so complicated that some computer scientists question whether or not computers will ever truly be able to mimic humans in language processing. However, it is important to not become too careless, as new and more powerful technologies are constantly being introduced, and it is important to prepare for the future.

Ultimately, what natural language processing means is this: we're going to be changing the way we interact with the internet, information, and each other in a major way as we move into the future. This is going to happen whether we pay attention or not. This means that it's important people understand the basic principles of the coming technology so we can not only use it effectively, but also keep ourselves safe from those who might abuse it. The time is coming soon when we decide what role this technology is going to play in our lives, and people had better be informed about the decision they're making.

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