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Tracing the metaphorical essence with the help of artificial neural networks

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Abstract. For years metaphor has been considered as mere language, a simple figure of speech, a matter of concern just for linguists. Apparently, during the past decade it has been greatly reevaluated and became a matter of great interest in many interdisciplinary approaches. The growing literature on metaphor pervades the fields of linguistics, psycholinguistics, cognitive science, neuropsychology, neurobiology, and artificial intelligence. A number of developmental theories have been proposed, according to which metaphor seems to play a central role in human cognition. In the light of a number of neurobiological experiments, scientists have started to consider, and gradually building the belief that the key to human comprehension and intelligence might be hidden in the decoding of metaphor interpretation and metaphor production mechanisms. In this paper we present an overview of various aspects in metaphor research and some ongoing projects that try to implement the new theories on metaphor in an altogether effort to go in depth into human cognition. We will finally present our effort to capture the metaphorical essence, based on George Lakoff's renowned theory of metaphor, with the use of artificial neural networks. We created a standard three-layer feed forward net. The first layer is used to represent a sentence and questions to the sentence, while the third layer is the answer to the questions. After being trained by a corpus of non-metaphorical sentences the network was tested by a set of metaphorical sentences. The results were satisfactory showing that artificial neural networks might provide a promising domain of research in the field of metaphor interpretation.

1 Introduction

A number of ideas present in modern theories of metaphor pre-existed in older theories. However, since the scope of this paper is not to present a complete historical overview, we will focus on contemporary theorists only, mostly because the study of metaphor has entered a new Era, especially after the second half of our century. Our objective is to present the progressive transition of metaphor studies from linguistics and philosophy to psychological, neurobiological and computational treatment. Theories deriving from different disciplines mingle together interacting in a most fruitful way. Although it is difficult to find the boundaries in such a broad interdisciplinary research, we try to categorize different aspects of metaphor study, according to some scientific domains.

Our connectionist model for metaphor interpretation, presented here, falls under these novel approaches, and exploits the potential of neural networks on this direction.

2 Theoretical overview

2.1 The Linguistic View - The Question about Truth

Linguists and philosophers are concerned with the question about the truth of metaphorical sentences. The traditional metaphor treatment, that regards metaphor as an anomaly of language, a simple figure of speech, started to change in linguistic theories about metaphor of our century. According to Black's [3] interaction view, metaphor does not just work on a level of word combination but it is treated as a cognitive phenomenon that wakens interactions between the conceptual structures behind words. It seems that Black does assign to metaphor an active role as a cognitive device.

Aarts and Calbert [1] semantic marker and selectional constraint's approach follows a strong linguistic tradition of semantics in interpreting metaphor. Simple as it may be, it also shows that metaphor is rather a conceptual phenomenon and its interpretation needs more world-knowledge than word-knowledge.

Ortony [27]with his "Salience Imbalance" theory tries to explain why metaphors emphasize some properties while de-emphasize others, a phenomenon later underlined by Lakoff.

2.2 The Psycholinguistic View – The Question about Language Acquisition

A more recent interest, in metaphor studies, enters the fields of psycholinguistics and cognitive science and raises the fundamental question about the way by which humans acquire their natural language. All recent evidence, based on work with children seems to point to the same conclusion: that metaphor is a key figure in language acquisition.

Gentner [14] [15]is well known for her work on analogy and child development. She observed that although children are able to produce metaphors from an early age, they are unable to understand metaphors presented to them during experiments. The problem actually seems to be the type of metaphors children use. It is obvious that younger children tend to produce object metaphors, that is metaphors based on outer appearance (i.e. using "snake" instead of "hose"). Their ability to understand and therefore create relational metaphors (i.e." She is a sunshine" instead of "She is happy") increases with age. It is only after long familiarization with the domains of references that children can actually understand the situation in which the metaphor is produced. Their familiarization with written language also plays a role. It is then obvious that language development is directly linked to cognitive development.

We observe the same developmental relational shift in metaphor interpretation and production depending on children's age in the work of Gardner and

Winner [35] [36]. In their work, there was a developmental trend toward appropriate apprehension of metaphor. Several steps preceding mature comprehension were observed. In general, cross-sensory metaphor proved easier to comprehend than psychological-physical metaphors.

Greenfield [16] supports that, in early ages, there is a common neural substrate that is responsible for both the development of speech and object manipulation. In order to achieve more complex combinations of both words and objects there must be a cortical differentiation with the corresponding specialization of each part.

2.3 The Neurobiological View – How Does Brain Function?

Even more recent, seems to be the interest on the neurobiology of metaphor. The study of the physiology of the brain, its structure and its processes may be very important in the study of metaphor and vice versa. For this reason we will also mention some neurobiological studies of language that seem to be growing rapidly.

Observation on brain-damaged people gave birth to the hypothesis that brain structure is somehow related to language competence. Paul Broca discovered a section in the left frontal lobe of the brain (Broca's area) that he claimed to be responsible for language processing.

However in an early study Winner & Gardner [37] carried out an experiment with left hemisphere-damaged (LHD) aphasic patients, RHD patients, bilaterally damaged patients and a non-neurological group. The participants were presented with a figurative sentence such as "he has a heavy heart" and asked to perform two tasks. One task involved matching the sentence to one of four pictures: a literal interpretation (i.e., a man carrying a large heart), an appropriate metaphoric interpretation (a crying man), a salient quality depicted by the metaphoric adjective (a 500 lb weight) and an illustration of the noun (a large heart). In the second task patients were asked to explain their choices. RHD patients selected the metaphoric picture much less frequently than LHD patients or the control group in the first task. However in the second task RHD patients were able to verbalize their choices using figurative language whereas LHD patients were unable to explain their 'correct' choices verbally. Winner & Gardner argue that these results show that the effective interaction of the hemispheres is important in appreciating figurative meaning. This study clearly shows that the figurative and literal language comprehension processes are not parallel processes in different hemispheres. It also indicates that at least some subcomponents of language comprehension, concerned with metaphoric processing, are linked to the RH. In short, the RH is needed in figurative language processing. .

The work of Danesi [8] reinforces these results. He contends that while localization of many speech functions in the left hemisphere of the brain is well documented, metaphorical language requires the interaction of left and right hemispheric functions. Research shows that the content of emotive language is controlled by the right hemisphere and only structured by the left. Experimental evidence also shows that the ability to understand and produce metaphors cannot be attributed just to the functions of the left hemisphere. His overall research evidence supports an interaction model in emotive and metaphorical language and denies the view that the right hemisphere is totally inactive in language processing. Further more he proposes a neurological model of metaphor [9] based on the brain's hemispheric modalities. Experimental and clinical evidence supports that there is indeed a task distribution for each hemisphere but in order to explain the cognitive process of metaphor what we really need is an interhemishperic model.

2.4 The Embodiment View – Are Bodies Necessary for Minds?

A major breakthrough on various theories about metaphor and language in general has been the theory of embodied language [20] [30]. It is a combination of linguistic and cognitive theories and it claims that we learn and produce language through our sensory-motor activities and bodily experience from outside world. In addition, the view about an objective reality is challenged on the basis that each person uses his/her senses and body together with cultural experiences in order to understand the world. Therefore they propose an experimentalist view of language in which the role of metaphor is considered as central.

According to this view, language is based on metaphorical concepts, by which we build our cognition. Most concepts are understood in terms of other concepts. There are certain central concepts (i.e. orientational like UP-DOWN, FRONT-BACK, IN-OUT, etc.) that are more sharply delineated than others and which allow us to conceptualize more easily other concepts that are less sharply delineated, like our emotions. We typically conceptualize the nonphysical in terms of the physical and therefore we create metaphors almost every minute of our existence, in order to understand the world in which we are living.

More technically, the metaphor can be understood as a mapping, tightly structured, from a source domain (i.e. journeys) to a target domain (i.e. love). The general theory of metaphor is given by characterizing such cross-domain mappings. And in the process, everyday abstract concepts like time, states, change, causation, and purpose also turn out to be metaphorical. Extending such metaphorical mappings creates novel metaphors, which are usually used in poetic language.

Metaphors fall under certain categories. There are spatialization metaphors (HAPPY IS UP, SAD IS DOWN, MORE IS UP, LESS IS DOWN), ontological METAPHORS (THE MIND IS A MACHINE, INFLATION IS AN ENTITY), or other less concrete metaphors (ARGUMENT IS WAR, TIME IS MONEY, LOVE IS A JOURNEY, IDEAS ARE FOOD, SEEING IS TOUCHING, LIFE IS A GAMBLING GAME).

HAPPY IS UP- SAD IS DOWN
I'm feeling up.
That boosted my spirits.
My spirits rose.
I'm feeling down.

I'm depressed.
My spirits sank.

CONSCIOUS IS UP – UNCONSIOUS IS DOWN
Get up.
Wake up.
I'm up already.
He rises early in the morning.
He fell asleep.
He's under hypnosis.

HEALTH AND LIFE IS UP – SICKNESS AND DEATH ARE DOWN
He's at the peak of health.
Lazarus rose from the dead.
He's in top shape.
As to his health, he's way up there.
He fell ill.

ARGUMENT IS WAR
Your claims are indefensible.
He attacked every weak point in my argument.
His criticisms were right on target.
I demolished his argument.
I've never won an argument with him.

TIME IS MONEY
You're wasting my time.
This gadget will save you hours.
I don't have the time to give you.
How do you spend your time these days?
That flat tire cost me an hour.
I've invested a lot of time in her.
You need to budget your time.
Put aside some time for ping-pong.
Thank you for your time.

LOVE IS A JOURNEY
Look how far we've come.
We're at a crossroads.
We can't turn back now.
We' re stuck.
I don't think this relationship is going anywhere.
We've gotten of the track.

Lakoff and Johnson claim that all of our linguistic expressions fall into one or more of these categories. Each metaphor may focus on certain aspects, while downplaying others. It is in this sense that, even though some metaphors may seem to contradict, we need them all in order to have a more holistic idea about a concept.

3 Models of Computational Treatment

3.1 Conventional Models

There are a number of existing conventional computational models of metaphor treatment. Some are based on just linguistic theories like the models of Fass [10] and Wilks [32] [33] [34]. Others are based on cognitive theories like Gentner's model of SMP theory [13] and Veale's and Keane's [31] hybrid (both traditional and connectionist programming) model.

3.2 Connectionist Models

The theory of embodied language had a major impact in AI research on the connectionist direction. Two major NLP projects that run at this time, try to implement Lakoff's and Johnsosn's theory with the use of ANNs. The first one is running at Berkeley, known as the Neural Theory of Language (now NTL, previously the L_0project), and the other one at the MIT Artificial Intelligence Lab (known as Cog – the humanoid robot).

NTL

The Neural Theory of Language (NTL) is an interdisciplinary research group of computer scientists, linguists, cognitive scientists, and psychologists working to answer questions about the way we think, learn, use and understand language. They use connectionist models and simulations of language and learning phenomena. Their goal is to explore the potential of neural systems in the procedure of characterizing specific concepts, such as spatial relations concepts, aspectual concepts (used in structuring events), abstract metaphorical concepts, and so on.

Regier [29] built a system that is able to "recognize" spatial relations, like "on" and "under", by reference to objects in a picture. Bailey's [5] thesis describes a system that uses model to learn the different senses of action verbs such as "push" and "slide" from labeled examples of structured event descriptions. Narayanan [26] built a system that uses metaphorical mapping and the simulation of events/actions to draw metaphorically entailed inferences from preparsed text input.

Cog

AI has for long tried to build disembodied intelligences considering brain as independent from the body and trying to implement brain's capacities in a machine instead of a body. Nouvelle AI is a new trend in AI that attempts to build embodied intelligences situated in real human bodies, or at least close to human. Nouvelle AI claims that the attempts made were very ambitious and that we cannot reach human intelligence unless we first achieve insect intelligence.

In MIT AI lab, a team of researchers [2] has built a humanoid robot known as Cog. Cog is provided with four microphones and a camera in order to detect sound and visual stimuli. It has a spine that gives it information about the posture. Cog is legless but it has an arm and a manipulating hand that are both equipped with heat sensors. It can also acquire tactile information by electrically conducting rubber membranes on the hand and arm.

The goal is to teach Cog to correlate noises with visual events and to extract human voices from background noise; and in the long run Cog will learn by itself some of common sense world knowledge, through its interactions with its environment and with human beings.

4 Our Model

4.1 The Network Architecture

The idea for our model was to implement Lakoff's theory by trying to model a metaphorical concept, like ARGUMENT IS WAR, and testing the level of generalization that a neural network can achieve. We created a standard three-layer feed-forward net. The first part of the first layer is used to represent a simple sentence, where the syntactic role of the word is given by its place in the input vector. So, for example, the first four bits of the input vector might be used to represent the different head nouns we will be using, the next four bits the various verbs and so on. The remaining part of the input layer represents the questions to the sentence that is represented in the first part of the input layer. The questions query some aspects of the sentence meaning. For example, we might have an input, which asks for the agent of the sentence, or some property value of the agent. The kinds of queries we have in mind fall under three categories: Questions about the agents and objects in the sentence, about the property values and the states of agents and objects. So given a sentence like "John kissed Mary", we might ask questions of the form "agent is", "patient is", "actor_has_property_value_animacy" (the answer is either animate or inanimate), "actor_has_state" (the answer here might be "infatuation", "love", "lust", or whatever), and so on. In each case the answer to the question would be provided as the output of the network. The output units would also consist of sufficient units to provide answers to the questions. So for example, in case of animacy, we might set aside one unit to handle that. (e.g., 1=animate, 0=inanimate).

The network was then trained with a set of sentences and questions. For any given sentence, several questions were asked. So, the sentence input was held constant while the questions were varied.

4.2 The Training Corpus

We compiled two sets of sentences from metaphorically related discourse domains. As we mentioned above we used the ARGUMENT IS WAR metaphor. So we might have sentences about Mary building a house, and Anna knocking down a house, and the house and Mary (or Anna) having various properties, and the house or whatever, having certain state following the action. We also have sentences about arguments, their properties and states. For example, arguments are not animate, nor are they concrete entities. However, they can be constructed and demolished, therefore their state can change after an action like the state of concrete objects.

4.3 The Metaphorical Dimension

The basic idea was to train the network on the details of construction and destruction of concrete objects (e.g., buildings, walls), and on the details of arguments as purely abstract entities. After training the network, we tested it using sentences in which we used the construction terms to talk about arguments. If all went well, what we expected to find is that when we queried the net after inputting something like "I demolished your objection", we should have found that the "state" of the concept "objection" is "broken", "not intact", or whatever. It should be noticed here that we have never used the verb "demolished" with the noun "objection" up until now. Therefore, if the network can generalize successfully to a property value or state, then we can say that the net has mapped the source domain (construction) to the target domain (argumentation).

5 Simulation Details

5.1 The Network

After having designed the implementation in the way we described above, we started the implementation using Stuttgart's Neural Networks Simulator (SNNS). We therefore created a three-layer network in which the input layer is used to represent a sentence and the questions about the sentence. The second is a layer of hidden units and the third layer consists of output units that represent the answers to the questions of the first layer. **??**

In more detail the first layer consists of 24 units of which the first 16 are used to represent the sentence and the remaining 8 represent the questions about that sentence. The first 3 units represent the agent of the sentence that might be "I", "You", or "She". The next two units represent the verb that is either "construct" or "demolish". The remaining units also represent several features of the object of the sentence. The remaining 8 units of the first layer, as we mentioned above, represent 8 different questions about the sentence represented in the previous 16 units. The questions refer to the agent of the sentence as well as to the object. For example, the first question asks about the animacy of the actor and the second about the state of the actor. The third is about the animacy of the object, the fourth about the size of the object and so on. The questions that are more interesting to us are the questions about the state of the object before and after the action. One purpose here is to teach the network the state of a concrete

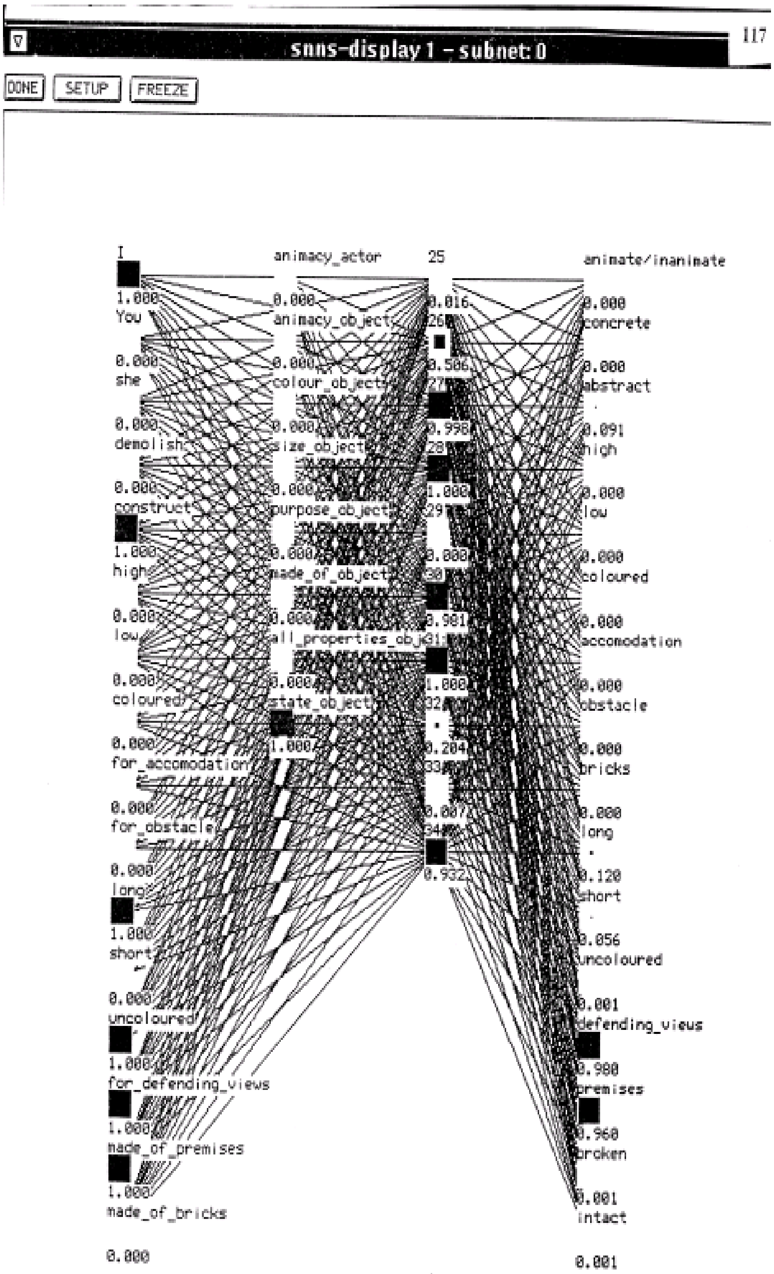

Fig. 1. Our Network

object before and after the action of demolition or construction and then test it to see how it will answer in the same question if the input sentence refers to an abstract object, like an argument.

After the layer of 10 hidden units, we have a layer of 16 output units that represent the answers to the questions. For example, there is a unit that represents the answer about the animacy (animate: activate, inanimate: deactivated). There are also units that represent answers about properties of the object and the state of the object, before and after the action.

Those are the units on which we expected the generalization to occur. The state of the object is "intact" before the demolition of a concrete object and "broken" after it, while it is "non-existent" before the construction and "intact" after it. We expected the same results for abstract objects as well.

5.2 The Pattern Files

After creating the network above, we then had to write down the training corpus, that is the training and testing pattern files.

The first one consisted of 228 patterns. The first 180 patterns refer to concrete objects. We therefore had sentences like "I constructed the building ", " You demolished the wall ", " She demolished the house " and so on and the 8 questions asked for each of those sentences as the input pattern. As an output pattern we had the answer to each of the questions. We also trained the network on 48 patterns with abstract objects (arguments) in order to differentiate them from concrete objects, like buildings. However we omitted the questions about the state of the object before and after the action, which had to be inferred by the network, after generalizing from its previous learning.

The questions referring to arguments that were omitted in the training pattern file were then asked in the test pattern file, where we had as input sentences that refer to arguments and the questions about the state of the object before and after "construction" and "demolition". In this file we did not have output patterns, so we could check what answer was given by the network, trained on the previous training corpus.

6 Simulation Results

In the above implementation several problems have occurred and we should say that we tried different architectures each time in order to achieve the performance that we required.

We used three-layer backpropagation feed-forward networks with momentum, all trained over 5000 cycles. We used a learning rate of 0.01 and 0.9 momentum. After the 5000 cycles all networks reached a minimum locus, after which the error rate was not reduced any more, or its reduction was very slow. The error tolerance that we used was 0.0005.

We experimented with different architectures, trying different input, output and hidden units and changing the pattern files each time. We finally concluded by using the architecture presented in detail above, which was different from the previous ones in three basic points. The first is that the question about all properties of the object was omitted because it seemed that this was why the network was confused and problems were caused in generalization. The second point is that we tried to increase the degree of overlap between the two contexts, by adding more features that they have in common, like the state of the actor. Finally we increased the number of implicit inferences derived from the presence of the verbs by asking about the prior state of the object. Therefore we now ask two questions when we test the network: one about the state of object before the action and one about the state of object after the action.

As we have already mentioned the results were very satisfactory, since the network achieved a very high level of generalization from the very beginning. After training it 15 times - every training session lasted 16 minutes - it could give the results we presented already, which are a high level of activation for generalization of this kind and show that the network could very successfully map the source to the target domain. More specifically on the construction metaphor we had activation values (degree of certainty about the answer) of the correct output unit ranging from 0.29 to 0.998 for the "state_before" question (average: 0.558) and from 0.20 to 1.00 for the "state_after" (average: 0.617) question. For the demolition metaphor we had activation values of the correct output unit ranging from 0.000 to 1.000 for the "state_before" question (average: 0.474) and from 0.045 to 0.944 for the "state_after" question (average: 0.643). In addition we did not have much problem with wrong generalization either. This meant that our first supposition about the "all_properties" question confusing the network was probably correct. We suspect that if we increased the features where the source and target domains overlap, the problem would be further diminished.

7 Conclusions

As good as the results may seem, the model we have presented is only a tiny example of work that can be done in this direction, and it is very far away from a real world implementation. It can only be used to suggest that generalizations of this kind might be possible and it is probably useful to take connectionist approaches under consideration.

We would like to make some suggestions of how we could elaborate the existing model and make its results more valuable. The idea here is to show that the results we obtained are stable when we vary some of the parameters of the model. One way of varying the training regime is to change the corpus, use a different metaphorical scheme or a different set of features. Once we can obtain the same results with different schemes or a different set of features one could conclude with more certainty that an architecture like this can be useful to explore phenomena like metaphor.

One thing seems to be certain though, whether it will be with conventional, connectionist or other kind of models, metaphor is going to be widely explored, as it represents a key figure in NLP and in the decoding of human intelligence and cognition.

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