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INTERPRETING METAPHORICAL LANGUAGE: A CHALLENGE TO ARTIFICIAL INTELLIGENCE

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Abstract. In recent years, numerous studies have pointed to the ability of artificial intelligence (AI) to generate and analyze expressions of natural language. However, the question of whether AI is capable of actually interpreting human language, rather than imitating its understanding, remains open. Metaphors, being an integral part of human language, as both a common figure of speech and the predominant cognitive mechanism of human reasoning, pose a considerable challenge to AI systems. Based on an overview of the existing studies findings in computational linguistics and related fields, the paper identifies a number of problems associated with the interpretation of non-literal expressions of language by large language models (LLM). It reveals that there is still no clear understanding of the methods for training language models to automatically recognize and interpret metaphors that would bring it closer to the level of human “interpretive competencies”. The purpose of the study is to identify possible reasons that hinder the understanding of figurative language by artificial systems and to outline possible directions for solving this problem. The study suggests that the main barriers to AI’s human-like interpretation of figurative natural language are the absence of a physical body, the inability to reason by analogy and make inferences based on common sense, the latter being both the result and the cognitive process in extracting and processing information. The author concludes that further improvement of the AI systems creative skills should be at the top of the research agenda in the coming years.

Key words: metaphorical language, analogical reasoning, artificial intelligence, LLM, metaphor interpretation, embodied cognition, inference.

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ИНТЕРПРЕТАЦИЯ МЕТАФОРИЧЕСКОГО ЯЗЫКА: ВЫЗОВ ИСКУССТВЕННОМУ ИНТЕЛЛЕКТУ

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Аннотация. Актуальность работы обусловлена тем, что в последние годы многочисленные исследования указывают на способность искусственного интеллекта (ИИ) генерировать и анализировать выражения естественного языка, однако вопрос о том, способен ли ИИ действительно интерпретировать человеческий язык, а не имитировать его понимание, до сих пор остается открытым. Дополнительную сложность для систем ИИ составляют метафоры как неотъемлемая часть человеческого языка, которые являются не только распространенной фигурой речи, но и преобладающим когнитивным механизмом человеческого мышления. На основе обзора результатов существующих исследований компьютерной лингвистики и смежных областей в статье выделен ряд проблем, связанных с интерпретацией небуквальных выражений языка большими языковыми моделями (LLM). Показано, что в науке нет четкого представления о способах обучения языковых моделей автоматическому распознаванию и пониманию метафор, способных приблизить их к уровню «интерпретационных компетенций» человека. Цель исследования – выявить возможные причины, препятствующие пониманию образного языка искусственными системами и обозначить возможные направления для решения указанной проблемы. Установлено, что основные барьеры на пути ИИ к человекоподобной интерпретации образного естественного языка обусловлены отсутствием физического тела, неспособностью мыслить по аналогии и делать инференции на основе здравого смысла, последние при этом могут быть охарактеризованы одновременно как результат и как когнитивный процесс при обработке и извлечении информации.

Ключевые слова: метафорический язык, рассуждение на основе аналогии, искусственный интеллект, LLM, интерпретация метафор, воплощенное познание, инференция.

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Introduction

Figurative and metaphorical language is a pervasive phenomenon in discourse, and figurative expressions play a critical role in communication and cognition. However, non-literal language is among unjustly neglected problems in natural language processing (NLP) research. It leaves the question of interpretability of figurative language by current large language models (LLMs) open. Multiple evaluations of the performance of current language models suggest that their abilities to recognize, analyze, generate and even interpret metaphorical expressions has improved dramatically, although they are still far from being similar to human ones.

As A. Ripley accurately notes, computer science defines AI as a human-like intelligence found in a robot, computer or some other machine. He clarifies further that, provided a machine succeeds in simulating things a human mind is capable of, one can refer to it as artificial intelligence [Ripley, 2021], and refers to the description of AI playing chess, found in the 2009 Rasskin-Gutman's book "Chess Metaphors: Artificial Intelligence and the Human Mind". The latter vividly captures how skillfully AI imitates the human mind and its processes:

"As a game, [chess] enables us to identify all the mental processes necessary to perform high-level cognitive activities. These include perception and recognition of patterns contained in the sixty-four squares of the board and its thirty-two pieces; long-term memory for remembering previously analyzed rules and games; working memory for paying attention, concentrating on the game, and effectively evaluating positions; search strategies for calculating and analyzing variations; and the psychological dimension resulting from the dialogue between two brains, two ideas, and two strategic concepts that depend on the personality of each chess player" [Rasskin-Gutman, 2009].

The major difference in metaphorical competence between human and artificial intelligence may lie in the following: AI is only able to create and process metaphors "on demand" (i.e. when prompted by humans). However, its ability to spontaneously generate novel metaphors, without being exposed to the "real" world, without a body and physical experience, is close to zero. Similar ideas can be found in J. M. Murry's 1931 book "Countries of the Mind" who wrote: "Metaphor is as ultimate as speech itself, and speech is as ultimate as thought. <...> Metaphor appears as an instinctive and necessary act of mind exploring reality and ordering experience" [Murry, 1931, pp. 1-2].

As previously pointed out in one of our recent studies, AI currently analyzes and generates language, and thus metaphors by means of Natural Language Processing (NLP), an interdisciplinary branch dedicated to recognizing, generating and processing spoken and written human speech. AI is still considered weak, as it relies on human-defined algorithm parameters for its capabilities and mostly requires training data for its results to be accurate [Skrynnikova, 2023, p. 220]. Recognizing and understanding metaphorical language is still an unsolved problem for AI systems, and the reason for this is primarily the inability of machines to think by analogy. Metaphorical thinking is "one of the hypostases of analogical thinking," and metaphoricity is an inherent property of modern social thinking [Ilyin, 2013, p. 22]. Therefore, in this paper we treat metaphorical reasoning as a means of expressing analogical reasoning.

Analogical reasoning

Analogies focus our attention on how similar two seemingly dissimilar things are. As a cognitive tool, they enable us to infer properties or predict the behavior of an unknown object based on its similarity to a known one. If an unknown thing or phenomenon is similar to a known thing or phenomenon in many ways, it is possible to draw a logical inference about the unknown based on its similarity to the known. Analogical reasoning is one of the most important cognitive tools we apply to structure our understanding and beliefs about the world.

Modern neural networks cope comparatively well with certain tasks, but using what they have learned in one situation and transferring it to another one, which is what analogy is all about, is not one of them. Reasoning abstractly and building analogies as well as recognizing two or more different situations as essentially similar are solely inherent to humans. The question arises if we can potentially endow machines with this ability, and if so, how should we do that? Computers can recognize images, drive cars, and play various games. But they cannot flexibly and quickly generalize the information they have acquired and apply it to new situations. The analogies we constantly and unconsciously draw assist us in making sense about something new and previously unknown. The ability to analogize, intuition and common sense is the bridge between deep neural networks and human intelligence [Skrynnikova, 2023]. Our strong claim is that, until we teach machines to reason by analogy, they cannot be considered sufficiently robust and flexible to deal with the real world. Taking into account how diverse analogies can be, constructing AI agents that are capable of interpreting and generating analogies should focus on building various skills to understand relationships between objects.

As viewed by J. Pavlus, understanding the cognitive process of analogy, in other words, the ways we, humans, establish abstract connections between similar ideas, perceptions, and experiences, is the critical task which will enable to unlock the potential of human-like artificial intelligence [Pavlus, 2021]. To draw an analogy is to be aware of the nature of a situation by projecting or conceptually mapping it to another one that is already understood and previously known to us from our bodily experience. As Pavlus rightly notes, the role of analogy in modern research should therefore become more prominent than ever, especially in the field of AI, whose major advances over the past decade have largely been driven by deep neural networks, a technology that simulates the multilayered organization of neurons in the mammalian brain [Pavlus, 2021].

But why is analogizing so critical to AI? The reason is that analogies are a fundamental thinking mechanism that will be of paramount importance if AI is to achieve the performance we seek for. Its significance has only become apparent today when experts finally recognized that it is a fallacy to concentrate exclusively on the laws applied by logic, statistics, and programming when it comes to developing the "rules of behavior" for a machine to solve new problems. For instance, showing a deep neural network numerous images of bridges may ultimately result in its recognizing a new image of a bridge. But its ability to abstract the concept of a bridge to our interpretation of bridging the generation gap is, as of today, far from being obtainable [Pavlus, 2021]. It appears that these networks cannot and do not learn to extract existing information and apply it to new unknown situations.

The past decades have seen considerable research efforts to train a machine to reason by analogy. One of the earliest attempts is the Structure Mapping Engine in the field of AI based on a cognitive simulation program for learning analogy-based information processing [Falkenhainer, Forbus, Gentner, 1989] which focuses on the logical representation of situations and the construction of analogies between them. However, the issue of learning itself has been largely excluded from these systems. Structural mapping is based on words with "human meaning" (e.g., *the Earth revolves around the sun* and *an electron revolves around a nucleus*), but lacks some internal model of what exactly it means to "revolve around." Other systems like Copycat have handled this task but have been unable to find ways to generalize and extend them to more abstract domains [Hofstadter, Mitchell, 1994].

More recent and new approaches, such as meta-learning, are applied for machines "to learn" better. Self-supervised learning enables GPT-3-like systems to acquire skills in completing a sentence with a missing word, which may seem an ostensibly convincing language generation task. The common claim NLP researchers make is that one merely needs to feed such systems sufficient data for them to easily perform analogy-making tasks. But it turns out to be not that simple. What we call "the meaning barrier" is still present. From M. Mitchell's perspective (2021), AI systems succeed in simulating understanding under certain conditions, but, deprived of them, become fragile and unreliable. Unlike humans, these systems cannot interpret the data they are dealing with. Another issue of concern is that there seems to be no consensus on what we mean by saying "understand the meaning of an utterance". Following M. Mitchell, we believe that the key to what we refer to as understanding is the mechanism of abstraction and analogy [Mitchell, 2021]. The latter allow for human flexibility preventing us from behaving like robots. It is due to reasoning by analogy that we find ourselves capable of comparing prior experiences to new formerly unknown or incomprehensible ones. We are adept in modelling what other people think, understand their goals, and predict what they are going to do by analogizing ourselves, putting ourselves in the other person's shoes, and matching our opinions to theirs.

Some researchers assume that deep learning is more promising in creating meaningful analogies, with deep neural networks "working wonders" between input and output layers. However, to this end, we need to create one large dataset to train and test the neural network. But having to train the system on thousands of examples suggests that the researcher has already lost. In this way, one misses the point of abstraction and deals with what machine learning experts call "few-shot learning" [Mitchell, 2021], i.e., training on a limited number of examples. For instance, the Abstraction and Reasoning Corpus (ARC) poses a serious challenge to machines to learn in a few steps. It is the case as the Corpus relies on the "basic knowledge" humans are endowed with since their birth. None of these systems are able to cope with providing machines with the ability to learn and reason using the background knowledge any child possesses. A machine is devoid of a physical body that provides humans with this basic knowledge the human brain resorts to to build numerous and novel analogies. Teaching a machine to reason analogically, in a humanlike manner, is only possible by its reliance on embodied experience which it currently lacks. The role of the body is critical when it comes to solving multiple problems requiring three-dimensional thinking and interacting with the world around, understanding how objects are connected in space.

Metaphorical embodiment

Throughout history, the human body has been viewed as a natural, purely biological entity, largely separate from the mind. A considerable body of embodied cognition research, on the contrary, argues in favour of heavy reliance of human abstract thinking abilities on people's knowledge of and experience with their bodies, predominantly through metaphorical reasoning. Bodily interaction with the world around and related experiences pervasively act as a source domain to alleviate and enhance our understanding of more abstract, intangible and loosely structured target domains (e.g., AFFECTION is WARMTH, a metaphor in which bodily reaction related to experiencing higher temperatures assists in better structuring our understanding of affection). Likewise, multiple source domains emerging from our daily bodily experiences are metaphorical per se.

G. Lakoff and M. Johnson brought greater systematicity to the analysis of metaphor as a cognitive mechanism in their conceptual metaphor theory (CMT), demonstrating the heuristic potential of applying the theory in practical research [Lakoff, Johnson, 1999]. L.A. Keefer and his co-authors in their study formulate the fundamental postulate of this theory as follows: the major source of primary metaphors is our body which is inseparable from a certain space and continuously interacts with its environment in different ways. According to this view, understanding of metaphorical expression occurs through a unidirectional projection of properties from a more concrete objectified source domain to a more abstract target domain. Further research has argued that if one formulates an abstract problem in terms of a bodily problem, the solution found to the latter can prompt a particular solution to a more complex, abstract problem [Keefer et al., 2014]. Cognitive linguistics, psychology, and medical anthropology provide sufficient evidence to illustrate how various bodily experiences are understood symbolically and metaphorically. A classical example is understanding the immoral nature of one person's deeds towards another (an abstract problem) in terms of physical dirt (a bodily problem) by means of the metaphor IMMORALITY is DIRT. Accordingly, to *cleanse the conscience* a person may resort to a method similar to washing away physical dirt – washing hands, taking a shower, etc. This supports the hypothesis that metaphors push us to new ways of understanding abstract entities and solving complex problems. Consequently, bodily experience is inherently metaphorical, according to the metaphorical embodiment hypothesis [Migun, 2020; Gibbs, 2021].

The embodiment approach suggests searching for answers concerning the role of sensorimotor processes in metaphor processing. Researchers are currently preoccupied with the question whether understanding metaphors necessarily relies on sensorimotor systems and, if so, to which extent they are involved in metaphor processing.

Metaphorical reasoning is a crucial tool for bridging the divide between concrete and abstract concepts, enabling a more flexible organization of human cognition and action. This distinctive human capacity poses a significant challenge for artificial intelligence (AI) systems, which must be capable of comprehending metaphors in order to effectively interact with humans. We see the solution to such an ambitious problem in endowing AI with a model of the body moving and acting in the environment, with the ability to test the machines' ability to learn something about their bodies [Skrynnikova, 2023]. This idea is in line with O. Holland's opinion that it is impossible to study the emergence of natural language in humans without linking language to the body [Holland, Knight, 2006].

Latest endeavors in metaphor understanding

Conceptual metaphor is a pervasive cognitive mechanism that aids our comprehending, experiencing, structuring, and reasoning of abstract concepts (the target domain), as noted by I.-M. Comsa et al. [Comsa, Eisenschlos, Narayanan, 2022], by mapping them to domains available to us from our body's everyday interaction with the environment (the source domain). As G. Lakoff and M. Johnson claimed in their seminal work "Metaphors We Live By", in the pervasive metaphor TIME IS MONEY, time is understood in terms of monetary value. Therefore, it may be "donated" to others, one can "run out" of time or "invest" it in an activity. In this analogy, money acts as a source domain, serving as a basis for comparison with time. The latter, in its turn, acts as the target domain, being understood in terms of financial resources. There is a systematic unidirectional mapping from the source to the target domain [Lakoff, Johnson, 2003]. Conceptual metaphors structure our everyday language and are applied to map physical experiences and emotions onto abstract concepts. They enable us to convey complex ideas, emphasize emotions, and make humorous statements [Fussell, Moss, 1998]. Still, even though words are related different from their conventional definition, communicators easily interpret metaphorical phrases, and discourse is rife with them [Shutova, 2011], on average every three sentences [Mio, Katz, 1996; Fussell, Moss, 2008]. To illustrate the critical role of metaphor in abstract discourse, we will examine the example presented by I.-M. Comsa et al. in their study: *The economy is suffocating.* From the CMT perspective, understand this statement becomes possible owing to mental simulation, i.e. connecting the abstract concept of the economy to a sick person experiencing trouble breathing. We use the same mental imagery to conclude [Comsa, Eisenschlos, Narayanan, 2022] that the economy, like the gasping person, is sick and can die of suffocation. How do people interpret such a metaphorical statement as *once infected with an interesting idea, it is hard to be cured of it*, when they read it? Understanding such metaphorical expressions is possible because of the unique human ability to think by analogy and infer based on common sense. Moreover, human creative thinking treated as the ability to generate original ideas based on establishing new analogies between objects and phenomena facilitates generating and understanding new metaphorical expressions.

Reaching human-like performance levels in LLMs, as Comsa and his co-authors show in their critical overview of previous studies, still looks as a surreal task, accounting for little progress which has been made in this area of research. They assume that heavy reliance on context-dependent word meanings in such tasks [Neidlein, Wiesenbach, Markert, 2020] can be one of the possible reasons for this, criticizing them for inability to measure a machine's ability to reason with metaphors [Comsa, Eisenschlos, Narayanan, 2022]. The new surge of attention to metaphor is solely related to natural language processing problems, with most tasks focused on its detection [Choi et al., 2021; Leong et al., 2020] predominantly in sizeable annotated corpora [Klebanov et al., 2016; Steen et al., 2010], which is not sufficient to reach near-human interpretability in LLMs.

As we have remarked before, researchers in recent years have been increasingly focused on creating systems capable of generating and recognizing metaphorical language, mostly combining AI reasoning and corpus-based modeling of formulaic expressions. However, they lack agreement and any clear idea concerning the ways of training the system not only to use metaphor, but also, which is more important, to endow it with inferencing abilities, where inferences are treated as the result and the very cognitive process associated with information processing and retrieval [Skrynnikova, 2023].

Metaphors are interpreted by AI using natural language processing based on a process referred to as metaphor analysis. Possible uses of metaphor analysis include translation software, political affiliation and social choice prediction. Education is another possible area of applying metaphors due to their ability to promote creativity and explain complex abstract phenomena and concepts [Shutova, 2015, p. 617]. To effectively interpret a metaphor, as A. Ripley suggests, the two main methods are mainly applied in computational linguistics research: metaphor explanation and metaphor paraphrasing. The overview of the existing approaches made in his research [Ripley, 2021] suggests that the essence of the former is to analyze and correlate the properties of the source and target domains while the latter focuses either on more literal expressions or commonly used paraphrases of the original metaphors. The explanatory method feeds into the Slipnet system, which uses concepts attributes common to both source and target domains, as well as facts found on the Web [Veale, Hao, 2008]. The authors particularly emphasize that this system can identify relationships between the source and target domains by creating substitutions and modifications to the definitions of these attributes. To ensure that a mapping is possible, as T. Veale and Y. Hao claim, the AI is attempting to identify as many common analogies as possible between the source domain and the target domain. They further note that paraphrasing of all the verbal components of the metaphorical phrase is the prerequisite for the AI to interpret the metaphorical phrase literally and, hence, understand it. There is also the general agreement in the computational linguistics community that the majority of metaphor interpretation methods involve replacing parts of a metaphorical phrase at some point [Veale, Hao, 2008].

The problem with the above-mentioned approaches is that AI relies entirely on human predefined interpretation algorithms. Notwithstanding, existing metaphor repositories include only conventional metaphors, and, therefore, when one needs to interpret non-conventional figurative expressions, AI is unlikely to cope with this very few benchmarks aimed at evaluating the ability of LLMs to reason with conventional metaphors. The existing body of research in this field has been critically analyzed by I.-M. Cosma and his team to include a collaborative multitasking test, the BIG benchmark [Srivastava et al., 2022], designed to test various LLM competencies and including four metaphor-related assignments. Its major flaw, in their view, is that its tasks do not enable us to assess the ability to use metaphorical knowledge in reasoning, although they contain novel non-conventional metaphors. The subsequent study by E. Liu et al. [2022] assumed an interpretation task, that asked models to choose the correct of two metaphor interpretations, and lacked any reasoning-related tasks. The same is true about Chakrabarty's research team [Chakrabarty, Choi, Shwartz, 2022] who elaborated a dataset containing multiple choice story continuations based on comparisons and idioms extracted from books [Comsa, Eisenschlos, Narayanan, 2022].

Combining metaphor understanding with common sense-based inference on the basis of a more systematic data source in the MiQA benchmark, proposed by Comsa and his colleagues [Comsa, Eisenschlos, Narayanan, 2022], seems a more promising endeavour to solve the problem of understanding metaphors by AI systems. As they rightly claim, the need to choose between two semantically similar items instead of items with opposite meanings is seen as another advantage of such a benchmark test. The results suggest that in the absence of cues, LLMs' ability to perform well on metaphorical language comprehension tasks, particularly in small datasets is considerably limited. It means that further research into improving the performance of smaller models, if possible, should be among the top research priorities in the short run. Furthermore, this reveals the LLMs' genuine ability to reason with conventional metaphors, not just recognize them. Even a more ambitious task in the coming years is to figure out whether this ability extends to non-conventional metaphors.

Conclusion

Summarizing the above considerations about the problems of natural language processing in general, and understanding metaphorical language by AI in particular, we can conclude that the further development of human-machine relations should be focused on the development of AI creative abilities necessary for the interpretation of figurative language. Nonetheless, it is obvious that the term "understanding", which is quite clear to us in the "human" sense, is characterized by complexity and ambiguity in the context of AI.

As we previously emphasized, with the latest achievements observed in terms of LLMs' capacities to detect and recognize metaphors, their ability to understand non-literal language is far from being comparable to a human one, and its further honing is an ambitious task for computational researchers [Skrynnikova, 2023]. The main difference from machine knowledge processing is seen in the fact that metaphor understanding is possible solely due to linguistic creativity and human creative efforts and can hardly be subject to the rules to which AI systems are currently subjected. The predictive power of existing systems remains considerably low. Automatic recognition of AI metaphors followed by the ability to interpret and reason with figurative expressions is still an ambitious task for the coming years, requiring integration of knowledge and combining the efforts of researchers from different fields. It has become evident that focusing solely on the laws of logic, statistics and programming in developing the "metaphorical competencies" of a machine to solve new problems has not achieved the desired results.

Thus, we believe that the fundamental obstacle preventing machines from genuinely interpreting metaphorical language is their inability to reason by analogy, which results from the lack of a physical body in their interaction with the world around them. This is further compounded by their inability to draw common sense inferences without being prompted by humans, as well as their limited predictive power. An ontological gulf stretching between human reasoning and artificial intelligence is still insurmountable. The unique creativity found in humans and not limited to the perception and understanding of texts, is the undebatable prerogative of human intelligence, which is not inherent in AI. It corroborates the idea that a creative mind and the imitation of a reasonable answer in solving a problem are profoundly different sorts of things.

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