On the importance of pictorial representations for the symbolic/subsymbolic distinction

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Abstract

Theories on pictorial representations are supported by psychological experiments as well as by computational experiments.

In this paper, we investigate the importance of theories on pictorial representations for the symbolic/subsymbolic distinction. We draw the following conclusions: 1) Pictorial representations should be viewed as specialized subsymbolic representations, because they share important properties with subsymbolic representations, e.g., local activation and inhibition operations. 2) Theories on pictorial representation lead to a hybrid representational framework including subsymbolic and symbolic parts.

Hence, the two extreme positions, a homogeneous subsymbolic represention (Smolensky) vs. a homogeneous symbolic representation (Fodor/Pylyshyn) should be rejected, because we view it as more important to find out which representation is best for which range of tasks within a hybrid representational framework.

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Zusammenfassung

Theorien über piktorielle Repräsenationen werden sowohl durch psychologischer Experimente, als auch durch Computerexperimente gestützt.

In diesem Beitrag wird untersucht, welche Bedeutung die Theorien piktorieller Repräsentationen für die Symbolismus/Subsymbolismus Debatte haben. Dabei wird folgender Standpunkt vertreten: 1) Piktorielle Repräsenationen sollten als spezialisierte subsymbolische Repräsentationen angesehen werden, da sie wesentliche Eigenschaften mit subsymbolischer Repräsentationen teilen, z.B. lokale Aktivierungs- und Inhibitionsprozesse. 2) Die Annahme piktorieller Repräsentationen legt ein hybrides Repräsentationssystem nahe, welches sowohl symbolische als auch subsymbolische Bestandteile hat.

Deshalb sollten die beiden extremen Positionen in der Debatte zwischen Fodor/Pylyshyn und Smolensky, einerseits homogene symbolische Repräsentationen und andererseits homogene subsymbolische Repräsentationen, aufgelöst werden zugunsten der Frage, welche Repräsentationsform besser geeignet ist für welche Klasse von Aufgaben innerhalb eines hybriden Repräsentationssystem.

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On the importance of pictorial representations for the symbolic/subsymbolic distinction

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1 Introduction

This paper is concerned with representational aspects of cognition. It is based on the two assumptions: 1) that cognition is information processing and 2) that mental representations and their manipulation are essential for cognitive processes. Both assumptions are the basis of the cognitive science research program. Given these assumptions there are mainly two different representational positions.

First, the *symbolic* position (e.g. [*Fodor + Pylyshyn 88*]) that favors the symbol system hypothesis. Symbolic and structured expressions composed of atomic representing entities are favored as representations within this theory, and structure sensitive operations are essential to process these representations. Second, the *subsymbolic*[1] position (e.g. [*Smolensky 88*]) that proposes the use of simple neuron-like elements as atomic representing entities and local activation and inhibition operations as mode of processing to model cognition. The dominant advocates of the symbolic camp claim that the mind/brain architecture is not connectionist at the cognitive level. On the other hand, the radical advocates of the subsymbolic camp completely reject symbolic accounts for cognition.

There is a third position besides the purely symbolic and the purely subsymbolic position: modeling cognitive processes by exploiting *pictorial* representations (see e.g. [*Paivio 71*], [*Kosslyn 80*], [*Pinker + Kosslyn 83*], [*Sterelny 86*], [*Rehkämper 87*], [*Lindsay 88*]). In general, the model of pictorial representations is supported by: 1) empirical evidence from experiments in psychology and physiology, 2) computational experiments in artificial intelligence, and theoretical

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[1] The term subsymbolic might be misleading because of the commitment to mental representations and therefore to symbols (see also [*Fodor + Pylyshyn 88*]), although these symbols might differ from symbols in 'classical' approaches. But in this paper we use it following Smolensky's definition.

insights, e.g., into complexity constraints and the usefulness of different representations and different styles of processing. Pictorial representations are only proposed for modeling a subclass of cognitive phenomena. Additional and more abstract propositional representations are necessarily assumed within these approaches. Typically, propositional representations complement pictorial representation to deal with high-level cognitive functions, e.g., for several aspects of language processing and for recognition. In addition, propositional representations are exploited as long-term memory.

Pictorial representations are mainly favored to model cognitive processes which are based on spatial or spatiotemporal relations between objects and object parts. Typical examples include the computation of spatiotemporal distances between visual objects, e.g., to avoid collisions, the mental rotation of objects, comparing the size of different objects, learning of typical object motion, the prediction of spatiotemporal behavior of objects, or top-down control of visual processes (see e.g. [*Kosslyn 80*], [*Pinker 88*], [*Gardin + Meltzer 89*], [*Steels 90*], [*Mohnhaupt + Neumann 90a*], [*Mohnhaupt + Neumann 90b*]).

In this paper, we focus on the importance of pictorial representations for the symbolic/subsymbolic distinction. Because we see significant evidence for pictorial representations, we want to elaborate what these models contribute to the symbolic/subsymbolic debate. We derive two main conclusions:

1. For two reasons, we view pictorial representations as specialized subsymbolic representations. First, local activation and local inhibition operations are essential for these representations. Second, pictorial representations do not have composed representing entities and structure sensitive operations. The representing entities are typically cells, which mainly represent location information and which are connected to its neighbors. These cells are in the same sense subsymbolic as in classical subsymbolic representations, because they slice represented entities into small atomic pieces (see [*Rehkämper 88*]).

2. Following conclusion one, we reject both the purely subsymbolic and the purely symbolic position. The reason is that using pictorial representations leads automatically to a hybrid representational system including pictorial subsymbolic and propositional symbolic parts. A hybrid model is necessarily assumed within the different approaches on pictorial representations, in psychological studies as well as in computational experiments. Pictorial

subsymbolic and propositional symbolic representations are used at different levels of abstraction for different cognitive tasks.

Therefore, the symbolic/subsymbolic debate changes from an 'all or none' question into a 'what is best for which tasks' question. Instead of finding out about one single 'language of thought', we view it as more important to identify subclasses of cognitive tasks, which are based on the same underlying computational architectures and the same style of processing. In addition, it has to be investigated how the different subsystems interact.

In Section 2 we review briefly the current discussion on symbol systems and connectionism. In Section 3 we consider the main empirical and computational arguments for favoring pictorial representations to model several cognitive tasks. In addition, we elaborate why pictorial representations should be viewed as specialized subsymbolic representations, which are complemented by propositional symbolic representations.

2 Symbol Systems and Connectionism

Recent discussions between the subsymbolic position (see [*Smolensky 88*]) and the symbolic position (see [*Fodor + Pylyshyn 88*]) offer very different models for cognition at the representational level. The authors have opposite views about the adequate description language for cognitive phenomena and about the appropriate level of description for many relevant phenomena. Below, we briefly review the two different positions. In addition, we add two general comments to the discussion, one concerning the importance of the debate for cognitive science, and the other concerning an assumption on which the debate is based.

2.1 Symbol Systems

Fodor and Pylyshyn define symbol systems as having representational states with combinatorial syntactic and semantic structure. They postulate one 'language of thought' based on structurally atomic and structurally molecular representations. The semantic content of molecular expressions depends on the semantic content of its syntactic parts. In addition, there are processes operating on the representations which are sensitive to the structure of the representation.

In Fodor and Pylyshyn's view several important aspects of cognition can be appropriately described by symbol systems: First, the unbounded expressive power of language (productivity of thoughts) can be explained only by non-atomic expressions. Second, the systematicity and the compositionality of thoughts should be viewed as a result of applying syntactic rules. Denying syntactic aspects of language would lead to an unnecessarily complex explanation. Third, the inferential coherence of thoughts can also be explained by a syntactic analysis. By inferential coherence the authors refer to several empirical facts, e.g. to the observation that humans know that $\mathbf{P}$ can be logically deduced from $\mathbf{P} \wedge \mathbf{Q}$ if they know that $\mathbf{P}$ can be logically deduced from $\mathbf{P} \wedge \mathbf{Q} \wedge \mathbf{R}$. Composed syntactic structures lead to a natural explanation of these empirical observations, because they would result from intrinsic properties of the representation and its processes. Explaining the same effects within a connectionist framework would require additional assumptions in terms of extra explicit connections between different substructures of a connectionist network.

Because composed syntactic expressions and structure sensitive operations cannot be found in the current connectionist framework, following Fodor and Pylyshyn, they draw the conclusion that connectionist theories are insufficient to explain cognition. They view connectionism as an implementation theory at the neural level.

2.2 Connectionism

On the contrary, Smolensky argues that connectionist[2] models can account for many, possibly all cognitive phenomena. He admits that structured expressions and structure sensitive operations are currently not completely understood or missing within connectionist framework, but he views these constructs as less important; in addition he is convinced that they could be developed in future connectionist work.

In his view the adequate description of cognition should be at a subsymbolic level, which is an intermediate level above the neural level but below a symbolic level. It is well suited to describe the 'intuitive processor', which Smolensky views to be the most important cognitive level. The subsymbolic level is composed of representations distributed over a large number of simple atomic neuron-like ele-

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[2] By connectionism we refer like Smolensky to PDP models (see [*Rumelhart + McClelland 87*]); localist models are viewed to be symbolic representations using a connectionist style of processing.

ments and their dynamic behavior. It is characterized by differential equations: the 'activation evolution equation' describing the temporal evolution of activations within the network, and the 'connection evolution equation' describing the evolution of the connection strength between elements. 'Hard' rules are replaced by 'soft' constraints and logical inference is replaced by statistical inference. The neuron-like style of processing includes local activation and inhibition operations between neighboring elements. It is called subsymbolic or numeric.

Smolensky's view does not eliminate high-level entities like goals, intentions and plans from cognitive theories, but by using the connectionist framework, he tries to explain these phenomena as emerging from the subsymbolic level.

2.3 Two comments

The symbolic/subsymbolic discussion received significant attention within the cognitive science literature. Unfortunately, the debate often leads to the impression that the symbolic/subsymbolic distinction is fundamental to any aspect of cognitive science. The reason for this misinterpretation is that two important questions often remain unanswered: 1) What is the domain of the debate, which aspects of cognitive science are completely unaffected by the debate?, and 2) What are the assumptions on which the discussion is based? Below, we comment on these two questions.

1. According to [*Marr 82*] information processing tasks like cognition must be understood at three different levels: at the level of the computational theory, at the level of representation and algorithms, and at the implementation level.

   It is important to note that symbolic and subsymbolic theories as described above are mainly concerned with the representational and algorithmic level of cognition.[3] Therefore, the computational theory is largely unaffected, although the choice of an adequate representation can lead to additional insight into the computational theory. But we cannot think of a situation where we discuss a representational system without a computational theory in mind, which is the core of any cognitive theory. Hence, discussing representational theories in isolation is important (and the main focus of this paper), but it does not address other significant questions concerning cognition.

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[3] This was also pointed out in a recent article by [*Chandrasekaran + Goel + Allemang 88*]

2. The basic assumption underlying the symbolic/subsymbolic discussion in the version described above is the following: All aspects of cognition are based on one single computational architecture including one basic style of processing[4] (see [*Newell 80*], [*Fodor 81*], [*Pylyshyn 84*], [*Pylyshyn 87*], [*Fodor + Pylyshyn 88*], [*Smolensky 88*]). Following this view, the main research goal is to investigate this basic 'language of thought'.

   There are other approaches which reject this strong hypothesis. Basically, proponents of the alternative models postulate that different cognitive task demands require differently adapted computational architectures including different styles of processing. This is analogous to the concept of different 'virtual machines' in computer science. The number of proposed cognitive virtual machines ranges from a small number (see e.g. [*Boden 88*], [*Lindsay 88*], [*Clark 89*], [*Zimmer + Engelkamp 88*]) to a possibly very large number (see [*Minsky 85*]).

As an example, consider the two tasks of predicting the path of a baseball in order to catch it, and of predicting the stock market development. The path of the ball is determined by universal physical laws (e.g. about gravity and air friction), and the knowledge necessary to solve the problem is well defined. The task can only be learnt through observation based on visual data and ongoing motor reaction. One very important constraint is the time available for an analysis (less than a second). Also, it seems advantageous to feed back the results of the ongoing analysis to the visual system to constrain the visual processes, which are generally very expensive.

On the other hand the behavior of the stock market is largely nondeterministic and a prediction must be based on a large portion of world knowledge. The knowledge can be acquired through different conscious processes, e.g., tutorial instruction. Universal laws are unknown. There is no obvious low dimensional and fixed parameter space by which the behavior can be modeled. A prediction is not constrained by very fast interaction between sensors and effectors.

Although we cannot rule out that these two tasks (modeled by two very different computational theories) are solved by the same kind of representation and the same style of processing, it does seem unlikely. In general, it seems more likely that the cognitive system consists of several (somewhat) specialized subsystems

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[4] In [*Clark 89*] this assumption is called the uniformity assumption

that are dedicated to certain classes of tasks. For example, subsystems might be specialized to deal specifically with 1) a collection of tasks all related to similar objects, or 2) a collection of tasks, the solutions to which are all well suited to a certain mode of computation. It is this latter type of specialization for which a pictorial subsystem seems to be designed. It is natural to view cognitive tasks in terms of the domain knowledge involved and the appropriate form of computation so that efficient use of modular design can be made.

3 Pictorial representations

Investigating the nature and the causal role of pictorial representations for cognition is a well known research topic since Paivio's work in the early seventies (see [*Paivio 71*]). The most prominent opponents of the so called 'imagery' debate are Kosslyn ([*Kosslyn 80*]) and Pylyshyn ([*Pylyshyn 84*]). Support for pictorial representation can be mainly based on two different kinds of arguments. First, they can be based on empirical results in psychology (e.g., reaction-time experiments and error analysis) and neurophysiology (e.g., experiments on brain damaged patients). Second, support for pictorial representations can be derived from computational experiments in artificial intelligence, and from theoretical considerations, e.g. about complexity constraints and the usefullness of different representations and different styles of processing.

3.1 Experimental and computational evidence

From research in Psychology, there is significant evidence for a distinct pictorial subsystem. Many empirical results can be explained by assuming an 2-dimensional image-like representation in which spatiotemporal relations (e.g. spatiotemporal neighborhood) of objects are explicitly available (see e.g. [*Shepard 78*], [*Kosslyn 80*], [*Pinker + Kosslyn 83*], [*Pinker 85*], and [*Pinker 88*]). There is also evidence that this representation is shared by perceptual and cognitive processes ([*Finke 85*]). Here, we do not review the experiments in detail, an excellent overview can be found in [*Finke + Shepard 86*] and [*Finke 89*]. The main empirical phenomena for which a pictorial subsystem leads to a natural explanation are the following: 1) identification and comparison tasks for viewed and imagined objects, 2) constraints on the resolution of non-visible objects, 3) judgement tasks for distances and angles between objects, 4) spatial transformation tasks of objects, e.g. mental rotation,

5) results on the interference of perceptual and cognitive tasks, and 6) conditions under which perception can be enhanced by cognition.

Recent findings in neurology also support the cognitive plausibility of a pictorial subsystem. These results suggest that: 1) mental images interact with perceptions (see [*Farah 85*], [*Farah + Peronnet + Gonon + Giard 88*]), and 2) the pictorial system itself is composed of distinguishable subsystems (see [*Farah 85*], [*Kosslyn 87*], [*Farah + Hammond + Levine + Calvanio 88*], [*Farah + Hammond 88*]). In particular, experiments on impaired patients show that a visual[5] pictorial representation can be distinguished from a spatial[6] pictorial representation.

Additional evidence for the usefullness of pictorial representations results from computational experiments and theoretical considerations. The main goals of these investigations are: 1) to answer the question why a pictorial representation would make sense for several information processing tasks from a computational point of view, and 2) to develop criteria to evaluate and to compare different representational schemes. Computational experiments are also important to test different representational frameworks, e.g. for consistency and temporal behavior. The different computational models have different degrees of psychological plausibility. The main tasks for which computational aspects of pictorial representations have been investigated are:

- *Understanding the behavior of physical objects and physical systems:* There are several approaches that model the behavior of physical objects using a quantitative spatial or quantitative spatiotemporal representation. In Funt's ([*Funt 80*]) approach, the interference of falling objects can be predicted using a spatial array and local operations to simulate object motion. [*Gardin + Meltzer 89*] also use a pictorial representation. They express the behavior of non-rigid objects and liquids by local interaction rules within a 2-dimensional representation. Inferences can be derived through simulation. In [*Larkin + Simon 87*] diagrammatic representations are exploited to understand the behavior of physical systems, e.g. pulley problems.

- *Path planning:* Steels ([*Steels 88*]) proposes a model to compute a path through obstacles based on a 2-dimensional array and a reaction-diffusion model of local interaction rules. [*Mohnhaupt + Neumann 90a*] use an explicit

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[5] for representing the appearence of objects

[6] for representing spatial relations between objects

4-dimensional representation (two spatial and two velocity dimensions) and local rules to model the behavior of observed objects. The model allows to predict object motion in the presence of obstacles and to predict the interference of moving objects.

- *Understanding verbal descriptions:* Other approaches are concerned with the use of pictorial representations to understand spatiotemporal relations such as the proposition 'in front of', to understand abstract descriptions (e.g. propositional descriptions of geometric figures) and to understand language in general. By visualizing the content of the description, that is filling relevant information into a pictorial representation, inferences can be simplified, previously implicit information is available, and consistency can be checked. (see e.g. [*Gelernter 63*], [*Waltz + Boggess 79*], [*Kosslyn 80*], [*Adorni and Di Manzo 83*], [*Pribbenow 90*]). There are also indications that a pictorial representation is advantageous for an adequate hearer model in some domains (see [*Neumann + Novak 86*]).

- *High-level control of perceptual processes:* This topic has mainly been investigated in computational vision, e.g. in the areas of expectation-based identification of objects or object motion (see [*Binford 82*], [*Tsotsos 87*] for overviews). Typically, object models can be used to compute the spatiotemporal appearence of objects from a certain viewpoint, which is then used for matching against bottom-up data provided by perceptual processes. The representation of a certain viewpoint is represented pictorially[7] to facilitate the matching process. In the area of motion prediction, [*Mohnhaupt + Neumann 90b*] use pictorial event models to predict the behavior of moving objects. The predictions allow to focus the visual processes and thereby lead to a significant speed up.

  The use of pictorial representations for top-down control of visual processes is psychologically plausible: It is known (see [*Rosch + Mervis + Gray + Johnson + Boyes-Bream 76*], [*Rosch 78*]) that information about basic level categories can facilitate perception, but priming with a superordinate category does not lead to a significant speed up. Basic level categories are the highest level of abstraction for which there is a clearly definable visual shape.

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[7] There are also logic-based representations for high-level vision (see [*Reiter + Mackworth 90*], and see [*Provan 90*] for counterarguments)

Rosch and coauthors conclude that top-down control is performed by forming mental images, which cannot be generated from superordinate categories. The results are consistent with a complexity level analysis of visual processes (see [*Tsotsos 90*] and [*Mohnhaupt + Neumann 90c*]).

- *Learning:* In [*Mohnhaupt + Neumann 89*] and [*Mohnhaupt + Neumann 90a*] several learning tasks with respect to object motion are considered using a pictorial representation. Starting with basic physical observables (location and speed) for describing event instances, typical object motion can be learned using local operations. There is a natural transition from single instances to prototypes. To make experience applicable to new situations, perceptual primitives like distances and relative orientations are computed. They can be extracted within the pictorial representation by simple spreading activation operations. This kind of representation as a starting point for further learning is plausible, because it is closely related to and can therefore be directly filled from perceptual processes. By building the model from observations within the pictorial representation, physical plausibility can be maintained without extra computation.

3.2 Central features

In this subsection we summarize important *computational* and *representational* features of pictorial representations. The representational features are then exploited to relate theories on pictorial representations to the symbolic/subsymbolic distinction.

The computational experiments on pictorial representations show that even if two representations are equivalent in terms of information content, they can differ drastically with respect to their temporal characteristics, e.g. the time needed to access relevant information. There are theoretical results showing the limitations with respect to tractability and efficiency of a general purely logic-based framework (see e.g. [*Levesque 86*]). Choosing representations which are specialized as a consequence of incorporated constraints of a particular domain is one way to overcome the limitations. Another strategy is to make relevant information explicit (see [*Palmer 78*]), that is, accessible at low costs. Of course, there is a trade-off between explicitness of information and storage requirements. In addition, several important physical constraints can be made intrinsic within pictorial representations. For example, the representation in [*Steels 90*] automatically allows only one object per position. Dynamic behavior, e.g. the behavior of moving objects, can be coded by explicit representation of the temporal dimension or by local interaction rules. Inferences can be derived through simulation. The inference process is non-proof-procedural ([*Lindsay 88*]). Physical plausibility can also be maintained by building up the models from concrete observations and subsequent local processing.

Pictorial representation allow for a natural integration of bottom-up perceptual data and top-down information computed from cognitive processes. This is advantageous because many cognitive processes are either based on visual data, or relate to visual data.

The symbolic/subsymbolic distinction is based on representational features (see Section 2), that is characteristics of the representing entities and the mode of processing. From this perspective two features are central to pictorial representations: 1) they are **subsymbolic**, and 2) they are **short-term** representations, which are complemented by propositional symbolic long-term representations. In the following, we focuss on these two aspects in more detail.

The representing entities of pictorial representations are typically cells connected to its local neighbors. They divide the spatial content and possibly other dimensions of a represented entity into small pieces. For example, a house can be represented by a rectangular set of connected cells, each representing a certain location on the xy-plane, or a non-rigid moving bar can be represented by set of connected cells each representing a certain piece of the bar. The cells as representing entities are in Smolensky's sense subsymbolic. They slice the represented entity into small entities (symbols) which are similar to entities in a distributed representation within the connectionist framework. The entities do not have any syntactic substructure.

The mode of processing includes the use of simple, local and parallel operations. The operations are either activation and inhibition operations or local search operations. They are used for different tasks, e.g. to compute spatial relations, or to compute a path through obstacles. There is no dependence on structural properties of the cell or its connected neighbors, the local search operations only depend on scalar values of the neighbors. Hence, the operations share important properties with operations in connectionist networks.

Pictorial representations are short-term representations complemented by symbolic long-term representations. The different approaches agree on the need for additional, more abstract, symbolic representations, e.g. to support long-term memory, for recognition, and for natural language communication. There is psychological evidence that pictorial representations do not serve as long-term memory (e.g. [*Phillips 83*], [*Marschark 88*]), but that they are instantiated on demand from long-term memory (see [*Kosslyn 80*], [*Pinker 88*], [*Kosslyn + Cave + Provost + Gierke 88*]).

From a computational point of view, efficiency supplies strong reasons to assume representations in long-term memory, which are more abstract and more compact than pictorial representations. Several computational models exploit propositional symbolic long-term representations for high-level tasks. For example, object recognition and event recognition is mainly treated within propositional frameworks (see e.g. [*Tsotsos 87*] [*Neumann + Novak 83*], [*Andre + Bosch + Herzog + Rist 86*]). It is interesting to note that a more fine-grained recognition might require an interplay between a propositional representation and a pictorial representation (see [*Mohnhaupt + Neumann 90*a]).

The work on event recognition also shows that propositional descriptions are well suited as a starting point for natural language communication. In [*Neumann + Novak 86*] propositional event models are used to fill a case-frame deep structure for natural language generation. The arguments for using 'classical' symbolic models in this domain are similar to the arguments by Fodor and Pylyshyn (see Section 2).

4 Summary

Within cognitive science several different representational theories are under investigation. Two extreme positions include those that favor a symbol system hypothesis and those that favor a subsymbolic account for cognition. We argue in favor of a theory which consists of both, symbolic and subsymbolic parts. Our argumentation is based on the importance of theories on pictorial representations for the symbolic/subsymbolic distinction. It consists of three steps:

First, there is empirical and computational evidence supporting Fodor's and Pylyshyn's arguments, that there are some tasks which can only be modeled by a symbolic representation, mainly in the area of language understanding. But this does not exclude different representations for other tasks. In fact, there is empirical and computational evidence that pictorial representations are used for several important tasks, e.g. for the computation of spatiotemporal relations between objects, mental rotation, path planning, and several prediction tasks with respect to object motion. For efficiency reasons and empirical evidence, pictorial representations are short-term representations instantiated under certain definable condition as a 'cognitive virtual machine'.

Second, we view pictorial representations as subsymbolic representations because local activation and local inhibition operations are essential for these representations. In addition, there are no composed representing entities and no structure sensitive operations within these approaches. The representing entities are in the same sense subsymbolic as in classical subsymbolic representations, because they slice a represented entity into small atomic pieces.

Third, modeling some cognitive processes with pictorial short-term representations necessarily results in rejecting the purely subsymbolic and the purely symbolic model. The reason is that additional symbolic long-term representations which complement pictorial subsymbolic short-term representation are viewed to be necessary. This leads to a hybrid model which includes subsymbolic and symbolic parts at different levels of abstraction for different tasks.

Following our view, the symbolic/subsymbolic debate changes from an 'all or none' question into a 'what is best for which tasks' question. Therefore, instead of finding out about the 'language of thought', it is more important to identify subclasses of cognitive tasks, which are based on the same underlying computational architectures and the same style of processing, and to investigate how different subsystems interact.

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