Overview

Psychology of knowledge representation

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Every cognitive enterprise involves some form of knowledge representation. Humans represent information about the external world and internal mental states, like beliefs and desires, and use this information to meet goals (e.g., classification or problem solving). Unfortunately, researchers do not have direct access to mental representations. Instead, cognitive scientists design experiments and implement computational models to develop theories about the mental representations present during task performance. There are several main types of mental representation and corresponding processes that have been posited: spatial, feature, network, and structured. Each type has a particular structure and a set of processes that are capable of accessing and manipulating information within the representation. The structure and processes determine what information can be used during task performance and what information has not been represented at all. As such, the different types of representation are likely used to solve different kinds of tasks. For example, structured representations are more complex and computationally demanding, but are good at representing relational information. Researchers interested in human psychology would benefit from considering how knowledge is represented in their domain of inquiry.

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INTRODUCTION

Humans accomplish amazingly complex cognitive tasks with relative ease. For example, we perceive light in the visible spectrum, allowing us to identify objects in our environment; we can correctly classify items as belonging to subordinate taxonomic categories (e.g., Siamese cats); we can solve novel problems, assess causality, and make purchase decisions. Since the beginning of psychological inquiry, philosophers and scientists have struggled to understand how. In the modern era, early researchers, like Wilhelm Wundt, tried to address the question by focusing on the immediate experience of individuals, while American behaviorists focused on objective observable behaviors.[1]

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This overview will focus on the contribution of the Cognitive Revolution, which made it possible to conceptualize mental states as powerful constructs that explain human thought and behavior. Mental states are believed to have content, but also structure, and corresponding processes that act on the information within the representation. The problem of mental representation is both fascinating and challenging because researchers cannot directly observe representations. Instead, cognitive scientists design experiments to gain evidence of representations with a particular structure or process by considering participant responses to tasks. They also develop computational models with specific representational forms and processes intended to mimic participant data.

In this overview, I start by defining mental representation and discussing why it is important to consider the structure of mental representations. Next, I review the major forms of mental representation and corresponding processes (i.e., spatial, feature,

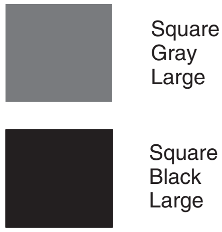


FIGURE 1 | Example objects to be represented (left) and feature list representation (right).

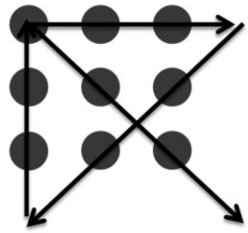


FIGURE 2 | The classic 9-dot problem with arrows showing the solution.

network, and structured), and give some examples of computational models.

WHAT IS MENTAL REPRESENTATION?

On the most abstract level, human thought involves three components: the world, the mental representation of the world, and the processes that manipulate the representation. We need to perceive elements of our environment, encode the content into a representation, and then either immediately process the content or store the content for later retrieval in memory. For example, as shown in Figure 1, assume that an individual views two objects and wishes to decide the extent to which the objects are similar. The two objects and their corresponding properties (e.g., square) are the elements in the world that need to be represented. To make the similarity judgment, the individual would form a mental representation of each object. For example, the individual could represent the two objects using lists of features or properties. One object could be represented as square, gray, and large, and the other object could be represented as square, black, and large. The final step is to use a process to compute the similarity that exists between the mental representations of the objects. Tversky[2] proposed one similarity process that can act on mental representations of feature lists. The feature lists are compared and objects with a high degree of overlap among the mentally represented features are judged to be similar, relative to objects with a low degree of overlap. In the simple world described, the objects would likely be assessed as being moderately similar given the presence of two matching features (i.e., large and square) and a mismatching color feature (i.e., gray versus black).

In many cases, as in the example above, the world that needs representing is external to the individual, but this is not necessarily the case. The world to be represented could be internal. For example, people represent or re-represent aspects of the self. An individual's mental representation of self is known as self-construal.[3] The self may be represented in terms of personal attributes, such as 'has brown hair' and 'likes soccer', and also social roles. As such, individuals regularly mentally represent internal states, such as beliefs or desires, as part of their self-construal. This mental representation can be augmented or even re-represented if there are major changes to one's sense of self. Consider a woman, who recently became a mother; she would need to add this social role to her self-construal and attach related representational content, such as memories and beliefs related to motherhood.

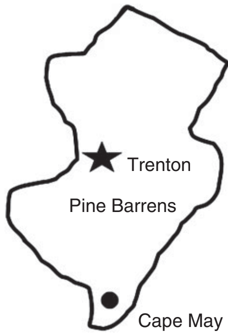
Re-representation of already internalized mental content is also common in problem solving. In a typical problem solving context, the problem is manifested in the world and key features of the problem are mentally represented. Individuals need to mentally represent the solution or goal of the problem, the givens (i.e., the initial information available), the means of transformation (i.e., the steps that are allowed in the problem context to move from the initial state to the goal), and any obstacles that exist between the initial state and the goal. These elements can be specified for well-defined problems but not necessarily for ill-defined problems.[4] For example, in the classic 9-dot problem,[5] individuals attempt to draw a line through each of nine dots using no more than four straight lines with the constraint that the pencil cannot be lifted from the paper and lines cannot be retraced (see Figure 2 for the problem and solution). After representing each of the problem elements, an individual may start using a search process to try to move from the initial state to the goal state because the individual believes this to be a well-defined problem. However, this problem is actually ill-defined and a critical insight is needed to solve the problem. So-called 'insight problems' are thought to require a change to the mental representation where critical elements of the representation are re-represented.[6] In the case of the 9-dot problem, individuals need to re-represent their assumption that it is a requirement to stay within the 3-by-3 grid and began to draw lines outside of the grid.

THE STRUCTURE OF MENTAL REPRESENTATION MATTERS

The type of structure proposed dictates both the kind of process that can be used to access the content in the mental representation and the information that is stored within the mental representation. That is, the structure of the mental representation places a cognitive constraint on our knowledge processes.[7] For example, if only lists of features are used to represent objects, as in Figure 1, then relational information (e.g., the gray square is *above* the black square) has been lost. Moreover, the process used to extract information from the representation would only need to manipulate feature lists, instead of both features and the relations among features. The idea that constraints are important and useful to the cognitive system has a long history; William James argued that only a small fraction of our experience enters consciousness.[1,8]

Moreover, by allowing some information to be abstracted away and not represented, processes can find the information needed within the representation more quickly and efficiently.[7,8] For example, when making a similarity comparison, only the relevant features should be represented and compared. If an individual is comparing the similarity between an elephant and a horse, it would be very inefficient to represent and compare sets of irrelevant features, such as 'weighs more than one pound', 'weighs more than two pounds', etc., and would make similarity untenable because of the possibility of an infinite number of represented features.[9]

The structure of the mental representation also dictates what tasks will be hard or easy to accomplish. Arguably the biggest representational debate of the modern era concerns the difference between analog and propositional forms of representation.[10–12] An analog representation has a structure that mirrors the structure of the object in the world. For example, one would represent a physical space with a spatial representation. In contrast, a propositional representation uses symbols to represent objects, even spatial objects in the world, and is not tied to any sensory modality. As shown in Figure 3, these representational types use a very different structure to represent the same information. On the left side of Figure 3, there is a map of New Jersey landmarks, which is an analog representation that uses space to represent spatial locations. On the right side of Figure 3, there is a propositional representation that uses language to describe the relative locations of the points using Trenton as a reference point. Using the analog representation, it would be easy to talk about the relative location of the points and the relative distances, while using the propositional representation, it would be easy to generate directions between points.



The Pine Barrens are south of Trenton.
Cape May is south of Trenton.
Cape May is further south of Trenton than the Pine Barrens.

FIGURE 3 | Analog representation (left) and propositional representation (right) of NJ landmarks.

The debate surrounding analog and propositional representation can most clearly be seen in the work on mental imagery.[13,14] Shepard and Metzler[13] documented behavior consistent with the use of analog representations in tasks that require mental rotation. In their work, participants were presented with two objects and asked whether one object was a rotation of the other. They found that the time for participants to decide was proportional to the degree of rotation used to create the object pairs. This suggests the use of an analog representation because the fixed rate of mental rotation of mentally represented objects corresponds to the fixed degrees of rotation of actual objects. However, given that propositions can also represent spatial information, researchers have argued about whether these findings entail analog representation.[15,16] The current consensus appears to be an acceptance that people use both types as needed.[8]

BASIC FORMS OF MENTAL REPRESENTATION

There are several basic representational forms (i.e., spatial, feature, network, and structured) that have been suggested for how we accomplish a range of cognitive tasks; whether the representation is considered to be analog or propositional depends on the relationship between the representation and the represented content. The type of representation used is likely determined by a combination of the task context and the goals of the individual. For each of these forms, I will describe the form and the corresponding process posited to access and use information in the representation. Because different representational forms have been proposed to deal with different cognitive capacities, the discussion below will also highlight the tasks for which certain forms of representation are best suited.

FIGURE 4 | Representation of people seated around a table.

Spatial

Spatial representations contain the notion of a space. This space might have two dimensions, as in a diagram, or many dimensions to capture complexity in the world being represented. For example, as shown in Figure 4, representing seat placements in a banquet hall involves a two-dimensional space in which people and tables are represented. This representation allows for basic relational spatial information to be processed, such as identifying who is to the left of Jon, and also quantitative information like distances. Most famously, Shepard[17] argued that psychological distance can help to explain how generalization occurs; that is, treating two instances as equivalent.

Distances could be computed in relative terms (e.g., Linda is closer to Jon than she is to Bill) or objectively (e.g., Linda is 1/2 inch from Jon in the diagram which would convert to 3 feet in the represented world). As discussed with analog representations above, a benefit of using space to represent space is that the same basic processes used to access information in the world being represented can be used with the representation. This is true if the representation is externalized as in a diagram or mentally represented. Because the representation is spatial, the processes utilized will also include a spatial component.

Spatial representations can also be very valuable in representing nonspatial information. We often think about representing ordinal information, such as our liking for different brands of peanut butter. This information could be represented on a classic Likert-rating scale with lower liking corresponding to lower locations or values on the scale. For a given individual, creamy peanut butters may occupy locations corresponding to greater preference and chunky peanut butters to areas of lower preference. Metaphorically, we think about greater liking as being higher spatially.[18]

One of the first, and most commonly discussed, uses of spatial representation for non-spatial content comes from research on taxonomic categories. Rips et al.[19] and Smith et al.[20] demonstrated that multidimensional spaces can elegantly represent category information to allow for similarity judgments (i.e., deciding the extent to which different category members are similar) and classification (e.g., deciding that a poodle is a dog). To build a spatial category representation, Rips et al. asked participants to generate similarity judgments for many pairs of items. For example, a participant would decide the extent to which the concepts dog and cat are related/similar. Next, using a technique called multidimensional scaling (MDS),[21] the similarity ratings were subjected to mathematical calculations that placed a point for each concept within a large multidimensional space that represented the differences in similarity ratings using corresponding distances. In this space, concepts that were rated as being more similar by participants were located more closely together than concepts that were rated as being less similar. For example, the concepts dog and cat would be represented more closely in space than the concepts dog and penguin. Given the use of a spatial representation, information can be extracted from the representation using basic distance calculations. If an individual internalized an MDS-style solution, it would be possible to extract similarity information by merely calculating the psychological distance between pairs of points.

For spaces with few dimensions needed to capture the variability in judgments, it is possible for researchers to provide labels for the dimensions using their intuition. For example, if similarity ratings were obtained for a collection of red apples, then it might be possible to capture the pattern of similarity ratings using two dimensions. The x-axis could be labeled as representing *size* and the y-axis could be labeled as representing *degree of redness*; apples that are both large and very red would appear in the upper right quadrant of the space.

It is also possible to represent spaces with a very large number of dimensions. For example, latent semantic analysis (LSA)[22] represents word meanings as points in a space with high dimensionality. The word meanings are constructed using only the locations of words in a large corpus of text fed into the model. The space is generated by transforming a matrix with rows representing words and columns representing contexts; a cell in the matrix would represent the frequency that a given word appeared in a context, such as within a paragraph. While hard to conceptualize, the matrix dimensions could be $50{,}000 \times 10{,}000$, if 50,000 words and 10,000 contexts were represented. Then, using a technique known as singular value decomposition, the matrix is transformed to create points or vectors for each word within a high dimension space. Points that are closer together represent words with more similar meanings.

Features

Featural representations symbolically represent elements of the world, decomposing them into sets of relevant features. For example, sets of feature lists may be used to represent different concepts.[23] The concept *owl* could be decomposed and represented using important features of the concept, such as *has wings*, *flies*, *has beak and feathers*, and *is wise*; while a turtle would be represented by a different set of features: *slow*, *has hard shell*, *quiet*, and *eats plants*. As in these examples, features may be representing elements that are more conceptual or more perceptual. Perceptual features can be generated from continuous representations as demonstrated in the categorical perception of speech sounds. It is commonly believed that the different phonemes, the sounds of language, are represented using sets of articulatory features. For example, the /ba/ and /pa/ sounds vary based on voice onset time (VOT), or the time it takes for the vocal cords to vibrate after air has been released. VOT is continuous but people perceive binary features; that is, a sound experienced is perceived as /ba/ or /pa/ and not some intermediate sound. Moreover, people may perceive speech sounds by relying on both the represented sounds of language and the corresponding visual representation of the speaker's lips. As demonstrated in the McGurk effect,[24] when a speaker's sounds and lip movements do not match (e.g., the sound is [ba] and the lips show [ga]), the listener perceives a nonexperienced sound (e.g., [da]).

Models of featural representations have emphasized how features within a set may or may not be related. First, features can be additive or substitutive. Additive features can be added to a representation regardless of the other features contained. For example, an entity may be represented as having eyes, but this does not necessarily preclude the existence of other features on the entity, such as having a tail. Substitutive features function differently. Psychological dimensions, like size, shape, and texture, limit the number of features that can be present on a single dimension.[8] For example, the top of a turtle's shell cannot be both hard and soft, and a turtle could not be described as simultaneously moving fast and slow. If *hard* is represented as a feature then *soft* could not be represented. Second, features can be thought of as either being independent within the represented set or related. For example, if an entity is represented as having eyes and ears, these two features could reasonably be considered to be independent. In contrast, for a bird, having wings and feathers allows for the feature 'flies'. Therefore, these features would be related.

Featural representations were popularized by Tversky's contrast model of similarity[2] and models of concepts and categories.[25,26] Tversky argued that similarity violated spatial distance axioms (e.g., the triangle inequality: Jamaica is similar to Cuba; Cuba is similar to Soviet Russia; Jamaica does not seem similar to Soviet Russia). In his model, he assumed that objects were represented by sets of features and that the similarity of objects was determined by the degree to which the object representations overlapped. For example, picture a Venn-diagram with two circles that overlap in the middle. The overlapping section represents the features that are shared across the two objects, while the nonoverlapping sections represent the features that are unique to both objects. Objects are thought to be more psychologically similar when there is a high degree of overlap or commonalities between the feature sets and a low degree of unique features or differences.

Within concepts and categories research, further consideration has been given to how sets of features or spatial representations are associated with the more general representation of the category. For example, Posner and Keele[26] argued that categories are represented by a general representation, or *prototype*, that may only contain the features that are most commonly associated with the category. In contrast, as argued by Nosofsky,[25] the category representation may be made up of individual examples of category members, or *exemplars*. Each exemplar would have its own feature set.

Network

Network representations symbolize entities in the world using nodes that represent concepts and links that represent relations or connections between concepts.[27–29] These representations have a more complicated structure as compared to either spatial or featural representations. Nodes can be connected both to other nodes representing concepts and nodes representing properties. For example, the node representing the category *bird* would be connected to the node representing the category *animal* and also to nodes representing types of birds, such as *robin* and *cardinal*. Moreover, like featural models, information about properties is explicitly represented. The node *cardinal* would be connected to nodes representing properties unique to cardinals, like *red*, while the node *bird* would be connected to nodes representing more general properties of all birds, such as *feathers*. Importantly, in network representations, the links have labels (shown below in capital letters) to specify the nature of the connection or the relationship. For example, as shown in Figure 5, the link connecting *cardinal* to *red* is an *IS* link while a *bird HAS feathers* and a *bird ISA animal*. These are all examples of directed links that are asymmetric (i.e., the link goes from bird to feathers and not the opposite). It is also

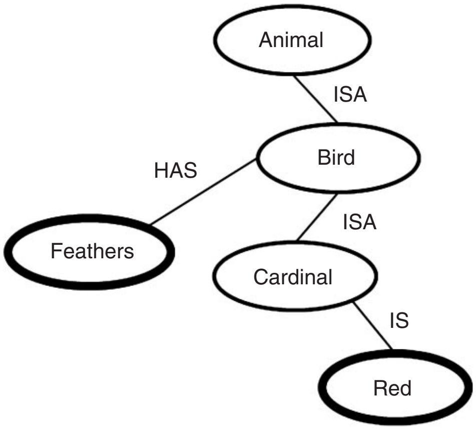


FIGURE 5 | Network representation with labeled nodes and labeled links.

possible to have undirected links if the relationship represented is symmetric.

Researchers have proposed that information in a network representation is processed using spreading activation.[29] In essence, thinking about a concept activates the node representing the concept. This activation then spreads to other connected nodes via the links in the network. Of note, the activation spreads over different modalities; thinking about a *bird* activates nodes representing conceptual information but also perceptual information, like the sound of a bird. At the point when the activation of a node reaches a threshold level of activation, the concept associated with the node is made available to conscious awareness. Spreading activation can explain how people determine the correct responses to queries, such as 'Does a shark feel rough?'. In this example, both the *shark* and *rough* nodes would be activated and activation would move in parallel into the network from these starting nodes. The answer to the question can be identified when the activation from *shark* encounters activation from *rough* while spreading in the network.

Further advancing network theory, Anderson[30] emphasized that the activation in a network could be considered to function like a finite resource that dissipates. He proposed that if an individual node is activated, not only does that activation dissipate over time (unless the node is kept active through a memory process like rehearsal), but the amount of activation is constant regardless of the number of connected nodes. For example, if a node is activated and there are 5 connected nodes, the activation would be divided among the 5 nodes; if there are 10 connected nodes, the activation would be divided among 10 nodes. Moreover, McClelland and Rumelhart[31] also posited that links can be either excitatory or inhibitory, thereby increasing or decreasing the activation of associated nodes, respectively.

There are two main classes of network models: semantic networks and connectionist/parallel distributed processing (PDP) networks. In semantic networks, as discussed, theoretically there are concepts, connecting links, and spreading activation. In PDP networks, instead of drawing on the mind-as-computer metaphor, inspiration is drawn from brain structure and function. In essence, PDP assumes that representations are distributed, such that patterns of activation are the representing elements.[32] Therefore, in these networks, the same set nodes can be used to represent different concepts because it is the activation within the set that is relevant. For example, category members are judged to be similar because the patterns of activation are similar, not because different nodes that are activated are connected as would be the case in a semantic network.

Representing concept knowledge in a network provides a processing benefit. Because nodes can exist in a hierarchical structure (i.e., *cardinal* is below *bird* which is below *animal*), it is possible to efficiently store properties in semantic memory.[8] As described above, the *bird* node could be connected to properties of birds. Because the *cardinal* node is connected to the *bird* nodes, it is not necessary to store all general bird properties with the concept of a cardinal. Instead, these properties can be inferred by traveling up the hierarchy from *cardinal* to *bird*. Early work by Collins and Quillian[28] demonstrated that properties that are directly linked to concepts (e.g., robins are red) are verified faster than properties connected to nodes higher in the hierarchy (e.g., robins can fly), and this same relationship obtains for class-inclusion or ISA relationships (e.g., a robin is a bird versus a robin is an animal).

Structure

Structured representations code for entities and features in the world while explicitly representing relational information and limiting the scope of the features. To understand structured representations, it is important to understand terminology that originated in predicate logic. *Predicates* are statements that are true (or false) in the world and could represent attribute or relational information. As shown in Figure 6, to represent attribute information about the checkered ball, the item would be represented as an element *checkered* that is assigned to the argument *ball* (i.e., checkered (ball)). To represent the relational information inherent in the scene, the relation *above* can be used (i.e., above (ball, box)). To

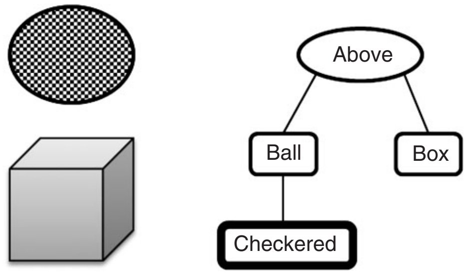


FIGURE 6 | Example objects to be represented (left) and structured representation (right) with the relation 'above', the objects 'ball' and 'box', and the attribute 'checkered' represented.

add complexity, it is possible to represent variables or items whose truth value in the world cannot be determined, as well as multiple layers of predicates.

Because representing relational information is psychologically important, structured representations have been used in many different areas of study from perception to general knowledge. In perception, Biederman[33] proposed that objects are represented by components called geons. His theory, Recognition-by-Components, stated that all objects could be decomposed and represented using combinations of geons. Furthermore, the object would be represented by including the relational configurations between the combinations of geons present in the object. For example, a coffee mug could be decomposed into a cylinder with a second smaller curved cylinder affixed to the side. In general knowledge, both schemas[34] and scripts[35] contain structured representations. Scripts provide a list of actions to expect in certain situations. For example, Schank and Abelson[35] mapped out the knowledge likely represented to depict how one should behave when attending a restaurant. The representation contains a hierarchy of events, such as entering the restaurant and ordering, and also information about the likely actors, such as a chef and cashier. As a general knowledge structure, the representation does not include a specific memory of visiting a restaurant, but instead has slots that can be filled and used to comprehend situations. For example, if one reads that Jon entered a restaurant and ordered a cheesesteak, it would be possible to use the script to infer that he both ate and paid for his meal even if that information was not explicitly stated.

Models using structured representations have also been used in analogical reasoning and similarity processing. Gentner[36,37] developed a theory known as structure-mapping to describe the process of comparing structured representations. In a context requiring an analogical inference, an individual would compare the structured representation from a base domain to the structured representation from another target domain with the goal of carrying over content from the base to the target domain. For example, consider an individual who wishes to draw an inference about the solar system (target domain) using information about an atom (base domain). Each domain would have a structured representation containing objects (e.g., sun and planet, and nucleus and electron, respectively) with attributes and relations (e.g., in the atom, the electron *REVOLVES AROUND* the nucleus). The comparison process involves placing elements in the two representations into correspondence following a set of principles, like *parallel connectivity* and *one-to-one mapping*. In this example, an individual could infer that plants revolve around the sun, if the objects are placed into correspondence (i.e., sun with nucleus and planet with electron).[38] As applied to similarity, Gentner and Markman[39–42] proposed the structural-alignment view and demonstrated that similarity could be assessed by considering relational and attribute commonalities between two items, *alignable differences* (i.e., differences that are tied to a commonality; for example, a red door and a blue door share a commonality in that both are doors but the color predicate varies), and *nonalignable differences* (i.e., differences not connected to a commonality).

COMPUTATIONAL MODELING

While many philosophers and psychologists focus philosophically and experimentally on the problem of knowledge representation, cognitive scientists build computational models of representations and processes that theoretically mimic human thought. Unlike conceptual models, these models are mathematical and can make quantitative predictions for human data. However, they are still rooted in human cognition and attempt to preserve elements that are believed to be true in human psychology.[43] Sakamoto et al.[44] have argued that computational models make the biggest advances in explaining human psychology when researchers focus on issues related to representation and process (Box 1).

BOX 1

HISTORICAL FOUNDATIONS OF COMPUTING

Modern computer modeling is rooted in early nineteenth century work on the Analytical Engine by Charles Babbage with the assistance of Ada Lovelace Byron. This machine was designed to accept cards that represented numerical operations and could compute when a set of cards was placed in an appropriate order.[45] An even more powerful representational device, the Turing machine, was devised by Alan Turing in the mid-twentieth century. The Turing machine used symbolic binary representations (either a 0 or 1) printed on a long tape and was capable of reading or writing/deleting symbols from the tape. While simple, the Turing machine can perform any computational process.[46]

Computational modeling has been used in a broad range of domains from category learning (e.g., SUSTAIN[47]) to analogy (e.g., MAC/FAC[48]) to reasoning about physical systems (e.g., Qualitative process theory[49]). For example, the structure-mapping engine[50] takes structured representations as inputs and uses the structural-alignment process to assess similarity. This process determines correspondences between representations by focusing on object correspondences, but with a preference for relational correspondences. In another domain, ACT-R[51] can represent both declarative memory using structured representations and procedural memory using production rules (i.e., IF, THEN rules).

Many computational models use more than one kind of representation. For example, in analogy, Hummel and Holyoak[52] developed LISA (Learning and Inferences with Schemas and Analogies) which relies on spatial and structured representations, and Forbus et al.[48] developed the MAC/FAC (Many are called/Few are chosen) model of analogical retrieval using feature and structured representations. Analogical retrieval is a difficult problem because analogical matches have an abstract structural similarity with the base situation but may lack any surface similarities. In MAC/FAC, there are both structural representations that code for relations and objects, but also feature vectors that only code for features. Feature representations are used in the first step of the retrieval process while structured representations, which are more computationally demanding, are used in the second step of the process when there are fewer possible matching items.

CONCLUSION

While primarily considered by cognitive scientists (e.g., cognitive psychologists, philosophers, and computer scientists), the study of the representation and processing of knowledge occurs across psychology and related disciplines. The challenge for scholars is to recognize the value of studying underlying representational issues. For example, Tversky and Kahneman[53] and Ahn et al.[54] considered the importance of different types of representation in person perception. Tversky and Kahneman demonstrated that individuals tend to focus on the similarity of a set of characteristics (i.e., a feature representation) when judging the degree to which an individual is typical or representative of a larger group. When presented with a description of a person that had characteristics commonly believed to be true of engineers, participants assigned a high likelihood that the person was an engineer even if this was unlikely given the low base rates of engineers in the sample population. In contrast, Ahn et al. demonstrated that the use of feature representation for clinical disorders as found in the Diagnostic and Statistical Manual of Mental Disorders (DSM) was insufficient in explaining how clinical disorders are assessed. They showed that providing a causal explanation (e.g., one problem caused another problem) increased the degree to which a patient was considered to be normal as opposed to be abnormal, by both novices and experts who were licensed clinical psychologists.

In this overview, the discussion of basic forms of representation has highlighted two main types: those that rely on more symbolic representations, like featural and structured, and those that use representations that are more continuous, like spatial or network models. As described, basic research on representation and process has led to breakthroughs in understanding a range of behaviors, like similarity judgments and analogical reasoning. Outside of laboratory work, interesting advances are being made by thinking about how representations are jointly held and created between people,[55] such as in aviation[56,57] and emergency medical teams.[58]

Knowledge representation issues are important for the study of human psychology. Researchers may benefit from considering the type of representation used to complete experimental and applied tasks because the kind of representation used dictates what tasks can be accomplished and the ease of performing tasks. Consideration should be given to both representations of content, and the encoding and retrieval contexts (i.e., transfer appropriate processing).[59] However, in order to make research advances, scientists need to be careful about generating a priori predictions and not postulating a particular form or process after seeing task data.[60]

Future research in the field of knowledge representation is likely to benefit from advances in cognitive neuroscience and grounded/embodied cognition. While Marr[61] stressed the importance of considering different levels of explanation (i.e., computational, algorithmic, and implementational) and that each level has value, research in cognitive neuroscience may be able to constrain representational theories once the underlying brain structures and functions are better understood. With the advent of computational models with neurally inspired cognitive architectures, neuroscience may be considered to be the new representational frontier. Likewise, work on grounded cognition emphasizes the importance of considering the brain states and other situational elements that ground cognitions. That is, grounded cognition emphasizes that there are modal elements to representations instead of considering representation to be purely symbolic.[62]

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