Creativity Research Journal
2005, Vol. 17, No. 2 & 3, 131–154

A "Small-World" Network Model of Cognitive Insight

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ABSTRACT: Despite many decades of study, scientists still puzzle over the process of insight. By what mechanism does a person experience that "Aha!" moment, when sudden clarity emerges from a tangled web of thoughts and ideas? This research integrates psychological work on insight with graph theoretic work on "small-world" phenomenon, to construct a theory that explains how insight occurs, how it is similar to and different from more typical learning processes, and why it yields an affective response in the individual. I propose that cognitive insight occurs when an atypical association, forged through random recombination or directed search, results in a "shortcut" in an individual's network of representations. This causes a rapid decrease in path length, reorients the individual's understanding of the relationships within and among the affected representations, and can prompt a cascade of other connections. This result is demonstrated by applying graph theoretical analysis to network translations of commonly used insight problems.

The phenomenon of insight, that sudden "Aha!" one experiences when the solution to a problem one has struggled with is suddenly and unexpectedly revealed, has intrigued scholars for more than a century. Researchers have attempted to study insight through laboratory studies (e.g., Davidson, 1986, 1995; Davidson & Sternberg, 1986; Duncker, 1945; Finke, 1995; Kaplan & Simon, 1990; Siefert, Meyer, Davidson, Patalano, & Yaniv, 1995; Weisberg, 1986), and detailed examination of historical accounts of some of the discoveries of great minds such as Charles Darwin, Albert Einstein, and Sir Isaac Newton (Csikszentmihalyi & Sawyer, 1995; Dunbar, 1995; Gruber, 1995; Ippolito & Tweney, 1995; Isaak & Just, 1995; Simonton, 1995, 1999a, 1999b). Yet despite such avid attention, the underlying mechanism of insight remains elusive. Though there are various explanations of what insight is, or how it might occur, many cognitive psychologists continue to struggle with questions about insight (Davidson, 1986; Davidson & Sternberg, 1984; Kaplan & Simon, 1990; Lockhart, Lamon, & Gick, 1988; Martindale, 1995; Mayer, 1995; Metcalfe, 1986a, 1986b; Metcalfe & Wiebe, 1987; Montgomery, 1988; Simonton, 1999a, 1999b; Wertheimer, 1985). As Metcalfe (1995, p. x) stated, "The persistent lack of a mechanism for insight, linked with the charge that the notion of insight is somehow supernatural, has shackled researchers who would explore this most important of cognitive processes. … We do not yet understand insight."

Interest in insight stems not only from the fact that it is a rather peculiar cognitive event, but also from the fact that insight may be one of the most powerful routes toward advancing human understanding available to us. Hebb argued that insight is at the core of animal and human intelligence (Hebb, 1949; Mayer, 1995). Though insight enables us to solve minor problems in our daily lives, it has also produced some of the most influential scientific breakthroughs in history. Harnessing its power has the potential to rapidly accelerate the pace at which science bounds forward.

This research builds on previous work on insight by integrating it with work done in graph theory on another peculiar phenomenon—that of "small worlds." Small-world networks are those in which the average path length between any two nodes is surprisingly

I would like to gratefully acknowledge the support and suggestions of Mark Runco, Joe Porac, Duncan Watts, Corey Phelps, Juan Alcacer, Dean K. Simonton, Shankar Ganesan, and Colin Martindale.

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short given the network's size, sparseness of connections, and clustering (Watts & Strogatz, 1998). Small-world properties cause a sharp and sudden phase transition in the connectivity of a network, radically altering its dynamics. In this article, I propose that small-world network properties have profound implications for understanding insight. By integrating research on networks, graph theory, and cognition, I build an explanatory theory that explains how insight occurs, how it is similar to and different from more typical learning processes, and why it is often accompanied by an affective response. From the perspective of this theory, most of the alternative views of insight that have been put forth over the last century are complementary pieces of the same puzzle and thus it should not be surprising that empirical evidence has been found for multiple views. This theory is also shown to be consistent with evidence from prior studies of insight, with emerging research on semantic networks, and with the physiological structure of neural networks. The theory also suggests explanations for why some people might be more insightful than others.

This article first reviews the previous research on insight, including definitions, requirements, and widely cited explanations of the process of insight. It then demonstrates that, by recasting existing explanations of insight into a simple network approach using nodes and links, prior competing explanations can be integrated into a single, unified view. Next, the article describes key results from work in graph theory on small-world networks, and how these findings are related to key concepts in insight. By applying the small-world findings from graph theory to the explanations of insight from psychology, the article shows that the moment of insight may be the formation of new small-world network properties in the mind. In so doing, the article argues that the revolutionary nature of insight is due to the dramatic decrease in path length in the network of connected representations—a mathematically verifiable property of small-world networks. The final section discusses implications and potential extensions of this work.

Insight: Definitions and Alternative Views

Insight is typically defined as a process whereby an individual moves suddenly from a state of not knowing how to solve a problem to a state of knowing how to solve it (Mayer, 1992, 1995). For instance, Kohler (1925, p. 217) described insightful problem solving as the arrival of "complete methods of solution" that occur suddenly, and had never been formerly practiced. Insight may involve the immediate knowing of something without the conscious use of reasoning (Siefert et al, 1995). Many scholars have argued that the period of struggling with the problem without obtaining an answer is as important as the sudden realization of a solution. For example, in Hebb's (1949, p. 160) definition of insight:

> The task must be neither so easy that the animal solves the problem at once, thus not allowing one to analyze the solution; nor so hard that the animal fails to solve it except by rote learning in a long series of trials. With a problem of such borderline difficulty, the solution may appear out of a blue sky. There is a period first of fruitless effort in one direction, or perhaps a series of attempted solutions. Then suddenly there is a compete change in the direction of effort, and a clean-cut solution of the task. This then is the first criterion of the occurrence of insight. The behavior cannot be described as a gradual accretion of learning; it is evident that something has happened in the animal at the moment of solution. (What happens is another matter).

This view is echoed in the definition provided in Siefert et al. (1995):

> To be referred to as *insightful*, the processes must not occur to most people immediately on presentation of the problem. The processes must seem to occur abruptly when they do occur and, once they have occurred, must result in a change in the solver's mental representation of the problem. (p. 129)

This view is also consistent with Perkins's (1995) description of insight as an example of a generative breakthrough event—a type of cognitive innovation that is similar to the sudden innovations that may occur in any kind of creative system.

The "Aha!"

One of the features distinguishing insight from more routine problem solving is the "Aha!" moment that a learner experiences upon realization of the solution. Gick and Lockart (1995) proposed that the "Aha!" is an affective response that arises because of the (a) unexpectedness of the solution (because the representation is so different from previous representations attempted) and (b) suddenness at which the correct representation leads to fruitful solution. The solution not only appears quickly, but also appears disconnected from previous solution attempts (Dominowski & Dallob, 1995).

The suddenness and disconnectedness at which a learner arrives at a solution has caused many people to view insight as an almost supernatural event. Some individuals appeared to be particularly gifted, with minds that gave rise to insights that could not be reproduced in others, nor scientifically explained. However, such a view is not very amenable to scientific study, and did not rest well with many researchers—particularly the behaviorists and the associationists (Mayer, 1995). Those camps tended to argue that insight was simply an extension of normal learning processes (Davidson, 1995; Perkins, 1981; Weisberg, 1986, 1992; Weisberg & Alba, 1982). Siefert et al.’s (1995) perspective was that, though there is evidence for insightful learning that is quite different from typical learning in that it involves quantum leaps of inspiration (and the individual may have had no prior expectation of the impending solution), such a process may arrive through known information-processing phases, and may thus still be amenable to scientific study and explanation. This perspective is the one most consistent with the theory advanced here.

The Benefits and Costs of Deep Knowledge Reservoirs

Many studies have suggested that dense clusters of domain-specific knowledge may be a necessary-but-insufficient condition for insight. Simonton argued that insight first requires preparation within a discipline and notes that the most insightful people have first built up huge reservoirs of discipline-relevant information (Simonton, 1999a, 1999b). Simon and Chase even quantified this expertise by studying chess grand masters and other experts, concluding that individuals need approximately 50,000 “chunks” of richly connected information prior to making a fruitful discovery (Simon & Chase, 1973). Other authors have observed that individuals typically require at least a decade of intense study in a particular domain of knowledge prior to making a significant contribution in that domain (Gardner, 1993; Hayes, 1989; Simonton, 1999a, 1999b). The more knowledge an individual has in a particular domain, the more likely they are to understand the nature of the relationships between different ideas. As associations within the domain are challenged or reinforced over time, the more accurate the pattern of associations should become, and the more efficient the individual should be in searching for a solution among them (Dosi, 1988; Harlow, 1959).

An individual’s degree of prior experience in a domain, however, can also inhibit creative problem solving (Wertheimer, 1945/1959). Individuals who are highly specialized within a domain are prone to “einstellung” or functional fixedness. *Functional fixedness* refers to a situation whereby an individual can only think of using an object for its most common use (Duncker, 1945). This is closely related to Luchins’ (1942) einstellung, whereby learners who have previously solved a problem a particular way will form a problem-solving set that mechanizes their problem solving, constraining them from developing creative solutions (Mayer, 1995). Both are examples of automatized thinking. Many forms of learning may become automatized such that, when faced with a particular situation, the learner automatically recalls a representation, and it is difficult not to do so (Gick & Lockart, 1995). When an individual has well-reinforced expectations about the direction a search path should take, it constrains their ability to explore different possibilities, and may prevent them from generating “preinventive forms” with a more natural or universal structure (Finke, 1995, p. 262). Similarly, an individual that is deeply immersed in the established orthodoxy of a field of study may find their creativity stifled by existing paradigms and institutional pressures to conform (McLaughlin, 2001). This is also argued by Simonton, who pointed out that being too highly specialized can inhibit cognitive insight: “Too often, persons fail to make significant insights because they exclude whole domains of elements from entering into the combinative hopper. Yet what appears logically irrelevant may actually provide the missing piece of the puzzle” (1995, p. 473). Extensive training in a particular field can thus impede cognitive insight (notably, both Einstein and Piaget claimed that formal schooling detracted from their intellectual development; Feldman, 1999). For these reasons, it has often been argued that marginal intellectuals (those who may participate in multiple intellectual domains but are central to none) are more likely to introduce creative breakthroughs than well-established experts in a domain (Ben-David & Collins, 1966; Dogan & Pahre, 1990; Martindale, 1995, p. 252; McLaughlin, 2001). The benefits and costs of having extensive knowledge and experience in a domain also suggest that there may be a curvilinear relationship between experience and creativity, and that the effect may be a function of an individual's tendency to rely on prior experience (e.g., Martinsen, 1994, 1995; Sternberg, 1988).

In a related line of research, scholars have studied cognition as a recombinant search process. This work suggests that a highly ordered search through a well-defined and local space of solutions may be more likely to result in incremental solutions than creative breakthroughs. Forging connections between two ideas that were already perceived as closely related, or finding a solution in a "homing space" wherein many clues lead to its almost inevitable discovery, may not result in the affective response characterizing insight (Perkins, 1995). Incremental progress on a problem may conform to the learner's expectations, and not elicit any sense of surprise or prompt any significant restructuring of existing representations. By contrast, when connections are made between ideas that had seemed unrelated or incongruent, the connection may be unexpected, and it may prompt the individual to rearrange other existing associations to one or more of the ideas.

The Role of Unexpected Connections

Several domains of research have suggested (explicitly or implicitly) that insight arises from an unexpected connection between disparate mental representations. At least five prominent hypotheses about the process of insight incorporate unexpected connections within or across representations as one of the underlying mechanisms: (a) completing a schema, (b) reorganizing visual information, (c) overcoming a mental block, (d) finding a problem analog, and (e) random recombination. All of these explanations turn out to be highly congruent when viewed from a network perspective. I first briefly describe each of the explanations, and then propose a unified synthesis.

1. Completing a schema. According to Mayer (1995), one of the earliest views of insight came from Otto Selz, who proposed that creative problem solving occurs when an individual figures out how the givens and goal of a problem fit together in a coherent structure. A problem may be a coherent set of information with a gap. To solve the problem, the individual must find a way to fill the gap in a manner that completes the structure (Humphrey, 1963; Mayer, 1995). This view contrasted with traditional associationism views because it posited that it was not the strength of association between ideas that lead learners to a particular solution, but rather the degree to which an idea fit the learner's schema of the requirements of the problem. This is consistent with Siefert et al.'s (1995) hypothesis that if a learner has stored a stable partial mental representation of an unsolved problem, an accidental encounter with external stimuli that provides relevant information may complete it in a way that is sudden and unexpected. Siefert et al. provided an illustrative example, modified from Mosler (1977). Two men walking through the desert discover a third man, lying on the sand, dead. The dead man has a small pack that contains fresh food and water, a larger pack on his back, and a large ring on his index finger. Puzzled about the cause of his death, the two men proceed onward. Later, one of the men accidentally drops his handkerchief while mopping his brow, and as it flutters to the earth he suddenly realizes how the man had probably died: His parachute had broken, and he had plummeted to the ground. This example demonstrates how a partial representation with a gap (a dead man with a pack, food, water, and a large ring) may be suddenly filled in a way that completes the coherent structure of the representation (the large pack contained a parachute, and the ring was from its pull cord).

2. Reorganizing visual information (or "reformulating a problem"). The Gestalt theory of perception posited that insight occurs when a learner looks at a problem in new way. A problem solver mentally redefines the givens or the goal of a problem (Mayer, 1995) or reorganizes the visual representation of the problem in such a manner that it leads to a sudden view of a solution (Duncker, 1945). A good example of this is demonstrated with the following problem. Students are asked to calculate the area contained in a shape resembling a puzzle piece (see Figure 1). Many participants struggle with finding a way to calculate the size of the rectangular portion, subtracting the circular missing portion, adding the protruding circular portion, and trying to account for the slight overlap between the circular portions and the rectangular portions. Other participants are able to solve the problem much more simply by reorganizing the problem. By realizing that the protruding portion fits into the concave

a) Original visualization of problem b) Reorganized visualization of problem

Figure 1. *Area of puzzle problem.*

portion of the rectangle, the participants are able to reformulate the problem into a simple calculation of the area of a rectangle (Mayer, 1977).

3. Overcoming a mental block. Another Gestalt view posed that insight occurs when individuals overcome functional fixedness or einstellung (Duncker, 1945; Luchins, 1942). As discussed previously, experience with solving a problem in a particular way can constrain individuals from coming up with new solutions (Mayer, 1995). Insight occurs when the learner overcomes this fixedness. For example, Wicker, Weinstein, Yelich, and Brooks (1978) found that participants who were directed to reformulate their initial view of a problem to avoid unnecessary assumptions about it were more likely to solve the problem successfully. Research has also shown that pretest tasks can be used to decrease functional fixedness in an individual. For example, Birch (1945) found that if participants are first encouraged to explore the general uses of a particular item, they will more quickly find solutions to problems that require the participant to use the item in novel ways. Birch created an experiment wherein some food was placed beyond the reach of an ape in a cage. The ape in the cage was given a hoe to “rake” the food into reach. Birch found that, if apes were given a few days to play with sticks prior to the experiment, they were much more likely to solve the problem. In playing with the sticks, the apes had explored many possible functions of stick-type objects, making such functions more readily available to them when given the hoe.

4. Finding a problem analog. Several researchers have suggested that insight occurs when an individual applies the structural organization of one problem to another problem (Gentner & Gentner, 1983; Gick & Holyoak, 1980; Holyoak, 1984; Wertheimer, 1945/1959). Numerous studies have demonstrated that adults, children, and even chimpanzees are often able to abstract structural elements common to two problems, and thus are able to use the solution to one problem to provide the solution to another problem, even if the specific features of the problem appear quite different (Bassok, 2001; Dunbar, 2001; Gentner, 1988; Goswami, 2001; Holyoak, 1984; Oden, Thompson, & Premack, 2001). For example, in a well-known insight experiment, participants solve a radiation problem (“how can a sufficient intensity of rays be used to destroy a tumor without damaging healthy tissue?”) by transferring the solution from a structurally similar military problem (“how can a sufficient number of army troops be used to capture a fortress if the roads to the fortress are narrow?”). The participants solve the problem (split up the rays/army into smaller units and send them to the tumor/fortress by multiple paths) by mapping the military solution to the tumor problem (Duncker, 1945; Gick & Holyoak, 1980). Such an analogical transfer is frequently depicted as the formation of new connections between the semantic network representations of the two problems. By priming individuals to forge such otherwise unlikely connections between an army and radiation, experimenters stimulate the participants to generate an insightful solution.[1]

5. The role of random recombination. Recently several researchers have argued that insight often occurs when the individual’s mind is allowed to engage in a subconscious random recombination of ideas that ultimately yields a fruitful synthesis of ideas (Siefert et

[1]There is a considerable body of work on the role of analogy in cognition and decision making that is beyond the scope of this article. For more comprehensive reviews, see Gentner, Holyoak, and Kokinov (2001), Gentner and Stevens (1983), Holyoak and Thagard (1995), and Vosniadou and Ortony (1989).

al., 1995; Simonton, 1995, 1999a, 1999b). For example, Simonton (1995, 1999a, 1999b) pointed out that many of the most famous scientific breakthroughs occurred through a free associative process (what Freudians might call "primary process thinking") whereby an individual generates many unusual combinations between different bodies of knowledge possessed by the individual and subjects that set to a screening process of selective retention, keeping only the best variations (much like Darwinian evolution). This view echoes the eloquent description by William James (1890):

> Instead of thoughts of concrete things patiently following one another in a beaten track of habitual suggestion, we have the most abrupt cross-cuts and transitions from one idea to another, the most rarefied abstractions and discriminations, the most unheard of combination of elements, the subtlest associations of analogy; in a word, we seem suddenly introduced into a seething cauldron of ideas, where everything is fizzling and bobbling about a state of bewildering activity, where partnerships can be joined or loosened in an instant, treadmill routine is unknown, and the unexpected seems only law. (p. 456)

Unlike Simon (1973), who argued that insight arises by a process that is intrinsically logical, whereby an individual makes an ordered search through possible representations, Simonton (1999a) argued that the role of chance is crucial in insightful discovery. He noted that if a problem is novel and complex, the number of possible representations expands exponentially, and if there is no precedent for its solution, there may be little basis on which to assign one algorithm a greater probability of solution than another. Thus individuals may find themselves blindly searching through an immense range of possibilities, even though they may be largely unaware that they are doing so. This random recombination appears consistent with illustrative anecdotes of some of the great discoveries of the past. For instance, in an oft-repeated quote, Poincaré (1921, p. 387) described how he came upon the idea of Fuchsian functions after having drunk coffee too late in the evening: "Ideas rose in crowds; I felt them collide until pairs interlocked, so to speak, making a stable combination. By the next morning I had established the existence of a class of Fuchsian functions" (in Simonton, 1995, p. 469).

Synthesis of Views Within a Network Perspective

Though each of the views described proposes a different mechanism for insight, modeling them using a network approach reveals that the basic processes underlying them are fundamentally the same. Using simple network diagrams to illustrate the first four explanations, it is possible to show that each perspective involves the addition or change of nodes or links, and the fifth explanation reveals why random (or *atypical*) connections between nodes might result in a more significant outcome, but only when those nodes are also embedded in dense clusters.

In several different disciplines (e.g., social networks, graph theory, complex adaptive systems, connectionism), systems are represented as groups of nodes that are interconnected in some way. These connections may be any kind of relationship, including physical connections (as in the wire between a string of lights), transaction connections (as in the relationships between buyers and sellers), familial relationships, the relationships between ideas, and so on. Each such connection may be referred to as a link. For example, in a semantic network a node can be used to represent a single concept or idea that is linked to other concepts through some association that may be reinforced or diminished over time (Fahlman, 1989; Martindale, 1995; Steyvers & Tenenbaum, 2002). In connectionist models, a network of nodes and links may represent patterns of communication among actual neurons or, more abstractly, the pattern of links between knowledge elements that collectively form a concept (Collins & Loftus, 1975; Gasser & Smith, 1998). Once forged, links provide a ready path that facilitates and guides future searches among knowledge elements. For example, the activation of a particular knowledge node (e.g., the concept of "volcano") might immediately activate other knowledge nodes associated with it (e.g., "crater," "lava," and "erupt"; Collins & Loftus, 1975; Steyvers & Tenenbaum, 2002).

Such a network approach can be used to depict the insight examples described previously. Creating simple network diagrams (similar to semantic network diagrams) of the problems and their solutions reveals the abstract commonalities among the different explanations for insight.

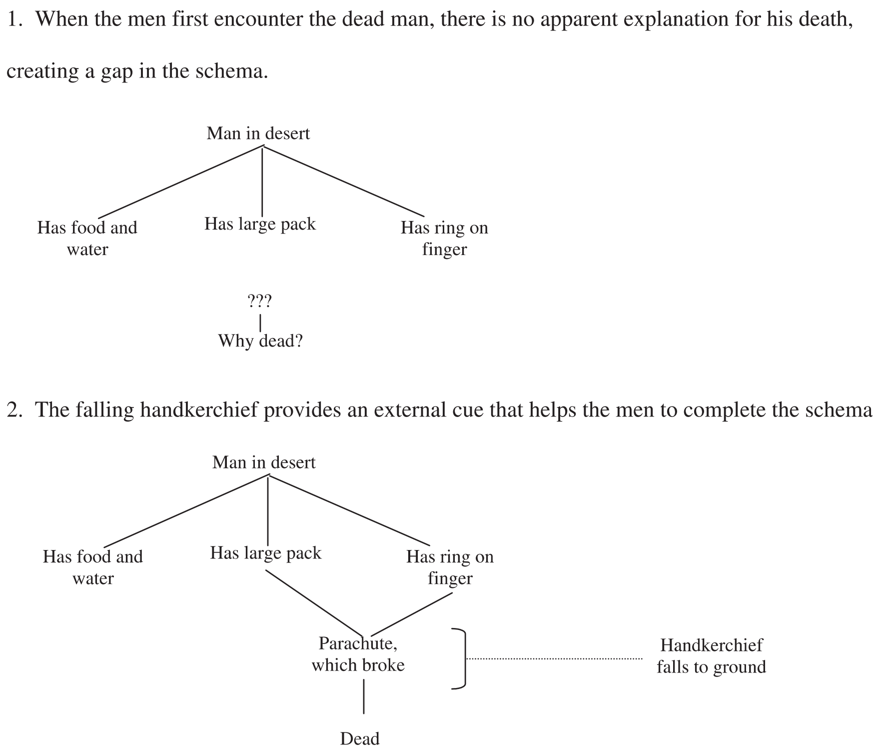


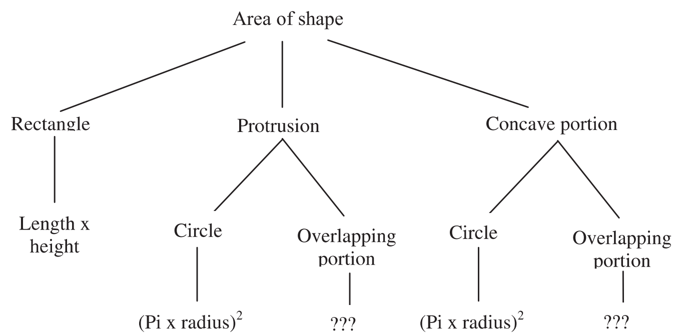
Figure 2. *Network diagram for completing a schema example.*

Figure 2 depicts the example described for *completing a schema*. The first panel shows the walking men’s initial knowledge of the deceased man: He has food and water, a large pack, and a large ring on his finger, but there is no apparent reason for his death. The gap between what is apparent about the man and his death results in a disconnected network. The second panel shows that the external stimulus provided by the handkerchief fluttering to the ground causes the men to think of a parachute, providing an explanation for the large pack, the large ring, and creating a path to the man’s death, thus completing the schema. In this example, a node has been added to the network with links that subsequently connect the network.

Figure 3 depicts the example provided for *reorganizing visual information (or reformulating a problem)*. Participants who attempt to complete the representation in panel A are stumped with how to measure the overlapping portions of the circles and rectangles that compose the shape. However, the realization of the equivalence of the protruding and concave portions of the shape creates a one-to-one mapping of each of the elements in the protrusion and the concave portion of the shape (see Figure 3, second panel). Because one is added to the shape’s area and the other is subtracted from the shape’s area, they cancel each other out. The associations between the elements resolve the problem; no new nodes are necessary.

In the example on *overcoming a mental block*, prompting a participant to consider many varied uses of an object increases the participant’s likelihood of discovering a solution. Consider the example involving apes, bananas, and sticks. From a network perspective, encouraging the ape to explore different functions of a stick created multiple possible pathways for association, increasing the likelihood that it would make an association that would successfully solve the problem. First, the ape discovers multiple attributes of and uses for a stick, creating the representations depicted in the first and second panels of Figure 4. When the ape is subsequently given a hoe, the associations between similar features of the stick and the hoe help the ape to realize that the hoe can also be used in similar ways as the stick, creating a series of associations that enables the ape to

1. Upon presentation of the problem, the subject may recall formulas for calculating the area of rectangles and circles, but is not sure how to deal with the slight overlap of the circles and the rectangles.



2. After visually reorganizing the shape so that the protruding area fits in the concave area (or after realizing the equivalence of the two subrepresentations for the protruding portion and concave portion), it becomes clear that the subject need only calculate the area of the rectangle.

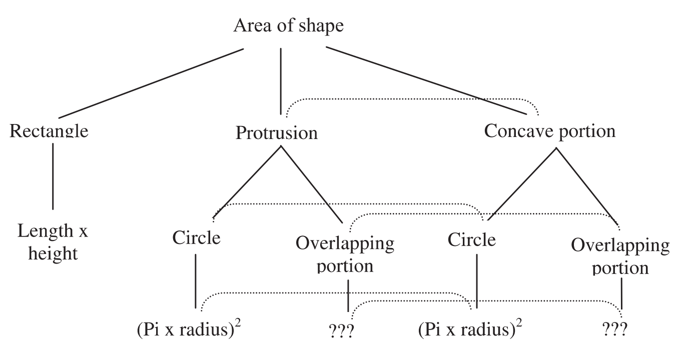


Figure 3. *Network diagram for reorganizing visual information example.*

connect the hoe to reaching the bananas. From a network perspective, both links and nodes have been added.

Studies in which participants are primed with solution analogs streamline the search process by stimulating a connection to a specific solution. Recall the ray and tumor example used to illustrate the *finding a problem analog* view of insight. The researchers could have provided participants objects such as toy guns and allowed them to experiment with them, thereby encouraging them to realize (among other things) that multiple guns can be shot at the same target from different angles. Instead, the researcher primes the participant with a story that yields a specific solution once the participant has mapped the details of the analog to the details of the problem at hand. There are a number of models for how such a mapping process takes place, but the net effect is the same: The researcher has encouraged the participant to make an association between two knowledge elements that initially seem quite different (e.g., "army" and "radiation") but that are embedded within patterns that share some symmetries. This prompts the participant to consider other possible associations, leading the participant to add links and nodes that make the representation of the

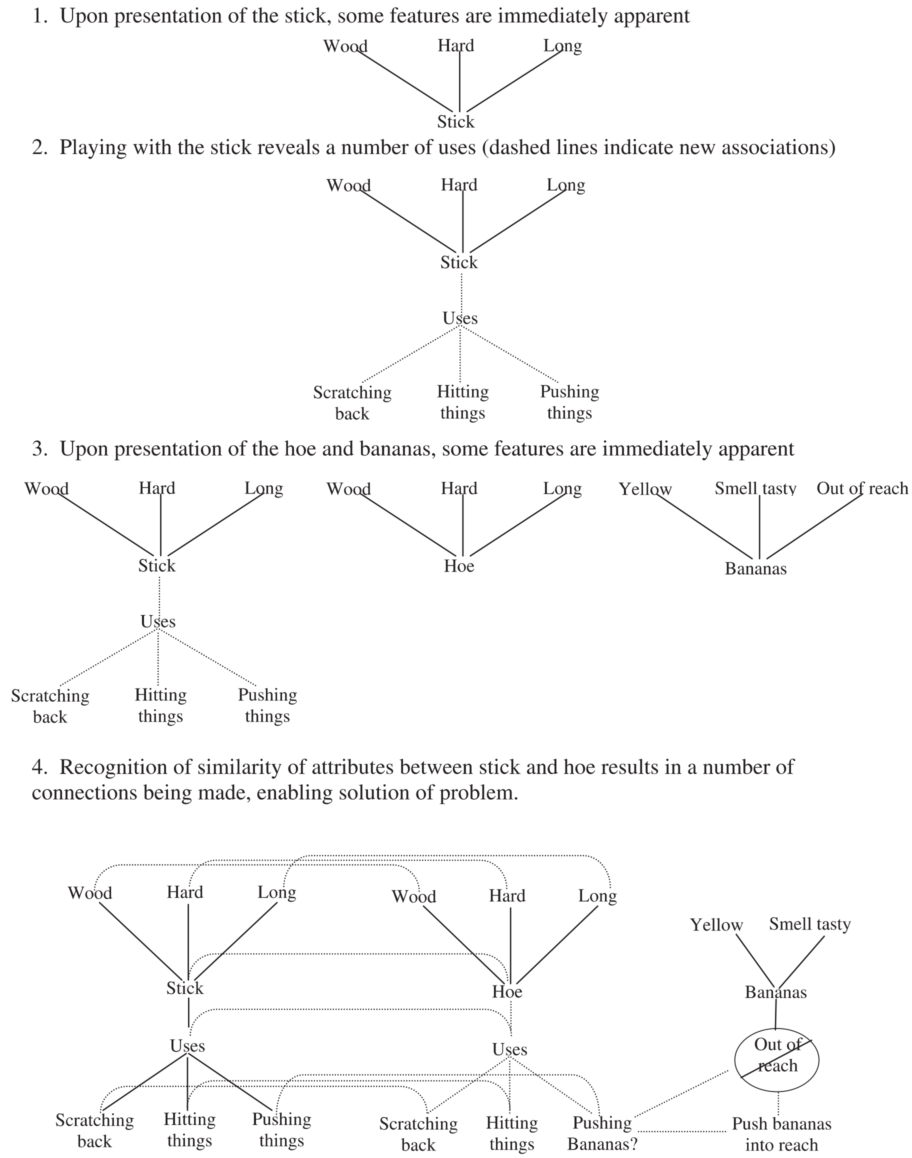


Figure 4. *Network diagram for overcoming a mental block example.*

problem and the analog almost identical, and revealing a solution to the problem (see Figure 5).

Though each example represents a different explanation of insight, in each case the underlying mechanism was fundamentally the same: The addition or change of nodes, links, or both. This process is not dissimilar to more typical learning processes that may involve the forging of new nodes and links; the key difference is that insightful learning may entail the forging of nodes or links that result in a more substantive shift or completion of a representation. The last view, *the role of random recombination*, provides direction as to why some link or node additions should result in such a substantive shift. If connections are successfully forged through random recombination (or searching "Klondike" spaces [Perkins, 1995]), such combinations are more likely to be unusual or to span long distances. Such connections bring formerly distant ideas into close proximity, and simultaneously reorient the individual's perception of

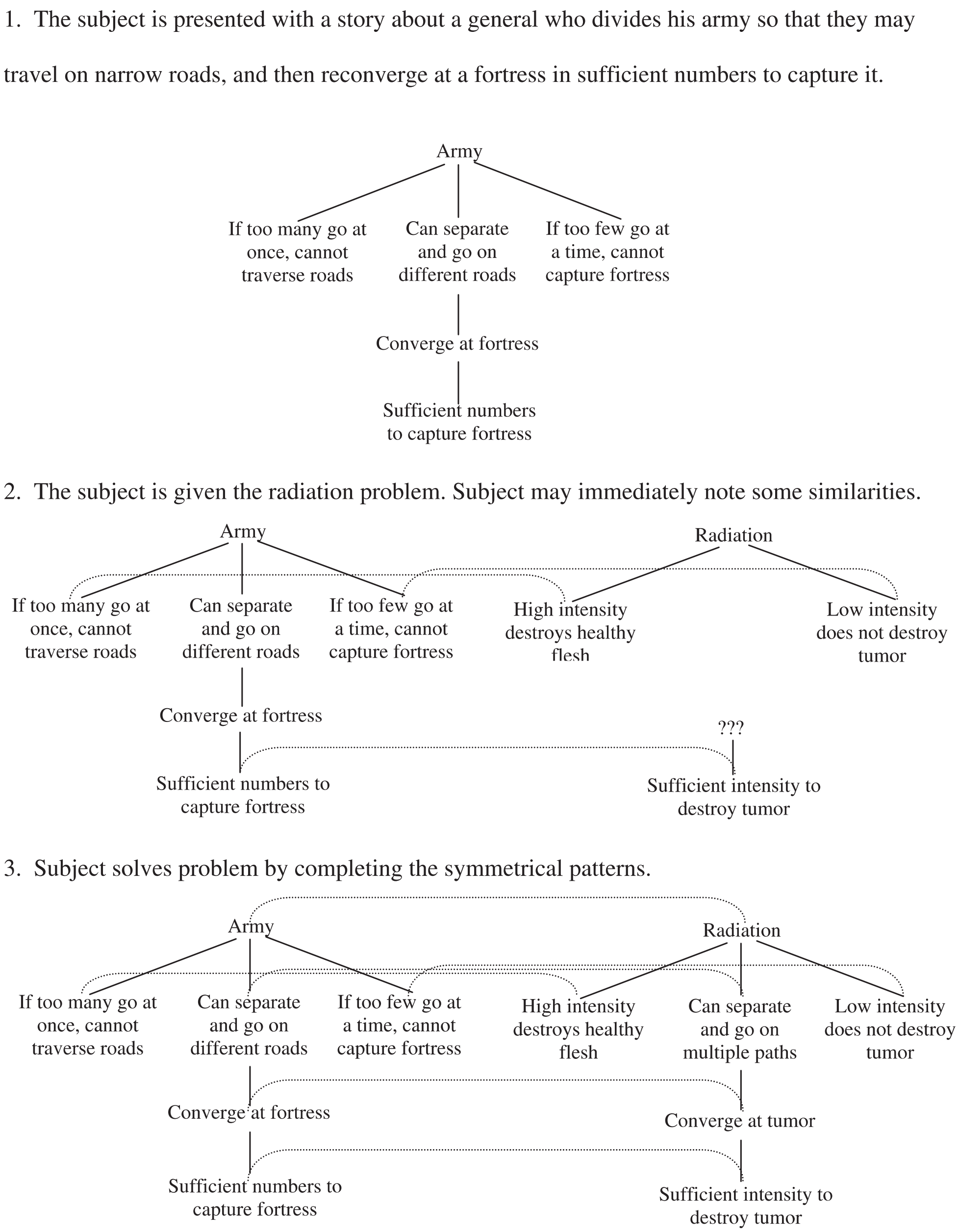


Figure 5. *Network diagram for finding a problem analog example.*

distance between other elements in the cognitive network. Thus it is precisely because random recombination can result in atypical or unexpected connections between ideas that it may yield dramatic results (Simonton, 1995). Simonton also noted that the tendency of creative individuals to make such unusual connections may be what makes them more likely to discover profound insights. As Simonton stated, "Those people who make their minds accessible to chaotic combinatorial play will also make their senses more open to the influx of fortuitous events in the outside world. Both the retrieval of material from memory and the orientation of attention to environmental stimuli are unrestricted … what appears logically irrelevant may actually provide the missing piece of the puzzle” (1995, pp. 470–473).

In sum, the preceding thus suggests that (a) insight may be a substantive shift or augmentation of a representation due to the addition or changing of either nodes (elements of information, or sets of information) or links (connections or relationships between nodes of information); (b) such a shift may often be the result of forging connections along a path that the individual perceives as atypical; and (c) the perceived significance or magnitude of the shift may be a function of both the unexpectedness of the connection, and the magnitude of change it creates in the network of representations. Integrating the preceding arguments with recent findings in graph theory on small-world network properties reveals why some connections result in a disproportionate payoff, yielding an explicit structural mechanism for insight.

Insight as the Formation of Small-World Network Properties

Graph theorists have demonstrated that particular network structures exhibit some surprising connectivity properties. As Watts and Strogatz (1998) demonstrated, a few random or long-spanning links in a densely clustered network dramatically decrease the network’s average path length while having negligible impact on its clustering coefficient. Small-world properties were first discovered in social networks but scientists soon realized they had profound implications for the dynamics of many kinds of networks, from the U.S. electrical grid to semantic networks.

Small Worlds in Social Networks

Small-world analysis has its roots in work by mathematical graph theorists (e.g., Erdos & Renyi, 1959; Solomonoff & Rapoport, 1951), but research specifically on the small-world phenomenon did not commence until the 1960s, when de Sola Pool and Kochen (1978) estimated both the average number of acquaintances that people possess and the probability of two randomly selected members of a society being linked by a chain of no more than two acquaintances. At around the same time, psychologist Stanley Milgram was conducting an innovative empirical test of the small-world hypothesis (1967).

Milgram addressed a number of letters to a friend in Boston who was a stockbroker. He then distributed these letters to a random selection of people in Nebraska. He instructed the individuals to pass the letters to the addressee by sending them to a person they knew on a first-name basis who seemed in some way closer (socially, geographically, etc.) to the stockbroker. This person would then do the same, until the letters reached their final destination. Many of the letters did eventually reach the stockbroker, and Milgram found that on average the letters had passed through about six individuals en route. Milgram had demonstrated that the world was indeed small, and this finding was dubbed “six degrees of separation” (Guare, 1990).

If links in social networks were formed randomly, we would expect short average path lengths even in sparse networks (Bollobas, 1985): If every person has z acquaintances, and every acquaintance also has z acquaintances, the number of people an individual can reach multiplies very quickly with the number of acquaintances they have and the number of steps taken. The number of degrees of separation increases only logarithmically with the size of the network, causing the average path length to be very small even for very large networks. Similarly, if a single (or few) central nodes connected to every other node in the network, it would again be expected that every pair of nodes would be connected by a relatively short path length through this central vertex. Finally, if the number of links relative to the number of nodes were large, we would expect very short path lengths. As the number of links per node approaches the number of nodes in the network (i.e., maximum density), it becomes possible for every node to be directly connected (i.e., path length of one) to every other node.

However, social networks are not random. Instead, they are highly clustered, with many local areas exhibiting significant redundance in links. Furthermore, social networks are (with some exceptions) decentralized and extremely sparse. The maximum number of acquaintances an individual has is a tiny fraction of the entire population (Watts, 1999). Intuitively, such clustered networks should require a long path to connect individual nodes in different clusters with one another due to the sparseness of connections between clusters. Thus intuition suggests that sparse and clustered networks would tend to be “large worlds” in that the average path length required to connect any two randomly chosen nodes is quite large. What made the findings of

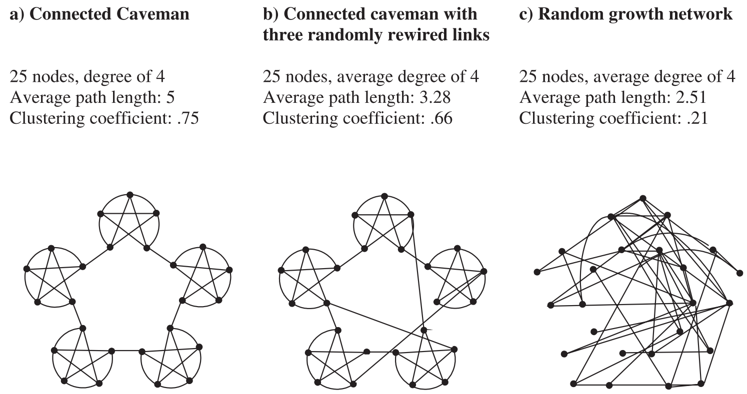


Figure 6. *Connectivity properties of "Connected Caveman" and random networks.*

small-world network research so surprising is that, despite such clustering, decentralization, and sparsity, many real-world networks demonstrate remarkably short path lengths. In their pivotal 1998 article, Watts and Strogatz demonstrated how this can occur: As a few random or long-spanning connections are added to a highly clustered network, the path length drops much more quickly than the clustering coefficient. Thus in the range between highly structured networks and random networks, there is an interval in which high clustering and short path lengths can coexist.

To better understand this, consider two extreme cases. The first is a network that consists of numerous highly clustered cliques that are connected to each other with only one link. Such a network is both highly clustered and extremely sparse. Watts (1999) referred to such a network as a "connected caveman graph" and argues that it is an appropriate benchmark for a large, clustered graph (see Figure 6, panel a). The contrasting case is a random graph, which exhibits minimal clustering and represents a good approximation for a network with minimal average path length (see Figure 6, panel c). Consistent with the aforementioned intuition, the connected caveman network has a very large average path length when compared with the random graph. The world is quite large in this scenario. However, highly clustered and globally sparse networks need not be large worlds. Watts and Strogatz (1998) demonstrated, that by randomly "rewiring" a very small percentage of links in the highly clustered graph, the network exhibits the small-world properties of high clustering and short average path length. Because nodes that are initially widely separated in the network are as likely to become connected as those that are near neighbors, the network contracts as ties within clusters are replaced with ties that span them (Kogut & Walker, 2001; Watts, 1999). In Figure 6, replacing three of the links in panel a with randomly generated links decreases the path length 34%, from 5 to 3.28, whereas its clustering coefficient decreases by only 12%, from .75 to .66 (see Figure 6, panel b).

Numerous studies have examined variations of this model in a wide range of empirical contexts. Though Watts and Strogatz (1998) initially used computer simulations to demonstrate the implications of small-world structures, they then replicated these results with data on the physical structure of networks as diverse as the neural pathways of the worm *C. elegans,* and the electrical power grid of the United States (Watts, 1999). Barabasi (2002) similarly showed that the pathways formed by hyperlinks on the Internet demonstrate small-world properties that are formed through the creation of "hubs" (i.e., some sites play a disproportionate role in the overall connectivity of the Internet, and cause its average path length to be quite short given its size).[2] Social network theorists have also demonstrated small-world

[2]The presence of such "hubs" in the network not only give it small-world properties, but also make it scale free. Scale-free networks are those in which the distribution of the number of links per node conforms to a power law. There is no "characteristic" (or typical) number of links per node, and there may be some nodes that have extremely high numbers of links. Though research has indicated that many networks demonstrate scale-free properties (Barabasi, 2002; Gladwell, 2000; Steyvers & Tenenbaum, 2002), other networks are not amenable to the scale-free structure (many knowledge networks, for instance, might be composed of nodes that are inherently constrained in the number of links they can support). Thus I emphasize the more general small-world network properties here.

properties in the network of associations formed by interlocking boards of directors (Kogut & Walker, 2001), Broadway musical actors and producers (Uzzi, 2004), and new product development teams within firms (Hansen, 2002). Management scholars have also showed that the alliance networks formed by industrial firms often demonstrate small-world properties, and that these properties are significantly related to knowledge flow through the network and subsequent innovation rates (Schilling & Phelps, 2004). Recently, Steyvers and Tenenbaum (2002) showed that semantic networks constructed from (a) word association tests, (b) WordNet, and (c) *Roget's Thesaurus* each demonstrate small-world connectivity. All three networks were very sparse and displayed average path lengths that were very short for the size of the networks (3.04 for the 5,018 words in the association test, 5.6 for the 29,381 words in *Roget's Thesaurus,* and 10.56 for the 122,005 words in WordNet).

The structural properties of small-world networks have significant implications for network dynamics. Watts (1999) demonstrates how the topology of a small-world network affects the degree to which a contagion (e.g., information, fashion, disease) diffuses throughout the network and the rate at which this diffusion occurs. Watts's simulation results demonstrate that a contagion can spread completely and far more rapidly in a small-world network than in a large world and nearly as fast as in a random network. A few links that span clusters decrease the average path length and dramatically increase the rate of diffusion. Yamaguchi (1994) obtained similar results in his examination of the rate of information diffusion in alternative network structures. Using simulations of a broad array of network structures, Yamaguchi found a strong negative relationship between the diameter of a network and its rate of information diffusion.[3]

Small Worlds in Cognitive Networks

Like social networks, cognitive networks demonstrate significant clustering and sparsity. The knowledge elements in the mind (including both ideas and concepts) are not randomly connected to one another, but rather are highly structured (Anderson & Hinton, 1989; Steyvers & Tenenbaum, 2002). Although not all ideas are as broad and abstract as concepts, both are information within a network of associations that give them meaning. Ideas or concepts tend to be associated with a probability that is some function of their similarity on one or more dimensions (sometimes termed "semantic distance" or "semantic relatedness"; Collins & Loftus, 1975; Rips, Shoben, & Smith, 1973). Association based on similarity results in significant clustering. Further, such networks are likely to be sparse. Forging and maintaining links between concepts in the mind has a cost in terms of time and effort (Simon, 1955), and links that are not reinforced over time can diminish (Martindale, 1995). These costs make it difficult (if not impossible) to densely connect every possible node in the network to every other node; instead cognitive networks are likely to be characterized by dense connectivity among closely related nodes, and much sparser connectivity (if any) between nodes that are only distantly related.

Though such order and clustering is extremely valuable in terms of giving structure and meaning to individual knowledge nodes and sets of knowledge nodes (Bartlett, 1932; Mayer & Greeno, 1972), it also results in relatively long path lengths in the network. Long path lengths make it more difficult and time consuming for individuals to search their cognitive networks and may make individuals less likely to find a solution that is not in the immediate domain of the problem. An atypical path in the network, however, can create a shortcut that brings many more nodes in the network within easy search range. This process is demonstrated below.

In Figure 7a, a line lattice is used to model a cognitive network that grows in a highly ordered fashion, whereby as each node is added to the network, it is connected to its four nearest neighbors. The path length of this network at each step of growth is shown in the accompanying graph. A network that grows in random fashion is also shown (Figure 7b), modeled by a line lattice in which each node is connected randomly to four other nodes. The average path length of this network grows much more slowly, as also indicated in the graph. By the addition of the 50th node in the structured line lattice, the average minimum distance between every possible pair of nodes is 8.58 links; in the random line lattice it is only 2.96 links. As already dis-

[3]The diameter of a graph is the length of the largest geodesic (i.e., shortest path between two nodes) between any two nodes in the graph. Both scale similarly with the addition of nodes to the graph since average path length is strictly less than or equal to diameter (Newman, 2000).

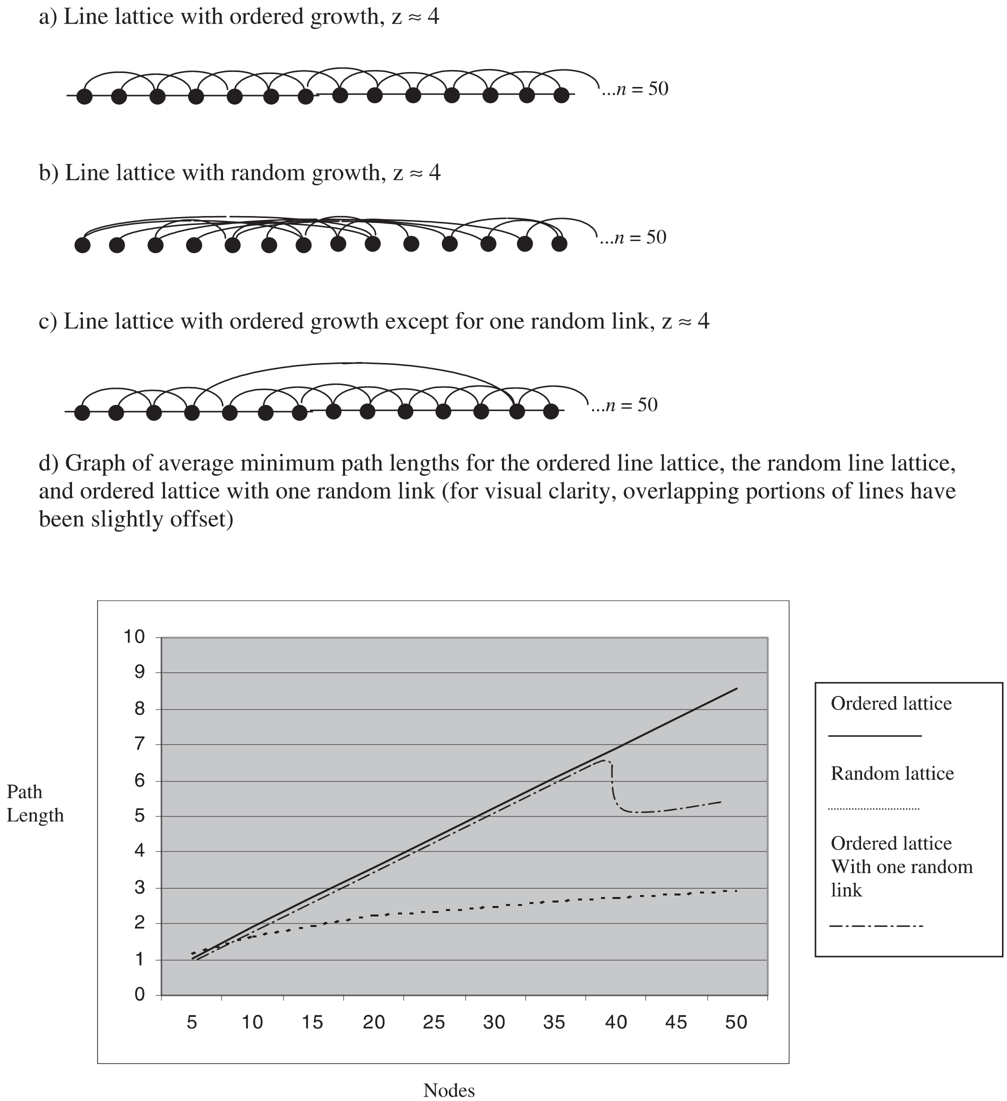


Figure 7. *Alternative models of knowledge network growth—ordered versus random.*

cussed, such random association is a poor model of cognition; ideas that are associated randomly would have little (if any) meaning. However, there is an attractive compromise to be struck. Substituting only a very few random or atypical links into the structured line lattice causes, on average, a significant decrease in the average path length.

Figure 7c shows a line lattice of 50 nodes in which only one link has been rewired randomly, and the associated change this causes in the growth of the path length. The graph shows the significant drop in path length that occurs at the step in which a node is added that has one random connection (both the choice of originating node and the node to which it is connected were generated randomly—in this case, the random connection occurred at the addition of the 40th node). Although very little of the clustering structure of the line lattice has been forfeited, the connectivity gains are substantial. Adding the random connection at the 40th node decreases the path length at that step from 6.92 to 5.70. By the 50th node, the path length has only reached 5.82 versus the 8.58 length of the purely ordered lattice.

If association networks are sparse, and search is constrained or costly (as is suggested by considerable research; see for example, Collins & Loftus, 1975; Collins & Quillian, 1969; Martindale, 1995; Simon, 1955), these results suggest that random or atypical connections can have a disproportionate payoff in terms of an individual's ability to search and access the network. Further, as shown in the graph in Figure 8, the decrease in path length created by a random or atypical path is not reaped gradually; rather it is a sudden and sharp drop—explaining why the moment of successfully forging such a connection "feels" so different from incremental learning processes.

Applying small-world network principles to the realm of cognitive networks thus provides a compelling explanation for insight. The quantum leap of understanding that occurs during insight, and the affective response it produces, may be due to the formation of a new small-world network of interconnected representations: One unlikely combination between two seemingly distant knowledge clusters suddenly results in a much shorter path length between a large web of connected representations. Furthermore, the dramatic decrease in path length between the two representations may prompt the individual to search for and note other similarities. Relationships that had never been previously considered may suddenly seem obvious, causing the rapid formation of new links between the representations without any prompting from external input. Consistent with this, recent work has demonstrated that insight can be graph theoretically verified as a restructuring that occurs when individuals note similarity between concepts that had previously appeared unrelated (Durso, Rea, & Dayton, 1994). Small-world network properties illuminate why such a restructuring is so different from incremental learning processes. The following example illustrates this process, while simultaneously integrating each of the views of insight described previously, demonstrating that they can be seen as complementary pieces of the same puzzle.

Example of Insight as the Formation of a Small World in a Semantic Network

Suppose a young child has a set of mental representations for dogs, cats, and humans as in Figure 8, panel a. Dogs and cats are in a category for "animals," separate from the category for humans.[4] Though humans share some similarities with dogs and cats (e.g., "two eyes"), the child considers the two categories to be quite different. One marked difference concerns legs: dogs and cats have four legs, whereas humans have only two legs. Humans also have arms. Though the child may have considered the possibility that arms are analogous to the front legs of dogs and cats, this possibility does not seem very likely for a number of reasons. First, a human's arms are much shorter than its legs, making walking on all fours very awkward—the child has verified this with their own experience! Second, the joint that appears to be midway down a dog or cat's front limbs permits the bottom portion of the limb to bend backward, while the joint midway down their hind limbs permit the bottom portion to bend forward. Thus dogs and cats appear to have knees where a human's elbow would be, and elbows where a human's knees would be (see Figure 8, panel b). Third, the number of digits further differentiates the arms and legs of a human from the legs of dogs and cats. Whereas humans have five fingers on each hand (including the opposable thumb, which children are often taught is specific to humans) and five toes on each foot, dogs and cats appear to have only four toes on each foot.

One day, however, while tickling the family dog's feet, the child discovers a small fifth toe, previously overlooked, on each of the dog's front legs. A quick inspection of the cat reveals fifth toes there too. This discovery might spur a series of connections in the child' mind, whereby the child begins to relate the dog's front legs to either human's legs or hands (see Figure 8, panel c). Looking at where the toe emerges on the dog's leg starts a restructuring of the child's understanding of the dog's skeleton: The toe emerges just below the joint that was considered by the child to be a knee, thus prompting the child to realize that perhaps that joint is actually more analogous to the human's wrist. Following the dog's leg up toward the shoulder reveals that, just before the shoulder, the dog has a knobby structure very akin to an elbow, permitting the rest of the leg to bend upward (Figure 9, panel a). In a series of quick realizations, the child equates what had been considered an elbow on the dog's hind limbs to

[4]This illustration uses an undirected hierarchical semantic network but the concepts would apply equally well to other network forms.

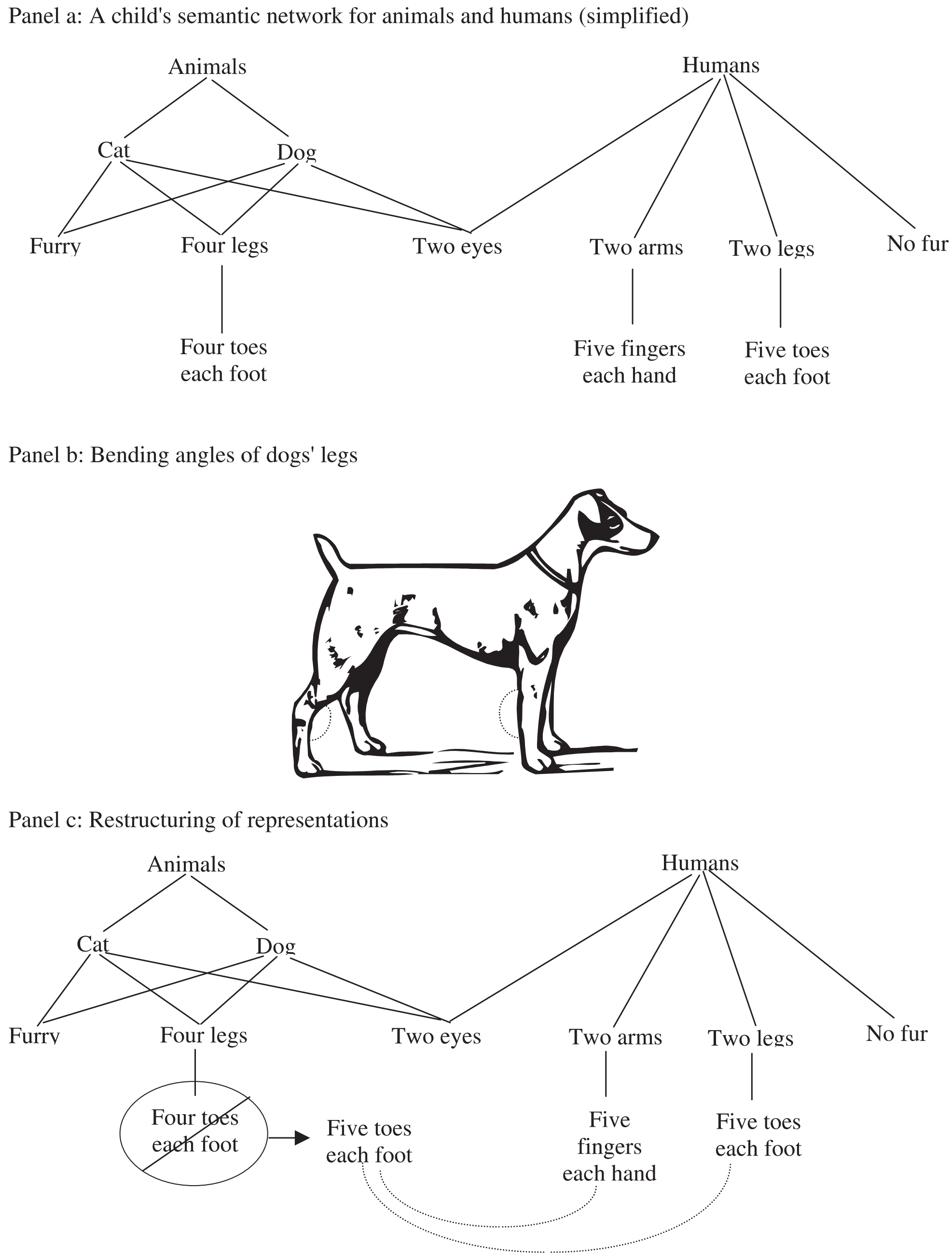


Figure 8. *A semantic network example of a cognitive insight.*

actually be the heel, and the round portion at the top of the dog's leg near the flank as a knee, and everything makes sense: Human arms and legs are roughly the same as dog legs, and dogs essentially walk on their fingertips and their toes. Such a realization is exciting! The child might even speculate that the bottom portion of dog and cat limbs is composed of several bones, like the human hand or foot (the child would be correct; the bottom portion of dog and cat limbs are composed of four metacarpals in the front limb, and metatarsals in the back limbs). The child's mind begins to restructure the representations for animals and humans. Whereas

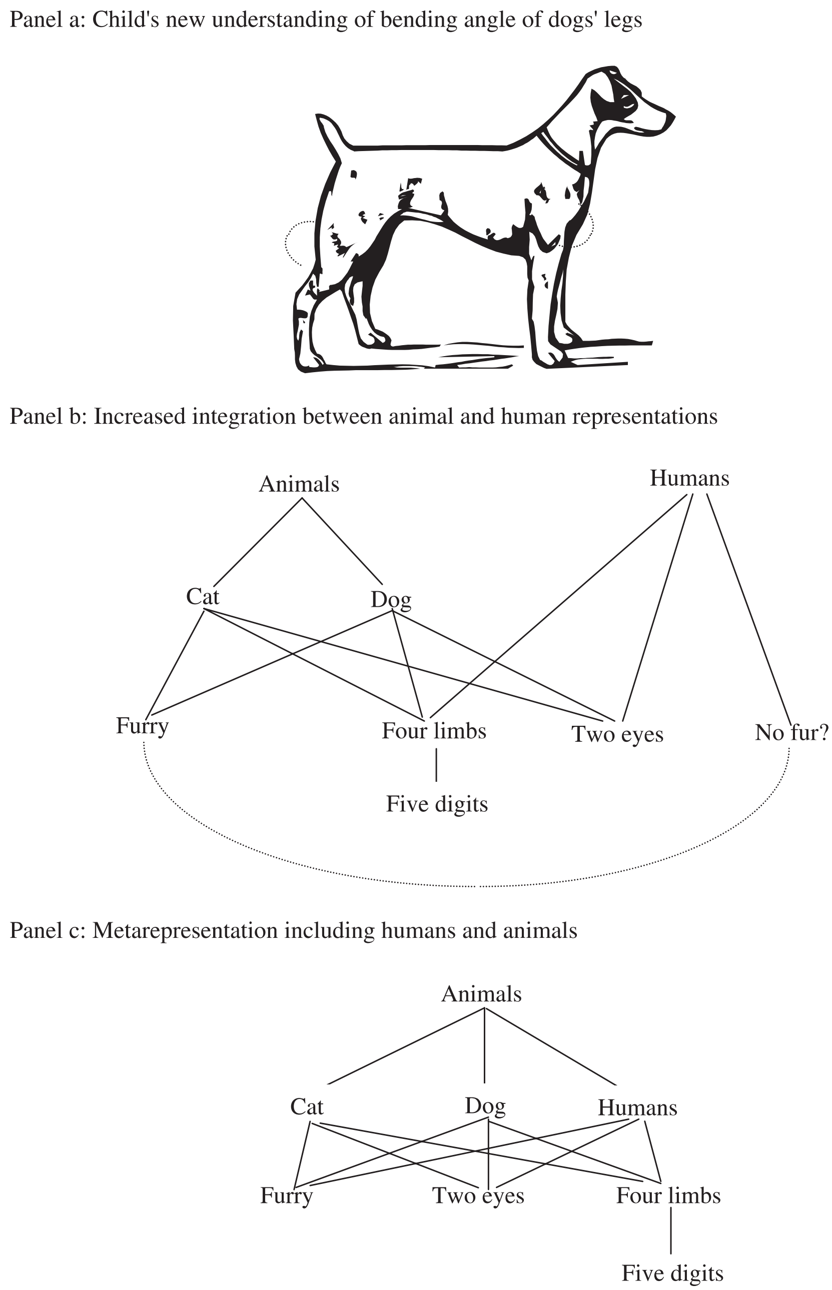


Figure 9. *Semantic network example, continued.*

previously the representations of humans and animals had been quite separate, they now become much more integrated (see Figure 9, panel b), causing the child to spontaneously form (or search for) other associations. For example, the child may suddenly consider the fur of the dog to be roughly the same as the fine hair covering the human body. The single relationship between the number of toes has, in a matter of moments, enabled the child to form multiple links between the representations, including one for which the child has no readily observable evidence (the bottom portion of the dog’s limb being composed of several bones). The child might even come to the conclusion that humans belong in the category of animals, thus creating a single metarepresentation as in Figure 9, panel c.

Describing this event in traditional insight terms demonstrates that any of the alternative views of insight discussed at the beginning of the article could have been used to describe the insight. The representations for animals and humans already shared common fringe elements (e.g., two eyes), but features such as the seemingly incongruent bending direction of the joints and apparent difference in number of digits had served as inappropriate cues, causing a recognition failure (*mental block*). The accidental discovery of the fifth toe (*random recombination with external stimuli*) forges a connection between dog paws and human feet and hands, resulting in a cascade of node and link changes. The presence of five toes rather than four and the position of the fifth toe suggests that the joint just above it is analogous to the human wrist (*finding a problem analog*). This both reorganizes the child's understanding of the dog's feet and legs (*reorganizing visual information* or *reformulating a problem*) and may prompt the recognition of other relationships between dogs and humans, ultimately resulting in combining the two representations (combining existing representations to *complete a schema*). Finding a fifth toe on the dog and the concomitant pattern of symmetry between dogs and humans was unexpected. The resulting restructuring event was of significant magnitude, in part, because the child was able to forge connections among a number of other elements in the two representations. The number of nodes and links affected by the restructuring was thus to some degree a function of how extensive the child's representations for humans and dogs were, indicating the importance of knowledge reservoirs.

It is much simpler to describe the event in graph theory terms: The average path length of the semantic network decreased from 2.74 to 1.90. The distance between any element in the child's representation for dogs and any element in the child's representation for humans has been significantly decreased. Taxonomically speaking, the world has gotten smaller.

A graph theoretical approach can also be used to analyze semantic network diagrams of known insight problems (Durso, Rea, & Dayton, 1994). The network statistics of the simple network diagrams used to illustrate the insight problems discussed previously indicate that their connectivity properties are consistent with small-world network results (see Figure 10).[5] For each of the network diagrams, the number of nodes and the average path lengths are calculated for each step, and the average path lengths are graphed. For visual clarity, the starting point of each graph has been set at one node and zero path length. Disconnected graphs are mathematically considered to have an infinite path length, but for graphical purposes the maximum average path length here is set at 20 (much higher than the average path lengths of any of the connected graphs). Though the network diagrams undoubtedly oversimplify the learner's representations of the problem and solution, each graph shows the characteristic drop in average path length of the network at the point of solution.

Random Recombination Versus Search

It is clear how the random recombination process described by Simonton (1995, 1999a, 1999b) or a random encounter with an external cue as discussed by Siefert et al. (1995) might result in the forging of an atypical path through a cognitive network. It is also possible, however, for such atypical paths to be discovered through a search process. Much of the emerging work on both recombinant search and graph networks invokes an assumption that the network is "searchable." That is, agents in a network do not blindly go down every possible path between any random set of nodes, but rather may intelligently seek out paths that appear more likely than others. Watts, Dodds, and Newman (2002) modeled searchable networks by creating identity vectors for each node that represent sets of characteristics measured along a number of dimensions. In their model, individuals form a measure of "social distance" by identifying the minimum distance between any two nodes over all possible social dimensions. Identity vectors may be what enable individuals to identify a "specific but distant target person" in a remarkably few number of steps. Similarly, it is likely that individuals often arrive at insightful solutions not through a truly random recombination process, but through a process that involves search through their cognitive network (Baughman & Mumford, 1995; Mumford, Baughman, Maher, Costanza, & Supinski, 1997). The associations linked to a knowledge node

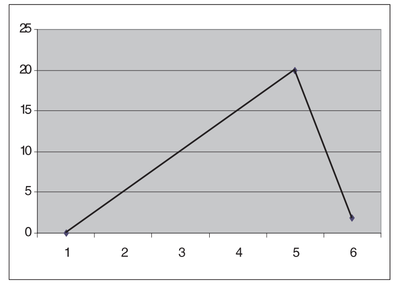
[5]These graphs are representations of actual insight problems; they are not generated with algorithms.

Insight Problems	Graph of Path Length

Man with parachute problem

Step 1. Nodes: 5, Average path length: Infinite

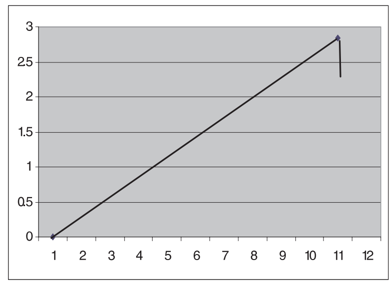
Step 2. Nodes: 6, Average path length: 1.87



Area of shape problem

Step 1. Nodes: 11, Average path length: 2.83

Step 2. Nodes: 11, Average path length: 2.36



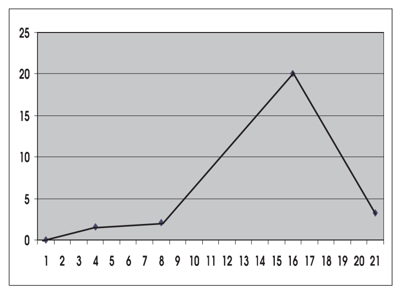
Hoe and banana problem

Step 1. Nodes: 4, Average path length: 1.5

Step 2. Nodes: 8, Average path length: 2.07

Step 3. Nodes: 16, Average path length: Infinite

Step 4. Nodes: 21, Average path length: 3.2



Radiation problem

Step 1. Nodes: 6, Average path length: 2.13

Step 2. Nodes: 10, Average path length: 2.733

Step 3. Nodes: 12, Average path length: 2.49

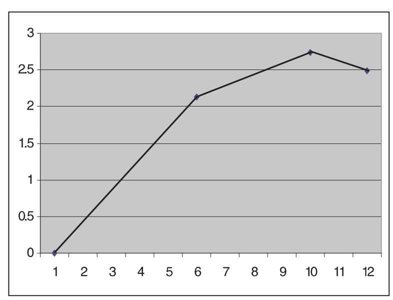


Figure 10. *Network statistics for insight problem diagrams.*

may create an identity map wherein associations serve as identifying features of varying salience. The cognitive network of associations thus may both guide, and be a product of, search.

Search might take place consciously or subconsciously (Siegler, 2000). If the path to a solution is not immediately apparent, the individual may begin to cast a wider net (Perkins, 1981, 1995). Priming (Birch, 1945), analogical solutions (Holyoak, 1984), or random encounters with external stimuli (Siefert et al., 1995), might encourage search in a particular direction, or increase the salience of identifying features that might otherwise be overlooked. Though the initial search may have required pursuing a long path through the network, once a successful combination is made and mentally verified, the point of origination of the search and its final destination may be linked by a very short path, bringing not only these elements much closer together in the network, but also their respective neighborhoods of elements. This explains both why having significant reservoirs of knowledge matters (because shortcuts will bring larger and denser clusters of knowledge together) and why one combination between two knowledge domains may stimulate a cascade of other connections (because many other nodes are now within a relatively close reach of each other).

In sum, I propose that (a) cognitive insight occurs when an atypical association results in a "shortcut" in an individual's network of representations, (i) causing a rapid and significant decrease in path length, (ii) reorienting the individual's understanding of the relationships within and among the affected representations, and (iii) possibly prompting a cascade of other connections; (b) This atypical path may be forged through a random recombination process (Campbell, 1960; Simonton, 1988) or through subconscious or conscious directed search (Baughman & Mumford, 1995; Mumford et al., 1997; Rips, Shoben, & Smith, 1973); and (c) The magnitude of the affective response is a function of (i) the unexpectedness of the connection and (ii) the size and density of the clusters that are brought into closer proximity.

This small-world network approach elucidates how insight is both similar to, and different from, more incremental learning processes. Insight may occur through the same search process that is used in typical problem solving, and both insight and more incremental learning processes may entail adding or changing nodes and their associations in the cognitive network. However, whereas regular learning processes involve the incremental creation, expansion, or refinement of representation networks in a progression that is consistent with (or at least not *inconsistent* with) the individual's perception of the relatedness of the ideas, insight's more revolutionary nature is due to the atypicality of the resulting connection and the reorientation of the network it inspires. This small-world network approach to insight thus offers an explicit structural mechanism underlying insight that (a) integrates previous views of insight, (b) is consistent with emerging theories of insight as the forging of random connections, and (c) is a mathematically verifiable property that can be used to distinguish insightful learning from more incremental learning.

Implications and Extensions

The relevance of small-world connectivity properties should be immediately apparent to scientists that use network models of cognition. As described previously, work has already begun to emerge on how semantic networks might demonstrate small-world properties (Steyvers & Tenenbaum, 2002). Connectionist network models should also be amenable to exploring the impact of small-world connectivity. Connectionist models are slightly more complex than semantic networks; however, the two approaches can be reconciled by considering semantic networks a simplified version of a connectionist model wherein concepts in the semantic network represent "meaning modules" in the connectionist models (Masson, 1991, 1995; Sharkey, 1990).[6] Though I do not know of any research that has begun to explore the possibility of small-world connectivity properties in connectionist models, it is likely that this work will begin to emerge in the very near future.

Why Some People Might Be More Insightful Than Others

This explanation of insight also suggests explanations for why some individuals appear to be more insightful than others. First, individuals may vary in their search proclivities and capabilities. Some individuals may be more likely to consider many possible search paths from a problem (Guilford, 1950, 1967; Khandwalla, 1993; Runco, 1991), increasing their

[6]In connectionist models, concepts are represented by a pattern of activation over the network rather than as a single node (McClelland & Rumelhart, 1986; Medin & Ross, 1992). The connections between units are weighted in such a way that they determine how much influence the activation of one unit has on another. Units that tend to occur together will activate each other, and units that rarely occur together will inhibit each other. McClelland Rumelhart refer to these sets of units as modules. As an individual learns, the weights between units may be adjusted, causing a stimulus to prompt the activation of a modified set of units.

likelihood of identifying a novel solution. This is consistent with early work by Mednick (1962) that suggested that some individuals may have a relatively flat associative hierarchy, meaning that for any given stimulus there are a great many associations that are available. Some individuals may also be more likely or more capable of searching longer paths through their cognitive networks, enabling them to reach more remote associations. For example, some individuals may tend to experience higher states of cognitive arousal, enabling typical spreading activation processes to reach an atypically wide range of connections (Collins & Loftus, 1975; Martindale, 1995). Both of these possibilities are consistent with evidence suggesting that creative people tend to prefer to think in novel ways of their own choosing, tend to be persistent, and tend to be highly motivated by the intrinsic reward of working on a problem they find interesting (Amabile, 1983, 1996; Sternberg & Lubart, 1999).

Second, some individuals might intuitively incorporate a degree of randomness into their association processes that increases their likelihood of insightful discovery. The theory here suggests that there may be some optimum combination of orderly clustering and randomness of association individuals should use if they desire to make insightful discoveries. This echoes and extends the views put forth by Simonton (1995), Cannon (1940), and others: Not only does introducing some randomness into the information connection process increase the likelihood of insightful discovery, but there may also be both upper and lower bounds on the ideal amount of randomness for insightful discovery. In pursuit of an insightful solution, an individual should avoid both being too ordered and being too random. This is consistent with findings that great discoveries are most often discovered by scientists that have considerable expertise in a given area, but who are also thought of as mavericks that do the unexpected (Price, 1963). Either explanation, unusual search abilities or incorporating random recombination, is consistent with a considerable body of research suggesting that the most insightful individuals tend to demonstrate exceptional intellectual versatility and an insatiable curiosity about fields of knowledge outside of their particular specialty (Raskin, 1936; Root-Bernstein, 1995; Simonton, 1976; White, 1931) and that those individuals most prolific in the production of insights commonly engage in many varied projects simultaneously, which evolve into a network of loosely connected enterprises (Gruber, 1989).[7]

Third, some individuals may be more flexible in their ability to reorganize a set of connections in their cognitive network in response to recognition of a new relationship (Guilford, 1950; Lubart, 2000–2001; Baughman & Mumford, 1995; Wicker, Weinstein, Yelich, & Brooks, 1978). To reap the connectivity benefits of an atypical association carving a shortcut through a cognitive network, individuals must be able (and willing) to revise their existing patterns of association. Thus to overcome functional fixedness, individuals must not only be able to consider atypical search paths or random recombination, but must also be able to restructure their network in response to forging a successful combination.

These multiple causal paths to the moment of insight do not imply that insight is poorly defined—rather, from a graph theory perspective, these paths are equifinal. This theory readily lends itself to developing very precise measures of the moment of insight, and even the degree of insight. Should empirical studies verify that insight is the creation of a new small-world network in the mind, we will have reached the verification stage of our own insight: One unlikely connection between cognitive psychology and graph theory may yield a profoundly new understanding of insight and stimulate the recognition of many other possible connections to be made.

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[7]Notably, Simonton also points out that creative people often have thought patterns similar to psychotic people, and may have bizarre conceptual tendencies such as clang associations and overinclusive thinking. Simonton further notes that creative geniuses often come from family pedigrees that contribute more than their expected share of psychiatric patients (1995, 1999b).

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