Chapter 8

Inductive Reasoning

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Inductive reasoning involves inferring likely conclusions from observations or other forms of evidence. For example, if your car starts making loud clunking noises, you might conclude that it probably has a serious and expensive problem. Without reasoning in this manner, the world would be a more primitive and confusing place. It would be impossible to develop scientific theories, forecast the weather, persuasively argue legal cases, learn from mistakes, make predictions about how a best friend will behave around strangers, use previous experiences to help transition to a new job, or think critically before making important decisions. Furthermore, people would probably be less creative (Goswami, 2011; Vartanian, Martindale, & Kwiatkowski, 2003). It even takes inductive reasoning to predict how life would be different without it. In short, this form of reasoning expands and deepens world knowledge, helps social interactions, and allows us to adapt to new environments (Heit, 2000; Rhodes, Brickman, & Gelman, 2008).

As implied above, induction is viewed as the most common form of reasoning that people use in their daily lives (Hayes & Heit, 2017). It can occur so automatically that we are often unaware of quickly using examples, observations, and other existing knowledge to draw conclusions or make predictions about the future. It might seem odd that we frequently rely on inductive reasoning, given that the conclusions from it are never guaranteed to be correct. The data on which they are based is always potentially incomplete or perhaps even flawed, which means the conclusions at their very best can only have a high probability of being right. There is always the chance that they will need to be modified or even rescinded in the future after new evidence is acquired.

Although induction never provides definitive answers, we habitually use it for two primary reasons related to being human. One, we categorize, infer causality, and reason by analogy in an attempt to explain and manage almost everything that happens around us (Feeney & Heit, 2007). For example, people who live near different kinds of dogs might use size, breed, and amount of barking to infer which ones will be friendly and which ones to avoid. Second, we reduce our uneasiness about an uncertain future by using past experiences to predict upcoming events or outcomes (Murphy & Ross, 2007). For example, if you take a new course from a professor who taught two of your other courses, you might reasonably assume that the same study skills that worked well for you in the other two courses will work well in this one.

Why is it important to learn about inductive reasoning? Knowledge about this topic provides us with insight into how humans use limited data to make rational inferences and how, across our lifespans, we generalize from the known to the unknown (Hayes & Heit, 2017). On a personal basis, it helps us learn how to construct strong persuasive arguments that could convince others to adopt our point

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of view (Jones, 2013). Additionally, induction is a major component of other fundamental cognitive activities, such as decision-making, categorization, and similarity judgments (Heit, 2007). In other words, we cannot comprehend the full-range of how humans think and behave if we do not understand when and how inductive reasoning is performed.

Given that inductive reasoning is a central part of being human, it has been examined through a wide variety of approaches. If you are a philosopher like David Hume (1739), you might conclude that inductions are a questionable habit of the mind because using past experiences to predict an unknown future is not logically justifiable. In other words, it is not rational to assume that life twenty years from now will closely resemble the world today. Furthermore, according to Goodman's new riddle of induction, if there is more than one possible future, it is not clear how best to distinguish which one to select (Goodman, 1983). Goodman's answer to his own riddle is that we make projections that are entrenched or well established simply because they are familiar and may have worked in the past. However, there are several psychological approaches to inductive reasoning that are data-driven and examine induction through a wide range of problems, methodologies, models, and developmental perspectives. This rich collection of research has increased our knowledge about the cognitive processes used to reach probabilistic conclusions and how these processes and their regularities relate to other forms of thinking and problem solving (Heit, 2007).

This chapter is divided into five sections. The first compares induction with deduction, the other commonly used type of reasoning. It then examines the attributes that help create strong inductive arguments, followed by descriptions of some different forms of induction. The fourth section reviews how inductive reasoning develops in children. Finally, the chapter's main points are summarized.

8.1 Comparing Inductive Reasoning with Deductive Reasoning

In the past, inductive reasoning has primarily been understood by contrasting it with deduction (Heit, 2007; see Chapter 7 for an in-depth review of deductive reasoning). Inductive reasoning is sometimes described as "bottom-up" logic because specific observations are often used to draw general conclusions or principles that explain the evidence (Johnson-Laird, 2000). For example, after observing that students who show up on time for my classes tend to perform better than ones who arrive late, I might induce that effective time management is a crucial component of academic success. In contrast, deductive reasoning is sometimes defined as the opposite because it often uses "top-down" logic to reason from general principles to derive specific conclusions (Johnson-Laird, 2000). For example, given the premises that every first-year student at my small college must live on campus and Brenda is a first-year student, I deduce that she lives on campus, which means I know how to track her down.

Table 8.1: Key differences between inductive and deductive reasoning.

Basis of Comparison	**Inductive Reasoning**	**Deductive Reasoning**
Typical Direction	Specific to general	General to specific
Type of Premise	Observations and patterns	General principles or facts
Common Type of Process	Often fast and automatic	Often slow and conscious
Conclusions	Go beyond the premises	Follow from the premises
Evaluation	Weak to strong arguments	Invalid/valid conclusions
Best Outcome	Highly likely to be true	Logically true and sound

However, it is important to note that recently the distinction between bottom-up and top-down processing is viewed by some researchers as too simplistic because it does not apply to all cases of induction and deduction (Feeny & Heit, 2007). For example, inductive reasoning sometimes results in specific conclusions. Consider the following problem: "It rained in Seattle yesterday. It rained in Seattle today. Will it rain in Seattle tomorrow?" This scenario requires the solver to determine a probabilistic conclusion that is specific rather than general. Furthermore, there are problems that some people solve inductively and others solve deductively, which means that problem type cannot be used to determine which form of reasoning is being used. Consider, for example, the task of buying a new car. One individual might observe which models are commonly or rarely found in car repair shops before inducing which type of car seems to need the least amount of mechanical work. Another individual might use the premises that "All cars made in Japan are good cars and Toyotas are made in Japan" to deduce that a Toyota is a good car that would be worth buying. Evidence that some problems can be solved either inductively or deductively has resulted in the process view of reasoning (Heit, 2007). Instead of the traditional procedure of using type of problem to determine the form of reasoning being applied, the focus is on the mental processes that each individual employs.

What are the current key differences between inductive and deductive reasoning? Unlike induction, deduction can be independent of external knowledge of the world or it may even contradict such knowledge (Goswami, 2011). The conclusion is completely derivable from the premises and additional information is not required. Consider, for example, the following problem: "All dogs fly. Fido is a dog. Does Fido fly?" The correct answer that Fido flies is unsound and counterfactual but logically valid because the premises, despite being false, require the conclusion to be logically true. If the problem had been "No dogs fly. Fido is a dog. Does Fido fly?" the correct answer that Fido does not fly is sound because it is logically valid and the premises, in reality, are true. In contrast, inductive arguments are dependent on world knowledge rather than on formal rules of logic and they are viewed on a continuum of weak to strong, rather than on the dichotomy of logically valid or invalid (Foresman, Fosl, & Watson, 2017). Extremely weak arguments have such little support that conclusions drawn from them are quite unlikely to be true. Ones that are quite strong are based on relevant, substantial, and compelling evidence. However, even if the premises or arguments are accurate and convincing, we cannot know that new information will be not be found that will overturn our earlier conclusions. In other words, inductive conclusions can be thought of as educated guesses based on our current knowledge. Deductively valid conclusions are not guesses; they are guaranteed to be logically true. Furthermore, inductive reasoning tends to happen more quickly, intuitively, and automatically than deductive reasoning, which often requires more conscious, analytical processing (Heit & Rotello, 2010). Some research has also found more activation in the brain's left prefrontal cortex during inductive reasoning than during deductive reasoning (Hayes, Heit, & Swendsen, 2010). Table 8.1 summarizes key differences between these two forms of reasoning.

There are several similarities between induction and deduction that deserve recognition. For example, both involve evidence, logic, working memory, and are central to critical thinking (Foresman et al., 2017; Süß, Oberauer, Wittmann, Wilhelm, Schulze, 2002). Both are used in the scientific method. As John Steinbeck (1954) describes,

> Everyone knows about Newton's apple. Charles Darwin and his *Origin of Species* flashed complete in one second, and he spent the rest of his life backing it up; and the theory of relativity occurred to Einstein in the time it takes to clap your hands. This is the greatest mystery of the human mind–the inductive leap. Everything falls into place, irrelevancies relate, dissonance becomes harmony, and nonsense wears a crown of meaning. (p. 20)

Although Steinbeck undoubtedly over-estimated the frequency of true inductive leaps, inductive reasoning is used to form hypotheses and theories that advance scientific knowledge. However, this is not nearly enough; scientists then need to use deductive reasoning to test their hypotheses and theories on specific situations in order to verify their accuracy. In addition, both forms of reasoning are continuous across our lifespans and are susceptible to similar heuristics and biases (Goswami, 2011).

8.2 Inductive Reasoning at Its Best

As noted earlier, we can never be 100% certain that our inductive conclusions are right. However, by keeping the following attributes in mind, we can reduce errors and biases, which increases the likelihood that our inductive arguments are strong and the conclusions are warranted, justifiable, and have a high probability of being true.

8.2.1 A Sizeable Sample

A large number of observations typically increases the strength of inductive arguments, which makes the conclusions more likely to be accurate (Nisbett, Krantz, Jepson, & Kundra, 1983). Consider the following two examples:

> *Observations*: Every morning for the past 8 months, George drank a large glass of milk and thirty minutes later his stomach consistently started hurting.
>
> *Conclusion*: George has lactose intolerance.
>
> *Observation*: Natalie ate a peanut and then had trouble breathing.
>
> *Conclusion*: Natalie has a peanut allergy.

The first example has a stronger argument than the second because it is based on approximately 250 observations or pieces of evidence rather than only one. Although there are exceptions (Osherson, Smith, Wilkie, Lopez, & Shafir, 1990), a large sample size helps maximize information, reduces distortions in the evidence, and makes the conclusions more likely to be correct (McDonald, Samuels, & Rispoli, 1996; Nisbett et al., 1983).

The importance of a large sample is highly relevant to both scientific research and inductive reasoning in our daily lives. Given that there are individual differences in human behavior, psychological research, in particular, needs to have a large number of participants and numerous experimental trials or survey questions in order for the data to be robust and trustworthy. Non-scientists have also been found to pay attention to number of observations, especially when making inductions about highly variable attributes. For example, Nisbett and his colleagues (1983) asked college students to estimate the percentage of obese male members of the Barratos tribe if they observed one obese tribesman, three obese tribesmen, or twenty of them. Results showed that participants were least likely to make strong inferences based on only one tribe member; conclusions were strongest for the highest number of observations. This finding is known as **premise monotonicity**, which means that a higher number of inclusive premises results in a stronger inductive argument than a smaller number (Osherson et al., 1990). However, as will be explained in the section on representativeness, individuals do not always take sample size into account as much as they should.

8.2.2 Diverse Evidence

Although the milk example presented earlier involves numerous observations, the conclusion that George has lactose intolerance would have a higher probability of being true if it were based on a wide range of evidence, such as George getting stomach aches after consuming other lactose-based foods, George's health history, and observations conducted at different times of the day and night. In other words, inductive arguments are stronger if they present a range of converging evidence taken from different sources (Heit, 2000). For this reason, scientific experiments are often conducted in various ways using different types of participants in order to test a single hypothesis. For example, inductive reasoning has been studied using objects, cartoon pictures, complex verbal arguments, computational models, and participants of different ages from various backgrounds (Heit, 2007).

Given that it would be time consuming and often impossible to collect every possible observation, people often use shortcuts or heuristics to reach inductive conclusions (see Chapter 10,"Decision Making", for more information about heuristics.). In many cases these heuristics can result in quick and highly probable conclusions. Unfortunately, sometimes they can cause errors. One of these heuristics or "rules of thumb" is the **availability heuristic**, which can undermine our diversity of evidence. We tend to use information that easily comes to mind, without also considering a significant number of cases that take longer to retrieve from memory. For example, when Amos Tversky and Daniel Kahneman (1973) asked people to predict whether there are more words in the English language beginning with the letter R or more words with R as the third letter, 69% of their participants erroneously predicted that more words begin with R. In other words, it is easier to generate words like "rutabaga", "rat", and "ridiculous" than it is to think of instances like "bard", "certify", and "dare." According to Tversky and Kahneman, "to assess availability it is not necessary to perform the actual operations of retrieval or construction. It suffices to assess the ease with which these operations can be performed" (p. 208). However, other researchers believe information must be retrieved from memory because it is used to guide and evaluate inductive inferences (Shafto, Coley, & Vitkin, 2007).

Moreover, the availability heuristic applies when people easily retrieve information from memory that indicates there is a relationship between events, categories, or attributes. They then base their inductive conclusions on this perceived correlation, which can often be quite useful. For example, if you remember that your professor has granted requests for paper extensions when he or she is in a good mood, you might take this information into account when you want permission to turn your paper in late. However, the availability heuristic can sometimes result in an **illusory correlation**, which means that people believe a relationship exists when, in reality, it does not (Hamilton & Lickel, 2000). For example, prejudicial conclusions are sometimes drawn when individuals have information readily available in memory that leads them to believe there is a correlation between negative personality traits and a particular group of people. In short, making predictions based only on easily retrievable evidence can result in wrongly assuming correlations exist, which lowers the strength of our arguments and reduces the likelihood that our inductive conclusions are correct.

Having a range of evidence, if it is chosen correctly, can also help prevent **confirmation bias**. We have a tendency selectively to seek data that supports our hypotheses, while overlooking information that would invalidate them. Suppose someone gave you the numbers 2, 4, and 6 that conform to a rule and asked you to discover the rule by generating sets of three numbers you think would fit. What do you think the rule is and which three numbers would you select to test your hypothesis? When Peter Wason (1960) gave this task to adults, his nonobvious rule was "three numbers in increasing order of magnitude" but most participants assumed the rule was "increasing intervals of two". Box 8.1 shows his instructions and examples of different ways of responding. Thirty-one percent of the participants practiced what Wason refers to as enumerative induction; they did not try to disconfirm their hypothesis by testing odd numbers or descending ones. As a result, they never discovered the correct rule. In science and in everyday life, it is essential to practice **eliminative induction** by seeking both confirming and disconfirming evidence before drawing conclusions.

The availability of different types of knowledge to inform our inductive reasoning is dynamic; it can change based on context and effects of prior experience (Shafto et al., 2007). More specifically, the information in the premises of an inductive problem can have an immediate consequence for which knowledge we retrieve from memory in order to make our generalizations. If we are told that dogs have a recently discovered illness, we might infer that cats will get it too because we remember they often live in the same households. However, if we discover that dogs have a recently discovered gene, we would be more likely to conclude that wolves also carry it because we remember that the two species are genetically closely related. In contrast, prior experience has long-term consequences for knowledge availability. For example, novices in a domain are more likely to retrieve taxonomic or categorical information than are domain experts, who tend to rely more on causal, thematic, and ecological relationships. Interestingly, if put under time pressure, experts often fall back on using taxonomic similarity to draw their conclusions (Shafto, Coley, & Baldwin, 2007).

Textbox 8.1: Examples of Enumerative and Eliminative Induction on the 2-4-6 task

Instructions

You will be given three numbers which conform to a simple rule that I have in mind. This rule is concerned with a relation between any three numbers and not with their absolute magnitude.... Your aim is to discover this rule by writing down sets of three numbers, together with reasons for your choice of them. After you have written down each set, I shall tell you whether your numbers conform to the rule or not.... There is no time limit but you should try to discover this rule by citing the minimum sets of numbers. Remember that your aim is not simply to find numbers which conform to the rule, but to discover the rule itself. When you feel highly confident that you have discovered it, *and not before*, you are to write it down and tell me what it is (Wason, 1960, p. 131).

Trial	Participant's # Sets	Type of Feedback	Current Hypothesis	Strategy	Overall Induction Type
1	4-6-8	"Yes"	Even & Increasing by 2s	To confirm	Enumerative (only confirming)
2	6-8-10	"Yes"	Even & Increasing by 2s	To confirm	
3	20-22-24	"Yes"	Even & Increasing by 2s	To confirm	
4	8-10-12	"Yes"	Increasing by 2s	To confirm	
Participant never gets the correct rule.					
1	22-24-26	"Yes"	Increasing by 2s	To confirm	Eliminative (both confirming & disconfirming)
2	6-4-2	"No"	Increasing by 2s	To disconfirm	
3	1-17-23	"Yes"	Ascending #s	To confirm	
4.	3-2-1	"No"	Ascending #s	To disconfirm	
Participant announces the correct rule.					

8.2.3 Representative Observations

To achieve strong inductive arguments, it is not enough to have several observations that include diverse evidence. The observations must also fully represent the entire population or category of interest. For example, suppose you wanted to predict whether the citizens of California believe the legal drinking age should be lowered from age 21 to 18. Polling undergraduates at several universities in California would probably tell you more about college students than it would about the beliefs of people in the entire state. To draw potentially accurate conclusions about drinking attitudes in California, it would be important to obtain opinions from a representative cross-section of the people who live there. Similarly, results from scientific studies can only be safely generalized to the population represented in the sample of participants. Experiments conducted on mice, college students, males, or individuals from a specific culture are often replicated using members of other populations so that the conclusions can encompass other species or all humans.

In solving inductive reasoning problems, individuals often use the **representativeness heuristic**. When trying to estimate the probability of an event, this short cut involves finding a comparable case or prototype and assuming that the two events have similar probabilities. Consider a problem developed by Tversky and Kahneman (1974): "Steve is very shy and withdrawn, invariably helpful, but with little interest in people, or in the world of reality" (p. 1124). Is Steve more likely to be a farmer, librarian, salesman, airline pilot, or physician? Using the representativeness heuristic, people are likely to respond that Steve has the highest probability of being a librarian because he best fits how they view a typical librarian. However, this conclusion can be inaccurate if important base rate information is not taken into account. At the time the study was conducted, there were more male farmers than male librarians in the United States.

In addition, people do not always take small sample sizes into account to assess representativeness. One demonstration of this is another study conducted by Tversky and Kahneman (1974). Ninety-five participants were asked the following question:

> A certain town is served by two hospitals. In the larger hospital about 45 babies are born each day, and in the smaller hospital about 15 babies are born each day. As you know, about 50 percent of all babies are boys. However, the exact percentage varies from day to day. Sometimes it may be higher than 50 percent, sometimes lower. For a period of 1 year, each hospital recorded the days on which more than 60 percent of the babies born were boys. Which hospital do you think recorded more such days? (p. 1125)

The answer options were (1) the larger hospital, (2) the smaller hospital, or (3) about the same (within 5 percent of each other) for the two hospitals. Over half of the participants predicted the recordings would be about the same, presumably because they assumed that both hospitals would be equally representative of male and female birth rates in the general population. However, the correct answer is the smaller hospital because about 15 babies born each day will show more fluctuation in the number of males and females born than will the bigger sample size at the larger hospital, which is more likely to reflect the statistic found in the general population.

8.3 Different Forms of Inductive Reasoning

Given that induction is central to our daily lives as we engage in a variety of activities, it is not surprising that there are different ways we use it. Four of these will be covered in this section.

8.3.1 Category-based Induction

Category-based induction has probably been studied more than any other form of inductive reasoning (Heit, 2007). In this type of reasoning, if people are told that one or more members of a category have a certain property, they then determine whether other members of the category are likely to have the same property. For example, if you observe that chimpanzees groom each other, you would probably infer that gorillas have the same behavior. Would you also conclude that groundhogs groom each other?

8.3.1.1 Premise Typicality

In a classic study conducted by Lance Rips (1975), participants were told that a particular species on an isolated island had a new contagious disease and then asked to estimate the likelihood that other kinds of animals on the island would contract the disease. Results indicated that species' typicality had a large influence on individuals' inductive judgments, even when similarity was held constant. In other words, if one species (e.g., a robin) is highly representative of an inferred superordinate category (e.g., birds), individuals were more likely to generalize to other members (e.g., sparrows) than if the same information was given about an atypical member (e.g., canary). It is more convincing to project the robins' disease onto sparrows than it is to generalize the disease from canaries to sparrows.

There is also premise-conclusion asymmetry, which means a single-premise argument is viewed as stronger if the more typical member of an inferred superordinate category is used in the premise rather than in the conclusion. For example, it is more convincing to project a property of lions onto bats than the other way around because lions are viewed as a better prototype of mammals than are bats (Smith, Shafer, & Osherson, 1993).

8.3.1.2 Category Similarity

Two categories are highly similar if they have several features in common and few distinctive ones they do not share. Perceived similarity between the premise category and the conclusion category strengthens inductive arguments and increases the likelihood that a novel property of one category will be generalized to another category (Hayes & Heit, 2017). For example, individuals are more likely to generalize a property from lions to wolves than from hippopotamuses to giraffes.

The similarity-coverage model (Osherson et al., 1990) posits that individuals automatically compute similarity and make inductive generalizations when (a) there is a great deal of overlap between the features of the premise and conclusion categories and (b) there is substantial similarity between premise features and the inferred superordinate category (e.g., mammals) that is inclusive of the premises and conclusion. This model is predictive of the premise-conclusion similarity effect found in many studies of category-based induction (Hayes & Heit, 2017). It can also account for the premise typicality results mentioned earlier. Typical premises have higher mean similarity to the inferred superordinate category than do atypical ones, which means that typicality provides better coverage.

8.3.1.3 Premise Diversity

After typicality and premise-conclusion similarity, probably the next most important attribute to consider is diversity of the actual premises. Other things being equal, arguments are stronger and conclusions are more probable if dissimilar subordinate categories are used as evidence (Smith et al., 1993). For example, if given the information that mice and lions share the same property, it is more likely that we will predict that elephants and other mammals also have the property than if we are told that cougars and lions share the property. Similarly, as mentioned earlier, premise monotonicity increases the amount of evidence and typically strengthens inductive arguments (Osherson et al., 1990). For example, information that mice, lions, bears, dog, and horses share a property is stronger evidence than knowing only about mice and lions.

The similarity-coverage model (Osherson et al., 1990) mentioned above accounts for this diversity effect; less similar subordinate categories tend to provide more coverage of the inferred superordinate category (e.g., mammals) than do subordinate categories that are quite similar. In the same way, premise monotonicity provides more coverage of the inferred superordinate category and makes a property more likely to be generalized.

Premise typicality, category similarity, premise diversity, and premise monotonicity involve taxonomic relationships between premises and conclusions. As noted earlier, novices in a domain are more likely than experts to be influenced by these taxonomic relations (Hayes & Heit, 2017). Experts tend to rely instead on thematic, causal, and ecological relations for their generalizations of properties related to their domain of expertise. For example, when tree experts were asked to infer which of two novel diseases would be most likely to affect all trees, they focused on causal-ecological factors related to how tree diseases work and "local coverage", which involves extending the property to other members of the same folk family. In other words, they were not very influenced by typicality and diversity of the premises (Proffitt, Coley, & Medin, 2000).

8.3.2 Causal Induction

Predicting what causes certain events and outcomes is an important part of being human. This form of reasoning is commonly used in both science and in our daily lives to advance knowledge and give us a sense of control. For example, predicting that not going to class or turning in the work will result in a failing grade can motivate students to attend and finish assignments. However, poorly executed causal reasoning can result in superstitions, such as believing that breaking a mirror causes seven years of bad luck.

Causal relations are so important to us that they typically outweigh other information. Even for non-experts, for example, the presence of a causal relation can over-ride taxonomic ones, such as premise typicality, category similarity, premise diversity, and premise monotonicity. In a demonstration of causality's strong influence (Rehder, 2006), participants were given a novel category (e.g., Kehoe ants) and told characteristic features of its members (e.g., their blood has high amounts of iron sulfate). Participants were then told about a novel property possessed by one of the category members (e.g., it has a venom that gives it a stinging bite) and asked to estimate the proportion of all category members that also possessed this new property. In some conditions, participants were told that the new property was caused by a characteristic feature they had previously learned (e.g., the stinging bite is caused by the high amounts of iron sulfate in its blood). When causal explanations were present, the standard effect of typicality was almost completely eliminated. Additional experiments demonstrated that causal explanations also drastically reduced the effects of premise typicality, diversity, and similarity.

John Stuart Mill (1843) was one of the first to propose a theory of causality and it includes five methods (or canons) of causal analysis that focus on the observation of patterns. Four of the five involve inductive reasoning and each of these is paraphrased and briefly described below. The first three help people practice Wason's (1960) notion of eliminative induction; ruling out some possible causes helps narrow the hypotheses for what actually is the cause.

1. Method of agreement: If all observed cases of a phenomenon have only one factor in common, then that factor is the likely cause of the phenomenon. For example, if you and the rest of your family got food poisoning after dining at a buffet, you and the health department would be highly motivated to determine the cause. Table 8.2 illustrates a systematic way to determine whether there was one item you all ate in common, while ruling out the others.

2. Method of disagreement: If a phenomenon occurs in one observed case and not in another and there is only one circumstance that differs between the two cases, then this circumstance is the likely cause of the phenomenon. If all of your family members got food poisoning except for you, determining the food they ate that you wisely avoided will allow you to infer the most probable cause of their illness. As shown in Table 8.3, the items you had in common are eliminated in order to detect the unshared one.

Table 8.2: Method of agreement indicating fish as the source of illness.

Member	**Salad**	**Bread**	**Fish**	**Pie**	**Ill?**
Mom	Yes	No	Yes	No	Yes
Dad	Yes	No	Yes	Yes	Yes
Brother	No	Yes	Yes	Yes	Yes
You	Yes	Yes	Yes	Yes	Yes

Table 8.3: Method of disagreement indicating pie as the source of iIllness.

Member	Salad	Bread	Fish	Pie	Ill?
Mom	Yes	No	Yes	Yes	Yes
Dad	Yes	No	Yes	Yes	Yes
Brother	No	Yes	Yes	Yes	Yes
You	No	Yes	Yes	No	No

3. Joint method of agreement and disagreement. As the name implies, this canon essentially combines the first two methods. Suppose you and your brother did not get food poisoning but, sadly, your parents did. As illustrated in Table 8.4, it would be important to know if there was anything your parents ate that you and your brother avoided. If there is, then this item would be a likely cause of their foodborne illness. The experimental method used in psychology fits this method well because one group of participants receives the experimental condition and the other does not; everything else is held constant for the two groups. If one group shows different behavior than the other, then it is appropriate to conclude that the experimental manipulation caused the difference. This is why results from scientific experiments can be used to draw cause and effect conclusions but surveys and naturalistic observation cannot.

4. Method of concomitant variation. If there is a high correlation in the variations occurring for two different phenomena, one phenomenon is likely to be the cause of the other or a third unknown variable might be causing the variation in both. Suppose you did not eat berry pie at the buffet, your mom had half a piece, your brother had a whole one, and your dad ate five pieces. You feel fine later that night, your mom feels a bit queasy, your brother is moderately sick, and your poor dad needs to be rushed to the hospital. A highly probable conclusion to infer from this evidence is that suffering from the effect (i.e., food poisoning) is proportional to the cause (i.e., the amount of pie consumed).

Mill's methods provide useful tools for finding potential reasons for effects but they are limited to what we choose to focus on. Potential causes will not be observed and found unless we already have relevant hypotheses about what the causes are likely to be. For example, in discovering the source of food poisoning, factors other than a buffet dinner might be involved.

Miriam Schustack and Robert Sternberg (1981) examined what sources of information people actually use when making causal inferences about un-

Table 8.4: Joint Method of agreement and disagreement indicating salad as the source of illness.

Member	Salad	Bread	Fish	Pie	Ill?
Mom	Yes	No	Yes	No	Yes
Dad	Yes	No	Yes	Yes	Yes
Brother	No	Yes	Yes	Yes	No
You	No	No	Yes	Yes	No

certain and complicated situations. For example, participants were given information about various cosmetic companies, including the facts that (a) a company did or did not have a major product under suspicion as a carcinogen and (b) the company's stock had or had not drastically dropped. Participants were then asked to infer the probability that some other cosmetic company would have its stock values drop drastically if it had a major product under suspicion as a carcinogen. Overall results indicated that people confirm a causal relationship in one of two ways. One, which is related to Mill's method of agreement, is based on evidence of the joint presence of the hypothesized cause (e.g., suspicion of a carcinogen) and effect (e.g., declining stock values). The other, which is related to Mill's method of disagreement, is based on evidence of the joint absence of the hypothesized cause and effect. Overall results also indicated that people disconfirm causality in one of two ways. The first focuses on the presence of the hypothesized cause but the absence of the outcome and the other is based on the absence of the cause, yet the outcome still occurs. These overall findings are supported by Rehder's (2006) result that an effect is viewed as more prevalent if the cause is also prevalent.

8.3.3 Analogical Reasoning

Even though many people hate answering analogy problems on standardized tests, this form of induction allows us to use familiar knowledge to understand something we do not know. For example, learning the structure of an atom might be easier if it is compared to already acquired knowledge about the solar system. The sun and its orbiting planets can help us comprehend the atom's nucleus and the electrons that move about it. Analogical reasoning can also cause us to consider familiar material in new ways. When Kevin Dunbar and his colleagues (Dunbar, 1995; Dunbar & Blanchette, 2001) videotaped immunologists and molecular biologists during their lab meetings, they discovered that the scientists frequently used analogies 3 to 15 times in any given meeting as an important source of knowledge and conceptual change. For example, when discussing the flagellar pocket, a postdoctoral fellow said, "Things get in, but things... It's like the Hotel California - you can check in but you can never check out" (Dunbar, 1995, p. 383).

As implied above, analogical reasoning typically works by comparing two domains of knowledge in order to infer a quality they have in common. The first domain is often the more familiar of the two and it serves as the base or source. It provides a model for understanding and drawing inferences about the target, which is often the more novel or abstract domain (Gentner & Smith, 2012).

Robert Sternberg (1977) used simple picture, verbal, and geometric analogies to determine the components of analogical reasoning (Figure 8.1 shows examples similar to the ones he used). Consider the following verbal problem, which involves choosing the best option for the end of the analogy.

A lawyer is to a trial as a surgeon is to:

(a) a stethoscope, (b) medical school, (c) an operation, (d) patients.

The successful analogy solver encodes the first two terms of the base (i.e., lawyer and trial), which includes forming an appropriate mental representation of them in memory. Next one or more relations between these two items are inferred (e.g., lawyers present their cases during a trial). The term 'surgeon' is then encoded and an overall relation is mapped between a lawyer and a doctor (e.g., they are both practicing professionals). This is followed by applying the relation in the base to the target. Finally, a response is prepared and given (i.e., operation is the correct answer because surgeons perform their procedures during an operation and lawyers perform theirs during a trial.)

Using mathematical modeling, Sternberg (1977) analyzed the amounts of time participants spent on the components of analogical reasoning mentioned above: encoding, inference, mapping, application of the relation, and preparation-response. Interestingly, he found that participants spent quite a bit more time on encoding and preparation-response than inference, mapping, and application. Furthermore, for all three types of analogies (picture, verbal, and geometric), the preparation-response component was the one most highly correlated with standardized tests of reasoning.

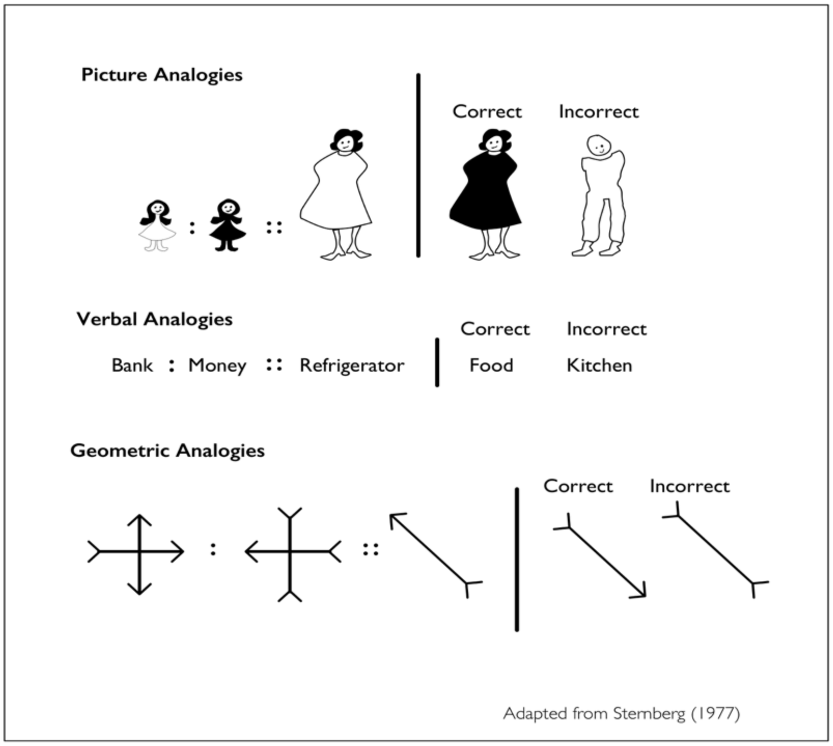

Figure 8.1: Examples of different types of analogies.

In later work, Sternberg identified higher-order components (metacomponents) that are used successfully to plan, evaluate, and monitor strategies and solutions for analogies and other problems. For example, some individuals do not form a connection between the first and second halves of an analogy because they do not select the lower-level component of mapping (Sternberg & Rivkin, 1979). Other individuals might not select the best strategy for combining lower-level components and they end up using an inefficient search strategy for inferring relations between the first two terms in an analogy (Sternberg & Keatron, 1982). Not surprisingly, Sternberg's work on analogical reasoning plays an influential role in his triarchic theory of intelligence (1988) and his theory of successful intelligence (1997).

As Sternberg's work indicates, the elements in an analogy need to be linked by a relation they have in common. In other words, relational (or structural) similarity is a basic constraint of this form of reasoning (Goswami, 2011). Surface similarity is not required; objects in each domain do not need to resemble each other physically or have the same behaviors. For example, computers and humans do not look or act alike but they are relationally similar in terms of information processing. However, surface similarities can facilitate the mapping of relations and improve performance (Gentner, 1989; Holyoak & Koh, 1987).

Interestingly, analogical reasoning is not always done consciously and deliberately. For example, Blanchette and Dunbar (2002) had participants read descriptions of a target topic (e.g., legalization of marijuana) and then read shorter information about a potential analogical base (e.g., prohibition). Afterwards, when participants were given a recognition test, they erroneously believed that their analogical inferences were concrete facts actually presented in the target description. In other words, they unconsciously inserted their inferences into their mental representations of the target domain.

8.3.4 Insight

Sudden insight into the solution of a seemingly impenetrable problem is another form of inductive reasoning (Goswani, 2011) or what Steinbeck (1954) referred to as the inductive leap. The Gestalt psychologists paved the way for later research on this creative and productive way of thinking, which occurs when an individual goes beyond old associations and suddenly views information in a new way (see Chapter 9, "Problem Solving", for more information about Gestalt theory and insight). A novel solution and a subjective feeling of "aha", or suddenly knowing something new without consciously processing how one arrived at it, often accompany this new perception of the situation (Topolinski & Reber, 2010). In contrast, an analytic process involves consciously and systematically evaluating the problem, using strategic thinking and deduction.

In support of this view of insight, Janet Metcalfe (1986a, 1986b; Metcalfe & Weibe, 1987) and Davidson (1995) found that incremental increases in feelings of confidence (or warmth) that one is nearing a solution negatively predict correct solution of insight problems but positively predict correct solution of deductive reasoning problems. In other words, individuals who felt they were gradually getting closer to solving insight problems tended to arrive at incorrect solutions; others who thought they were far from solving the insight problems and then suddenly realized the answers tended to be accurate. Metcalfe concludes that insight is a subjectively catastrophic process, not an incremental one.

An important source of insight involves cognitive restructuring of a problem's components, which can occur multiple times as an individual moves from general to specific mental representations of a problem (Mayer, 1995). Unlike routine or well-defined problems, ill-defined or non-routine ones are more likely to require individuals to search through a space of alternative approaches (Newell, & Simon, 1972) because the givens, goals, and obstacles are not clear. However, it should be emphasized that insight is process rather than problem oriented. One individual may solve a problem by having an inductive leap; another person may solve the same problem incrementally and consciously, especially if it is familiar (Davidson, 1995; Webb, Little, & Cropper, 2016).

The Gestalt psychologists believed that people's inability to restructure a problem's components and produce an insightful solution is often due to their fixation on past experience and associations. For example, in what is now seen as a classic insight problem, Karl Duncker (1945) gave individuals three small cardboard boxes, candles, matches, and thumbtacks. The participants' task was to mount a candle vertically on a screen so that it could be used as a reading light. The solution is to light a candle, melt wax onto the top of a box, stick the candle into the wax, and tack the box to the screen. Participants who were given boxes filled with tacks, matches, and candles had much more difficulty solving the problem than did those who received the same supplies outside of the boxes. According to Duncker, seeing a box serve the typical function of a container made it difficult for many individuals also to view the box as a structural support. This phenomenon became known as **functional fixedness**.

Similar types of mental blocks can interfere with insightful problem solving. In particular, even when we realize that we are approaching a problem incorrectly, we often cannot break our fixation on this approach in order to change our strategies or search for new evidence. Fortunately, taking a break when we reach an impasse often allows us to stop this fixation and see material in a new way when we return to it (Davidson, 2003).

8.4 How Does Inductive Reasoning Develop?

Young children have limited knowledge about the world and they have a lot to learn in a relatively short amount of time in order to adapt well to their environments. Inductive reasoning allows them to acquire new information and fill in gaps in their knowledge. Not surprisingly, research shows this form of reasoning appears early in development. For example, infants between 9-16 months of age make inductive inferences based on perceptual similarities of objects, expecting new ones to wail when squeezed if they physically resemble a previously squeezed one that wailed (Baldwin, Markman, & Melartin, 1993). Although inductive reasoning is relatively continuous across the human lifespan, it becomes more complex as children's cognitive skills, experience, and knowledge base expand and they become better able to evaluate and apply evidence to draw likely conclusions (Goswami, 2011; Hayes, 2007).

8.4.1 How Children Use Inductive Evidence

8.4.1.1 Sample size

Do children, like adults, take sample size into account when making inductive generalizations? Evidence indicates that they do if the tasks are made simple enough. Grant Gutheil and Susan Gelman (1997) asked 8-10 year old children to make inductions based on small and large samples of observable features. For example, children were shown a picture of one butterfly and told that it has blue eyes. They were also shown a picture of five butterflies and told that all of these butterflies have gray eyes. The experimenter then looked at a picture but did not show it to the children and asked whether they thought the butterfly in the picture has blue eyes or gray eyes. The children were significantly more likely to generalize traits, such as eye color, from the large sample than from the small one.

Similarly, it has been found that children younger than age 6 take number of observations into account for their inductive generalizations if the task involves only one sample of evidence (Jacobs & Narloch, 2001; Lawson & Fisher, 2011). If they need to compare a larger sample with a smaller one, the cognitive demands are too great for them to do this well (Gutheil & Gelman, 1997; Lopez, Gelman, Gutheil, & Smith, 1992).

8.4.1.2 Diversity

As discussed earlier, adults are more likely to make inductive generalizations from different types of converging evidence than from only one type. The results for children under age 10 have been more mixed, with some studies finding no evidence of diversity effects (Carey, 1985; Gutheil & Gelman, 1997; Lopez et al., 1992) and others finding that young children often over-generalize from diverse data (Carey, 1985; Lawson & Fisher, 2011). However, if the tasks have low cognitive demands and no hidden properties, young children seem capable of taking diversity into account. For example, when shown pictures of three very different types of dolls played with by Jane and three quite similar dolls played with by Danielle and then shown a picture of another kind of doll, 73% of participants ages 5 and 6 inferred that Jane rather than Danielle would want to play with the new type of doll (Heit & Hahn, 2001). However, it was also found that children were less likely to use diverse evidence when making inferences about remote categories or hidden properties of objects.

Interestingly, Margorie Rhodes and Peter Liebenson (2015) found that children ages 5-8 appropriately used diverse evidence more than non-diverse information when making inductions about novel categories but not when making them about familiar natural kinds (e.g., birds). In other words, category knowledge interfered with their diversity-based reasoning. In contrast, children ages 9 and 10 generalized more broadly from diverse samples than non-diverse ones when reasoning about both novel categories and natural kinds. These results indicate both developmental continuity and change in diversity-based inductions. At least by age 5, children have the cognitive mechanisms for incorporating different types of information into their generalizations, as shown by their use of diverse evidence when reasoning about novel categories. However, there is developmental change for the situations in which children access these mechanisms.

8.4.1.3 Typicality

Several studies have found that young children are similar to adults in making inductive inferences based on premise typicality or how well an item represents a familiar category. For example, Gelman and Coley (1990) showed 2-year-old children a picture of a typical bird (e.g., robin), told them it was a bird, and asked them about one of its properties (e.g., "Does it live in a nest?"). The children were then shown atypical (e.g., dodo) and typical (e.g., bluebird) category members without the category name (e.g., bird) being repeated and asked if each one lives in a nest. The results were that children projected the property (e.g., living in a nest) to typical category members (e.g., bluebird) 76% of the time and to atypical members (e.g., dodo) only 42% of the time. Similar behavior was found for 3- and 4-year old children (Gelman and Markman, 1986). In addition, as with adults, premise-conclusion similarity also increased inductive inferences.

8.5 Development of Forms of Induction

As implied by the previous section, young children can usually perform category-based inductive reasoning, causal reasoning, and analogical reasoning if the tasks are simple and the children have the requisite knowledge about the properties, categories, and causal or functional relations that are used in the tasks (Goswami, 2011; Hayes, 2007). As Goswami notes about the development of analogical reasoning, "in the absence of the requisite knowledge, it is difficult to reason by induction" (p. 405).

Research indicates that by the time children are around age 5, they most likely use the same broad relations and cues that adults use for their inductive inferences (Hayes, 2007). The developmental changes that do occur are mostly quantitative and gradual, with some types of information, such as causal relations, being applied more frequently and across more domains. As they develop, children's knowledge base increases, their inhibition and memory retrieval processes become more efficient, and their relational working memory capacity improves (Perret, 2015). These cognitive changes allow children to perform more complex category-based inferences, causal inductions, and analogical reasoning.

In addition, some research indicates that children age 6 or older are more likely to have insights than those who are younger. For example, Tim German and Margaret Anne Defeyter (2000) gave children aged 5-7 an analogous task to Duncker's candle problem described earlier in this chapter. Their results showed that 6- and 7-year-olds in the experimental condition were significantly slower to think of the solution, which involved emptying and turning over a wooden box and using it as a support, than the same-age control group that received an empty box. Interestingly, the 5-year-olds in the experimental condition were significantly faster to think of the solution than their older cohorts. Furthermore, they were equally as fast as their same-age peers in the control condition. German and Defeyter conclude that around age 6, children develop a more narrow criterion for an object's function than they had earlier in life. Seeing the box used as a container placed that function in their initial representation of the problem. As with the adult participants in Duncker's experiment (1945), these children had to overcome functional fixedness and restructure their initial representation of the problem before they could insightfully solve it. In contrast, the 5-year-olds' fluid conception of the box's function required no restructuring or insight.

To conclude, both children and adults habitually use different forms of inductive reasoning to help make sense of their worlds and to predict future events. Throughout the human lifespan, this form of reasoning is influenced by similar attributes and constraints. These characteristics include number of observations, knowledge base, inhibitory processes, working memory capacity, memory retrieval processes, and the cognitive ability to detect relational similarity (Goswami, 2011; Perret, 2015). As individuals gain experience and expertise in multiple domains, their inductive reasoning becomes increasingly sophisticated for a wider-range of problems.

Summary

1. In inductive reasoning, conclusions are inferred from evidence but are never guaranteed to be correct. Their degree of certainty is based on a continuum of weak to strong evidence. Strong inductive arguments are based on a substantial number of observations, diversity of evidence, and representativeness of the observations.

2. Inductive reasoning is often compared to deductive reasoning. Both of these forms of reasoning are central to critical thinking and involve evidence, logic, and working memory. However, induction and deduction differ in the types of evidence on which they are based and how they are evaluated. In addition, inductive conclusions go beyond the evidence or premises and are educated guesses; deductively valid conclusions follow directly from the premises and are guaranteed to be logically true.

3. Inductive reasoning is widely used in everyday life. Humans often automatically make predictions about what will happen next based on what occurred in the past. In addition, this form of reasoning plays an important role in other cognitive activities, such as decision-making, categorization, and similarity judgments.

4. The availability heuristic is a cognitive short-cut used when people easily retrieve information from memory and perceive it as relevant evidence for the likelihood of a phenomenon. Although this heuristic is sometimes useful, it can undermine the diversity of evidence needed for strong inductive arguments. It can also result in illusionary correlations.

5. Confirmation bias also limits the diversity of evidence. This bias occurs when people use enumerative induction and only seek observations that support their hypotheses. Eliminative induction is more informative because it is based on seeking evidence that both confirms and disconfirms a tentative hypothesis.

6. The representative heuristic allows us to infer the probability of an event by assuming it is similar to a prototype event. However, this heuristic can result in weak inductive arguments if base rate and sample size are not considered.

7. There are several forms of inductive reasoning, including category-based inductions, causal inductions, analogical reasoning, and insight. At some level, they are all based on finding similarities in a situation.

8. Category-based induction involves generalizing a property of one category member to a member of another category. Premise typicality, premise-conclusion similarity, premise diversity, and premise monotonicity are taxonomic relations used by novices when reasoning inductively about a relevant domain. In contrast, experts in a domain apply causal, ecological, or thematic relations.

9. Causal induction involves predicting what causes outcomes. If a hypothesized cause and effect are both present at the same time and absent at the same time, a causal induction is confirmed. If one is present when the other is not, the induction is disconfirmed. When causal relations are indicated in category-based problems, they over-ride the use of taxonomic relations in making inductive generalizations.

10. Analogical reasoning involves comparing two domains in order to infer a quality they have in common. Relational similarity is necessary for this form of reasoning, although surface similarity can foster the mapping of relations between the domains.

11. Insight involves perceiving information in a new way, which often requires cognitive restructuring of our mental representations. It is often accompanied by a subjective feeling of "Aha" or not consciously knowing how one arrived at the new perception. Functional fixedness or fixation on unproductive procedures can hinder this form of inductive reasoning.

12. Inductive reasoning begins early in life and there is evidence of both continuity and change in its development. Cognitive changes and a larger knowledge base allow older children to perform more complex category-based inferences, causal inductions, and analogical reasoning, while becoming more susceptible to functional fixedness.

Review Questions

1. If you want to make a strong inductive argument, what attributes should you keep in mind?
2. When and why do people make mistakes when they perform inductive reasoning?
3. If you are an expert in one domain and not in another, how will this alter your category-based inductions related to each domain?
4. When would you be likely to use category-based induction, causal induction, analogical reasoning, and insight in your daily life?
5. As you developed from infancy to adulthood, how did your inductive reasoning change and how did it stay the same?

Hot Topic

Janet E. Davidson

My research on insight began in 1982 when Robert Sternberg and I developed a three-process theory of insight. According to this theory, the cognitive processes of selective encoding, selective combination, and selective comparison are used to restructure one's mental representation of the givens, the relations among the givens, and the goals found in a problem in order to find a novel solution.

Selective encoding occurs when an individual suddenly finds one or more important elements in a problem situation that previously had been nonobvious. Selective encoding elicits insight by abruptly restructuring one's mental representation so that information that was originally viewed as being irrelevant is now seen as relevant for problem solution and vice versa.

Selective combination occurs when an individual discovers a previously nonobvious framework for the relevant elements of a problem situation. In many problems, even when the relevant features are known, it is often difficult to know that these features should be combined and then to find a procedure to combine them appropriately. Selective comparison occurs when one suddenly discovers a nonobvious connection between new information and prior knowledge. Analogies, for example, can often be useful for solving new problems.

To be referred to as insightful, the relevant selections must not occur to people immediately upon presentation of a problem. After individuals reach an impasse, they must spontaneously search for and select previously overlooked relevant elements, methods for combining the elements, or connections between prior knowledge and the problem situation. Also, successful search for this relevant information must result in a seemingly abrupt change in the problem solver's mental representation of the problem.

In studies conducted with adults and gifted and non-gifted children as the participants, it was found that the three insight processes play an important role in the solution of non-routine problems and in individual differences in intelligent behavior. More specifically, individuals who solved the non-routine problems correctly were more likely than those who solved them incorrectly to (a) have above average intelligence as measured by standardized tests, (b) apply spontaneously the three insight processes, (c) switch mental representations as a result of these processes, (d) experience a sudden and dramatic increase in feelings of confidence that they were nearing a solution, and (e) take longer than others to solve the problems. The last finding supports the view that successful insights can require additional time to restructure a mental representation for a problem and verify the solution. Correct performance on the nonroutine problems was also more highly correlated with scores on a standardized test of inductive reasoning than on scores for deductive reasoning. In addition, it was found that school-age children can be trained on the three processes to perform insightful problem solving; the training effects are transferable and durable. Future work will examine whether preschoolers at a science museum apply the three processes when they solve non-routine problems.

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Glossary

availability heuristic A cognitive shortcut that results in basing estimates of the probability of an event only on how quickly and easily relevant evidence is retrieved from memory. 137

confirmation bias Selectively seeking evidence that confirms a hypothesis and overlooking evidence that invalidates it. 137

eliminative induction Seeking evidence that both confirms and disconfirms a hypothesis. 137

functional fixedness A cognitive bias that occurs when an individual's notions about the function of an object inhibit the individual's use of the object for a different function. 145

illusory correlation Believing a relationship exists between variables when, in reality, the variables are not related. 137

premise monotonicity The strength of an inductive argument increases as the number of inclusive premises increases. 136

representativeness heuristic When trying to estimate the probability of an event, this shortcut involves finding a prototype of the event and assuming that the two events have similar probabilities. 139