Introduction to Chapter 32

Simple Heuristics that Help Us Win

According to Gary Klein (1998), fireground commanders make around 80% of their decisions in less than 1 minute. Severe time constraints prevent them from implementing anything like a complete search for all possible alternatives and complex weighting and integrating information into one verdict. They cannot help but rely on principles of bounded rationality such as sequential search, one-reason decision making, and aspiration levels. Many real-world contexts require professionals to make split-second decisions, some of which involve human lives; in others, such as sports, fame and success are at stake. In fact, there are few domains where speed and frugality matter more than in sports. For instance, shots are often as fast as 100 miles per hour in professional soccer, leaving the goalkeeper and defense players barely any time to decide where to move. In team sports, an individual player usually has only a very limited perspective on the playing field, in which players move around quickly and in complex patterns. At the same time, the massive amount of practice involved in many sports gives rise to automatic processes that can be exploited by simple heuristics. Altogether, these conditions may make sports one of the quintessential domains for studying fast-and-frugal heuristics. Yet relatively few such investigations exist (see Chapter 31 for an illustration of how the recognition heuristic can be used to study sports forecasting). This chapter by Will Bennis and Thorsten Pachur (a revised version of Bennis & Pachur, 2006) summarizes existing research on heuristics in sports and illustrates the potential of this approach to provide further insights into how athletes, coaches, and fans make decisions. For instance, how could the well-known "belief in the hot hand" arise from the use of a fast-and-frugal heuristic? How does the performance of such a heuristic depend on the structure of the environment, and when would such a heuristic be adaptive?

CHAPTER 32

Simple Heuristics that Help Us Win

Will M. Bennis and Thorsten Pachur

Abstract: This chapter summarizes the fast-and-frugal-heuristics (FFH) approach to judgment and decision making, particularly as it applies to sports. The aim is to provide a framework through which current sports psychologists may apply this approach to better understand sports decision making. FFH are studied using a variety of methods, including (1) computer simulations and mathematical analysis of heuristic performance as it depends on environmental structure (what we call the ecological rationality of heuristics); (2) empirical analysis of the heuristics' performance in naturally occurring environments; and (3) experimental research examining whether people actually use the identified heuristics. Simulations and analysis have shown that FFH can perform as well as complicated optimizing models while using less information and without integrating this information. Furthermore, in many cases FFH are more robust than optimizing models, outperforming these models when generalizing to new cases. FFH depart from many models of human decision making in that they set a reasonable standard of rationality based on real-world constraints such as limited time, information, and cognitive capacity; decision tasks that may have no calculable optimal solution; and the structured environments within which humans have learned and evolved. These simple heuristics are particularly appropriate in the sports domain, in which athletes often have to make rapid, high-stakes decisions with limited information and divided attention.

How can we model experienced baseball or cricket players catching a fly ball? For simplification, imagine that the ball is already on its descent and that its trajectory is in line with the ball-catcher. At first glance the task still seems an extraordinarily complex one, as a multitude of factors—such as the ball's distance, angle, velocity, and acceleration of descent, as well as the wind speed and direction—influence where the ball will land. Nevertheless, experienced baseball players—but also fish, flies, and bats—accomplish the feat of catching fly balls or intercepting other flying objects with apparent ease. But does this mean that they consider all these variables

and can perform the necessary calculations? Optimizing approaches to cognition often assume (at least implicitly) that organisms are equipped with tremendous computational capabilities (e.g., Bayesian cognitive models; Oaksford & Chater, 2007). Given the constraints of time, information, and processing capacity that baseball players (and other boundedly rational agents) have to deal with, this assumption seems highly unrealistic. An alternative approach to model how players catch a fly ball would be in terms of heuristics, which neither require all relevant information nor integrate the information that is used.

In the case of the outfielder catching the ball, one heuristic that players rely on has been called the *gaze heuristic* (Gigerenzer, 2004). The gaze heuristic involves three steps: (1) Fixate one's gaze on the ball, (2) start running, and (3) adjust

one's speed so that the angle of gaze remains constant. The gaze heuristic does not require estimating any of the variables necessary to compute the ball's trajectory, yet it enables outfielders to catch successfully. Empirical evidence shows that experienced ball-catchers use the gaze heuristic and similar heuristics, as do dogs when trying to catch Frisbees (McLeod & Dienes, 1996; Shaffer, Krauchunas, Eddy, & McBeath, 2004).

The gaze heuristic exemplifies what Gigerenzer and Goldstein have called a "fast-and-frugal heuristic" (1996b, Chapter 2, this volume; Gigerenzer, Todd, & the ABC Research Group, 1999). "Frugal" refers to the fact that these heuristics use little information and require few cognitive steps. "Fast" refers to the speed with which decisions can be made: the outfielder does not wait and calculate the trajectory before he runs toward the point where he predicts the ball to hit the ground. Note that much of the power of the gaze heuristic stems from our evolved capacity to track objects. This highlights the fact that although heuristics themselves are fast, simple, and effective, they often exploit evolved capacities that, though requiring little cognitive effort, may not be simple at all. To illustrate, we cannot design a robot able to catch fly balls as well as a skilled child can. The purpose of this chapter is to describe and discuss how fast-and-frugal heuristics have been and can be used to understand decision-making in the sports domain.

EXISTING RESEARCH ON FAST-AND-FRUGAL HEURISTICS IN SPORTS

This section will review some existing research on heuristics in sports. These include take-the-first (TTF), a heuristic that can be used by players to choose from among practical options; the recognition heuristic, which relies on partial ignorance to make powerful inferences; and take-the-best (TTB), which allows for inferences about known options based on limited search. The latter two heuristics have been primarily tested with sports forecasting (i.e., predicting which teams or athletes will win) rather than with decisions by athletes or coaches.

Take-the-First (TTF)

How do athletes generate different options and subsequently choose among them given the limited time they often have to make decisions? Consider the constellation of players in a handball match depicted in Figure 32-1a. What options does the center back (CB) have?[1] One option would be to attempt a shot on the goal. Alternatively, he might prefer to pass the ball to one of his teammates, the left wing (WL), left half-back (HL), center front (CF), right half-back (HR), or right wing (WR). But to whom and how?

Investigating such a situation, Johnson and Raab (2003) found that experienced players do not try to exhaustively generate all possible options. Instead they seem to rely on the order in which options are spontaneously generated in a particular situation and choose the first option that comes to mind. Johnson and Raab called this strategy *take-the-first* (TTF; see Table 32-1).

Why should options generated quickly be more useful than those generated more slowly? Taking an associative network perspective, Johnson and Raab (2003) argue that better options are more likely to be activated first in a particular situation due to their stronger connections in the network. This, however, requires that the player has experience with the task and has learned how suitable possible options are in different situations. In other words, once a player has some expertise with the task, he can rely on the quality of spontaneously generated options and "take the first." Work by Gary Klein provides empirical evidence for a positive correlation between generation order and quality of an option (Klein, 1998; Klein, Wolf, Militello, & Zsambok, 1995).

TTF shares some properties with other fast-and-frugal heuristics. For instance, like the fluency heuristic (Schooler & Hertwig, 2005, Chapter 4, this volume) it exploits the fluency with which memory traces are made available by the cognitive system. Moreover, it is based on sequential information search and uses simple search and stopping rules. It also "bets" on a particular pattern in the task environment, namely that there is a correlation between the position
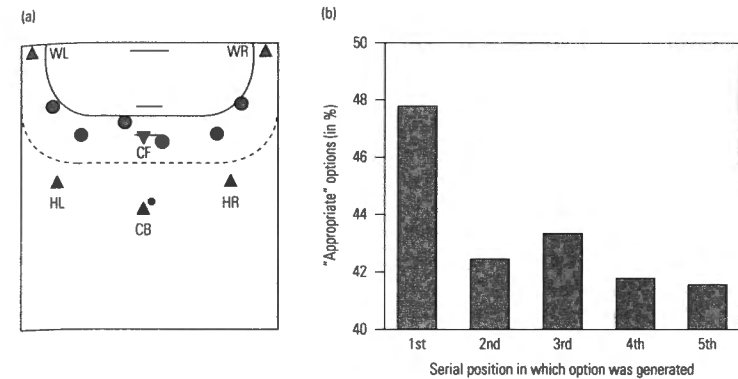

Figure 32-1. (a) Typical position of the offensive players in the handball scene, at the point where it was "frozen" to begin each trial. Triangles represent offensive (attack) players, circles represent defensive players. CB, center back; WR, wing player on the right; WL, wing player on the left; HL, half-back player on the left; HR, half-back player on the right; CF, center-front (pivot) player at the 6-meter line; long solid line, goal; short solid line, 6-meter line (defense zone); dotted line, 9-meter line (from Johnson & Raab, 2003). (b) Mean percentage of "appropriate" decisions per participant, as rated by experts, summed over trials, for the generated options in each serial position.

Table 32-1. Overview of Efficient Heuristics for Decision Making in Sports

Heuristic	Rule	Function	Bets on
Gaze heuristic	"(1) Fixate one's gaze on the ball, (2) start running, (3) adjust one's speed so that the angle of gaze remains constant."	Catching a fly ball	Ball is on descent and trajectory is in line with the catcher
Take-the-first	"Choose the first option that comes to mind"	Making allocation decisions	Good options are generated faster than bad ones
Recognition heuristic	"Choose the recognized option"	Forecasting the winner in a competition	More successful athletes or teams are more likely to be recognized
Take-the-best	"(1) Search through cues in order of their validity, (2) stop search if a cue discriminates between the objects, (3) predict that the object with a positive cue value has the higher criterion value."	Forecasting the winner in a competition	Skewed distribution of cue weights
Hot-hand heuristic	"If an athlete has scored two or more times in a row, predict she will score on her next attempt."	Making allocation decisions	Good players show streaks more frequently than bad players

of an option in the generation process and the option's quality. Finally, TTF relies on evolved capacities which allow it to accomplish a computationally difficult task. In this case, the evolved capacity is the ability to match the current situation with previously experienced ones and to retrieve successful solutions to these previous constellations efficiently.

Investigating teenage handball players from area handball clubs in an empirical study,

Johnson and Raab (2003) indeed found support for some of the predictions of TTF. They presented the players with situations from a handball match on a video screen, froze the picture after 10 seconds, and asked the players which option first came to mind for that specific situation. Participants were then allowed to inspect the still-frozen video picture for another 45 seconds, generated further options, and finally picked from the generated options (including the first) the one they considered best overall. The quality of the generated options was subsequently rated by four coaches from professional-level handball teams.

Supporting the assumption that options most likely to be activated quickly are successful ones, the percentage of options judged by the coaches as appropriate decreased markedly after the first position (see Figure 32-1b). Did participants also "take the first"? As it turned out, they chose the first option that came to their mind in around 60% of the cases. Although this result provides support for TTF, it is not immediately obvious how strong that support is. In 40% of the cases, participants' final choice differed from their first choice. Note, however, that in Johnson and Raab's (2003) experiment participants had 45 seconds after making their immediate choice during which they were explicitly instructed to generate additional options. In a real handball game, of course, players would make their choices in seconds or fractions of a second with little if any consideration of subsequent options, in which case all or nearly all of their choices would correspond to TTF. As Johnson and Raab's analyses show, these choices would often be good ones.

As such, a more telling question than whether players stuck to their first choice after deliberation may be which of the two choices would have in fact contributed to a better outcome: (a) the *first* choice, corresponding to TTF and the choice players would likely make during actual handball matches, or (b) the *final* choice, involving 45 additional seconds of deliberation and option generation. As it turned out, extended option generation did not improve the quality of participants' final choices. If participants had not generated any further options after the first,

their choices would have been better than the options that they finally picked. Less time would have been more, which is exactly what might be expected of a heuristic adapted to the competitive sports environments, where "taking the first" may be all that time allows.

Recognition Heuristic

Less can be more not only with respect to the time available to make a decision. It can also be more with respect to knowledge of a domain. The *recognition heuristic* (Goldstein & Gigerenzer, 2002, Chapter 3, this volume) is a strategy to predict which of a set of objects has a higher value on some criterion (e.g., which team or athlete will win a competition). In binary choice, the heuristic can be used when out of two opponents (players, teams), one is recognized but the other is not. The recognition heuristic predicts that the recognized opponent will win the competition (see Table 32-1). The heuristic is ecologically valid if the recognition validity (defined as the proportion of cases where a recognized object has a higher criterion value than an unrecognized one) is substantially higher than chance.

Note that in order to apply the recognition heuristic, partial ignorance is required. When both opponents are recognized the recognition heuristic cannot be applied. Note also that, as with take-the-first, the recognition heuristic relies on a particular pattern in the environment: it "bets" that successful athletes or teams are also more frequently mentioned in the media, and thus are more likely to be recognized (Pachur & Biele, 2007, obtained evidence for this pattern).

Goldstein and Gigerenzer (2002) analytically showed that the recognition heuristic can lead to a counterintuitive *less-is-more effect*. This effect concerns the relationship between the number of objects recognized (from among a set of objects)—for instance, the number of teams or athletes—and the overall accuracy achieved when all objects are compared. One condition for the effect to occur is that the recognition validity is higher than the validity of further knowledge about the objects. Assuming that both validities are independent from the number

of objects recognized, they showed that full knowledge can be associated with fewer successful predictions than when fewer objects are recognized. Recent work by McCloy, Beaman, and Smith (2008, Chapter 18, this volume) has examined the recognition heuristic when an inference has to be made among more than two objects. The authors find that a less-is-more effect also occurs in this situation.

Several studies have examined the recognition heuristic in the context of sports. Three questions have been of primary interest. First, can the recognition heuristic predict people's forecasts? Second, how well does recognition predict outcomes in sports compared to other predictors? And, third, is there evidence for the less-is-more effect?

Concerning its descriptive accuracy (i.e., whether or not it predicts people's judgments), there is consistent support for the recognition heuristic in situations where the recognition validity is substantial (Ayton & Önkal, 2004; Pachur & Biele, 2007; Scheibehenne & Bröder, 2007, Chapter 33, this volume; Serwe & Frings, 2006; Snook & Cullen, 2006). For instance, Serwe and Frings asked tennis amateurs to make forecasts of matches at the 2003 Wimbledon tennis tournament and used the recognition heuristic to model the forecasts. It was found that more than 90% of the time when a recognized player played against an unrecognized player, the tennis amateurs predicted the recognized player to win (similar results were found for soccer matches by Ayton & Önkal and Pachur & Biele and for hockey players by Snook & Cullen).

The second question is prescriptive. Can recognition help to make correct forecasts? In other words, is reliance on recognition an ecologically rational strategy in the sports domain? Snook and Cullen (2006) found that when a recognized National Hockey League (NHL) player was judged to have achieved more career points than an unrecognized one, this inference was correct more than 86% of the time. Pachur and Biele (2007), studying the recognition heuristic in predicting the winners at the 2004 European Football Championship, found that recognition was considerably better than chance—although

it was not able to reach the predictive accuracy of "expert" indicators such as rankings, previous performance, or betting odds.

Serwe and Frings (2006) examined how well recognition was able to predict the actual winner of tennis matches at Wimbledon (see also Scheibehenne & Bröder, 2008, Chapter 33, this volume). They compared recognition to three alternative prediction benchmarks: betting odds from an online bookmaker and two types of official world-wide rankings from the Association of Tennis Professionals (ATP): the Champions Race (ATP-CR), which ranks male tennis players based on their performance over the current calendar year; and the Entry Ranking (ATP-ER), which ranks them over the preceding 52 weeks. Among laypeople, the recognition heuristic performed significantly better than chance (making correct predictions 67% of the time), although it did not outperform ATP rankings (70–72% correct predictions) or the betting market (79% correct predictions). Among amateurs, however, recognition performed markedly better, correctly predicting 73% of the winners and outperforming the rankings, which correctly predicted the winner 68–69% of the time. The betting market still performed best, predicting the winner in 78% of comparisons.[2]

Finally, what of the less-is-more effect? When Ayton & Önkal (2004) studied forecasts for matches in the English FA Cup by both British and Turkish participants, it was observed that in spite of their greater knowledge about English soccer teams, the British participants were on about the same performance level as their Turkish counterparts. A similar result was reported by Snook and Cullen (2006) in their study where participants had to judge which of two NHL players had achieved more career points. Comparing participants with different levels of knowledge (in terms of the number of teams that they recognized), the authors found that judgmental accuracy increased as the number of recognized players increased until about half of the players were recognized. Beyond this point accuracy leveled off, akin to the less-is-more effect.

Pachur and Biele (2007) highlighted an important boundary condition of the less-is-more

effect. In their study on lay forecasts of soccer matches at the 2004 European Football Championship, although the average recognition validity was higher than the validity of knowledge beyond recognition—fulfilling the condition for a less-is-more effect specified by Goldstein and Gigerenzer (2002)—there was no less-is-more effect. Pachur and Biele proposed that this failure of the effect to manifest itself was due to the positive correlation between the number of recognized objects and the recognition validity that they observed (i.e., participants who recognized more teams tended to have a higher recognition validity). In Goldstein and Gigerenzer's analytical investigation of the less-is-more effect, these two variables were uncorrelated. (For a systematic analysis of the impact of validity dependencies on the less-is-more effect, see Pachur, 2010).

Take-The-Best (TTB)

The recognition heuristic requires ignorance. Often, however, sports forecasters have a considerable knowledge base, barring them from using the heuristic. To illustrate, most of the soccer experts studied by Pachur and Biele (2007) had heard of all the teams participating in the European Football Championship and thus were never able to exploit ignorance. In such cases, other strategies must be used to make an inference. Take-the-best (TTB; Gigerenzer & Goldstein, 1996) is one candidate. As with the recognition heuristic, this heuristic relies on limited search. TTB searches cues in order of their validity, beginning with the most valid. If this cue discriminates between the two objects being compared (i.e., two athletes have different values on the cue), the information search is ended and the object with the higher value on this cue is inferred to have a higher criterion value. If the cue does not discriminate between the objects (i.e., if two athletes both have the same value for that cue), TTB moves on to the next most valid cue, continuing down the line of cues in order of validity until it comes upon a cue that does discriminate.

As with other heuristics, environmental structure is critical to TTB's performance. For example, TTB's performance is influenced by whether or not the environment is *noncompensatory*. A noncompensatory environment is one in which the weight for each binary cue is greater than the sum of all subsequent cues, assuming the cues are ordered by weight. Within such environments, when cue validities are known, TTB matches the performance of optimizing models (in this case, multiple regression; Martignon & Hoffrage, 2002, Chapter 12, this volume). For further investigations of the conditions under which TTB outperforms complex models, and vice versa, see Hogarth and Karelaia (2007, Chapter 14, this volume) and Gigerenzer and Brighton (2009, Chapter 1, this volume).

Analytical tests of how TTB's performance depends on environmental structure address just one aspect of its ecological rationality; another aspect is how it performs in natural environments. For instance, how well does TTB perform in sports forecasting environments? Furthermore, in addition to examining a heuristic's ecological rationality, it is important to assess whether people actually use the heuristic. Do sports forecasters use TTB?

Todorov (2001) compared TTB to Bayes' rule with respect to its ability to predict the results of 1,187 games in one season of the National Basketball Association (NBA). Bayes' rule is an example of an optimizing model of rational choice that starts with an initial estimation of a team's probability to win, and updates this probability based on the outcome of subsequent matches. As it turned out, TTB performed as well as Bayes' rule (for similar results, see Gröschner & Raab, 2006). In a second study, this time examining whether or not people actually use the heuristic when predicting sports outcomes, Todorov found that participants ordered cues based on their validity, just as take-the-best would predict. Moreover, the heuristic predicted participants' forecasts very well.

In sum, simple models that rely on limited search, such as take-the-first, the recognition heuristic or take-the-best offer efficient and robust decision tools in the sports domain. Moreover, both sports athletes and forecasters seem to rely on ordered and limited search, as exemplified by these heuristics. Fast-and-frugal heuristics thus offer a powerful framework for understanding decision making in sports.

THE BELIEF IN THE HOT HAND: REFLECTION OF AN ADAPTIVE HEURISTIC?

Studying the psychology of sports using a heuristics framework is a relatively new endeavor and few heuristics have been well specified for this domain. Indeed, of the four heuristics discussed above, only two (the gaze heuristic and take-the-first) are about making decisions in the heat of competition (the other two are about forecasting winners). At the same time, because decisions by athletes, coaches, and referees usually must be made quickly based on limited information, fast-and-frugal heuristics likely play a dominant role in sports decision making. As such, the sports domain is particularly promising area for applying this approach. Using the phenomenon of a "belief in the hot hand" (Gilovich, Vallone, & Tversky, 1985), in this section we illustrate how established phenomena in sports decision making can be studied from the perspective of fast-and-frugal heuristics.

Gilovich, Vallone, and Tversky (1985; Tversky & Gilovich, 1989) found that although many people (including players and coaches) believe that a basketball player's chance of making a basket are greater following a success (and streak of successes), there was no empirical evidence for such a "hot hand". Although the existence of a hot hand in sports continues to be debated (Bar-Eli, Avugos, & Raab, 2006; Frame, Hughson, & Leach, 2006; Oskarsson, Van Boven, McClelland, & Hastie, 2009), the psychological phenomenon seems to be established: people, including the athletes themselves, think that athletes who succeeded on their previous attempt—or streak of attempts—are more likely to succeed on the subsequent attempt, and allocation decisions in a game are based on this belief. How would this phenomenon be studied from a fast-and-frugal-heuristics perspective?

Three questions are central: (1) What simple heuristic might give rise to a belief in a hot hand? (2) How does such a heuristic perform in actual basketball games or in other sports to which it is applied and what is the range of environments across which it is successful? In short, what is the ecological rationality of the heuristic? (3) What evolved capacities might such a heuristic exploit?

For instance, consider the following *hot-hand heuristic*: "If an athlete has scored two or more times in a row, predict she will score on her next attempt" (see Table 32-1). Bruce Burns (2004) suggested that an important consideration regarding heuristics in general, and ball allocation decisions in particular, is whether they help decision makers achieve their goals rather than whether they rely on correct beliefs. Burns pointed out that even if there is no such thing as a hot hand in basketball, using streak information to decide where to pass the ball can help get the ball to better shooters. Because streaks occur more often and over longer duration among players with higher overall shooting percentages, the occurrence of a streak is an indicator of the player's overall shooting percentage.

Admittedly, there are some complicating factors with this example. Professional basketball players and coaches know their teammates' shooting percentages, and so it is unclear how they would benefit from such a heuristic unless players really do get "hot". Nevertheless, there may be sports in which players are more likely to have teammates or face opponents who are still on a strong learning curve, in which case a hot-hand heuristic would likely be more effective than longer-term shooting percentage information (indeed, this might be the case in high-school or college basketball, where most NBA players developed their skills and may have developed their belief in the hot hand). Moreover, in some sports, or at non-professional levels, base-rate information may be unavailable and a hot-hand heuristic may be a useful tool for inferring it. Finally, as noted earlier, there remains controversy as to whether the original finding that players do not sometimes get "hot" is accurate. Perhaps basketball players get "hot" in ways not apparent from statistical measures simply because the opponents are aware of the hot hand and compensate with stronger defense on the hot player. If athletes truly get hot hands, then allocation decisions based on immediately preceding streaks may be adaptive above and beyond their cue validity for determining the longer-term base-rate performance levels of the athlete.

One way to examine these issues would be by studying the belief in a hot hand in a sport for which the opposition cannot selectively increase defensive pressure. Raab, Gula, and Gigerenzer (2009) conducted such a study, examining the hot hand among twenty-six of the top players in German first-division volleyball players. In volleyball, a net separates the teams, and the possibility of increasing defensive pressure against a particular "hot" player is limited. The authors found that not only did players believe in the hot hand and used it to make allocation decisions, but also that players did get "hot" beyond expectations of chance. In other words, these allocation decisions were adaptive.

A final step in investigating the hot-hand heuristic from a fast-and-frugal-heuristics perspective would be to specify the evolved capacities that the heuristic recruits. For instance, certain regions of the brain seem to be particularly sensitive to patterns in sequences of events (even if these patterns occur randomly; Huettel, Mack, & McCarthy, 2002). This ability to detect patterns in the environment is a prerequisite for, and is thus exploited by the hot-hand heuristic.

CONCLUSION

How does and how should a football (soccer) player decide where to kick the ball when making a corner kick, when to shoot for a goal, or to whom to pass the ball? How do basketball coaches decide whether and which players to substitute for another? How do players decide

when it is best to foul members of the opposing team, or whether to try for a three-point basket? How does a snooker player decide between playing offensively or defensively, a tennis player decide when to go to the net, or a Nascar racer decide whether to try to pass another driver? What cues can a referee or judge use to assess a performance or identify an illegal play given that their view is sometimes from an unreliable perspective? And in all these cases, how does the choice and performance of the strategy adopted depend on the structure of the environment? Rather than assuming an optimizing rational demon equipped with omniscience and unlimited computational power, the fast-and-frugal-heuristics approach acknowledges that such decisions often have to be made quickly and based on little information. Therefore, this approach promises to be particularly relevant to the study of decision making in the sports domain, where speed is of the essence and multiple tasks and goals limit cognitive capacity, but where the decision makers are often experts.

NOTES

1. The center back (CB) is depicted by the triangle with a small circle, representing the ball, next to it.
2. Note that the performance of the betting market and the two ATP rankings differed for laypeople and amateurs. This was because comparisons were limited to cases when the recognition heuristic could be applied, which differed between the two groups.

Introduction to Chapter 33

How Dogs Navigate to Catch Frisbees

The evolution of species has been investigated at the level of morphology, nervous systems, or communication abilities, but relatively little is known about the evolution of cognitive strategies, or heuristics. Heuristics are simple only because they exploit evolved or learned capacities. One important capacity is tracking—that is, the ability to trace moving objects against a noisy background. The gaze heuristic (see Chapter 32), and the related *LOT* heuristic described in the article by Dennis Shaffer, Scott Krauchunas, Marianne Eddy, and Michael McBeath exploit this cognitive ability. The gaze heuristic can be relied on unconsciously, as with outfielders who cannot explain what they do automatically, or consciously. In sailing, for instance, beginners are taught to use it to avoid collisions. When fixing their gaze on the other boat, sailors determine whether the angle of gaze remains constant over time: If so, a collision is doomed to occur, unless the boat's course is changed. The same heuristic was also consciously relied upon in the "miracle of the Hudson river" on January 15, 2009. With both engines out after the plane struck a flock of birds during takeoff, the pilots of US Airways Flight 1549 had to decide whether they could make it to LaGuardia Airport. Copilot Jeffrey Skiles explained how they made this decision using the gaze heuristic (Charlie Rose, *The Charlie Rose Show*, February 11, 2009):

> "It's not so much a mathematical calculation as visual, in that when you are flying in an airplane, a point that you can't reach will actually rise in your windshield. A point that you are going to overfly will descent in your windshield."

For an outfielder, the gaze heuristic works only when the object is already high in the air. Otherwise, it needs to be modified to the LOT heuristic described in this article, by exchanging a building block. The evidence that dogs, bats, flies, and other animals also rely on these heuristics implies two possible interpretations. First, *homology*, which is a similarity of structures (here: heuristics) between different species based upon their descent from a common evolutionary ancestor. This is to be contrasted with, second, *analogy*, which is a functional similarity based upon something other than a common ancestor. We do not know which interpretation is correct. But we can safely assume that the original goal of the tracking heuristics was to intercept prey or mates, as well as the opposite, to avoid being caught. Humans appear to recruit these heuristics beyond the initial purposes such as for performing in competitive sports.

Catching a Frisbee is a more challenging task than catching a ball because the Frisbee can change direction and speed in dramatic ways. One fascinating result of the article by Shaffer and colleagues is that their dogs nevertheless managed to solve the task relying on the same simple heuristic.