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# How Evolution Outwits Bounded Rationality

The Efficient Interaction of Automatic and Deliberate Processes in Decision Making and Implications for Institutions

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**ABSTRACT**

Classic behavioral decision research has intensively explored deliberate processes in decision making. Individuals were assumed to be bounded rational actors who, because of limitations of cognitive capacity, use simple heuristics which are successful in certain environments. The first postulate of this paper is that the underlying assumption of limited cognitive capacity is only partially valid if automatic processes are considered. The parallel constraint satisfaction (PCS) approach is outlined, which aims at describing these automatic processes, and evidence in favour of this approach is summarized. The second postulate is that the understanding of decision making necessitates models that take into account the interaction between automatic and deliberate processes. With the PCS rule, such a model is presented, which aims at integrating heuristic and automatic approaches. The third postulate is that such an interaction model allows bounded rationality to be overcome and has further evolutionary advantages. Implications for the efficient design of institutions are outlined. The fourth postulate is that evolutionary forces have already shaped the German legal system to be an efficient institution. It supports efficient decision making by silently implementing many of the prescriptions that could be derived from the PCS rule without explicit knowledge about the underlying processes.

## INTRODUCTION

One of the most intriguing psychological phenomena is the human ability to make decisions in a complex and uncertain world. Decision experts, like managers and lawyers, usually have to decide on the basis of a multitude of pieces of probabilistic and incomplete information. In the tradition of the bounded-rationality approach (Simon 1955), it has been repeatedly argued that fast-and-frugal heuristics, which are based on simple decision rules and the ignorance of information, offer one important way to find solutions to such complex decision tasks (Gigerenzer 2006). In this paper theoretical models and empirical findings will be summarized that suggest an extended perspective: Individuals are able to integrate multitudinous information by partially relying on intuitive-automatic processes. Specifically, it is argued that individuals make use of automatic parallel constraint satisfaction (PCS) processes that have been developed in evolution on the basis of processes of perception. PCS processes can be mathematically simulated using connectionist networks. Both accounts will be discussed in the light of recent evidence. With the PCS rule, a hierarchical network model will be described that integrates both approaches and takes into account the interaction between automatic and deliberate processes in decision making. The evolutionary advantage of such a model will be outlined. Finally, implications for the development and improvement of institutions will be discussed.

**THEORIES IN BEHAVIORAL DECISION RESEARCH**

In classic behavioral decision research, two major approaches can be differentiated. First, modifications of rational choice theory (RCT) have been provided that hold to the general assumption that information is integrated in a *weighted compensatory* manner. For instance, prospect theory (Kahneman and Tversky 1979) postulates that individuals select the option with the higher subjective expected utility, which is calculated as the weighted sum of subjective utilities and subjective probabilities. Transformation functions from objective values and probabilities to subjective ones have been specified in the light of empirically observed systematic deviations from RCT. Second, following the fundamental critique of Simon (1955) – that such complex computations might overload the human cognitive capacity – several heuristic models have been developed that postulate that individuals apply simple integration rules and thereby ignore most of the information. The currently most influential model of this *bounded-rationality approach* is the adaptive-toolbox model (Gigerenzer, Todd et al. 1999). It postulates a set of fast-and-frugal heuristics that are adaptively applied and lead to very accurate decisions by exploiting the structure of the environment. The prototypical fast-and-frugal heuristic is the Take-the-Best heuristic, in which only the most valid information is inspected. If this information favours one option, it is instantly selected; only if this is not the case is the second-most valid information inspected and so on. The priority heuristic extended this concept to classic gambling decision tasks (Brandstätter et al. 2006).

There has been a long theoretical and empirical controversy about which approach is more appropriate, and it continues (e.g., Brandstätter et al. 2006; Glöckner and Betsch submitted a). While focussing on this conflict and the debates within both approaches, a third idea that had a long tradition in cognitive psychology (Schneider and Shiffrin 1977) and social psychology (Bargh  and Chartrand 1999; Petty and Cacioppo 1986) has been discussed less intensively in decision research for many years: the *dual-processing approach* (Kahneman and Frederick 2002; for an overview). According to this approach, in decision making, individuals rely on both a deliberate and an intuitive system. In contrast to the controlled deliberate system, in which information is consciously integrated according to certain rules and in a stepwise manner, the intuitive system relies on unconscious processes in which information is automatically processed.[1] Research and theory building in behavioural decision research on processes of the intuitive system are still in the early stages, and findings from cognitive and social psychology have not yet been sufficiently considered. Even less is known about the interaction between the deliberate and the automatic system. Prominent general approaches that have the potential to explain processes of the intuitive system are memory-storage and retrieval models (cognitive approaches: Anderson and Lebiere 1998; Busemeyer and Townsend 1993; Dougherty et al. 1999; Ratcliff et al. 1999; affective approaches: Damasio 1994; Slovic et al. 2002) and PCS models. The former postulate that automatic processes of storage into and retrieval from long-term memory are utilized in decision making; the latter assume that automatic processes of maximizing consistency between information in temporarily activated networks drive our decision process. In this paper the focus will be on the latter models.

## THE PARALLEL CONSTRAINT SATISFACTION APPROACH TO DECISION MAKING

Many cognitive operations function without deliberate control. Behavioral research provides a multitude of empirical findings evidencing the power of the unconscious automatic system. For instance, in the course of adaptive learning, organisms automatically record fundamental aspects of the empirical world such as the frequency (Hasher and Zacks 1984) and the value (Betsch, Plessner et al. 2001) of events or objects. It has been repeatedly demonstrated that automatic processes even overrule deliberately formed intentions: individuals behave against their intentions and fall back into routines if they have to make decisions under time pressure (Betsch et al. 2004); individuals can not prevent stereotypes and prejudices from beeing automatically activated (Devine 1989); and the deliberate intention not to think about an object even increases the likelihood that the object will come to mind (Wegner 1994).

Automatic processes are essential to make sense of a world that provides incomplete information. Automatic processes of perception and social perception enable individuals to immediately recognize objects and social constellations even if only a small fraction of the total information is available. Classic gestalt-psychological research (Koffka 1922) provided persuasive demonstrations of these unconscious mechanisms. Individuals who are presented

[1] Kahneman and Frederick (2002) use the terms *automatic*, *process opaque* (unconscious) and *parallel* to describe process characteristics of the intuitive system. It has to be noted that these characteristics are not independent, yet neither do they perfectly coincide. Unconscious processes have to be automatic, but in some cases people could be consciously aware of automatic processes. Similarly, parallel processes have to be automatic, but automatic processes can also rely on serial information integration (i.e., production rules). Thus, automatic processing could be considered the core characteristic of the intuitive system. Thereby, automatic processes can equally act upon affective and cognitive content. Thus, it is rather unlikely that the intuitive system is limited to integrating affective information only (but see Kahneman and Frederick 2002).

with a skip figure like the "rubinian vase" perceive either a vase or two faces on the basis of exactly the same information. By shifting the focus of attention, the perception may flip to the opposite interpretation. Conceptually, multitudinous conflicting information is unconsciously integrated in one consistent interpretation (e.g., vase). In this process the interpretation of information is modified. Information that speaks against the dominant interpretation (e.g., an object which shades a part of the figure) is suppressed, whereas information that supports the dominant interpretation (e.g., a characteristic shape) is highlighted.

The PCS approach to decision making is based on the same principle (Read, Vanman and Miller 1997; Holyoak and Simon 1999). As soon as individuals are confronted with a decision task, automatic processes set in that operate towards forming a consistent mental representation of the task. In the process, information supporting the emerging mental representation is accepted and conflicting information is devaluated. Conceptually, automatic processes weigh interpretations of information against each other by taking into account the complex constellation of the information. The best interpretation wins the competition and the conflicting information is wiped out as far as possible. Individuals are not aware of these processes; they only become aware of the results.

**Connectionist Implementation of Parallel Constraint Satisfaction Processes**

Connectionist networks allow us to model PCS processes for complex decision tasks. Initially PCS networks were developed to model processes of word perception (McClelland and Rumelhart 1981). Later it was argued that the underlying organization principle of maximizing consistency between pieces of information is fundamental to a wide range of psychological phenomena like social perception (Read and Miller 1998), analogical mapping (Holyoak and Thagard 1989), the evaluation of explanations (Thagard 1989), dissonance reduction (Schultz and Lepper 1996), impression formation (Kunda and Thagard 1996), the selection of plans (Thagard and Millgram 1995), legal decision making (Holyoak and Simon 1999; Thagard 2003; Simon 2004), preferential choice (Simon, Krawczyk and Holyoak 2004) and probabilistic decisions (Glöckner 2006; Glöckner in press; Glöckner and Betsch submitted b).

For pragmatic reasons, the discussion here will focus on simple probabilistic decision tasks, which have been dominantly used to investigate fast-and-frugal heuristics (Gigerenzer, Todd et al. 1999). One prominent example is a decision in which, from two cities, the one with the larger population should be selected based on different probabilistic information. Conceptually, a decision has to be made about a distal criterion (i.e., population of the city) on the basis of proximal probabilistic *cues* (e.g., is it a state capital?) with dichotomous *cue* *values* (i.e., yes / no) that differ in *cue validity* (i.e., the conditional likelihood that the option is better on the criterion, given a positive / negative cue value).

Connectionist models provide different possibilities to model such probabilistic decision tasks. Fitting connectionist models to empirical data a posteriori lends only week support for such models. Therefore, Glöckner (2006) applied an a priori modelling approach in which a general structure for a connectionist network for such probabilistic decision tasks was suggested (Figure 1) and used in systematic a priori simulations.

In the suggested network, cues and options are represented by nodes, which may have different levels of activation $a$. Nodes are interconnected by links which have a certain strength, represented by weights $w$. Links are all bidirectional and can be excitatory ($w > 0$) or inhibitory ($w < 0$). Options and cues are connected by links which represent cue values. Positive predictions of a cue about an option are represented by excitatory links, whereas negative predictions are represented by inhibitory links. Options are interconnected by strong inhibitory links, because only one option can be chosen. Cues are connected with a general validity node, which is used to activate the network and has a constant activation of 1. The strength of the links $w_V$ represents the initial subjective cue validities that result from learning experience or explicitly provided information.

-- Please insert Figure 1 about here --

The network captures the logical constraints of the decision problem as represented in the temporarily activated network. In this structure some elements support each other (e.g., cues and options for which the former make a positive prediction) and others conflict with each other (e.g., cues and options for which the former make a negative prediction). The activation of each node can be interpreted as a subjective judgment of the goodness of the underlying concept (i.e., the attractiveness of the options and the subjective validity of the cues). Note that there is an important distinction between the initial validity of cues, which are represented by the links $w_V$, and the perceived validity of cues, which are represented by the activation of the nodes $a_C$. The former are stable constraints in the network, and the latter, which will be referred to as *resulting cue validities*, are results of the PCS processes.

As soon as the network is constructed, PCS processes set in and change the activation of nodes until a solution with a high level of consistency is found. Mathematically the process can be captured by an iterative updating algorithm, which simulates spreading activation in the network (McClelland and Rumelhart 1981):

$$a_i(t+1) = a_i(t)(1-decay) + \begin{cases} if\ input_i(t) < 0 & input_i(t)(a_i(t) - floor) \\ if\ input_i(t) \geq 0 & input_i(t)(ceiling - a_i(t)) \end{cases} \quad (1)$$

The activation $a_i$ at time $t+1$ is computed by the activation of the node at time $t$ multiplied with the decay factor plus the incoming activation for this node, $input_i(t)$, multiplied by a scaling factor. The scaling factor limits the activation of the nodes to the range -1 to +1 and leads to an *S*-shaped activation function. The $input_i(t)$ to node $i$ is computed as the sum of the activation of all other nodes multiplied by the weight of the connection with node $i$:

$$input_i(t) = \sum_{j=1 \to n} w_{ij} a_j(t) \tag{2}$$

The updating algorithm maximizes the consistency (i.e., the degree of organization) in the network and minimizes contradiction or energy. The energy can be computed by (Read, Vanman and Miller 1997)

$$Energy(t) = -\sum_i \sum_j w_{ij} a_i a_j \tag{3}$$

in that (a) all weights $w_{ij}$ are multiplied by the activations of the pair of nodes they connect and (b) the resulting products are added up. This means, for instance, that positive connections between positively activated elements increase the level of consistency, whereas negative connections between positively activated concepts decrease it (cf., Heider 1958). The iterative updating algorithm operates to maximize consistency. After a number of iterations, a state of maximal consistency under the given constraints is usually found and activations reach asymptotic levels. The option with the highest activation is selected. The number of iterations the algorithm needs to find the stable solution can be interpreted as the decision time predicted by the model.

Please note that the PCS approach, in contrast to memory-storage and retrieval models, does not describe long-term learning processes of relations in the network. PCS processes simulate ad-hoc interpretations of the available evidence based on constraints that result from learning or from the provided information. Only the interpretation of the evidence is temporarily changed to form a consistent mental representation.

**Predictions**

Based on theoretical considerations and systematic simulations (Glöckner 2006), five distinct predictions of the PCS approach can be derived:

*(a) High computational capacity:* Individuals are able to quickly integrate a multitude of information by relying on automatic processes.

*(b) Coherence shifts:* The decision process is inherently constructivist. Subjective cue validities are changed in the decision process to fit the emerging representation of the decision task, resulting in coherence shifts (Simon 2004): cues that point away from the favoured option are devaluated and cues that support the favoured option are strengthened. Thus,

resulting cue validities depend on the structure of the decision task and differ from initial cue validities.

*(c) Approximation of weighted compensatory models:* Choices roughly approximate the weighted compensatory integration of cue values and cue validities.

*(d) Decision time differences:* Decision time increases with a decrease in the initial consistency between the pieces of information. If all the cues point towards the same option, consistency is high and decision time is short. If almost equally strong sets of cues favour different options, consistency is low and decision time is long.

*(e) Confidence judgment differences:* The subjective confidence in a choice is higher in decision tasks in which the consistency between pieces of information that can not be resolved in the PCS process is low. If a highly consistent solution is found, confidence is high; if the resulting interpretation is still rather inconsistent, the confidence in the decision is low.

Note that this set of predictions differs from that of most other decision-making models and therefore allows for empirical testing against these models. Most decision-making models, including RCT, the adaptive-toolbox model and memory-storage and retrieval models, rely on the assumption that decision making is based on *unidirectional reasoning*: individuals are assumed to select information from a set of given information and to integrate it using certain algorithms to make a decision. Information is merely put into different algorithms; the information itself is not being changed in the process. In contrast, the PCS approach suggests that decision making is based on *bidirectional reasoning* (Holyoak and Simon 1999): the constellation of information and options is considered in a holistic process, and options and evidence are jointly weighed in this process. Thus, individuals should not only reason from information to options, but the validity of cues is also inferred from the informational constellation in a kind of automatic backward reasoning.

According to the adaptive-toolbox model and the bounded-rationality approach, individuals should not be able to quickly integrate information in a weighted compensatory manner because human cognitive capacity is too limited. Decision times should not be sensitive to the fact that different pieces of information convey conflicting evidence; only the number of computational steps needed to apply the heuristic should count (Brandstätter et al. 2006); and confidence judgments should only depend on the validity of the cue that differentiates between options (Gigerenzer et al. 1991).

**Summary of Empirical Evidence**

*Coherence Shifts*

The most comprehensive empirical work on coherence shifts in decision making was carried out by Dan Simon and colleagues (Holyoak and Simon 1999; Simon, Krawczyk and Holyoak 2004; Simon 2004). In part of their experiments, participants were presented with complex legal cases and had to judge the subjective validity of the evidence before and after the decision was made. The authors were able to demonstrate strong coherence shifts (i.e., differences in the ratings of the evidence before and after the decision). People were not aware of these shifts and the ensuing decision was "experienced as rationally warranted by the inherent values of the variables, rather than by an inflated perception imposed by the cognitive system" (Simon 2004, p. 545). Interestingly, Simon was able to show that PCS processes not only influence information directly involved in the decision, but also beliefs and background knowledge. Motivation and attitudes influenced the direction of coherence shifts. In line with the assumption that PCS processes are based on temporarily activated networks, it could be shown that coherence shifts are of a transitory nature and disappear after a certain time. Using different material, Glöckner, Betsch and Schindler (submitted) found that coherence shifts instantly set in as soon as a decision task is perceived, even without a decision being made at all. Furthermore, it could be shown that coherence shifts occur in city-size decision tasks (see example above). In line with the predictions of the PCS approach, coherence shifts seem to be a stable and general phenomenon that can be observed in a broad range of decision tasks.

*Fast Compensatory Information Integration*

Bröder (2003) extensively investigated individual decision strategies in probabilistic decision tasks. He found that some of the participants searched for information and selected options in line with the predictions of fast-and-frugal heuristics. Furthermore, in line with the predictions of the adaptive-toolbox model, he found that individuals adapted their behaviour to the structure of the environment. However, he finally concluded that "a [weighted] compensatory strategy may be something like a default strategy that is applied at the beginning of the procedure" (p. 617). Considering the fundamental bounded-rationality argument – that human cognitive capacity is limited – this finding seems surprising. Why should individuals use a complex strategy as a default strategy that might easily overload their cognitive capacity?

Glöckner (2006) carried out several experiments to further investigate decision strategies in city-size decision tasks. All information was presented simultaneously to measure human’s computational capacity, without limiting information search by the research method (Figure 2). Participants were instructed to make good decisions and to proceed as fast as possible.

-- Please insert Figure 2 about here --

A maximum likelihood analysis of the individual choice patterns revealed that, for most of the participants, choice patterns were most likely produced by the weighted compensatory integration of cue values and cue validities. The median decision time was below three seconds. Thus, in line with the predictions of the PCS approach, individuals are indeed able to quickly integrate multitudinous information in a weighted compensatory manner. Our data converge with findings by Bröder (2003), indicating that this kind of information integration seems to be the default strategy if no feedback is available that indicates that a different strategy should be used.

*Decision Time and Confidence Judgments*

In order to test the predictions concerning decision times and confidence judgments, Glöckner and Hodges (submitted) carried out a series of experiments on memory-based decisions. American students learned information about real German cities and were afterwards asked to make a memory-based decision concerning which city is larger (cf., Hastie and Park 1986). Monetary incentives for correct decisions were used to assure high motivation. Consistency was varied between decision tasks; an example for this manipulation is presented in Figure 3. For participants that estimate the cue "1$^{st}$ league soccer team" as the least valid cue, consistency is lower in the left-hand depicted decision task than in the right-hand decision task. According to fast-and-frugal heuristics (i.e., Take-the-Best heuristic, Equal-Weight heuristic), decision times should not differ between the two decision tasks because the number of computational steps that are necessary to select an option does not differ between decision tasks. According to the PCS approach, in the decision task depicted on the left, decision time should be higher and confidence judgments should be lower than in the decision task depicted on the right. Both predictions were able to be empirically supported, and the findings were able to be replicated using different decision tasks, different materials, and also in online decision tasks.

-- Please insert Figure 3 about here --

In sum, the predictions of the PCS approach are empirically well supported. Individuals are able to quickly integrate multitudinous information in a weighted compensatory manner; they even seem to use this as a default strategy; the interpretation of information is changed in the decision process; decision times and confidence judgments are systematically influenced by the level of consistency in decision tasks.[2]

[2] Additionally, it should just be noted that the PCS approach can be understood as a generalization of the most prominent model for jury decision: the story telling model (Pennington and Hastie 1992). That model is

**What about Bounded Rationality?**

Obviously, the findings conflict with the bounded-rationality approach and specifically with the adaptive-toolbox model. Could the reported findings be explained by the fact that decision tasks induced the usage of decision strategies other than fast-and-frugal heuristics? Or could the PCS approach just be understood as another tool that belongs to the adaptive toolbox? To discuss these questions, it is worthwhile to recapitulate the three fundamental premises of the adaptive-toolbox approach (Gigerenzer 2001).

First, the research program proposed by Gigerenzer and colleagues aims to "understand how actual humans (or ants, bees, chimpanzees, etc.) make decisions, as opposed to heavenly beings equipped with practically unlimited time, knowledge, memory, and other infinite resources" (p. 38). Decisions rules should be *psychologically plausible* (i.e., they should be based on the cognitive repertoire a species indeed has) since they rely on simple search, stopping and decision rules. In the light of the findings reported above, the adaptive toolbox underestimates the human ability for information integration. As postulated by the PCS approach and demonstrated by empirical evidence, parallel automatic processes that allow for quickly integrating multitudinous information in a complex way are a part of the cognitive repertoire of humans. Consequently, PCS processes seem to be psychologically plausible, without relying on simple search, stopping and decision rules. In contrast to the prevailing view, it must be recognized that the mathematical complexity of the algorithm that leads to a decision (i.e., the number of elementary information processes; Payne et al. 1988) is not a valid measure of the effort to solve a decision task as soon as automatic processes are considered. According to the reported findings, people are able to make decisions based on complex algorithms that even computers take several seconds to calculate.

Second, the "adaptive toolbox offers a collection of heuristics that are specialized rather than domain general as would be the case in subjective expected utility (SEU)" (Gigerenzer 2001, p. 38). Thus, it is argued that the structure of the domain induces the application of different decision algorithms. Although the evidence does not yet allow for final conclusions, the above reported data indicate that PCS processes are rather general because they automatically set in as soon as a decision task is perceived. Individuals are not aware of them and often can not avoid them. The PCS mechanism itself is always the same, but the structure of the temporarily activated network is adapted to the specific decision task;

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empirically well supported, and part of the evidence (cf., Hastie and Wittenbrink 2006) lends additional support to the PCS approach.

it reflects the subjective perception of the specific content, learning experiences and general knowledge.

Third, according to the adaptive toolbox, the structure of the environment has to be taken into account when exploring the efficiency of decision strategies. Heuristics are claimed to be successful because they are domain specific; they are adapted to the structure of the environment. In comprehensive simulations of real world data, it has been shown that there are domains in which fast-and-frugal heuristics lead to very accurate decisions, for instance in the mentioned city-size decision tasks (Gigerenzer and Goldstein 1996). Thus, the domains used in the above reported experiments have to be closely investigated before premature conclusions are drawn. However, the dominant usage of compensatory strategies was observed precisely in the city-size domain. Why did participants not behave adaptive to the environment? A closer inspection of the simulation data reported in Gigerenzer and Goldstein (1996) reveals one possible answer: on average the performance advantage of the Take-the-Best heuristic in cross prediction was 3 percent. Although people have powerful mechanisms of frequency learning, it would take them far more than 100 learning trials with perfect feedback to learn this advantage. Usually, real life does not provide such a perfect and highly repeated learning environment. Consequently, it is rather unlikely that such a small difference will be learned.

Furthermore, abstracting from the process of information integration and considering choices only, it is often overlooked that fast-and-frugal heuristics are always a special case of weighted compensatory decision strategies (Bergert and Nosofsky in press; Lee and Cummins 2004). Fast-and-frugal heuristics (i.e., Take-the-Best heuristic and Equal-Weight heuristic) can always be perfectly modelled by weighted compensatory strategies. Thus, for pure mathematical reasons, fast-and-frugal heuristics can never be better at predicting choices than weighted compensatory models, except when non-optimal weights are used (as may be the case in cross prediction).

In sum, the materials used in the experiments make it very unlikely that the findings can be simply explained by the fact that the decision tasks hindered the application of fast-and-frugal heuristics and induced the usage of more complex strategies. Furthermore, the PCS approach can not be seen as just another fast-and-frugal heuristic because it conflicts with basic premises of the adaptive-toolbox approach: the PCS approach is not based on simple rules for information integration; it does not ignore the majority of information (i.e., it is not frugal); and it does not seem to be domain specific but rather general. However, in the next paragraph, ideas will be summarized that integrate the adaptive-toolbox approach and the PCS approach into a more general model.

## TOWARDS AN INTEGRATIVE INTERACTIONIST APPROACH

As argued above, according to the majority of decision-making models, the decision process is seen as a simple unidirectional process in which information concerning a decision task is searched or retrieved and integrated in order to come to a decision. Often the underlying processes are considered to be deliberate; some more recent models assume automatic processes. Most models consider either deliberate or automatic processes but not the interaction between them. Finally, based on the observation that patterns of information search differ systematically, particularly models based on the bounded-rationality approach conclude that individuals have a set of decision strategies from which they can select, in contrast to just one universal decision strategy (Lee and Cummins 2004; cf., Glimcher et al. 2005).

### The PCS Rule and its Evolutionary Advantage

Based on the general PCS approach outlined above, Glöckner and Betsch (under review b) suggested that the *PCS rule* be viewed as an alternative integrative model for decision making (Figure 4). It is postulated that automatic PCS processes form the computational core of decision making and that deliberate processes merely supervise and modify the network that these automatic processes act on. A two-level network architecture is assumed: in the primary network evidence and options are weighed in their complex constellation; in the secondary network, if necessary, deliberate strategies are weighed that support consistency maximizing in the primary network and allow for quick adaptations.

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#### *The Primary Network*

As soon as individuals are confronted with a decision task, automatic processes of information search and retrieval set in that lead to a construction of a temporarily activated network (cf., Figure 1). Within the network, PCS processes set in that operate to maximize consistency by changing the activation level of the contained elements. The architecture of the network provides the constraints under which the quest for consistency evolves. Thus, the final level of consistency is bounded by the structure of the network. If the level of consistency in the network ($C$) exceeds a certain threshold ($\theta$), the PCS processes are terminated and the option with the highest activation is chosen. The network of options and information is referred to as the *primary network*.

It is argued that primary networks also capture the automatic processes of behavioral selection in animals, and thus could be considered the evolutionarily old part of decision-making processes. Parallel to processes of object perception, information is weighed in its complex constellation; the dominant interpretation is automatically detected and accentuated. This may explain the finding that even sticklebacks have the computational capacity to select mating partners by integrating trait information in a complex compensatory manner (Künzler and Bakker 2001; see also Glimcher et al. 2005). For human decision making, the operations of the primary network lead to the often described phenomenon of "intuition": it is instantly *seen* which option should be selected. No deliberation is necessary to reach this insight; no deliberation seems necessary to validate it. The preferred option can be instantly chosen. The level of awareness of the resulting mental representation can differ. In some cases, individuals are totally aware of the consistent mental representation and are able to explicate it; in other cases just a vague feeling enters awareness.

*The Secondary Network*

If the level of consistency *C* in the primary network is below the threshold, a secondary network is formed. The secondary network is instrumental to the primary network. In the secondary network, deliberate strategies that can support consistency maximizing in the primary network are weighed against each other. It is postulated that deliberate processes can not directly influence automatic PCS processes; they can only modify the network that PCS processes act on. For instance, deliberate processes may be used to include additional information into the network or change the structure of the network. Such deliberate processes that aim to modify the primary network are referred to as *deliberate constructions*. It is assumed that deliberate constructions are also weighed and selected based on PCS processes. The deliberate construction that is most activated is carried out. It is thereby reasonable to assume that deliberate constructions become automatic if repeatedly trained (cf., Anderson and Lebiere 1998).

There are two main reasons for a low level of consistency. First, insufficient information is included in the network, or the network is almost empty. In this case deliberate processes of information search and information production are used to add information to the network. Second, the degree of contradiction in the network can be so high that it can not be sufficiently resolved by PCS processes. To avoid a long period in which one is incapable of action, deliberate processes can temporarily modify the structure of the network or additionally activate or inhibit elements in order to increase consistency. This mechanism can also be used to simulate (cf., Bischof 1987; Hastie and Wittenbrink 2006) different interpretations of the data that were not able to be reached by mere automatic processes. The reason for this may be that the PCS algorithm has gotten caught in a local maximum of consistency, thereby overlooking a global maximum (Read, Vanman and Miller 1997).

In contrast to lower animals, humans have developed the ability to supervise and deliberately manipulate the powerful but inflexible automatic processes of the primary network (Betsch 2005). It is assumed that the relations between elements in the primary network are mainly determined by slow learning processes. Thus, changes in these relations usually take a long time, and quick adaptations to environmental change are not possible (Betsch et al. 2001; Betsch et al. 2004). The evolutionary advantage of the additional deliberate system is that it facilitates faster behavioral adaptations, allows for directed information search, qualified information production and simulations to find the global maxima. However, without the automatic system, the deliberate system would be chronically computationally overloaded.

**Integrating Fast-and-Frugal Heuristics and the PCS Rule**

One of the essential findings of the adaptive-toolbox research program is that individuals adapt their decision strategy and particularly their information search to the environmental structure. Simply stated, if individuals receive repeated feedback that in a certain environment the usage of less valid cues is not useful, after sufficient learning trials, individuals focus more on the most important cue (Bröder 2003; Rieskamp 2006; Rieskamp and Otto 2006). It is important to differentiate two classes of situations: situations in which information is instantly accessible and situations in which this is not the case (cf., Glöckner and Betsch submitted c). In the latter case, which is dominantly used in experimental research, the primary network is initially almost empty and consistency is low. Thus, the secondary network is formed to support consistency-maximizing processes. Repeated feedback reinforces the deliberate construction "look up information for the most important cue only", and after sufficient trials, individuals change from a default deliberate-construction strategy (e.g., "look up all information along options") to the alternative deliberate-construction strategy. From this point in time, the primary network consists of the options and the information of the most important cue only. Consequently, choice predictions align with that of the Take-the-Best heuristic. From such a perspective, the Take-the-Best heuristic (as well as other fast-and-frugal heuristics) can be understood as one of a multitude of deliberate-construction strategies that are possible elements of the secondary network. However, in each case the decision is finally based on the resulting activation in the primary network.

In situations in which information is instantly accessible, the primary network is instantly constructed. Individuals will make decisions based on the network. However, from repeated feedback, the structure of the environment will be learned. Thus, in a non-compensatory environment (i.e., an environment in which the most valid cue is stronger than all the remaining cues taken together), after certain learning trials, the dominance of the initial validity of the most valid cue will become more pronounced. As a result, although the lower valid cue information will not be ignored, its influence on the decision will decrease. In the long run, this also leads to choices that align with the predictions of the Take-the-Best heuristic.

In sum, it is argued that the adaptive learning processes highlighted by the adaptive-toolbox model are important in decision making. However, they can be integrated in the PCS rule: changes in the relations between elements in the primary network as well as the relations between specific deliberate constructions for certain decision tasks in the secondary network are learned from feedback. Further research will be needed to differentiate and test this hypothesis empirically.

## THE PCS RULE AND INSTITUTIONS

Work on the PCS rule is still in its early stages: The model must be further specified and empirically tested. However, the model provides a fruitful starting point for rethinking issues of relevance for the development and design of institutions. Jointly considering cognitive processes and the structure of institutions allows learning from institutions and for institutions (cf., Engel and Weber submitted). It has to be assumed that – similar to humans – institutions are shaped by evolutionary forces and learning mechanisms that optimize their structure over time (Hodgson 1988). If the PCS rule is a valid model, indirect evidence for the model can be derived by investigating whether successful institutions align with its predictions. On the other hand, it can be assumed that a better understanding of the cognitive processes allows for enhancing institutions more quickly than by an evolutionary process based on trial and error only. Some of the major hypotheses concerning the structure of efficient institutions according to the PCS rule will be outlined in the following.

### Predictions of the PCS rule for the Design of Efficient Institutions

*Prediction 1:* Individual decisions are good as long as the structure of the primary network represents the structure of the environment. Efficient institutions support the construction of representative primary networks.

*Prediction 2:* The structure of the primary network is influenced by unconscious motivational and emotional factors. Institutions have been developed to reduce the influence of these factors and to increase the objectivity of the network.

*Prediction 3:* PCS mechanisms artificially increase the consistency of information by wiping out contrary information, which naturally leads to overconfidence. Efficient institutions reduce overconfidence by forcing individuals or groups to consider alternative interpretations.

*Prediction 4:* Decision making in diverse groups is problematic because members can form different but rather stable interpretations of the situation. PCS processes increase divergences in the interpretation of information and make them more resistant to change. Institutions have been established to nevertheless reach decisions in time and without the group breaking apart.

*Prediction 5:* Decisions based on automatic PCS processes are hard to communicate and to justify, because parts of the mental representation of the decision might be unconscious. Institutions provide rules that make decisions easier to communicate and that facilitate an increase in the level of acceptance of the decision.

*Prediction 6:* Institutions increase the consistency of decisions over time by providing a set of explicit rules for deliberate constructions (secondary network). As a result, certain important information is always included in the primary network, and it stabilizes the general structure, which in turn increases consistency over time.

*Prediction 7:* Efficient institutions leave room for and make use of PCS processes. The structure of the environment should be analyzed, and decision makers should be provided with the results. These results can facilitate the construction of more adequate mental representations. However, it is not necessary to provide decision makers with overly simple decision rules, because they can handle complexity.

*Prediction 8:* PCS processes enhance the efficiency of social interaction in organisations. If institutions ensure that the fundamental goals of the organisations are always included in the primary network, individual decisions – also in new situations – are automatically aligned to the organisational goals. The effortful (and usually ineffective) specification of a complete set of behavioral rules for all kinds of situations becomes obsolete.

*Prediction 9:* Effective institutions make use of the error detection capabilities of PCS processes and leave room for the exploration of feelings of mismatch. The conscious part of the mental representation is not equivalent to the whole representation and might overlook important facts that unconsciously wield an influence.

*Prediction 10:* Efficient institutions make use of trained expert decision makers. Expert decision makers are able to handle larger informational networks than lay people. Expert decision makers learn to automatically include a large set of important elements into the network.

*Prediction 11:* Efficient institutions establish revision units that test the inclusion of all relevant information into the consideration and provide learning feedback for deliberate constructions as well as for the structure of the primary network.

**German Law and the PCS rule**

As outlined above, successful institutions could be investigated to test the predictions of the PCS rule. It is assumed that successful institutions in a process of evolution and learning have already implemented part of the prescribed mechanisms. German law may be considered one such efficient institution; this is the reason it was selected in the initial investigation of the predictions of the PCS rule for institutions.

*Construction of Representative Primary Networks*

One of the most fundamental aims of modern legal systems is probably that all relevant evidence be taken into account according to its level of importance (cf., Jackson 1996). For example, a decision of the German Federal Supreme Court explicitly forbids the application of simple, schematic rules (i.e., heuristics) in expert assessments of the trustworthiness of eyewitness reports (Decision of the Federal Supreme Court [BGH] July, 30 1999, Az.1 StR 618/98). In contrast and in line with the above stated predictions (i.e., predictions 1, 6 and 7), a set of valid cues [*Realkennzeichen*] is specified, which has to be considered in the assessment. With this prescription, the institution ensures that these cues are included in the primary network. On a more general level, the principle of the exhaustive appreciation of relevant evidence is a fundamental requirement imposed by the German code of criminal procedure (Schoreit 2003; StPO §261). The code even obligates judges to take into account not only the formal evidence of the case, but also cognitions formed on the basis of the holistic impression of the trial [*Gesamteindruck der Hauptverhandlung*; Schoreit 2003].

*Ensuring Objectivity and the Requirement to Consider Alternative Interpretations*

Another basic aim of the legal system is that decisions be made objectively, and that alternative interpretations be considered (cf., predictions 2 and 3). For instance, the different roles of prosecutors and defenders should ensure that all the relevant information is available to be included in the primary network and that different interpretations are considered. This should allow the neutral judge to weigh interpretations against each other and to find global instead of local maxima of consistency. Likewise, the German code of criminal procedure obligates judges to consider all plausible alternative assessments (or interpretations) of the evidence (Schoreit 2003). A consideration of evidence is erroneous if only one of various equally plausible interpretations is looked at (Schoreit 2003).

*Decision Rules in Multiple-Judge Courts*

Legal institutions have implemented voting rules to allow making decisions even if different stable interpretations of the case have been formed by judges of multiple-judge courts (cf., prediction 4). It is sometimes not necessary to convince all the judges to agree with one interpretation; often majority rules are applied. In German law, this is, for instance, the case in the Federal Constitutional Court. Interestingly, particular decisions of the Federal Constitutional Court are used as objective argument in further legal argumentations (cf., prediction 5).

*Installing Revision Units*

Appellate courts can be considered revision units in the German legal system. The German code of criminal procedure regulates that decisions be revised if decisions are erroneous because of procedural violations. This is for instance the case if it can be proved that relevant aspects have not been included in the consideration or alternative interpretations of the evidence have not been considered (Schoreit 2003; cf., predictions 1 and 11).

*Making use of Expert Decision Makers*

Taking a somewhat broader perspective, German legal doctrine can be interpreted as providing a large set of features that have to be considered as a complex constellation in legal cases. It can be assumed that, when thinking about a case, experienced lawyers automatically and unconsciously include many (or hopefully all) of the relevant aspects in their primary network, whereas law students use deliberate-construction strategies to include them in a stepwise manner (cf., predictions 8 and 10). Furthermore, within defined intervals German law allows judges latitude in their judgment and thus allows judges to rely on impressions that result from automatic PCS processes (cf., prediction 9).

In sum, there is tentative evidence from German law that supports the PCS rule. Many of the predictions for efficient institutions are already implemented. However, a further systematic investigation will be needed to strengthen this argument and to inspire a purposeful improvement of the institution of German law as well as the improvement of other institutions, if necessary.

## CONCLUSIONS AND OUTLOOK

The PCS rule is a very complex model, and at the moment it has to be considered a work in progress. Particularly to strengthen the model, it is necessary to further specify the secondary network and carry out empirical tests on the interaction between the networks. Nevertheless, evidence already clearly supports its central claim: individuals are capable of quickly integrating a great deal of information in decision making. Based on this finding, some suggestions for institutions that have been derived from the bounded-rationality approach should be rethought; others are being highlighted even more. As argued by Gigerenzer et al. (2001), it is very important to understand the environmental structure of decision tasks in order to enhance the quality of decisions. However, according to the PCS rule, institutions should try to support individuals in constructing more adequate mental representations of the decision task (cf., Gigerenzer and Hoffrage 1995). In some cases this might be achievable by instructing individuals to include only the most valid information in the network, but in most complex decision tasks this will probably not be the case.

Besides investigating the PCS rule from a psychological and an institutional perspective, it would be very fruitful to investigate the model from a neuroscientific perspective. The fact that the PCS rule is based on network models which partially rest on a rough abstraction from neuronal connections speaks for this. Wagar and Thagard (2004) suggest a sub-symbolic network that more closely resembles neurons and aims to copy relevant areas in the brain. However, it may be questioned whether the symbolic representations used in the PCS rule (in contrast to sub-symbolic ones as used by Wagar and Thagard 2004) are sufficient to catch the major mechanisms of decision making. Furthermore, the close relation of the PCS rule to models of perception might allow for comparing patterns of activation using neuroimaging techniques and taking into account recent neuroscientific findings on perception and perceptual decision making (Heekeren et al. 2004; Summerfield et al. 2006). Finally, proving a double dissociation between primary network activations and deliberate constructions would strongly support the model.

Obviously, evolution has equipped animals and human beings with powerful automatic mechanisms to integrate large amounts of information. According to the PCS rule, humans have additionally developed the ability to deliberately supervise and manipulate the primary network. Although the deliberate processes are rather limited in their computational capacity, they allow for better and faster adaptations by providing further information and temporarily changing the network so as to quickly find a consistent solution and a global maximum of consistency.

It seems that evolution was miles ahead of scientific endeavours: while decision researchers were still focusing on deliberate decision strategies and arguing about the boundaries of rationality, evolution had long taken care of the problem by enduing humans (and animals) with powerful computational capabilities. This paper aims to make a contribution so that we might catch up with the fascinating inventor, evolution. Here, we may take it as a positive sign that the father of bounded rationality already considered the possibility of unconscious processing:

> My first empirical proposition is that there is a complete lack of evidence that, in actual choice situations of any complexity, these [expected utility] computations can be, or are in fact, performed... but we cannot, of course, rule out the possibility that the unconscious is a better decision maker than the conscious (Simon 1955, p. 104).

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**Figure Captions**

*Figure 1.* The general structure of the PCS network for probabilistic decision tasks. Boxes represent nodes. The activation *a* of the nodes is modified within the PCS process. Lines represent links between nodes that are all bidirectional and can be inhibitory or excitatory. Links have different weights *w* and are fixed constraints in the network that result from learning or from explicitly provided information.

*Figure 2.* Example for a city-size decision task.

*Figure 3.* Decision tasks with less consistency (left-hand side) and more consistency (right-hand side).

*Figure 4.* Schematic process model of the PCS rule.

Figure 1

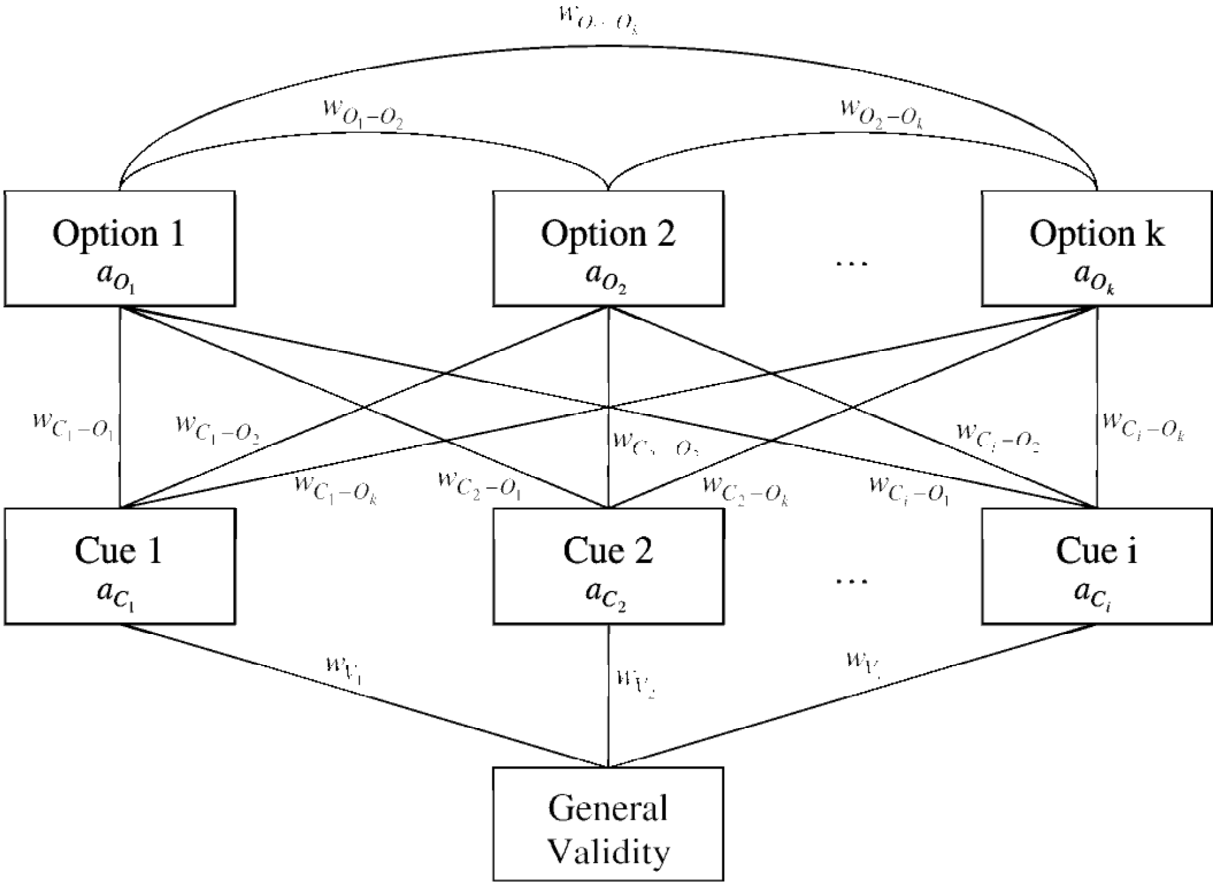

$w_{O_1-O_2}$
$w_{O_2-O_k}$
Option 1
$a_{O_1}$
Option 2
$a_{O_2}$
…
Option k
$a_{O_k}$
$w_{C_1-O_1}$
$w_{C_1-O_2}$
$w_{C_1-O_k}$
$w_{C_2-O_1}$
$w_{C_2-O_k}$
$w_{C_i-O_2}$
$w_{C_i-O_1}$
$w_{C_i-O_k}$
Cue 1
$a_{C_1}$
Cue 2
$a_{C_2}$
…
Cue i
$a_{C_i}$
$w_{V_1}$
General
Validity

Figure 2

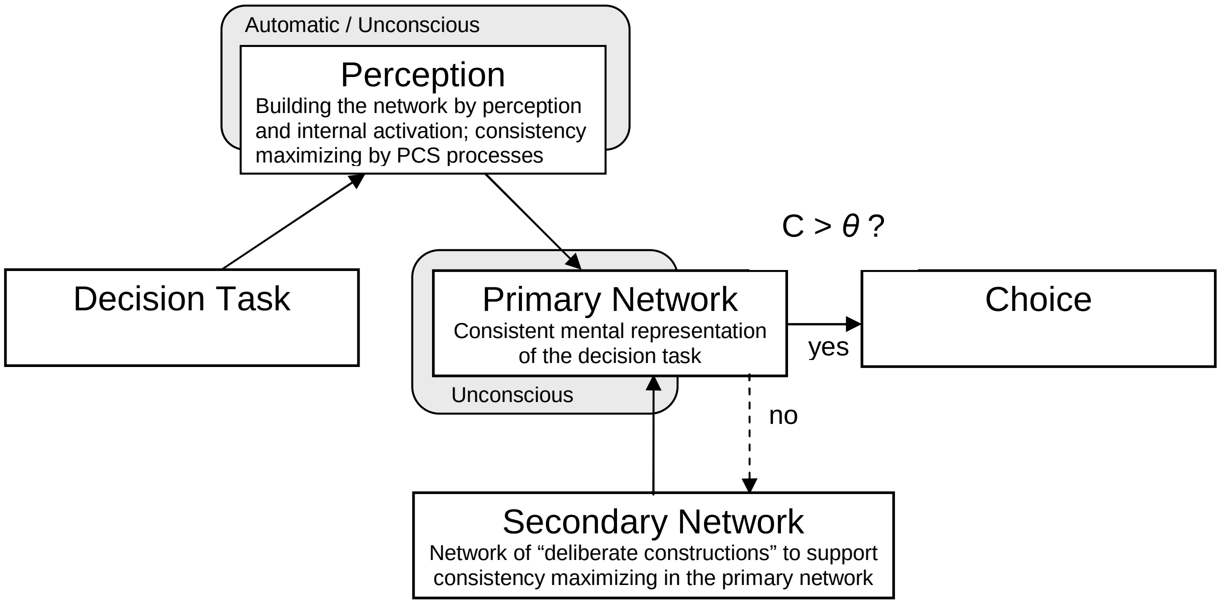
| | City A | City B |
|---|---|---|
| State Capital | + | − |
| University | + | + |
| 1st League Soccer Team | − | + |
| Art Exhibition | + | − |
| Airport | − | + |
| Cathedral | − | + |

Figure 3

| | Wiesbaden | Freiburg |
|---|---|---|
| State Capital | + | − |
| University | − | + |
| 1st League Soccer | − | + |

| | Dresden | Leverkusen |
|---|---|---|
| State Capital | + | − |
| University | + | − |
| 1st League Soccer | − | + |

Figure 4


Automatic / Unconscious
Perception
Building the network by perception and internal activation; consistency maximizing by PCS processes
C > θ ?
Decision Task
Primary Network
Consistent mental representation of the decision task
Unconscious
yes
Choice
no
Secondary Network
Network of “deliberate constructions” to support consistency maximizing in the primary network