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Human Rationality

Observing or Inferring Reality

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Abstract
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This thesis investigates the boundary of human rationality and how psychological processes interact with underlying regularities in the environment and affect beliefs and achievement. Two common modes in everyday experiential learning, supervised and unsupervised learning were hypothesized to tap different ecological and epistemological approaches to human adaptation; the Brunswikian and the Gibsonian approach. In addition, they were expected to be differentially effective for achievement depending on underlying regularities in the task environment. The first approach assumes that people use top-down processes and learn from hypothesis testing and external feedback, while the latter assumes that people are receptive to environmental stimuli and learn from bottom-up processes, without mediating inferences and support from external feedback, only exploratory observations and actions.

Study I investigates selective supervised learning and showed that biased beliefs arise when people store inferences about category members when information is partially absent. This constructivist coding of pseudo-exemplars in memory yields a conservative bias in the relative frequency of targeted category members when the information is constrained by the decision maker's own selective sampling behavior, suggesting that niche picking and risk aversion contribute to conservatism or inertia in human belief systems. However, a liberal bias in the relative frequency of targeted category members is more likely when information is constrained by the external environment. This result suggests that highly exaggerated beliefs and risky behaviors may be more likely in environments where information is systematically manipulated, for example when positive examples are highlighted to convey a favorable image while negative examples are systematically withheld from the public eye.

Study II provides support that the learning modes engage different processes. Supervised learning is more accurate in less complex linear task environments, while unsupervised learning is more accurate in complex nonlinear task environments. Study III provides further support for abstraction based on hypothesis testing in supervised learning, and abstraction based on receptive bottom-up processes in unsupervised learning that aimed to form ideal prototypes as highly valid reference points stored in memory. The studies support previous proposals that integrating the Brunswikian and the Gibsonian approach can broaden the scope of psychological research and scientific inquiry.

Keywords: supervised learning, unsupervised learning, adaptation, niche picking, prototypes, rules, exemplar memory.

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List of Papers

This thesis is based on the following papers, which are referred to in the text by their Roman numerals.

I Henriksson, M. P., Elwin, E., & Juslin, P. (2010). What is coded into memory in the absence of outcome feedback? *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *36*, 1–16.

II Henriksson, M. P., & Enkvist, T. (2015). *Adaptation to task environments*. Manuscript submitted for publication.

III Henriksson, M. P. (2015). *Abstraction of ideal prototypes in multiple-cue judgment*. Manuscript submitted for publication.

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Contents

Abbreviations

AIC	Akaike Information Criterion
BIC	Bayesian Information Criterion
CAM	Cue Abstraction Model
EBM	Exemplar-Based Model
GCM	Generalized Context Model of Classification
JDM	Judgment and Decision-Making
PBM	Prototype-Based Model
RMSD	Root Mean Square Deviation (of the models)
RMSE	Root Mean Square Error (of the judgments)

Introduction

The boundary of human rationality and why people err and not learn from experience has always been of concern in judgment and decision-making research (JDM). The way people acquire knowledge and adapt to their environment in everyday life has also been of concern in highly different ecological and epistemological approaches to human adaptation: the Brunswikian (e.g., Brunswik, 1955) and the Gibsonian approach (e.g., Gibson & Gibson, 1955). The first approach assumes that people learn from hypothesis testing strategies and external feedback while the latter assumes that people learn from exploratory observations and actions with no external feedback involved. For example, when a recruitment officer infers the suitability of different applicants based on different attributes, and receives feedback about their suitability after a probationary period, or when a recruitment officer observes a portfolio containing the attributes and outcomes of former employees as an aid to future recruitment decisions. The main objective of this thesis is to study the relative efficiency of these learning modes in different task environments and investigate the possibilities for an integrative ecological approach. Supervised learning, i.e. when people learn from external feedback, is thus predicted to exploit inferential top-down processes. Unsupervised learning, i.e. when people learn without external feedback, is predicted to exploit receptive bottom-up processes.

Both two ecological approaches assume that people adapt their process to underlying structures in the environment. One important property in natural environments is absent or selective information, either due to selective sampling of information by the decision maker, or due to the selectivity imposed by the external environment. Study I investigates the different forms of selective supervised learning and its repercussions on achievement and biased beliefs in three computer-based experiments.

Another characteristic concerns the underlying complexity of the environmental stimuli that may exhaust and deplete the cognitive resources of the decision maker, depending on how he/she processes them. These characteristics are manipulated in several computer-based experiments in Studies II and III respectively, with the aim of studying involved processes in supervised and unsupervised learning and the relative efficiency of these depending on the underlying structure in the task environment.

The cognitive process models predicted to capture some of the inferential top-down or bottom-up processes, respectively, were a cue abstraction model and an exemplar memory model. The first assumes that people test hypotheses about underlying relationships and integrate abstracted information by an additive rule. The latter assumes that people are receptive to stimuli in task environments and encode the exemplars in memory as multiple reference points for subsequent similarity-based judgments. Study III offers a third alternative, a prototype model, which assumes that people abstract underlying environmental regularities across the flow of exploratory observations, and form ideal prototypes as highly valid reference points stored in memory for subsequent similarity-based judgments.

The Rationality Debate

The concept of rationality has puzzled philosophers, mathematicians, and other thinkers for centuries. The theme has also dominated psychological research in judgment and decision-making since the late 1940s and early 1950s. As will be outlined below, the focus in JDM research has often been on human irrationality and inferior judgment and decision-making. One line of research has mostly focused on questions concerning coherence and whether decision-making or choice conforms to logical and statistical norms. Another line of research has mostly focused on questions concerning correspondence and whether judgments or beliefs correspond or approximate to objective facts as a function of experiential learning. Nonetheless, the two lines of research intersect and both contribute to the general state of knowledge in JDM. The present thesis focuses on correspondence and the effects of different forms of experiential learning: supervised and unsupervised learning.

Paul Meehl's influential work on inferior expert prediction in 1954 started an intense debate surrounding inferior expertise and the notion of rationality that has spurred research in judgment and decision-making ever since (e.g., see Goldstein & Hogarth, 1997, for a comprehensive historical perspective). In general, expert judgment and decision-making did not meet the expectations when comparing with statistical predictions. Not even when comparing with novices. Over the years, experts in social, medical, legal, and financial areas have been scrutinized (e.g., Bornstein & Emler, 2001; Dawes, Faust & Meehl, 1989; Goldberg, 1959; Koehler, Brenner, & Griffin, 2002) and even researchers themselves have not been spared the critical scrutiny (e.g., Fiedler, 2011; Gigerenzer, 1993; 2004). Amos Tversky's and Daniel Kahneman's work in the 1970s and 1980s on heuristics and biases soon became paradigmatic for JDM research. Their research program was founded on the notion that the cause of human irrationality can be traced to fast intuitive "system 1" processing that usually dominates, or overrides, slow analytic "system 2" processing. Inferior and biased judgment and decision-making were considered to be the net effect of using different heuristics, or rules of thumb, intended to reduce task complexity and facilitate judgments (Gilovich, Griffin, & Kahneman, 2002).

In the mid-1950s, Herbert A. Simon began to formulate what was to become known as the theory of bounded rationality (Simon, 1955; 1956; 1990). Using scissors as a metaphor, Simon argued:

> "Human rational behavior […] is shaped by a scissors whose two blades are the structure of task environments and the computational capabilities of the actor." (Simon, 1990, p. 7).

Simon acknowledged the inherent limitations of the human mind, such as its limited working memory capacity (e.g., Miller, 1956) and argued that rationality is bound by the internal constraints of the decision maker and the constraints imposed by the external environment. In line with Zipf's (1949) principle of least effort to achieve maximal gain, Simon (1956; 1990) suggested that rational judgment and decision-making is to adaptively choose the most cost-effective process or strategy that "satisfices" or affords the best accuracy for the task. Thus, in order to study rationality, it is important to investigate the process and the structure of the environment in which the individual agent operates.

Ecological Rationality

The interplay between the individual and the environment is emphasized in theories of perception proposed by Egon Brunswik and James Gibson, who both stressed that humans should be studied in their natural environment. The Gibsonian (e.g., E. Gibson, 1969; J. Gibson, 1979) and the Brunswikian approaches (e.g., Brunswik, 1955; Hammond & Stewart, 2001) share the view that experiential learning is an adaptation to functional relevant regularities in the external environment. However, they differ in respect to the epistemological question how people acquire knowledge (Heft, 1981). Direct realism, as implied by the Gibsonian approach, assumes that people observe reality as it is, without mediating inferences or reconstructions. The indirect realism, as implied by the Brunswikian approach, assumes that people infer and reconstruct reality, in this case, through a lens of proximal cues. Thus, Egon Brunswik's constructivist approach to human adaptation emphasized inferential top-down mechanisms in experiential learning (Brunswik, 1955; Dhami, Hertwig, & Hoffrage, 2004; Gregory, 1970; Hammond & Stewart, 2001), while James Gibson's direct perceptual approach emphasized receptive bottom-up mechanisms in experiential learning (Gibson, 1966; 1979).

The main argument in this thesis is that supervised and unsupervised modes of learning tap the different theoretical and epistemological views, and that the learning modes are differentially effective for achievement depending on underlying regularities in the task environment.

Gibson's Direct Perceptual Approach

"Affordances" and "invariants" are two central concepts in the Gibsonian view (Gibson & Gibson, 1955; Gibson, 1979)[1]. Affordances are what objects in the environment offer the individual agent in terms of potential goal-attaining actions (e.g., how the individual can physically interact with the objects in the environment). Invariants are underlying sophisticated structures or regularities in the environment. Direct perception suggests a receptive or bottom-up mechanism and refers to how an individual observer picks up, or extracts, sophisticated information about the task environment from the flow of exploratory observations and actions.

James Gibson (1966) described the reciprocal relation of the environment and the individual agent using a metaphor of a radio: the environment "broadcasts" information and the individual agent must actively "tune in" to the specific "waves" in order to be calibrated to the environment. Eleanor Gibson, who introduced the direct perceptual approach to developmental psychology and categorization, argued that learning and differentiation among stimuli is not mediated by external feedback but by manipulating objects in the environment, for example by comparing and sorting them. Feedback is more an integral part of the sensory experience, and in that sense internal for the individual agent whose manipulation of objects enables detection of contrasts and underlying regularities (E. Gibson, 1969).

Thus, the core in the Gibsonian theory is that direct perception is not mediated by inferential top-down processes; direct perception requires only exploratory actions or observations to automatically be tuned in to the regularities (i.e. invariants) in the environment. Similar reciprocal relationship between the individual and the environment is found in research on embodied or situated cognition, where mental and behavioral operations are assumed to be shaped by multimodal and contextualized information stored in long term memory. Concepts and categories are thus not processed in isolation but in a context or environment. Such situated conceptualizations serve to facilitate goal pursuit and action, for example by mental simulations of future events using the memory of past events (e.g., Barsalou, 2003; 2009; 2010 for review; and Schöner, 2008 for a related computational account).

[1] "Gibsonian" refers here to both Eleanor and James Gibson. Though James and Eleanor Gibson focused on different questions in their respective research, they shared the same fundamental view of a direct perceptional account of experiential learning.

Brunswik's Constructivist Approach

Egon Brunswik proposed the lens model to illustrate the relationship between the environment and the mind of the individual agent (e.g., Dhami et al., 2004; Hammond & Stewart, 2001). As shown in Figure 1, the left side of the lens model describes environmental characteristics, while the right side describes the mind of the individual, inferring reality through the lens of selected and proximal cues. Thus, the individual agent cannot directly observe reality, only approximate reality through inferential mechanisms.

Brunswik argued that natural environments provide a rich variety of cues but the multiple cues are imperfect indicators of the distal criteria owing to probabilistic or uncertain relationships among cues, or between cues and the criteria. The validity of cues for the criteria (i.e., the ecological validity) sets a standard for the cue weights that are inferred by the individual. Adaptation to task environments is when achievement (i.e., judgment accuracy) improves and the cognitive system starts to approximate the environmental system and subjective cue weights match objective cue validities.

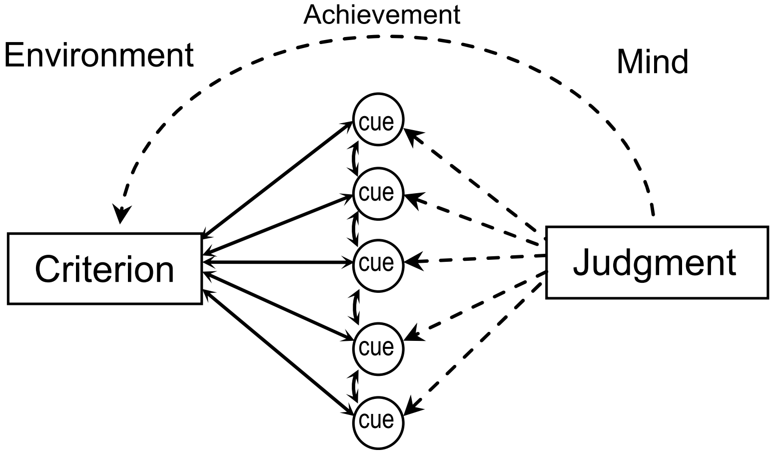

Figure 1. Brunswik's lens model, conceptualizing the relationship between a criterion and cues in the external environment and the mind of the individual agent.

Brunswik argued that there is an important functional trade-off between cues in the environment. His term "vicarious functioning" refers to the adaptive substitution of cues by other correlated cues, equally valid for the criterion of interest. This implies that in some situations non-present cues can be replaced by other cues present, or that the number of cues can be efficiently reduced. Such mechanism handles some of the selectivity that people are exposed to in everyday life and Study I is a further investigation on how people tackle missing information, for example, when information about outcomes is selectively missing and constrained by the decision maker's own selective sampling behavior or by the external environment.

Multiple-Cue Judgment

Kenneth Hammond (1955) applied Brunswik's probabilistic functionalism to social domains and judgment and decision-making (e.g., Brehmer, 1988; Cooksey, 1996) and with this framework, it was possible to further investigate expert judgments in different domains, for example, social, clinical, judicial, or financial judgments. For example, to study when a psychologist infers clients' levels of depression based on the multiple indicators or attributes (i.e., cues) believed to signal depressive tendencies (i.e., assessing a continuous criterion), to study when a judge takes a stand based on the various indicators (i.e., cues) that are provided by the prosecutor and the defense counsel (i.e., assessing a binary criterion), or to study when a recruitment officer asses the suitability for a job based on applicants' cue-profiles (assessing a continuous or a binary criterion). Cue learning and the repercussions for expert decision making can hardly be ignored. DSM-V (American Psychiatric Association, 2013), the diagnostic manual for psychologists to assess different disorders, is in this respect a collection of graded or weighted cues for different disorders. Instead of learning those cues from experience, psychology students receive them in an accessible format for future assessments.

The relationship between the individual agent and the environment implied by Brunswik's lens model, was also further elaborated into a statistical lens model (Hursch, Hammond & Hursch, 1964; Tucker, 1964). Although it has been critizised (e.g., Gigerenzer & Kurz, 2001; Hoffman, 1960), many have used multiple regression analyses as a standard tool for investigating decision quality and accuracy, and the focal point in multiple-cue judgment research has been on how much the individual can learn about the functional relationship between proximal cues and the distal criterion (e.g., cue validities, cue directions, linear or nonlinear relationships between cues and the criterion; e.g., Anderson, 1991; Brehmer, 1988; Deane, Hammond, & Summers, 1972; Einhorn, Kleinmuntz, & Kleinmuntz, 1979).

Multiple-cue learning has mostly concerned assessments with criteria varying in a continuous dimension, as in estimation tasks, but can also concern criteria in a binary dimension, as in categorization tasks. Similarly, cues can vary on binary dimensions (e.g., with or without hair; high or low grades), nominal dimensions (e.g., brown or blue eyes), or continuous dimensions (e.g., number of dots). These characteristics and underlying relationships are important in research when investigating the determinants for inferior judgment and decision-making. For example, when a psychologist use a more controlled integration and add information from indicative cues for a disease, unknowing that they are highly correlated and nonlinearly related to the criterion, he/she will most likely grossly overestimate the probability for the diagnosis. As will be outlined below, underlying nonlinearities in task environments may best be handled by other strategies. Such strategies exploit similarity assessments to past cases stored in memory. This thesis investigates whether such similarity-based assessments are derived from an unsupervised learning mode whereas a deliberate rule-based integration is derived from a supervised learning mode: two modes of experiential learning hypothesized to tap different ecological and epistemological approaches to human adaptation. Thus, the investigation tries to answer if the learning modes mediate an adaptive shift between an inferential mode and a receptive mode of acquiring knowledge.

Shifts in Cognitive Process

Cognitive Continuum Theory

Kenneth Hammond formulated the Cognitive Continuum Theory to describe quasi-rational processing as the common mode of cognition, and argued that the judgment policy can shift and be pulled along a continuum ranging from automatic and intuitive to deliberate and analytical thinking (e.g., Brehmer, 1988; Cooksey, 1996, Dhami et al., 2004). For example, the judgment is pulled towards the intuitive mode when the number of cues is large, when cues are correlated, are presented in a pictorial format, or when fast judgments are required. In contrast, the judgment is pulled towards the analytical thinking mode when the number of cues is small (less than 4) or time is unlimited (e.g., Cooksey, 1996; Hammond, Hamm, Grassia, & Pearson, 1987). The main determinant for movement along the continuum is failure, while successful cognition maintains the status quo (e.g., Cooksey, 1996).

There are several studies that have shown that people can adaptively shift between different cognitive processes. In categorization, an exemplar memory account (e.g., Brooks, 1978; Medin & Schaffer, 1978; Nosofsky, 1986) has often been compared with a prototype account (e.g., Homa & Cultice, 1984). Both exemplar and prototype theories assume that people exploit similarity assessments to stored instances in memory but the first assumes that people store all past cases (i.e., exemplars) in memory, while the latter assumes that people abstract and store only a prototypical representation of all cases within a category. In multiple-cue judgment research, the exemplar-based model has been compared with a cue abstraction model, which assumes people abstract cue weights, and integrate the information by an additive rule analog to multiple regression (e.g., Juslin, Jones, Olsson, & Winman, 2003). The "rule-bias" that has been observed, with a shift from a rule-based or abstracted process to a less taxing exemplar-based process, has been taken as evidence that people have a propensity for abstracted and rule-based processing (Ashby, Alfonso-Reese, Turken, & Waldron, 1998; Bourne, Healy, Kole, & Graham, 2006; Erickson

& Kruschke, 1998; Johansen & Palmeri, 2002; Juslin et al., 2003; Juslin, Karlsson, & Olsson, 2008; Kalish, Lewandowsky, & Davies, 2005; Karlsson, Juslin, & Olsson, 2007; Logan, 1988; Raijmakers, Schmittmann, & Visser, 2014; Rickard, 1997; Smith, Patalano, & Jonides, 1998). Study II and III investigates if this rule-bias, in part, is mediated by the recurrent use of a supervised learning mode within a constructivist research paradigm, and as such also invites the hypothesized inferential top-down processes.

Shift-Inducing Characteristics

As noted above, people adapt their processes to underlying environmental regularities, regardless if they are aware of the impact of those characteristics or not, and there are numerous identified characteristics that are able to induce shifts in cognitive processing (e.g., Hammond et al., 1987). For example, research has shown that a more analytical cue abstraction is more likely in task environments where the criterion is continuous rather than binary as in categorization tasks (e.g., Juslin et al., 2003; Olsson, Enkvist, & Juslin, 2006), and is even more likely when cues, the attributes, vary on continuous rather than binary dimensions (e.g., Karlsson et al., 2007), notably because that more fine-grained dimensions enable a better detection of how much a change on the various cue dimensions can predict a change on the criterion dimension. This assessment, and the abstraction of cue weights, is facilitated when cues are linearly and additively related to the criterion (e.g., Deane et al., 1972; Juslin et al., 2008; Karlsson et al., 2007). There are several reports that cue abstraction may be obstructed in task environments with underlying nonlinear or multiplicative cue-criterion relationships (e.g., Brehmer & Qvarnström, 1976; Deane et al., 1972; Klayman, 1988a). One explanation is derived from limitations in working memory and difficulties in testing various hypotheses about cue weights, and at the same time mentally control for the intrinsic intercorrelation among cues. Thus, the task of inferring cue weights in nonlinear cue-criterion environments places a heavy load on limited working memory capacity because the relative impact of one cue on the criterion always depends on other cues present (e.g., Stewart, 1988).

Salient cue directions or cue polarities are also important because they discern if cues are positively or negatively related to the criterion, thus facilitating the abstraction of cue weights (e.g., Bröder, Newell, & Platzer, 2010). Of course, cue abstraction is also facilitated when the individual receives prior and "feedforward" information about the underlying relationship between cues and the criterion in terms of cue directions and the validity of cues for the criterion (e.g., Björkman, 1972; Doherty & Balzer, 1988; Lindell, 1976; Newell, Weston, Tunney, & Shanks, 2009; Rolison, Evans, Dennis, & Walsh, 2012; von Helversen, Karlsson, Mata, & Wilke, 2013; von Helversen & Rieskamp, 2008; 2009).

The way stimuli are presented can also induce certain processes, for example, cue abstraction can be facilitated when the individual is allowed to make paired comparisons (Pachur & Olsson, 2012). Strategic cue search is also more likely when the stimuli are presented as written descriptions than as pictures, while the pictorial format has been shown to induce fast similarity-based prototype judgments (Bröder & Schiffer, 2003; 2006).

The exemplar-based process has been suggested to be an alternative way to solve the task with relatively good accuracy for the individuals. This process has also been reported as more likely in nonlinear cue-criterion environments where cue abstraction is difficult. Thus, people may shift from cue abstraction to exemplar memory as a function of demands in the task environment (Juslin et al., 2008; Karlsson et al., 2007) or successfully be guided by instructions to "go with the flow" and store exemplars (Olsson et al., 2006). This thesis suggests that the learning modes can also induce certain processes and predicts that supervised learning induces inferential top-down processes that can be captured by the cue abstraction model. Unsupervised learning is predicted to exploit receptive bottom-up processes with no inferences involved, which initially invite a cost-effective exemplar encoding. In Study III, this receptive exemplar encoding in unsupervised learning is predicted to shift to prototype abstraction when the task environment strongly triggers abstraction and obstruct memory processes.

Rules, Prototypes, or Exemplars

Of the numerous computational models in research, surprisingly few have been generalized and adapted to different task structures. The cue abstraction model (CAM) and the exemplar-based model (EBM) are two rare process models adapted to various task structures as when cues and the criterion vary in binary or continuous dimensions. There are no prototype models adapted to task structures when the criterion is continuous. In order to test different accounts of abstracted processes in supervised and unsupervised learning, Study III introduces the cognitive rationale for and tests the prototype-based model (PBM) applicable to various task structures. To test specific assumptions of the models, participants in computer-based experiments experienced various stimuli in a training phase and were tested later on in a separate phase where some old training exemplars reoccurred along with some new ones. In that respect, the ability to correctly extrapolate judgments to new instances can be detected. It thus serves to differentiate between the process models as will be outlined below.

Cue abstraction model (CAM)

The *Cue Abstraction Model* (e.g., Juslin et al, 2003) suggests that the individual abstracts cue weights and integrates the information by an additive rule in order to assess missing criterion values. CAM assumes that, for each cue, the individual agent infers C_m, a weight ω_m (m=1…M). Through addition of all the information from cues, the criterion $\hat{c}$ of a test probe i can then be estimated;

$$\hat{c}_i = k + \sum_{M=1}^{M} \omega_m \cdot C_m. \tag{1}$$

As many rule-based models normally assume, CAM assumes that judgments are independent of the concrete exemplars experienced in training, and therefore predicts no systematic differences in judgment accuracy for the "old" exemplars previously encountered and new ones (i.e., no old-new differences). CAM thus predicts extrapolated judgments and correct assessments of the criteria of those new exemplars residing outside the criterion range of training exemplars (DeLosh, Busemeyer, & McDaniel, 1997), even if the individual has not experienced these new exemplars.

CAM is analog to a multiple linear regression model and several researchers have raised concerns regarding the use of statistical models (Gigerenzer & Kurz, 2001; Hoffman, 1960), mostly for their impressive ability to account for judgments regardless of whether the parameter values for the model are reasonable (Dawes, 1979; Dawes & Corrigan, 1974). Nevertheless, there is evidence that multiple regression models like CAM are not merely paramorphic or "as if" models but can capture the underlying process (e.g., Brehmer, 1994; Einhorn et al., 1979; Juslin et al., 2003; 2008, Klayman, 1988b). SIGMA is a processing account of how people learn the weighting of cues by a controlled, sequential adjustment of cue information to infer the criterion (Juslin et al., 2008). Consistent with prevalent findings of "rule bias" and a human propensity for abstracted processes (e.g., Johansen & Palmeri, 2002; Kalish et al., 2005; Raijmakers et al., 2014), one assumption of SIGMA is that cue abstraction is the primary process that people use. If this fails, the exemplar memory can act a backup process with relatively good performance (Juslin et al., 2008, see also Platzer & Bröder, 2013, for similar conclusions). As noted above, Studies II and III, investigates if the notion of a bias toward rule-based processes may be reinforced by the prevalent use of a supervised learning mode in research.

Exemplar-based model (EBM)

The Context Model of classification (Medin & Schaffer, 1978) and the Generalized Context Model of classification (GCM; e.g., Nosofsky, 1986) have been extensively investigated and supported in various studies. Estes (1994) argued that the exemplar memory is form of an episodic memory and, as exemplar models assumes, exemplars encountered are encoded in memory and people use them as multiple reference points in subsequent similarity-based judgments.

For binary tasks, where the individual assigns the stimuli to two contrasting categories (e.g., suitability or unsuitability for a job) based on multiple cues, categorization is both a function of similarity and the relative frequency of categorical exemplars stored in memory. The predicted probability that a test probe *i* is judged as 'suitable', *p* (*S*|*i*) is given by:

$$p(S \mid i) = \frac{\sum_{j=1}^{J} sim(i, x_j) \cdot c_j}{\sum_{j=1}^{J} sim(i, x_j)}, \tag{2}$$

where x_j, is the stored exemplar $j=j \ldots J$), *sim* (i, x_j) is the similarity of a test probe *i* to exemplar x_j in memory, and c_j is the criterion of stored exemplars (i.e., with binary criterion: suitable, S=1 and unsuitable U=0).

With the exemplar model adapted to a continuous criterion (e.g., Delosh, et al., 1997; Juslin et al., 2003; 2008; Olsson et al., 2006; von Helversen & Rieskamp, 2009), the inferred criterion $\hat{c}$ of a test probe *i* is a weighted average of the criteria of the stored exemplars, with the similarity as the weight:

$$\hat{c}_i = \frac{\sum_{j=1}^{J} sim_{ij} \cdot c_j}{\sum_{j=1}^{J} sim_{ij}}, \tag{3}$$

where the sim_{ij} is the similarity and the c_j is the criterion of exemplar *j* in memory. For both Equation 2 and 3, overall similarity *sim* between test probe *i* and exemplar *j* in memory is an exponential decreasing function of their distance d_{ij} in a psychological space,

$$sim(i, x_j) = e^{-d_{ij}}. \tag{4}$$

The distance is given by:

$$d_{ij} = h\left[\sum_{m=1}^{M} \omega_m \left|(x_{im} - x_{jm})\right|^r\right]^{1/r}, \tag{5}$$

where *h* is the sensitivity for the differences between exemplars, ω_m is attention weights on cue *m* (*m*=1…*M*), and x_{im} and x_{jm} are values of the probe *i* and the exemplar *j* on cue *m*. Each attention weights may vary between 0 and 1, but all are constrained to sum up to 1. The sensitivity may vary from 0 to infinity. The metric is given by r and the city-block metric corresponds to r=1, while the Euclidian metric corresponds to r=2. The city-block metric has been proposed as suitable for separable cue dimensions and the Euclidian metric is more suitable for confusable stimuli with separable cue dimensions or for integral cue dimensions where the different cues may be difficult to separate, such as saturation and brightness in perceptual tasks (Nosofsky, 1985; Shepard, 1964).

Because EBM assumes similarity assessments to stored instances, the model predicts better judgment accuracy for old, previously encountered exemplars than for new ones (i.e., predicts old-new differences). Thus, the judgments cannot extrapolate, and the assessments of new exemplars beyond the criterion range of training exemplars becomes inaccurate since the assessed criterion is assumed to be a weighted average of the criterion values stored in memory where the similarity is the weight (Delosh et al., 1997).

Exemplar models have received substantial support over the years (e.g., Brooks, 1978; Estes, 1994; Hintzman, 1986; Medin & Schaffer, 1978; Nosofsky, 1986; Nosofsky & Johansen, 2000; Nosofsky & Zaki, 2002) but have also received critique, for example, for being limited to tasks where few and distinct exemplars are repeatedly presented, or on the grounds that the exemplar model can easily account for the judgments with additional adjustable parameters. Prototype-based accounts have instead been offered as more suitable process models (e.g.; Homa, Proulx, & Blair, 2008; Homa, Sterlin, & Trepel; 1981; Minda & Smith, 2001; Smith & Minda, 1998; 2000).

Prototype-based model (PBM)

Some exemplars can represent the category better than others, and this observation has led to prototype-based accounts of categorical data (e.g., Homa & Cultice, 1984; Posner & Keele, 1968; Rosch, 1975; Rosch & Mervis, 1975; Smith & Minda, 1998). Prototype models usually assume that people abstract and store prototypes in memory and assess similarity to these representations in subsequent judgments. With two contrasting categories, as in a categorization task, the "centroid" or most typical member in each category (usually defined as the mean or modal cue value) is used as a prototype. Thus, instead of the memory being overloaded by storage of memory traces of all encountered cases, only the most typical cases or representations are stored and used in subsequent judgments. "Prototype enhancement effect" is believed to be an indication of prototype abstraction and refers to when the prototype (though never directly experienced) is assessed more accurately than old previously encountered exemplars or other new exemplars introduced in a test phase (Minda & Smith, 2011).

The prototype can sometimes be better represented by the most extreme or "ideal" category member relative to the contrasting category (Barsalou, 1985; Lynch, Coley, & Medin, 2000; Massaro & Friedman, 1990; Palmeri &

Nosofsky, 2001; Rosch, 1975; Voorspoels, Storms, & Vanpaemel, 2013). Barsalou (1985) argued that the defining attributes of the ideal prototype are determined by functional goals, as when a dieter categorizes food using its similarity to representations of ideal or extreme food items with zero calories, rather than similarity to abstracted food items with mean or median calories. Thus, the similarity to such "ideal" prototypes can facilitate for people to reach functional goals. As has been shown, experts seem to rely on ideal and extreme prototypes more than novices, who are influenced by the prototypical central tendency (Lynch et al., 2000). Rosch and Mervis (1975) discussed the importance of cue validities for achievement and argued that achievement is not affected as long as the attributes of the prototype are also highly valid for the category.

Ideals have been suggested as important reference points with which options can be compared in order to facilitate decision-making (e.g., Coombs, 1958; De Soete, Carroll, & Desarbo, 1986; Kerimi, Montgomery, & Zakay, 2011; Zeleny, 1976). Mitchell and Beach (1990) proposed that different images or ideals can be used as reference points, which, like Barsalou's (1985) ideal prototypes, serve to facilitate goal-attaining behaviors and enhance achievement. Nonetheless, these models are confined to binary judgment dimensions and cannot readily be applied to multiple-cue tasks. One exception is the Fuzzy-Logical Model of Perception (FLMP; Massaro & Friedman, 1990) which makes assumptions about the estimation behind binary choice. FLMP assumes that decisions are based on a multiplicative integration of "fuzzy-truth values" for cues, signifying the subjective match to an ideal and extreme prototype. Massaro and Friedman argued that FLMP can be conceptually equivalent to Bayesian integration if the "fuzzy-truth values" are interpreted as conditional probabilities. Robert Nosofsky (1992) argued that FLMP is equivalent to a multiplicative-similarity prototype model, and as such would also be equivalent to the proposed PBM. Although FLMP makes assumptions about the estimation behind choice, and would presumably be a suitable model for tasks with continuous judgment dimensions, the cognitive rationale remains unclear and has also been questioned (e.g., Gigerenzer, 1989).

The prototype-based model (PBM) introduced in Study III can be used in various task structures, regardless of whether dimensions for cues and the criterion are binary or continuous, and the model uses the same similarity function and equations as for EBM outlined above. PBM assumes that the ideal prototypes are the most extreme exemplars at each end on the continuous criterion dimension, and as such, are defined by cues that reveal the cue directions most clearly (e.g., have the most extreme attributes or cue profile). The formation of these prototypes is mediated by the abstraction of cue directions. As Eleanor Gibson noted, "abstraction occurs when an invariant relation is discovered over a number of varying objects or events" (E. Gibson, 1969, p. 108). The ideal prototypes in tasks with a binary criterion may then be those with the most extreme cue values in each category. Thus, the ideal or extreme prototypes serve to differentiate between categories. As noted above, salient cue directions are important for efficient cue abstraction (e.g., Bröder et al., 2010; Doherty & Balzer, 1988; Lindell, 1976; Newell et al, 2009; Rolison et al., 2012; von Helversen et al., 2013; von Helversen & Rieskamp, 2009). As it seems, CAM and PBM may be ecologically rational in exploiting valid characteristics of the task structure as cue weights and cue directions. Thus, information about cue directions can be used either for hypothesis testing of cue weights, as CAM assumes (e.g., Brehmer, 1994; Deane et al., 1972; Einhorn et al., 1979) or, as PBM assumes, to form the ideal prototypes. Study III directly tests the hypothesis that the two different learning modes engage different abstraction processes. Supervised learning exploits an abstraction based on hypothesis testing of cue weights while unsupervised learning exploits a receptive bottom-up process to abstract cue directions across the flow of exploratory observations to form prototypes.

Learning With or Without Feedback

Supervised Learning

In supervised learning, the external environment "feeds back" information contingent on the individual's inferences or hypotheses, and the individual is supposed to adjust the hypotheses and minimize the prediction error. There are many different ways to learn and in Study II various supervised learning modes, such as feedback and intervention training, are tested. For example, in feedback training the individual infers a missing criterion value based on the cues presented and receives feedback about the correct criterion, as when a manager infers the suitability of different applicants and receives feedback on the suitability after a probation period. In intervention training the individual infers those cues that predict a target criterion and receives feedback about the criterion of the inferred exemplar, like a headhunting practice when a manager tests ideas about relevant characteristics that predict suitability and after headhunting those individuals for a probation period, receives feedback on the suitability.

Feedback training is undoubtedly the most investigated mode of learning in research, and has more or less implicitly been regarded as a hypothesis testing strategy with feedback assisting adjustment of inferences about, for example, cue weights (e.g., Brehmer, 1974; 1980; Einhorn et al., 1979; Juslin, et al., 2008; Klayman, 1988a; Speekenbrink & Shanks, 2010). There are reports suggesting that feedback may not always enhance achievement, and may even have negative effects (e.g., Castellan, 1974; Hammond, Summers, & Deane, 1973; Kluger & DeNisi, 1996; Maddox, Love, Glass, &

Filoteo, 2008). Cognitive control usually refers to consistency in maintaining attention and adequate behavioral responses. As has been reported, repeatedly receiving probabilistic or noisy outcome feedback can obstruct cognitive control of the task, with low achievement as a consequence (Hammond et al., 1973). Note that, feedback can describe the environmental characteristics (e.g., correct criterion values), the behavioral response (e.g., if answers or inferences were right or wrong), or "cognitive feedback" (e.g., the subjective cue weights compared with the objective cue validities or cue directions). As has been reported, feedback directed toward the individual may affect self-image and motivation in a way that sometimes impairs achievement: negative feedback, for example, may be demoralizing. Too much positive feedback can, on the other hand, reinforce an illusion of validity (see Kluger & DeNisi, 1996, for review). As noted above, cognitive feedback and prior "feedforward" information about the underlying task structure can facilitate cue abstraction and increase achievement (e.g., Björkman, 1972; Deane et al., 1972; Doherty & Balzer, 1988; Lindell, 1976; Newell et al., 2009; Rolison et al., 2012; von Helversen et al., 2013; von Helversen & Rieskamp, 2009).

In a seminal paper, Berndt Brehmer (1980) proposed several factors that help to explain why people err and hardly learn from experience. Confirmation bias is one such factor: People tend to search for evidence that confirm their hypotheses or beliefs about reality instead of, in a Popperian way (Popper, 1963), searching for evidence that refutes the hypotheses. Since Wason's (1960) paradigmatic experiment on confirmatory search, a large body of research has provided support for the confirmation bias (e.g., see Klayman, 1995 and Nickelson, 1998, for reviews). Inertia in human belief systems and conservatism in revising prior beliefs pose a serious challenge to learning (Edwards, 1968; Fischhoff & Beyth-Marom, 1983; Geller & Pitz, 1968), but may be adaptive from a Bayesian point of view if the person is exposed to uncertain, unreliable, or ambiguous events (e.g., Corner, Harris, & Hahn, 2010). Nonetheless, repeatedly ignoring evidence from feedback not only may in the long run, obstruct learning but will reinforce faulty beliefs about one's own ability to make accurate assessments, with overconfidence and an illusion of validity as a consequence (e.g., Einhorn & Hogarth, 1978; Fischhoff, Slovic, & Lichtenstein, 1977). Learning may also be obstructed when the individual faces the outcomes of (faulty) predictions made in the past and believes that he actually knew the correct outcome all along, i.e., overestimates the probability that the observed outcome was foreseeable (e.g., Fischhoff, 1975). Such hindsight biases may prevent the individual from taking the necessary steps to avoid repeating the same error in the future.

Learning from feedback is investigated using different forms of supervised learning, hypothesized in this thesis to initiate inferential processes to "fill in" or predict missing information. In Studies II and III the inferential mechanism is used to infer the relationship between cues and the criterion, in a deliberate integration of abstracted cue weights. This cue abstraction may be obstructed in categorization tasks with a binary judgment dimension in favor of exemplar memory processes (e.g., Juslin et al. 2003; Olsson et al., 2006). Thus, in Study I, the inferential mechanism in selective (semi) supervised learning is hypothesized as serving to store inferred details in memory when outcome feedback is missing, therefore being responsible for the encoding of pseudo-exemplars into memory.

Selective Supervised Learning

Natural sampling usually refers to repeated random sampling of information. Such sampling would, of course, be unbiased but, as Klaus Fiedler (2008) argues, such sampling is costly and takes time for the individual. Peoples' sampling of information are usually biased and tailored for the task at hand rather than for general purposes. Meta-cognitive insight into sampling biases, coupled with a computational capability, would normally correct biased beliefs. However, as has been shown, a persistent meta-cognitive myopia or nearsightedness, limited to the proximal information seems to prevent the individual to gain an unbiased representation of the external environment (e.g., Fiedler, 2000; 2008).

As noted in research, learning from selective feedback poses a serious challenge, with biased judgments and overconfidence as a consequence (e.g., Brehmer, 1980; Denrell, 2005; Einhorn & Hogarth, 1978; Eiser, Fazio, Stafford, & Prescott, 2003; Elwin, Juslin, Olsson, & Enkvist, 2007; Fazio, Eizer, & Shook, 2004; Fetchenhauer & Dunning, 2010; Fischer & Budescu, 2005; Smillie, Quek, Dalgliesh, 2014; Tindale, 1989). Selective supervised learning refers in this thesis not to situations where cues are selectively missing (e.g., Garcia-Retamero & Rieskamp, 2008; 2009; Johnson, 1987; Rubin, 1976; White & Koehler, 2004) but to when outcome feedback is selectively missing dependent on the decision maker's own selective sampling behavior (*selective decision-contingent feedback*) or dependent on a selectivity imposed by the external environment (*selective outcome-contingent feedback*).

Selective Decision-Contingent Feedback

There are several situations in our daily life where selective sampling may affect beliefs and attitudes, for example, sampling of products, media, friends, housing environment, hobbies etc with some expected positive outcome (e.g., Hogarth, 2006). Thus, the individual searches for and samples experience from the environment. For example when a manager decides to recruit some applicants, feedback about their suitability will be received after the applicants have been tested on the job. However, the manager's beliefs about the rejected applicants' unsuitability will not be disconfirmed since they were not tested on the job.

As illustrated in Figure 2, positive decisions, such as decisions to select and sample information, can confirm or disconfirm our beliefs about the selected event (from hits or false alarms) but decisions to reject will never disconfirm potential erroneous beliefs about those events because no feedback is received about them. The implication is that avoidance of potential negative events may lead to an increasingly conservative sampling behavior, with sampled information always confirming and reinforcing prior negative beliefs (Einhorn & Hogarth, 1978). Thus, an initial negative impression will most likely to be reinforced and persist owing to learning from selective decision-contingent feedback. In social domains, an initial negative impression of a person will most likely terminate interaction and sampling of further information that may disconfirm an erroneous belief that this person has genuinely undesirable qualities (Denrell, 2005; 2007; Fetchenhauer & Dunning, 2010). Similarly, beliefs about the variability of negative and positive attributes of a social in-group would most likely be well adjusted owing to repeated sampling of observations, whereas beliefs about out-group members can be generalized and negatively biased if no repeated sampling takes place that makes disconfirmation possible (e.g., Fiedler, 2000; 2007).

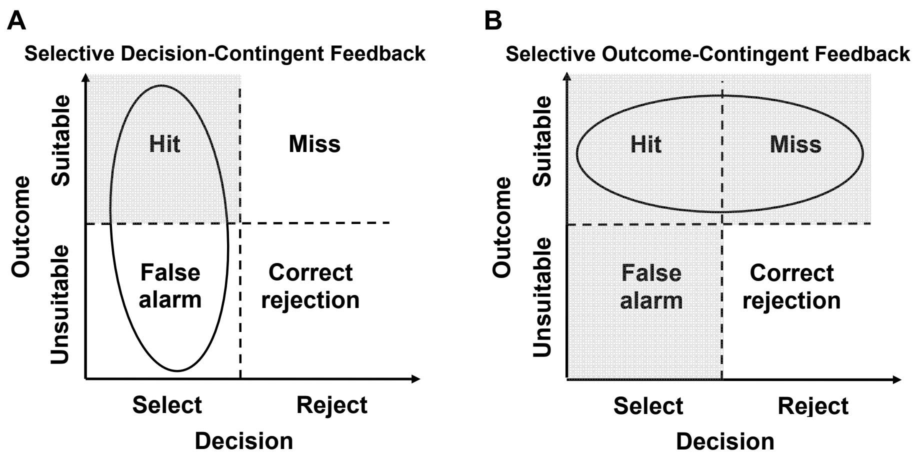

Figure 2. The four possible decision outcomes of the choice to select or reject. "Selective decision-contingent feedback" (Panel A) refers to feedback received for positive decisions (hits or false alarms). "Selective outcome-contingent feedback" (Panel B) refers to feedback received for positive outcomes (hits or misses). Darker areas signify what is stored with the label "suitable" according to the constructivist coding hypothesis.

Nonetheless, it has been demonstrated that selective decision-contingent feedback, compared with complete feedback, has little negative effect on accuracy (i.e., overall level of learning), but that the resulting beliefs about the base rate (e.g., the relative frequency of targeted category members) are more likely to be conservative, with estimates lower than expected (e.g., Denrell; 2005; 2007; Denrell & March, 2001; Eiser et al., 2003; Elwin et al., 2007; Fazio et al., 2004; Fetchenhauer & Dunning, 2010; Smillie et al., 2014; Tindale, 1989). Thus, beliefs about the frequency of targeted category members after selective decision-contingent feedback becomes conservative and the base rate is underestimated, while the frequency of rejected (non-targeted) category members is overestimated. The important implications of this selective sampling are that invalid positive beliefs will be corrected by sampling these events but that invalid negative beliefs will most likely not be corrected since these events are rejected, and therefore unavailable for disconfirming experience.

Selective Outcome-Contingent Feedback

The advertising industry thrives on what seems to be a fundamental need among individuals, companies, or organizations to give a positive impression or have a favorable image. While positive aspects and examples are in the limelight, less flattering aspects or examples are withheld. The importance of selective environmental information can hardly be underestimated. Learning from selective external environmental information may also induce biased beliefs, for example when the individual is selectively exposed to information about policy in firms that survived while policy in terminated firms is no longer available. If underestimating the probabilistic nature of events in learning from the policy of firms that (by chance) made them succeed, then the vicarious learning of management policy may culminate in liquidation (e.g., Denrell, 2003). The information in the external environment is rarely representative and unbiased due to availability and saliency and, as has been reported, the probability or relative frequency of salient events is often exaggerated or overestimated (Tversky & Kahneman, 1973).

Selectivity of information constrained by the environment is perhaps more insidious than selective decision-contingent feedback, since the contingencies may be less evident and difficult to mentally control in experiential learning. “Selective outcome-contingent feedback” refers, in this thesis, to the external environment alerting the decision maker to all events with positive outcomes, such as all the candidates who are objectively suitable for a job, but remaining silent concerning the individuals who are objectively unsuitable for a job. As illustrated in Figure 2, regardless of decisions, the external environment reveals information about outcomes whenever there are suitable applicants (from hits and misses), but not about unsuitable applicants. Although selective decision-contingent and outcome-contingent types of feedback describe very different situations for learning, Study I tests the prediction that both exploit the same inferential mechanism but produce opposing biased beliefs, in this case about the base rate of suitable applicants in a sample judged (e.g., the relative frequency of suitable persons). Thus, a conservative base-rate bias is more likely with selective decision-contingent feedback, while a liberal base-rate bias is more likely with selective outcome-contingent feedback. The inferential mechanism involved is the constructivist coding of exemplars with the most likely inferred outcome on non-feedback events (Elwin et al., 2007). Thus, the assessment in learning is based on the presented cue profile of an exemplar and its similarity to stored instances up to that point. If no outcome feedback is received after assessment, the inference about the outcome is encoded, with resulting pseudo-exemplars, carrying inferred details, stored in memory.

Constructivist Coding Hypothesis

In line with a Brunswikian approach, stressing an adaptive vicarious functioning and the replacement of missing cues by other other indicative cues (Hammond & Stewart, 2001), Garcia-Retamero and Rieskamp (2008; 2009) argued that people adaptively and efficiently infer missing cue information. They suggested that ignoring missing cues is not adaptive at all. In a similar vein, Elwin et al. (2007) argued that ignoring missing outcome feedback is not adaptive and proposed a constructivist coding hypothesis on how people treat missing outcome feedback. The authors showed that selective decision-contingent feedback does not hamper overall learning and the resulting conservative base-rate bias is due to a constructivist coding of exemplars with the most likely inferred outcome stored on non-feedback events. Thus, when the individual receives (from feedback) a hit or a false alarm, it is correctly coded into memory as a suitable or unsuitable exemplar respectively. However, when no feedback is received after a rejection decision, the exemplar is accordingly coded into memory as unsuitable in line with the assumption behind the decision.

There are imaging studies that have indicated that both inferred and observed feedback engage the same neural areas (Daniel & Pollman, 2012; 2014; Cincotta & Seger, 2007). The inability to separate inferences from observations has been the focal point in a large body of research on mechanisms involved in the generation of false memories (e.g. Echterhoff, Hirst, & Hussy, 2005; Johnson, 2006; Johnson & Raye, 1981; Roedinger & McDermott, 1995). Elisabeth Loftus's research on misinformation and eyewitness identification has had a major impact on policy in legal settings. Similar to a constructivist coding of inferred outcomes, Loftus suggested that lost memory traces or unattended episodic details may be replaced by inferred details that make sense in that particular context or by an interviewer's suggestions (e.g., Loftus; 1979; 2005; 2013; Loftus & Hoffman, 1989).

The "filling-in" mechanism, as implied by constructivist coding, relates to an increasing body of machine-learning studies where labeled categorical data are used to infer non-labeled data by means of different algorithms (usually referred to as semi-supervised learning; e.g., Chapelle, Schölkopf, & Zien, 2006; Gibson, Rogers, & Zhu, 2013). As has also been discussed in research, the validity of statistical inferences also depends on how missing research data are interpreted and treated. There are, for example, several statistical imputation methods where partially lost data can be replaced on the basis of existing data (e.g., Horton & Lipsitz, 2001; Sinharay, Stern, & Russell, 2001). The validity of learning from partially missing information is investigated in Study I and extends Elwin et al.'s (2007) study on constructivist coding by also considering the situation when information is constrained by the external environment. In addition, to test a computational account of the constructivist coding of exemplars, this coding assumption was integrated in the *Generalized Context Model* of classification (GCM: Nosofsky, 1986) and compared with two other coding assumptions integrated in GCM: positivist and agnostic coding.

All coding assumptions make the same prediction when there are observed feedback events (i.e., a correct coding of observed exemplars) but differ regarding non-feedback events. Constructivist coding assumes a coding of exemplars with the inferred outcome of non-feedback events. Positivist coding does not entail coding of exemplars on non-feedback events; thus, this coding assumes that only feedback events are used and stored in memory for subsequent use by similarity assessments. Like the notion of "soft labels" in machine learning accounts of selective supervised learning (Gibson et al., 2013) or random coding on non-reinforced trials (Reber & Millward, 1968), agnostic coding assumes unsystematic and random coding of the outcomes of non-feedback events. The overall level of learning and the base-rate bias (i.e., conservative bias for decision-contingent and liberal for outcome-contingent) is assumed to be a function of a constructivist coding and the initial model concerning the category structure. Assuming that learning starts with no knowledge of suitability or unsuitability, initial random guesses with selective decision-contingent feedback would give a more valid starting point and a more representative model of categorical members in the task environment (from hits and false alarms). Selective outcome-contingent feedback, on the other hand, is confined to correct information about members of only one category (from hits and misses), a selectivity that affords poor cognitive control of the feedback contingency from the individual's point of view, if not coupled with a meta-cognitive awareness of external contingency (Fiedler, 2000). Thus, selective outcome-contingent feedback offers a poor initial model of the task environment compared with decision-contingent feedback.

Unsupervised Learning

Unsupervised learning takes place when the external environment does not "feeds back" information contingent on some inference or prediction. Learning is based on pure observation. There are different variants of observational learning: some studies refer to the learning of categorical structures from observation of attributes, without category labels being provided (Ahn & Medin, 1992; Ashby, Maddox, & Bohil, 2002; Billman & Heit, 1988; Billman & Knutson, 1996; Clapper, 2006; Clapper & Bower, 2002; Colreavy & Lewandowsky, 2008; Compton & Logan, 1993; Fried & Holyoak, 1984; Homa & Cultice, 1984; Love, 2002; 2003; Zeithamova & Maddox, 2009). Others refer to vicarious learning by observing when other individuals receive negative or positive feedback while learning a task (e.g., Bandura, 1977; Bellebaum, Jokisch, Gizewski, Forsting, & Daum, 2012; Bellebaum, Rustemeier, & Daum, 2012). In Studies II and III, unsupervised observational training refers to an individual observing the criterion and cues defining different exemplars, as when a manager observes a portfolio containing the cue profiles and criterion of former employees as an aid to future recruitment decisions. No judgments are made and no external trial-and-error feedback is received. There is a growing interest in such learning mode (e.g., Ashby, Maddox, & Bohil, 2002; Cincotta & Seger, 2007; Estes, 1994, Fiser, 2009; Hoffman & Murphy, 2006; Love, 2002; Love, Medin & Gureckis, 2004; Markant & Gureckis, 2014; Newell, Lagnado, & Shanks, 2007; Poldrack et al., 2001; Reber & Millward, 1968; Schmitt-Eliassen, Ferstl, Wiesner, Deuschl & Witt, 2007; Shohamy et al., 2004; Smith & McDowall, 2006) which poses a challenge for error-driven models of learning to explain (e.g., Bott, Hoffman, & Murphy, 2007; Rescorla & Wagner, 1972) because there is no feedback that signals a prediction error intended to adjust any beliefs or hypotheses. Nevertheless, it has been suggested that certain events can induce a surprise that would update beliefs in a similar vein as explicit feedback (Billman & Heit, 1988; Love et al., 2004). On a neural level, such internally generated feedback can act similarly to external feedback (e.g., Cincotta & Seger, 2007).

Statistical Learning

Statistical learning usually refers to the unsupervised and implicit learning of statistical regularities as mean, variance, relative frequencies or probabilities, conditional probabilities, covariance, and spatiotemporal correlations (e.g., Barlow, 1989; Brady & Oliva, 2008; Fiser, 2009; Fiser & Aslin, 2001; 2002; Mundy, Honey, & Dwyer, 2007; Turk-Brown, Scholl, Chun, & Johnson, 2009). It seems to be present in infancy, plays an important part in language acquisition (e.g., Saffran, Aslin, & Newport, 1996), infant cognition (e.g., Goldstein, Hasher, & Stein, 1983; Kirkham, Slemmer, & Johnson, 2002), and for cognitive functions across the life span (Hasher & Zacks, 1979; 1984; Petersen & Beach, 1967; Sedlmeier & Betsch, 2002).

As has been shown, without category labels, obvious category structures, or prior knowledge that can guide the individual in the categorization task, there is hardly any learning from exposure to randomly presented stimuli (e.g. Homa & Cultice, 1984; see also the related discussion in Anderson, 1991). However, blocked sequences of categorical stimuli (e.g., categorical sequence: A, A, A…, B, B, B…) can induce learning, presumably because of the more salient shift between categorical members across the presentation of stimuli (Clapper & Bower, 2003; Clapper, 2007). Zeithamova and Maddox (2009) argued that contrasts among stimuli are essential for learning and, as noted above, surprising or unexpected events across the stimuli presentation can act as internally generated feedback that adjust or update beliefs (see also Bott et al., 2007; Clapper & Bower, 2003; Love et al., 2004, see also E. Gibson, 1969, p.99 about contrasts). Thus, across the flow of events, certain information might become more salient and "pop out" without intention or explicit hypothesis testing being involved (Fiser, 2009; Gibson, 1969). As has also been shown, learning is enhanced once a person is engaged in the task by sorting or comparing stimuli (e.g., Ahn & Medin, 1992; Compton & Logan, 1993; Fried & Holyoak, 1984; Homa & Cultice, 1984), which would be in line with the Gibsonian assumption that physical engagement and manipulation of objects in the environment permits differentiation (Gibson, 1969; 1979). As shown in research, abstraction of sophisticated information about the task environment in terms of cue weighs seems to be favored by paired comparisons (Pachur & Olsson, 2012).

Although Brunswik introduced the phrase "the intuitive statistician", he did not examine the mechanisms behind such intuitive statistical processing in detail (e.g., Goldstein & Wright, 2001). But as Berndt Brehmer (1980) noted, people do not seem to learn much from trial-and-error feedback intended to correct hypotheses about cue weights, and as outlined above, statistical learning seems to benefit more from an unsupervised learning mode and receptive bottom-up processes. Study III seeks to investigate the basis for abstraction in supervised and unsupervised learning and if it is based on hypothesis testing of cue weights or based on receptive bottom-up processes to form prototypes.

Observation vs. Feedback

There are hardly any studies that have compared supervised and unsupervised learning and have tested different cognitive process models. Estes (1994) is a rare exception who noted that exemplar-based processes are more likely among observational learners than feedback learners. Most research indicates that feedback training requires a more effortful and cognitively demanding process than observational training. Although some have suggested that observation involves hypothesis testing strategies, albeit less effective ones (Markant & Gureckis, 2014), the evidence mostly suggests, rather, a less taxing process in observational learning. For example, observational training seems to offer patients with fronto-striatal dysfunctions, as in Parkinson's disease, a way to learn that is not achievable from feedback training (Ashby, Noble, Filoteo, Waldron, & Ell, 2003; Knowlton, Mangels & Squire, 1996; Schmitt-Eliassen et al., 2007; Shohamy et al., 2004; Smith & McDowall, 2006). It has also been shown that feedback training recruits the specific fronto-striatal routes in the brain that are important for error processing and task or set shifting (Cincotta & Seger, 2007). Age-related decline in executive and fronto-cortical functions (Nyberg et al., 2010) may also explain why elderly people have difficulties in learning from feedback training, but not from observation (Schmitt-Eliassen et al., 2007), or cannot efficiently exploit rule-based processes like CAM (Mata, von Helversen, Karlsson, & Cüpper, 2012). Similarly, fronto-cortical regions that have not fully matured— regions important for working memory or executive functions —may explain why children have difficulties in learning from feedback training and cannot efficiently exploit cue abstraction despite facilitating instructions (von Helversen, Mata, & Olsson, 2010). Thus, research indicates that unsupervised observational training exploits some more fundamental processing mechanism that is present early in life, and can be used whenever deliberate hypothesis testing fails. This thesis suggests that unsupervised learning involves a less taxing bottom-up mode of processing, primarily an exemplar memory encoding that may shift to a prototype abstraction. The observed relative efficiency of the different learning modes in aging and clinical populations creates scope to customize the environment in a way that enhances individual performance. As pursued in Studies II and III, the investigation of the efficiency of the learning modes in different task environments is therefore an important step in this direction.

Overview of the Empirical Studies

Aims

The first study aims to investigate how inferential mechanisms in selective supervised learning can lead to biased beliefs as when information is constrained by the decision maker's own behavior or by the external environment. The second study seeks to investigate involved top-down or bottom-up processes in supervised and unsupervised learning and the relative efficiency when cues and the criterion are linearly and additively related or multiplicatively related. The third study aims to further investigate abstraction in supervised and unsupervised learning in task environments known to trigger abstraction and obstruct memory performance.

General Task Descriptions

The task in Studies I and II is framed as one of recruitment, to learn about the suitability of the applicants presented. The task in Study III is framed as one of survival, to learn about the toxicity of various bugs. Study I is a computer-based categorization task where the participants learned from selective feedback if sequentially presented exemplars, defined by cues functionally related to a criterion, belonged to one of two contrasting categories. Studies II and III are computer-based multiple-cue judgment tasks where the participants learned the continuously varying criterion values of sequentially presented exemplars defined by multiple cues. The judgment and the criterion dimension are therefore binary in Study I and continuous in Studies II and III. The participants in all three studies experienced the exemplars in a training phase and were tested later on in a separate phase. To test the prevalence of different cognitive processes, some of the exemplars were omitted in training and present only in the test. The generation of stimuli and the mathematical equations for the relationships between cues and the criterion of interest in each task are detailed in the respective paper.

Computational Modeling and Dependent Variables

All studies used a computational modeling approach to investigate the cognitive processes involved. The general idea of computational modeling is to calculate the predicted judgments according to the model concerned and measure the deviation from the observed judgments. The *Root Mean Square Deviation (RMSD)* is one measure for this deviation, and the smaller the RMSD the better fit of the model. Study III also presents *AIC weights* (Akaike Information Criterion; Akaike, 1974) and *BIC weights* (Bayesian Information Criterion; Schwarz, 1978), which denote the probabilities for the models concerned. AIC measures the Kullberg-Leibler divergence of the fitted models from a hypothetical true model and BIC measures the degree of belief that the model is the true model generated by the data (Wagenmakers & Farrell, 2004).

To measure model fit, the best fitting parameters must be estimated by minimizing functions in mathematical software as Mathcad or MatLab. The minimizing function tests different parameter values for the models until the solutions converge and produce the least possible deviation from the observed data. Although an individual fitting procedure may be preferable, since it takes theoretically interesting individual differences into account, it can also be conducted at group level where the participant data in each experimental cell are used as if they related to one individual with multiple repeated judgments. Modeling data at group level may be appropriate when the number of observations per participant is small or the individual responses may be subject to sampling variability or noise (Lewandowsky & Farrell, 2011).

In line with the classical test theoretical assumption that all measurements include some error, the amount of noise in the data limits the variance the models can account for. If the model accounts not only for true variance but also error variance, the model is said to be overfitted (e.g., Pitt & Myung, 2002). One cause of overfit is the number of parameters: the more free parameters there are, the greater the risk of overfitting the model. However, overfitting can be reduced by different cross-validation methods (e.g. Browne, 2000), the generalization criterion method (Busemeyer & Wang, 2000), or penalizing for additional parameters by AIC or BIC-measures (Akaike, 1974; Schwarz, 1978).

With cross-validation, the data are split into two sets. Half of the data are used as a calibration set for estimating the best fitting parameters. The other half are used to calculate and measure the deviation between the model's prediction and the judgment observed (Browne, 2000). Like cross-validation, the generalization criterion method (Busemeyer & Wang, 2000) requires two different data sets, but the calibration set must contain items that hypothetically provide precise parameter estimates for the models in question, and the other set for model validation must contain items that hypothetically differentiate between the models. AIC (Akaike, 1974) penalizes, in a more direct way, the more complex models with many free parameters, while the penalty term becomes even stricter with BIC (Schwarz, 1978). Corrected AIC values can be calculated and used as an alternative, especially when the number of observations per parameter (and participant) is low and the responses may be subject to sampling variability (Burnham & Anderson, 2002).

The fit of the models in Studies II and III was also accompanied by other empirical indicators of the processes involved. As outlined above, the indicators are "old-new differences" and "the prototype enhancement effect", which are assessed by comparing the judgment accuracy for the old exemplars with new matched ones, or new extrapolated exemplars presented in the test phase. Judgment accuracy is measured by *Root Mean Square Error (RMSE*) between the judgments and the criteria. The lower the RMSE is, the better the judgment accuracy: a RMSE of zero denotes perfect judgment accuracy. In Studies II and III, the RMSE for every test exemplar measures achievement or the overall level of learning. In Study I, achievement, i.e., the overall level of learning, is measured by the proportion of correct judgments.

The Empirical Studies

Study I: What is Coded into Memory in the Absence of Outcome Feedback?

The aim is to investigate how inferential mechanisms in selective supervised learning can lead to biased beliefs when information is constrained by the decision maker's own sampling behavior or is constrained by the external environment. Elwin et al. (2007) suggested that decision maker's own sampling behavior produce biased beliefs about the base rate (the relative frequency) of suitable applicants in an assessed sample, as when feedback is received after positive recruitment decisions but not after negative rejection decisions. They argued that biased belief depended on a constructivist coding of inferred outcomes when outcome feedback were absent.

Biased decision-making may also be the net effect of information being selectively constrained by the external environment. An example is how the media highlight events that conveys a positive image but is silent concerning events that manifest a less desirable image (e.g., Denrell, 2003). Study I therefore extends Elwin et al. (2007) in several ways: by also considering situations in which information is selectively constrained by the external environment and to develop a computational account of the constructivist coding assumption. The constructivist coding assumption was therefore integrated in the Generalized Context Model of classification (GCM; Nosofsky, 1986) and compared with other coding assumptions in GCM using data from three different experiments. These computer-based experiments were all framed as recruitment tasks and the participants learned about the suitability of applicants based on selective feedback constrained by their own sampling behavior (e.g., outcome feedback was received after selection decisions, not after rejection) or by the external environment (e.g., outcome feedback was received for those who were objectively suitable, not unsuitable). To investigate the effects of selective supervised learning, equally many suitable and unsuitable exemplars (i.e., the base rate of suitable applicants is .5) were presented to the participants, to simulate a situation of "all things being equal" and when the distal variable is equally probable (i.e., unbiased) before experiencing the sample.

Predictions

Constructivist coding was compared with positivist and agnostic coding assumptions. The "positivist" assumption is that no information is coded into memory in non-feedback trials, while the "agnostic" assumption is of unsystematic or random coding of outcomes in non-feedback trials. While the positivist, constructivist, and agnostic assumptions predict different coding in non-feedback trials, they make the same prediction about coding in feedback trials (i.e., that exemplars on feedback trials are always correctly coded).

Figure 3, Panel A, illustrates how coding assumptions affect beliefs about the base rate when feedback is selectively contingent on positive decisions (*decision-contingent feedback*) in learning. The figure exemplifies a recruitment officer with above-chance performance in judging 100 applicants of whom 50 are objectively suitable (i.e., the base rate of suitable applicants is .5). With representative and complete feedback, the officer receives 40 hits, 10 false alarms, 10 misses, and 40 correct rejections. However, with experience of selective decision-contingent feedback, beliefs about the base rate of suitable applicants will vary depending on what is coded into memory in non-feedback trials.

The positivist ignores non-feedback trials and relies on what is coded in feedback trials from hits and false alarms. In the case of a naïve positivist, if 40 out of 50 cases were suitable candidates this would result in a belief that 80% are suitable. A sophisticated positivist has the same selective experience as the naïve but adds an inference strategy about the overall non-feedback events, thus inferring that performance mirrors that of the feedback events (i.e., 10 misses and 40 correct rejections). The sophisticated positivist would then correctly believe that 50% are suitable.

The constructivist in Figure 3, Panel A, correctly codes the 40 hits and 10 false alarms but codes the inferred outcome of non-feedback events. Thus, non-feedback trials concern applicants rejected on the grounds that they are unsuitable, and this is also what is coded into memory. A constructivist coding would then result in a belief that 40% (40 out of 100) are suitable. Like the constructivist, the agnostic encodes the unseen outcomes, but in an unsystematic and random way, with a .5 probability of coding the case on a non-feedback event as suitable. Thus, the agnostic coding would result in a belief that 65% (65 out of 100) are suitable.

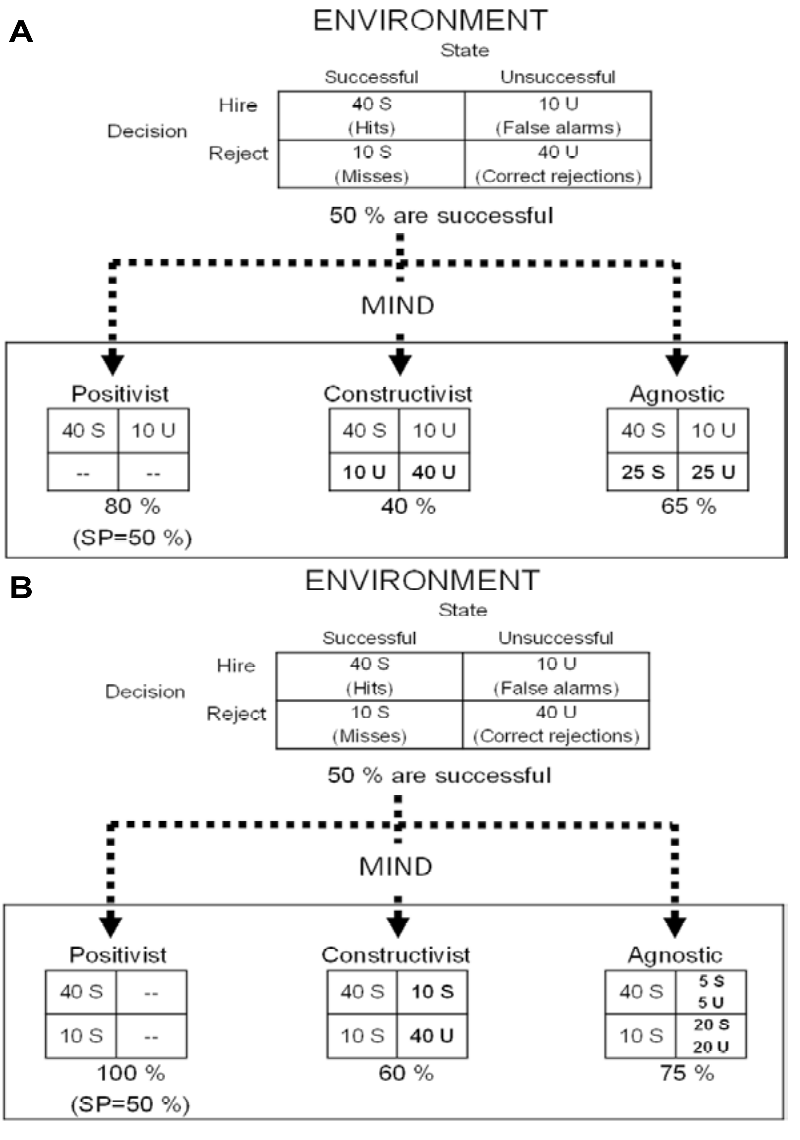

Figure 3. Schematic illustration of how the three coding alternatives affect the frequency of stored exemplars in memory (where SP is Sophisticated Positivist). The example involves a job recruitment officer judging 100 applicants, 50 of whom are actually suitable for the job. The recruitment officer performs better than chance and 40 out of the 50 suitable candidates are indeed hired (hits), while 40 of the 50 unsuitable candidates are rejected (correct rejection). However, 10 candidates are erroneously classified as suitable (false alarms) and 10 candidates are erroneously classified as unsuitable (miss). Panel A: Decision-contingent feedback; Panel B: Outcome-contingent feedback. Copyright © 2010 by the American Psychological Association. Reproduced with permission. No further reproduction or distribution is permitted without written permission from the American Psychological Association.

The constructivist correctly codes all observed hits and misses on feedback trials as suitable applicants. However, in non-feedback trials, unsuitable applicants inferred to be unsuitable or suitable are coded in line with the inferences. Constructivist coding would then result in a belief that 60% (60 out of 100) are suitable. The agnostic codes the outcomes in non-feedback trials (with false alarms and correct rejects) in an unsystematic and random way with the probability of .5 that the outcomes are coded as suitable. Thus, agnostic coding would result in a belief that 75% (75 out of 100) are suitable.

In sum, constructivist coding is predicted to result in biased beliefs concerning the relative frequency of targeted category members (e.g., suitable applicants). This base-rate bias becomes conservative in relation to a .5 base rate when the information is selectively constrained by the decision maker's own behavior and liberal when information is selectively constrained by the external environment.

Method

The participants were given a computer-based task framed in terms recruitment and were sequentially presented with descriptions of applicants defined by four cues, each ranging from 0 to 10 on a pseudo-continuous scale. The cues were linearly and additively related to the binary criterion describing whether the applicant was suitable or unsuitable for the fictive job (.5 base rate of suitable exemplars). The three experiments used factorial between-subject designs with random assignment of participants to the experimental conditions. All participants were presented with the same exemplars in the training phase (but received feedback in different ways depending on the feedback contingency). The participants were tested later in a separate phase in which they were all presented with the same exemplars and none received feedback. The participants received explicit information about the feedback contingencies prior to the training task, but no information about the base rate or the number of training or test trials.

The *task constraints* concern the two forms of selective supervised learning, that is, selective decision-contingent or selective outcome-contingent feedback. Experiment I investigated only selective-outcome contingent feedback and Experiments 2 and 3 compared the two forms of selective supervised learning with complete supervised learning in which feedback was received after every judgment. All experiments manipulated *task focus* (to identify suitable or unsuitable applicants) and *selective feedback contingency* (feedback only about positive decisions/outcomes or feedback only about negative decisions/outcomes). Positive and negative decisions concerned selection and rejection decisions respectively, whereas positive and negative outcomes concerned suitable and unsuitable applicants respectively. Experiment 3 also manipulated *feedback attributions*, i.e., when the feedback label was attributed to the decision maker's behavior (e.g. the label of "correct" or "incorrect") or to the external outcome (e.g., the label of "suitable" or "unsuitable"). No incentives contingent on the decisions were used in order to minimize the risk of the participants becoming focused on probability matching strategies and maximize short-term earnings (Gescheider, 1997; Healy & Kubovy, 1981), rather than their learning and judgment accuracy.

The manipulations of task focus and feedback contingencies were intended to test framing effects on learning but the consistent effect was of *task constraints,* i.e., selective decision-contingent or selective outcome-contingent feedback. The data were therefore collapsed across conditions and experiments to more clearly capture the regularities and convey the effect of task constraints. For example, the individual test data were recoded and collapsed across the conditions so that the dependent variable, proportion decisions R, measures the relative frequency of assessed cases that represents the "feedback-category", i.e., the inferred category (for decision-contingent feedback) or observed category (for outcome-contingent feedback) on which the individual had received feedback in training.

The exemplars, as experienced in training by the individual participants, were coded in line with the coding assumptions and used as memory content for the different versions of GCM. The various coding assumptions integrated in GCM were then compared by fitting the models to test data at individual and group level (see Computational Modeling and Dependent Variables for the model fitting procedures). The predicted binary response for the test exemplars according to GCM is a function of frequency and similarity relations among test exemplars and the stored categorical instances, and GCM is therefore an ideal computational model for comparing the different coding assumptions.

Results and Discussion

Learning and Proportion of Affirmative Decisions

The proportion of correct judgments in test was .81 for complete feedback. Although participants with selective decision-contingent feedback received approximately 50% fewer feedback trials in training compared with those with complete feedback, the proportion of correct judgments was .74 in the test and not far from the learning level for complete feedback. Learning was poor but above chance level for those with selective outcome-contingent feedback, where the proportion of correct judgments was .67. The statistical analyses confirmed that the main effect of the learning modes (complete and selective supervised learning) was significant at the conventional level of p less than .05.

The overall level of learning for selective decision-contingent feedback indicated that this contingency offers more cognitive control of the task and, initially, a more representative model of the task environment by disclosing information about suitability (from hits) and unsuitability (from false alarms) that is then used for subsequent similarity-based judgments with and without feedback. On the other hand, poor achievement with selective outcome-contingent feedback indicated that being alerted only to suitable applicants regardless of decisions offers poor cognitive control and an initial model that is skewed and unrepresentative of the task environment.

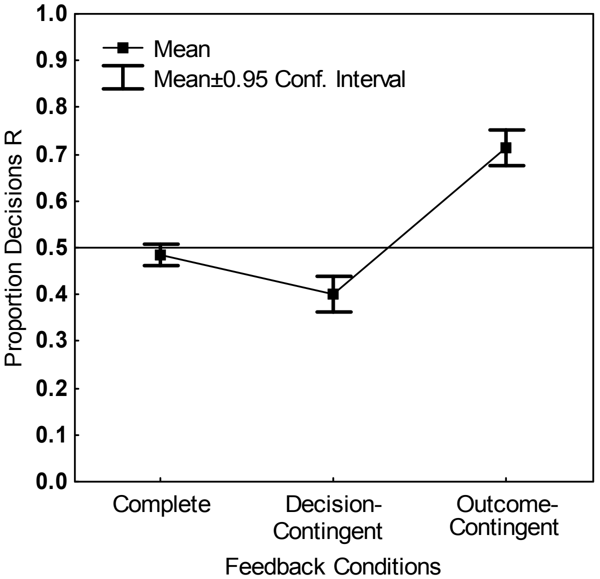

Figure 4. Observed mean proportion of decisions with respect to the feedback category, with 95% confidence interval, for complete feedback (n=44), selective decision-contingent (n=64), and outcome-contingent feedback (n=96). The dotted line represents neutral responding to a base rate of .5.

In line with the predictions, feedback learning, the proportion of decisions at test suggested no bias for complete feedback but a conservative bias for selective decision-contingent feedback and a liberal bias for selective outcome-contingent feedback. Figure 4 illustrates the proportion of decisions for the two forms of selective supervised learning compared with complete supervised learning. Thus, for selective decision-contingent feedback, the relative frequency of assessed exemplars, representing the category on which the individual had received feedback, is consistently lower than .5. For selective outcome-contingent feedback, the relative frequency of assessed exemplars, representing the category on which the individual had received feedback, is consistently higher than .5.

Coding Assumptions

As in Elwin et al., (2007), the predicted proportion of positive outcomes was calculated by coding the individual training experience according to the positivist (naïve and sophisticated), the constructivist, and the agnostic assumptions. The deviation between the proportion of positive outcomes as experienced in training and the observed proportion of positive decisions at test was measured by RMSD. Thus, less deviation signals better correspondence between the predicted proportion and the observed proportion at test. In line with the prediction, Figure 5, Panel A illustrates that the constructivist coding is the alternative that could best predict the proportion of affirmative test decisions. The statistical analyses confirmed that the main effect of the coding scheme was significant for both selective decision-contingent feedback and selective outcome-contingent feedback.

The sophisticated positivist approach includes an inference strategy that goes beyond what can be tested using GCM, and was therefore excluded in the computational modeling. As illustrated in Figure 5, modeling at group level reveals, as predicted, the best fit for the constructivist coding assumption. The standard error of measurement in Figure 5, Panel B also suggests that variance not accounted for by the constructivist coding can be attributed to noise. The statistical analyses revealed that the main effect was significant for both selective decision-contingent feedback and selective outcome-contingent feedback. Similar trend was obtained when the coding schemes in GCM were fitted to data at individual level. Categorizing the participants as positivists, constructivists, or agnostics by the GCM alternative with the lowest RMSD revealed that among those with decision-contingent feedback, 65% were constructivists, 29% were positivists, none agnostic, and 6% undefined (i.e., with identical RMSD). For outcome-contingent feedback, 91% were constructivists, 2% were positivists and 6% were agnostics.

Summary

The data showed a conservative base-rate bias when the information was selectively constrained by the decision maker's own sampling behavior and a liberal base-rate bias when the information was selectively constrained by the external environment. The results suggest the bias depends on constructivist coding of "pseudo-exemplars" in memory. Thus, the characteristics of the mode of learning (i.e., selective or semi-supervised learning) and the characteristics of the task environment (i.e., binary criteria inviting exemplar processes; e.g., Juslin et al., 2003) constitute a situation where the cognitive process is determined by a mix of both inferential strategies and receptive exemplar encoding.

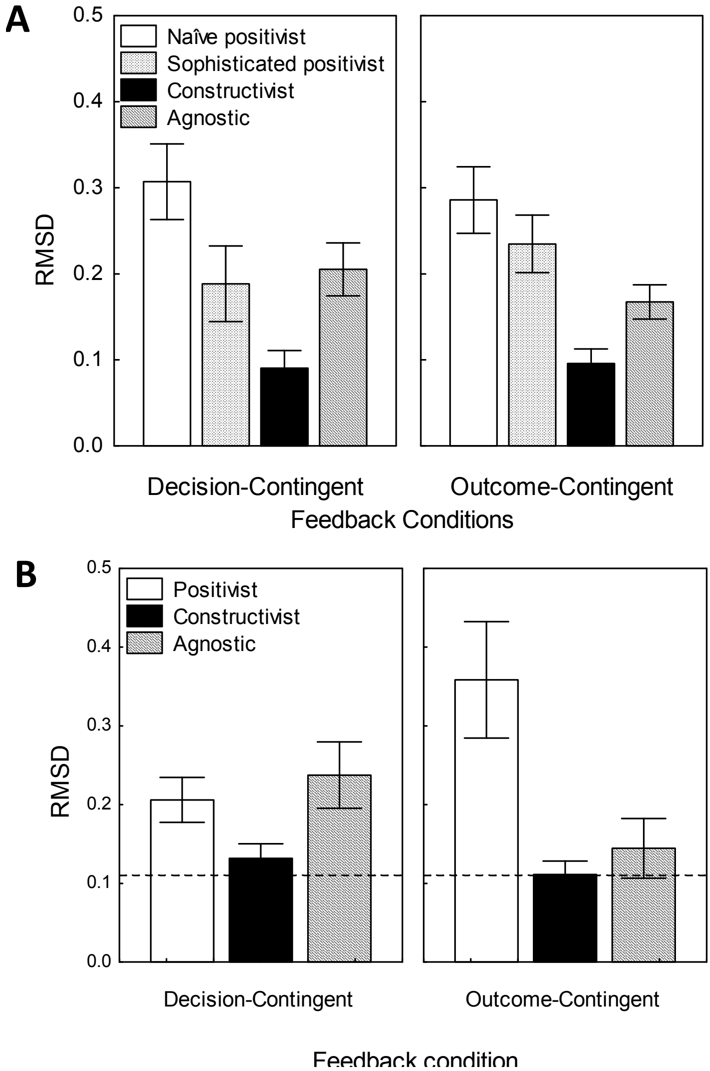

Figure 5. Panel A: Prediction error as Root Mean Square Deviation (RMSD) between the predicted and the observed proportion of positive recruitment decisions for each individual participant in the conditions with decision-contingent (n= 64) and outcome-contingent feedback (n= 96), for each of the three coding alternatives. The whiskers denote .95 confidence intervals. Panel B: Model fit of GCM implementing each of the three coding alternatives as applied to the 6 data sets with decision-contingent feedback and 10 data sets with outcome-contingent feedback. The whiskers denote .95 confidence intervals. The dotted horizontal line is the standard error of measurement for the predicted data points.

Note that learning usually starts with random guesses that may provide the individual an initial model of the category structure for use in subsequent judgments, with or without feedback. In this respect, selective decision-contingent feedback initially offers a more representative model because of the exposure to members from both categories that becomes correctly encoded into memory. However, the participants with selective outcome-contingent feedback are confined to members from one category, which initially offers a highly skewed and unrepresentative model of the category structure and a poor basis for learning. The differences in level of learning and the extremity of the base-rate bias between decision-contingent and outcome-contingent feedback may be understood in terms of ability to mentally control the effect of feedback contingency. Thus, learning from selective decision-contingent feedback offers cognitive control of the feedback contingency, but not when learning from selective outcome-contingent feedback where the contingency is controlled by the external environment. There was clearly no meta-cognitive awareness of the explicit contingency stated in the instructions prior to the task. Instead, the similarity-based inference had priority when participants faced missing outcomes and stored pseudo-exemplar in memory.

Study II: Adaptation to Task Environments

The aim is to investigate the efficiency of top-down or bottom-up processes in supervised and unsupervised learning in interaction with the demands imposed by the underlying structures in the task environment. In three experiments, observational training was compared with feedback and interventional training to test the assumptions that unsupervised learning, as represented by observational training, instigates bottom-up processing and exemplar memory encoding, while supervised learning, as represented by feedback and intervention training, instigates inferential top-down processing and integration of abstracted cue weights by an additive rule.

Past research has indicated that cue abstraction is more likely in linear additive task environments and exemplar memory processes more likely in more complex nonlinear task environments where the individuals shift to exemplar memory as a function of the demands of the task environment (e.g., Juslin et al., 2008). Study II is a further investigation of adaptive shifts and tests whether learning can be improved by selecting the training mode that instigates the most effective process for the task environment at hand. Study II also directly tests the prediction that unsupervised and supervised learning engage different ways to acquire knowledge as implied by the Brunswikian and the Gibsonian approach.

Predictions

With feedback training, people observe different cue profiles, infer the missing criterion values, and receive feedback about the correct criterion of the observed exemplars. With intervention, people infer which cue combination that may predict a targeted criterion value and receive feedback about the correct criterion of the inferred exemplar. With observational training, people observe the criterion values and cue profiles of different exemplars. Although feedback and intervention training were both predicted to involve inferential mechanisms and hypothesis testing strategies about the relationship between cues and the criterion, intervention training was predicted to be a more suitable mode for investigating this relationship by enforcing an active experimentation.

Study II tests the prediction that feedback training and, especially, intervention training instigates inferential top-down processes as cue abstraction, and would therefore improve learning in linear additive task environments where such process has shown to be most adaptive. Observational training is predicted to instigate receptive bottom-up process as exemplar encoding and would therefore improve learning in nonlinear task environments where such process has shown to be most adaptive (e.g., Juslin et al., 2008). Thus, training mode and the task environment are predicted to yield an interaction that affects the judgment accuracy.

Method

Participants in three experiments were given a computer-based task framed in terms of recruitment and were instructed to learn about the level of suitability of various applicants presented. The participants were presented with different descriptions of applicants defined by four cues with varying impacts on the continuous criterion. In Experiment 1, the cues were given binary values with nominal labels. To increase the probability of cue abstraction, Experiments 2 and 3 used cues, each ranging from 0 to 10 on a pseudo-continuous scale (Karlsson et al., 2007). In the additive task environment, the exemplars were defined by cues linearly and additively related to the criterion. In the nonlinear multiplicative task, the exemplars were defined by cues multiplicatively related to the criterion.

All experiments used factorial between-subjects designs with random assignment of participants to the experimental conditions. Experiment 1 compared observational training with feedback training in additive and multiplicative tasks. Experiment 2 compared observation with intervention training in additive and multiplicative tasks. Experiment 3 compared observation with both feedback and intervention in additive and multiplicative tasks to investigate the relative involvement of top-down processes in the two forms of supervised learning.

Participants received explicit instructions prior to the task about the training mode they were about to experience. None received information about cue directions, cue validities, or the scaling of the continuous criterion. If they asked for the scale, they were told to learn this from experience. In Experiment 3, the training phase was divided into three sections, with a test phase at the end of each training session. The repeated test procedure was intended to more clearly capture adaptive shifts in cognitive process and how the training modes interact with demands of the task environment. Thus, the more cognitively taxing supervised learning was predicted to be the more accurate option in the less complex linear additive task environment, whereas the less taxing unsupervised learning was predicted to be the more accurate option in the more complex nonlinear task environment.

Results and Discussion

Experiment 1 revealed, as predicted, a significant interaction effect on judgment accuracy. Figure 6 illustrates that the less taxing unsupervised observational training results in better judgment accuracy in the more complex multiplicative task, while the more the more taxing supervised feedback training results in better judgment accuracy in the less complex additive task.

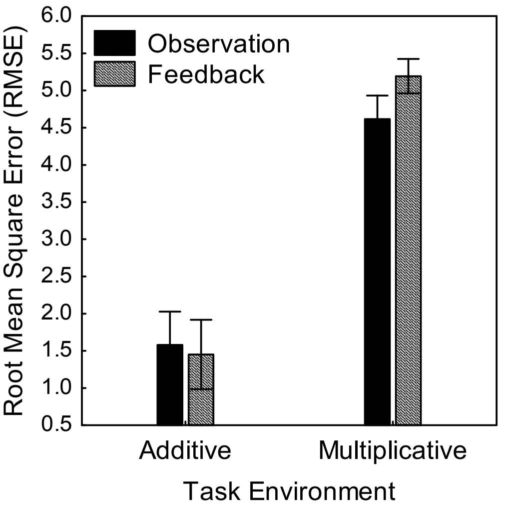

Figure 6. Judgment accuracy, *RMSE* (*Root Mean Square Error*) for observation and feedback learners in the additive and the multiplicative task of Experiment 1. Lower RMSE signals better learning. The whiskers denote .95 confidence intervals.

The analyses on model fit revealed no main effect of training modes but there were signs of more exemplar memory processes among observational learners but not among feedback learners when analyzing the judgment accuracy for old and new matched exemplars. Although there was a main effect of task environment with more EBM in the multiplicative task than in the additive task, the responses indicated EBM in all conditions. It was hypothesized that the invited processes by the training modes may be more evident earlier in training. Similarly, the less evident advantage of feedback in terms of accuracy in the additive task suggests that both task environments may have triggered EBM, but more so in the multiplicative task. Binary cues with nominal labels may not easily disclose information about cue directions and without salient cue directions in Experiment 1, CAM processes may have been obstructed for those with feedback learning. Experiment 2 therefore used exemplars defined by continuous cues to more easily reveal information about cue directions. Feedback training was also replaced by intervention training, which was predicted to strongly trigger inferential processes and cue abstraction from active experimentation. The total number of training trials was reduced to 180 to detect the predicted main effect of training modes on cognitive processing.

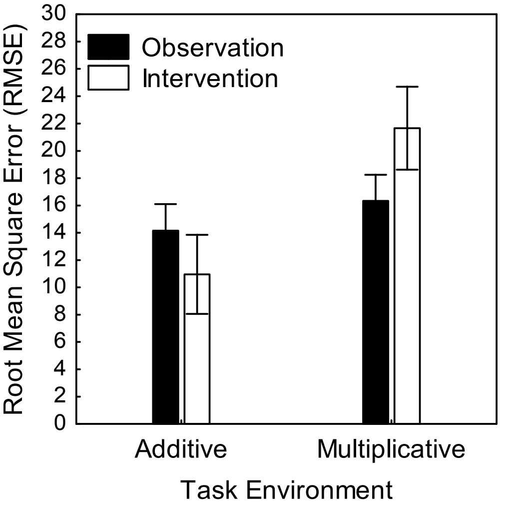

Figure 7. Judgment accuracy, *RMSE* (*Root Mean Square Error*) for observation and intervention learners in the additive and the multiplicative task of Experiment 2. Lower RMSE signals better learning. The whiskers denote .95 confidence intervals.

As Figure 7 illustrates, Experiment 2 replicates Experiment 1 with a significant interaction on judgment accuracy. The less taxing unsupervised observational training proves to be the more efficient learning option in the more complex multiplicative task, while the more taxing supervised intervention training is the more efficient learning option in the less complex additive task. In line with previous research (e.g., Karlsson et al., 2007), the model fit clearly revealed CAM in the additive task and EBM in the multiplicative task. Evidently, the intended manipulations with continuous cues in Experiment 2 seemed to have, as predicted, fostered more CAM, a process that intervention training efficiently exploited in the less complex additive task but not in the more complex multiplicative task.

There was no evidence of a main effect of training mode on model fit even though the training trials had been reduced to capture processes invited by the training modes earlier in training. Experiment 3 therefore used a repeated test design to better capture processes operating early in the training. Experiment 3 also compared unsupervised observational training with both feedback and intervention training, to better capture the relative impact of inferential mechanisms involved in the two forms of supervised learning.

In Experiment 3, the interaction effect on judgment accuracy shown in Experiments 1 and 2, was not evident in the first test phase but started to emerge in the second test phase (starting in the multiplicative task). As Figure 8 illustrates, the interaction is clearly evident in the third and final test phase. As in previous experiments, the less taxing observation training is found to be superior in the more complex multiplicative task and the more taxing intervention training to be superior in the less taxing additive task, with feedback training in an intermediate position between the two other training modes. Clearly, the interaction between training mode and underlying task structure emerges as a function of experience of the task.

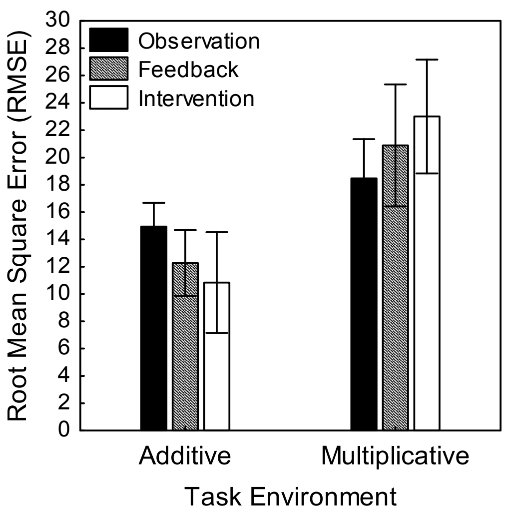

Figure 8. Judgment accuracy in Experiment 3 in terms of *RMSE* (*Root Mean Square Error*) for observation, feedback, and intervention learners in the additive and the multiplicative task. Lower RMSE signals better learning. The whiskers denote .95 confidence intervals.

The main effect of task environments on model fit shown in Experiment 1 and 2, was evident in the first test phase of Experiment 3, with CAM in the additive task and EBM in the multiplicative task. This significant main effect continued to affect the cognitive processes in the second and the third and last test phase.

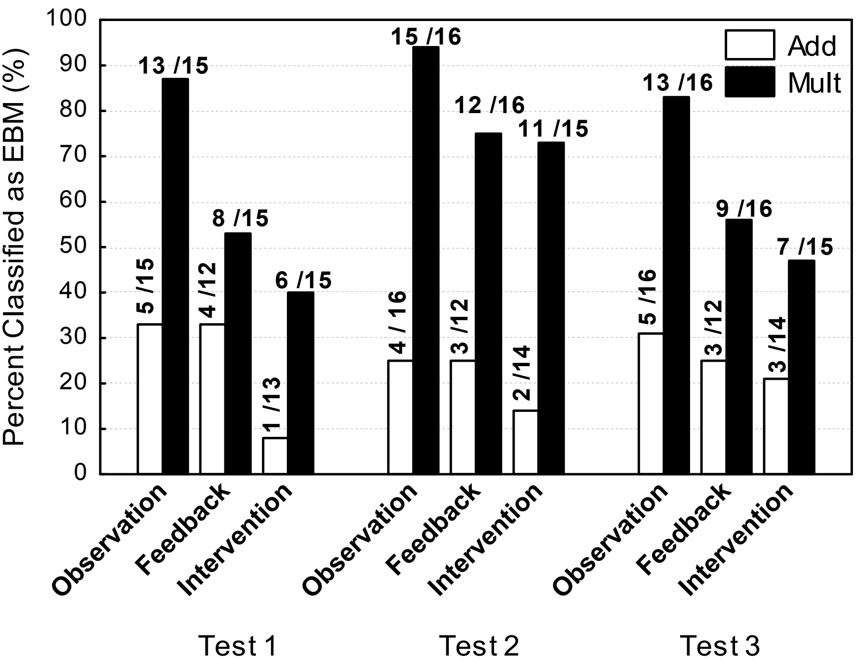

Figure 9. Percentages of participants in Experiment 3 categorized as a EBM responders in observation, feedback, or intervention traning, in the additive task (i.e., Add) and the multiplicative task (i.e., Mult). The absolute number in relation to the total number of participants is shown at the top of each bar.

As expected, the main effect of learning modes on model fits was evident in the first test phase, with clear signs of EBM in unsupervised observational training and CAM in supervised feedback and intervention training. The accuracy for old and new matched exemplars clearly suggested the same: exemplar processes among unsupervised observational learners and cue abstraction among supervised feedback and intervention learners. There were still signs of this main effect in the second test phase, but it was no longer evident in the third and final test phase. Similar trend was shown after categorizing the participants as EBM or CAM by the model with lowest RMSD. As illustrated in Figure 9, EBM responses are predominant in the multiplicative task but not in the additive task (where CAM responses predominates). Collapsed across the task environment, the effect of training mode becomes more evident and, as illustrated in Figure 10, EBM responses are predominant in unsupervised observational training but not in supervised feedback and intervention training (where CAM responses are more predominant).

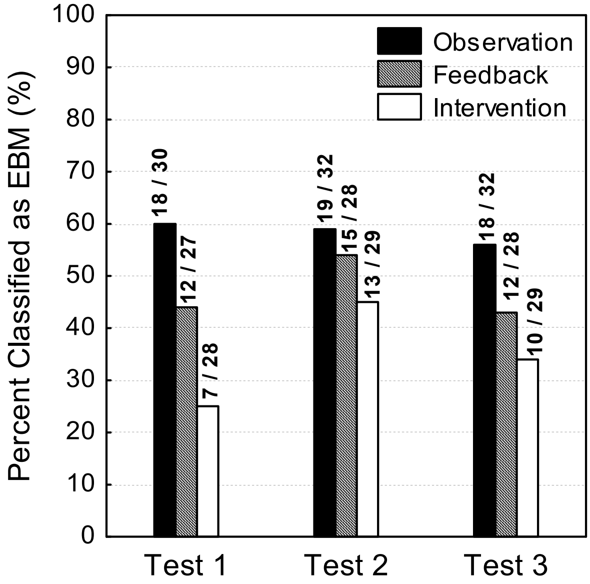

Figure 10. Percentages of participants categorized as a EBM responders in observation, feedback or intervention training, collapsed across the task environments in Experiment 3. The absolute number in relation to the total number of participants is shown at the top of each bar.

In sum, as training proceeds, the training mode and the task structure begin to interact. While the invited process of training mode diminishes, the effect of task environment continues to pull the judgment to the most adaptive process for the task environment at hand. Learning and achievement were clearly enhanced when the process initiated by the training mode was also favored by the task environment. The results support the prediction that top-down or bottom-up processes in supervised and unsupervised learning are differentially effective, depending on the complexity of the underlying task structure. The more taxing supervised learning was the better learning option in the less complex additive task, while the less taxing unsupervised learning was the better learning option in the more complex nonlinear task.

Study III: Abstraction of Ideal Prototypes in Multiple-Cue Judgment

The third study aims to investigate the involved top-down and bottom-up processes in supervised and unsupervised learning by studying how these interact with characteristics known to trigger abstraction and obstruct exemplar memory processes. In Estes (1994) and Study I, unsupervised learning invited a receptive exemplar encoding. The question is what happens when the task structure obstructs memory performance and triggers abstraction, for example when continuous cues are linearly related to a continuous criterion. Such task structure is known to trigger cue abstraction (e.g., Karlsson et al., 2007). What is less known is the impact of the number of exemplars, or sample size, in such task structures since the sample of exemplars presented to participants has usually been large and presented only once. Thus, if abstraction is based on hypothesis testing, as supervised learning is predicted to do, a large sample may be crucial for an efficient cue abstraction to test all hypotheses on. A small sample may not be sufficient, and repetitions will not facilitate cue abstraction since it will only repeat the same cue configurations to test the hypotheses on. If abstraction is based on receptive bottom-up processes, as unsupervised learning is predicted to do, the number of unique training exemplars may have little or no impact, only the saliency of the continuous cue dimensions. Although such dimensions may introduce "stimulus confusion" (Rouder & Ratcliff, 2004) and obstruct memory performance, continuous cue dimensions easily discern cue directions that can be used to form ideal prototypes. Study III introduces therefore the *prototype-based model* (*PBM*) to compare with CAM, and the manipulation of number of exemplars (or sample size) will therefore reveal the process behind abstraction in the different learning modes.

As has been shown, strategic cue search is more likely when stimuli are presented as descriptions rather than as pictures, while the pictorial format has shown to induce similarity-based prototype processing (Bröder & Schiffer, 2003; 2006). Study III therefore manipulates stimuli presentation (i.e., images vs. descriptions) in order to capture any effects on achievement beyond that of training mode.

Predictions

In a task that introduces stimulus confusion and obstructs exemplar processes (Rouder & Ratcliff, 2004), Study III predicts that CAM and an abstraction based on hypothesis testing, becomes more efficient with a supervised learning mode, and is sensitive for the number of unique training exemplars to test hypotheses on. Supervised learning is thus predicted to be more accurate with many exemplars than few.

PBM and an abstraction of cue directions to form ideal prototypes, is predicted to become more efficient with an unsupervised learning mode and is insensitive for the number of training exemplars, only the scaling of cue dimensions to detect cue directions. Unsupervised learning with many confusable exemplars is thus less accurate than supervised learning, which is close to optimal with many training exemplars. Unsupervised learning with few confusable exemplars is predicted to be more accurate than supervised learning, which underperforms with few training exemplars. The predictions would then yield an interaction between learning mode and number of training exemplars similar to the interaction found in Henriksson (2012). Henriksson (2012) also found evidence for CAM in supervised learning but mixed processes for unsupervised learning (i.e., CAM and strong old-new differences which indicate exemplar processes). Study III introduced and tested therefore PBM as an alternative to CAM and EBM.

Method

The participants were given a computer-based multiple-cue task, framed in terms of survival, to learn the toxicity of various bugs varying on a continuous criterion dimension. The four weighted cues defining the exemplars, had cue values ranging from 0 to 10, and the cues were linearly and additively related to the criterion of interest. Two cues were positively related to the criterion and two were negatively related, to prevent identification of cue directions becoming trivial (e.g., high cue values always being associated with high criterion values). Two sets of training exemplars were sampled from a large pool of possible exemplars (i.e., 11^4 or 14641 exemplars), one small sample (16 exemplars) and one large sample (160 exemplars). The 16 exemplars in the set with few unique training exemplars were also represented in the set with many unique training exemplars, containing 160 unique exemplars. The 16 critical exemplars recurred in the test phase, where 16 new exemplars were introduced to test the processes involved. Four of these new exemplars resides outside the criterion range of training exemplars experienced. The second most extreme exemplars residing outside this criterion range were intended to test a prototype enhancement effect whereby the ideal prototypes (the two most extreme exemplars) are judged more accurately than the two second most extreme exemplars.

The experiment was a 2 x 2 x 2 factorial between-subjects design with random assignment of participants to experimental conditions. The independent variables were stimuli presentation ("image bugs" vs. "description bugs"), learning mode (observational learning vs. feedback learning), and number of training exemplars (few vs. many exemplars). Those in the condition with few training exemplars observed 16 exemplars repeated 10 times in a randomized order. Those in the condition with many exemplars observed 160 exemplars once in a randomized order. Figure 11 illustrates a screenshot from a hypothetical training trial when a feedback learner is presented the correct criterion for an image bug (Panel A) or a description bug (Panel B). For observational training, the information displayed is the same as in Figure 11 except that no estimates are made, thus no feedback is received in training. The toxicity level is simply stated beneath the image or the list of cues.

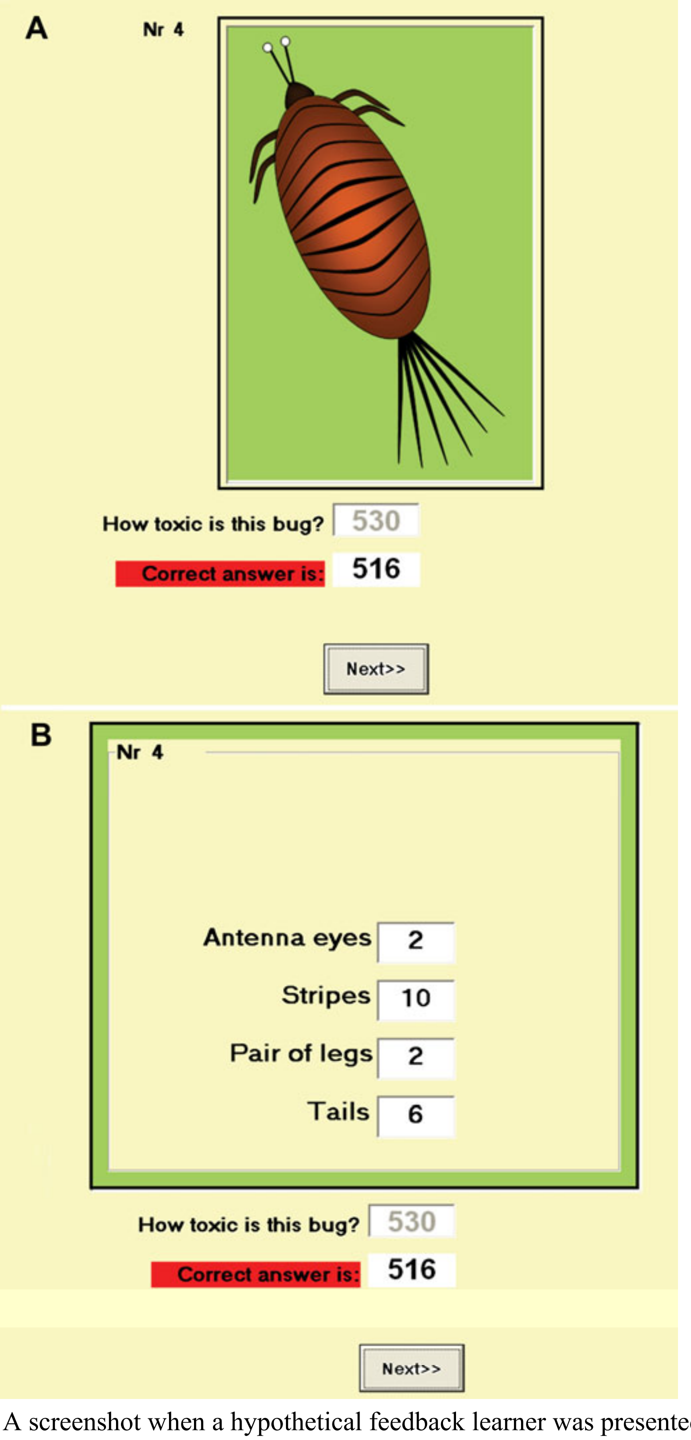

Figure 11. A screenshot when a hypothetical feedback learner was presented with the correct criterion for an image bug (Panel A) or for a description bug (Panel B).

In test, the 32 exemplars were shown twice and in a randomized order. Observational and feedback learners were asked to estimate the criterion value of each presented exemplar presented and received no feedback about the correct criterion. Figure 12 illustrates the two ideal or extreme bugs introduced in the test phase, residing at each endpoint of the criterion dimensions. To control for semantic effects of the description bugs or the saliency of the cues of the image bugs, the four cue validities (i.e., 4, 3, 2, and 1) were counterbalanced to the different cue labels or types (i.e., antenna eyes, pair of legs, stripes, and tails) across the participants.

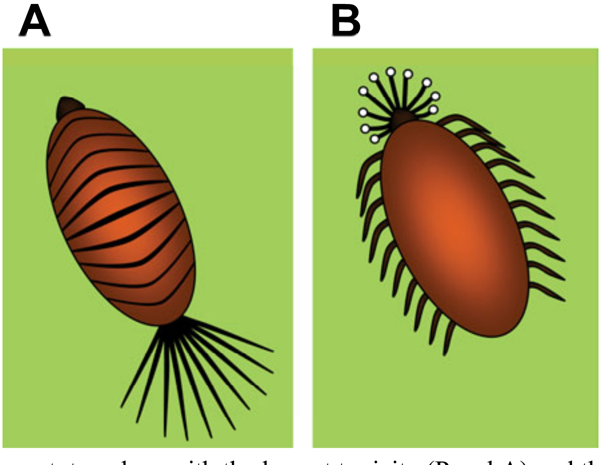

Figure 12. The prototype bug with the lowest toxicity (Panel A) and the one with the highest toxicity (Panel B).

The participants received explicit instructions prior to the task about the training mode they were about to experience and the total number of training trials they would undergo. None received information about cue directions, cue validities or the scaling of the continuous criterion. As in Study II, if participants asked for the scale they were told to learn this from experience.

Results and Discussion

As predicted, Figure 13 illustrates that unsupervised observational training is the more accurate learning option when there are few unique training exemplars, while supervised feedback learning is the more accurate learning option when there are many unique training exemplars. The significant interaction on judgment accuracy replicates Henriksson (2012) and clearly indicates that the different learning modes exploit different processes. Although research has suggested that the stimuli presentation may affect accuracy (e.g., Bröder & Schiffer, 2006), no main or interaction effect is found in Study III and this variable was therefore excluded in the following analyses.

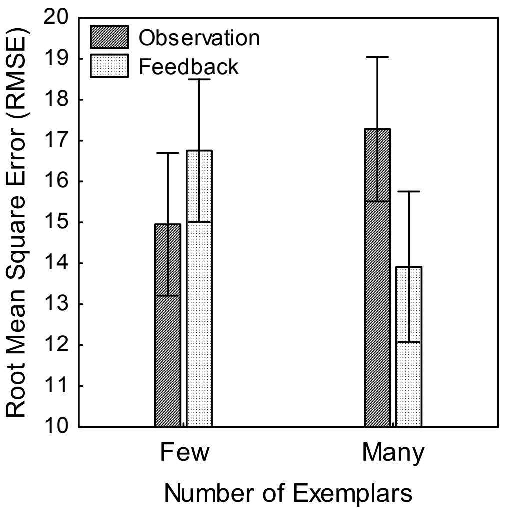

Figure 13. Judgment accuracy RMSE (Root Mean Square Error) for observational and feedback training with few or many unique training exemplars. Vertical bars denote 95% confidence intervals. Lower values of RMSE signify better judgment accuracy (i.e. better learning).

There is a main effect of the number of training exemplars, with slightly better fit for the models in the condition with many exemplars. As illustrated in Figure 14, PBM and CAM are equally good candidates to account for the judgments and did not differ from each other, but EBM could clearly not account for the data.

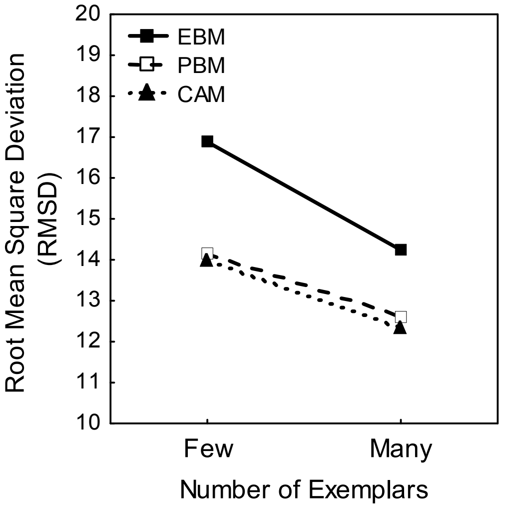

Figure 14. Root Mean Square Deviation (RMSD) for the Exemplar-Based Model (EBM), the Prototype-Based Model (PBM), and the Cue Abstraction Model (CAM), after training with few or many unique exemplars. Lower values signify a better fit.

One of the parameters in PBM indicates the sensitivity for the prototypes in memory, with higher values suggesting higher sensitivity. A closer inspection of this parameter offers support for the hypothesis that observational learners are more sensitive to the ideal prototypes than feedback learners. The same trend is shown after categorizing the participants as EBM, PBM, or CAM responders by the model with lowest RMSD. For those with PBM responses, sensitivity to the ideal prototypes is significantly higher after observational training than after feedback training.

To verify a prototype enhancement effect and reliance on prototypes, the judgment accuracy for the ideal prototypes is compared with the second most extreme exemplars introduced in test. In line with the assumptions for the models, those individuals categorized as PBM show signs of a prototype enhancement effect but not those categorized as CAM or EBM. To verify exemplar-processes, judgment accuracy for "old", previously observed exemplars, were compared with new ones, all matched by the criterion values. In line with the assumptions of the models, those categorized as EBM are significantly more accurate when assessing old exemplars, while those categorized as CAM had no systematic differences in judgment accuracy between these critical exemplars. However, there are signs of an old/new difference for those with PBM responses, with better judgment accuracy for the old than for the new ones, suggesting a residual effect of an exemplar memory encoding.

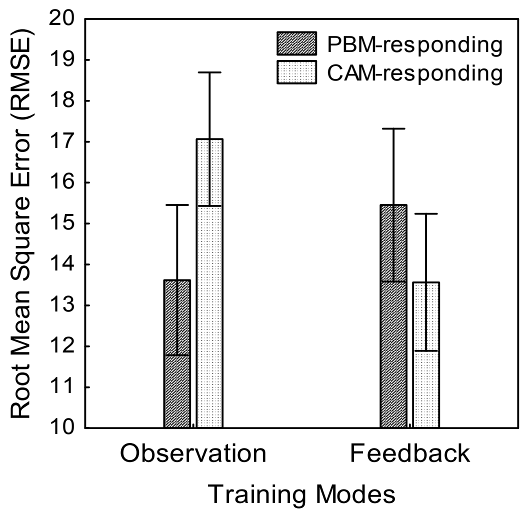

Figure 15. Judgment accuracy, RMSE (Root Mean Square Error) for the participants categorized as having PBM or CAM responses after observation or feedback training. Vertical bars denote 95% confidence intervals. Lower values of RMSE signify better judgment accuracy (i.e., better learning).

As predicted, the two abstraction styles are differentially efficient for the learning modes. Figure 15 illustrates that for unsupervised observational training, PBM responses are more accurate than CAM responses. The opposite is true for supervised feedback training, where CAM responses are more accurate than PBM responses.

The few participants categorized as having EBM responses, clearly indicated that EBM is not favored by a task with exemplars defined by continuous cues, although the exemplars were few and presented repeatedly. The frequency of participants with PBM and CAM responses shows that CAM is more likely with many exemplars, but that PBM and CAM are equally likely, with few exemplars. When CAM is penalized for its extra free parameter by AIC and BIC-corrections, PBM became more likely in all conditions except for feedback with many unique training exemplars, where CAM remained dominant.

In sum, in line with the hypotheses, the data shows better judgment accuracy for supervised feedback training, with many unique exemplars, but better judgment accuracy for unsupervised observational training, with few exemplars. PBM responses are clearly favored by an observational training mode to perform well, while those with CAM responses are favored by a feedback training mode to perform well. Study III provides support that the different learning modes base abstraction on fundamentally different processes: abstraction is based on hypothesis testing strategies in supervised learning and abstraction is based on receptive bottom-up processes in unsupervised learning.

General Discussion

Selective Sampling and Selective Samples

Study I shows how biased beliefs about a distal variable, in this case the base rate suitable individuals in the task environment, arise as consequence of a constructivist coding of inferred outcomes when learning is based on partially missing outcome feedback. Although a more sophisticated inference was more likely when the information was constrained by the decision maker's own sampling behavior, the conservative base-rate bias suggested an aversion to risk or uncertainty when people selectively samples from the external environment. Risk aversion (Denrell, 2007; Denrell & March, 2001) and resistance to change, as implied by conservatism or inertia in human belief systems (e.g., Edwards, 1968; Fischhoff & Beyth-Marom, 1983; Geller & Pitz, 1968), is a phenomenon commonly found in JDM research and, it seems, the uncertainty from selective sampling also results in slight underestimation of the probability or the relative frequency of targeted category instances. As has often been shown in research, biased beliefs, overconfidence, and an illusion of validity may stem from a confirmatory sampling of evidence (see Klayman, 1995; Nickelson, 1998, for reviews of confirmation biases).

Study I is in line with Elwin et al. (2007) and Tindale (1989), with relatively high achievement but a conservative bias regarding the category members targeted. Similar results have been obtained in simulation studies (Ghaffarzadegan & Stewart, 2011; Smillie et al., 2014) and studies on attitude formation where selective decision-contingent feedback has been the major determinant for biased beliefs (e.g., Denrell, 2005; 2007; Fazio et al., 2004; Fetchenhauer & Dunning, 2010). The proposed explanation is that false negative beliefs or expectations will most likely persist because these events are never sampled, and no experiences will therefore disconfirm those faulty beliefs. Thus, overconfidence and an illusion of validity (e.g., Einhorn & Hogarth, 1978) will likely persist if individual agents believe they have valid knowledge from their selective experience and find it hard to believe, or perhaps ignore, evidence when others impose a differing view on their subjective representation of the external environment. With meta-cognitive myopia from a limited insight into the sampling bias, no corrections of biased belief can be expected (e.g., Fiedler, 2000).

Selective outcome-contingent feedback is used in Study I to capture situations when the external environment manipulates attitudes, beliefs, and behaviors by imposing selective information on the decision maker, for example when media, advertising or other people selectively expose positive information and conceal negative information. The selectivity imposed by the external environment is orthogonal to the selective decision-contingent feedback, and is perhaps more insidious and difficult to handle because of the lack of control of feedback contingencies, both cognitively and behaviorally. In Study I, the overall learning was poor with selective outcome-contingent feedback, and the liberal base-rate bias implied an overestimation of the relative frequency or the probability of targeted category instances. Thus, the lack of control of the feedback contingencies resulted in liberal decision-making.

Advertising agencies are a prime example of agents who manipulate the saliency and the availability of information by highlighting ideals, but the same manipulation can be expected in different social contexts where a positive image is considered as important for the individual in order to gain or maintain the social status in groups. The saliency of information has been identified as a potential cause of exaggerated estimates of probabilities and inferior decision-making (e.g., Tversky & Kahneman, 1973) and the saliency of information through media exposure can be exploited by companies and organizations paying "great sums for a place in the recognition memory of the general public" (Goldstein & Gigerenzer, 2002, p. 87). As has been noted on vicarious learning of managerial policy, selective information and undersampling of examples of failures may result in false beliefs of a positive association between different policies and success of surviving companies where risky, invalid, or inefficient policies are incorrectly perceived as advantageous. Like selective outcome-contingent feedback in Study I, the consequence of vicarious learning from selective outcome-contingent information is risky behaviors that may end in poor performance and, presumably, liquidation of the firm (e.g., Denrell, 2003).

The results of Study I suggest that more studies on the selectivity imposed by the external environment are warranted, specifically the combination of different sources of selectivity as decision-contingent, outcome-contingent, or randomly missing feedback (e.g., LeMens & Denrell, 2011). As has been noted in research on personality and social identity, an ecological approach is warranted to gain a true understanding of human adaptation where the interaction between individual and environmental factors is in focus (e.g., Fiedler, 2007; Kruger & Johnson, 2008; Roberts, Wood, & Caspi, 2008). Situational selections and situational evocation are opposing forces that affect the individual (Funder, 2008) and, similar to sampling of information from selective decision-contingent feedback, the individual can choose which environment to act upon and therefore seek and sample experiences that are consistent with prior beliefs, personality, or temperament, thus increasing the ideal fit to the (selected) environment. Although such niche-picking may offer comfort, predictability, and control, the cognitive representations from such experience may, in the long run, become biased in a similar way as selective decision-contingent feedback in Study I. However, similar to the learning experience from selective outcome-contingent feedback in Study I, there are situations where the individual cannot escape the effect imposed by the external environment, such as the workplace or school. If the individual becomes exposed to multicultural diversity, for example, such settings can act as important platforms for learning, and for changes in beliefs and attitudes that would not have happened in more homogeneous or self-selected social environments. A more thorough investigation of the interaction between individual and environmental factors is warranted (e.g., Fiedler, 2007), where the sampling of information by the individual and the information imposed by the external environment are orthogonal sources of constraints that constitute the two blades of a scissor that Herbert Simon (1955; 1956; 1990) once used to metaphorically describe bounded rationality.

Pseudo-Exemplars in Memory

The implicit assumption of the constructivist coding hypothesis in Elwin et al. (2007) is that the underlying process is the exemplar memory process. Study I therefore integrates the coding assumption in the *Generalized Context Model of classification* (Nosofsky, 1986) to allow a computational account of the process assumed by the constructivist coding hypothesis. It is also reasonable to expect exemplar memory processes in tasks with binary criterion dimensions, such as categorization tasks (e.g., Juslin et al., 2003; Olsson et al., 2006). The mode of learning (i.e., inferring a missing outcome and receiving selective outcome feedback), combined with a task environment that engages more exemplar processes (i.e., binary criterion; Juslin et al., 2003), was assumed to result in a constructivist coding characterized as a mix of an inferential strategy and a receptive exemplar encoding. Thus, when outcome feedback was missing, the similarity-based inference about the outcome was stored in memory along with the cue profile of the exemplar. The implication of such pseudo-exemplars stored in memory is that they affect subsequent similarity judgments and future coding of exemplars, with increasing biased beliefs about the relative frequency of targeted category members as a consequence.

The constructivist coding of pseudo-exemplars is related to a large body of research on false memories (e.g., Echterhoff et al., 2005; Johnson, 2006; Johnson & Raye, 1981; Loftus; 1979; 2005; 2013; Loftus & Hoffman, 1989; Roedinger & McDermott, 1995). The function of “filling-in” or imputing inferences in an incomplete or fragmented representation may be that it offers a coherent and stable representation that makes sense and gives the individual a sense of predictability. As has been shown in judicial settings, the downside is that the validity of the memory content is questionable (e.g., Loftus; 1979; 2013). However, false memories may vary in validity, depending on the sophistication of the inferences. Statistical imputing practices in research are prime examples of how different imputation methods can, for example, affect validity, depending on how the researcher treats missing data (e.g., Horton & Lipsitz, 2001; Sinharay et al., 2001). Important factors are how representative existing data are for the population of interest and to what extent missing data points can be inferred from existing ones. Low response rates in surveys are a challenge to researchers and the difficulty is to handle the feedback contingencies, presumably constrained by the external environment, and understand why some data are missing. For example, if it is some random factor that causes some people to refrain from answering a questionnaire or if missing information has some systematic cause. Needless to say, ignoring or not expecting systematic causes that depend on some population characteristic may have a serious negative impact on the validity of the study. In Study I, the validity of the inferences regarding missing information is implied by the initial representation of categorical members in the task environment. Selective decision-contingent feedback offers an initial model of the task environment that is more representative (from correctly coded exemplars representing both categories), while selective outcome-contingent feedback is confined to members of only one category, offering a highly skewed and unrepresentative model of the task environment. Stimulus contrasts are important for differentiation among stimuli (e.g., Zeithamova & Maddox, 2009; see also E. Gibson, 1969, p. 99). However, with an initial skewed model of the environment, without cognitive control of the feedback contingencies (Hammond et al., 1973) and with no meta-cognitive ability to correct the sampling bias (e.g., Fiedler, 2000); judgments in such task environments may be extremely poor and invalid.

It could be argued that a constructivist coding and a base-rate bias is limited to task environments where exemplar memory processes are more likely (e.g., binary judgment dimensions). It has been shown that explicit instructions that guide the individual to test hypotheses about cue validities can reduce the base-rate bias (Elwin, 2013), indicating the potential involvement of cue abstraction by amplifying the inferential strategy of searching for abstracted knowledge about the underlying task structure. Task environments with continuous criterion dimensions may also engage cue abstraction processes to a greater extent (e.g., Juslin et al., 2003) and the focus in learning may be on updating a rule. Thus, the individual may transcend the immediate stimulus dimension and become less receptive to the individual exemplars. This would most likely alleviate a base-rate bias even though feedback is selective (cf., Griffiths & Newell, 2009). In the future, it is important for researchers who investigate missing information to consider the underlying process of the task and, in addition, analyze how this process is affected by the characteristics of the decision-maker. It is therefore necessary to take a closer look at individual differences in order to understand how selectivity interacts with various individual factors and identify practical solutions for minimizing biased beliefs at individual level.

Observing or Inferring Reality

Study II aims to investigate inferential top-down and receptive bottom-up processes in supervised and unsupervised learning by studying the interaction with characteristics of the task environment, such as cue-criterion relationships. The data revealed evidence that more complex nonlinear structures are better handled by means of unsupervised observational training, which instigates less taxing bottom-up processes, primarily by encoding exemplar information and secondarily abstracting ideal prototypes across the flow of exploratory observations. Numerous studies have shown that (i.e., feedback) learning in nonlinear task environments is difficult (e.g., Brehmer & Qvarnström, 1976; Deane et al., 1972; Klayman, 1988a). With a more or less implicit assumption that learning (i.e., from feedback) is characterized by top-down processes and testing hypotheses about cue-criterion relationships, it has been suggested that nonlinear task environments are too difficult to learn, given people's propensity for adding strategies and limited working memory capacity (e.g., Brehmer, 1980; 1994; Brehmer & Qvarnström, 1976; Cooksey, 1996; Dawes & Corrigan, 1973; Speekenbrink & Shanks, 2010). More specifically, to abstract cue weights in nonlinear task environments, the individual must mentally control for the inherent intercorrelation between cues when predicting the missing criterion, a task that may tax a limited working memory capacity (e.g., Deane et al., 1972; Klayman, 1988a; Stewart, 1988). As has been shown in such studies using supervised learning, instead of entirely failing in the nonlinear task, people spontaneously shifted from cue abstraction to exemplar memory processes (e.g., Juslin et al., 2008) or could be efficiently guided by instructions to encode exemplars (Olsson et al., 2006). Study II shows that, instead of futile attempts to engage in taxing cue abstraction processes initiated by feedback training in complex task structures, unsupervised observational training can directly help the individual to achieve high accuracy by exploiting cost-effective bottom-up processes and encode exemplars.

If unsupervised observational training is a more effective means of tackling nonlinear tasks, the linear relationship is better handled by means of supervised feedback and intervention training, instigating top-down processes to abstract cue weights and integrate the information by an additive rule. Although the two supervised training modes were hypothesized as both instigating a cue abstraction process, intervention training was assumed to be a more suitable tool for investigating the relationship between cues and the criterion. Similar to selective decision-contingent feedback in Study I, intervention training in Study II involves a sampling of information. However, the intervention training mode requires the individual to sample information in a controlled way by testing hypotheses about cue-criterion relationships, as when a manager tests hypotheses about the necessary attributes for suitability by headhunting and employing such individuals. The effect of the criterion dimension on cognitive processing (e.g., Juslin et al., 2003; Karlsson et al., 2007), which is binary in Study I and continuous in Study II, add to the effect of training mode. Thus, the inferential mechanism in intervention training in Study II is used not only to infer or “fill in” missing information, but also to test explicit cue-criterion relationships.

Feedback training was shown in Study II to instigate cue abstraction but learners could shift to exemplar memory if the task became too difficult to solve, as in the multiplicative task environment. Shifts may not always be automatic (Karlsson, Juslin, & Olsson, 2008; Olsson et al., 2006) and the results in Studies II and III offer an additional explanation: the training modes may affect the judgment and obstruct or delay adaptive shifts. Nevertheless, it is worth noting that, for a feedback learner, shifting from an inferential mode to a perceptual mode may be a matter of changing to a receptive state of mind and wait for feedback to reveal the correct criterion. Thus, for a feedback learner, the information displayed after feedback has been received is the same information that is displayed to an observational learner from the start. As has been suggested, it is sometimes counterproductive to “think harder” and it may be more constructive to stop thinking and “go with the flow” if the individual is stuck in an unsolvable or difficult task (Olsson et al., 2006, p. 1371). Study II clearly indicates that the less taxing receptive bottom-up mode of processing may have advantages in more complex nonlinear task environments.

Abstraction in Supervised and Unsupervised Learning

If Study I shows the impact of the external environment imposing selective information about ideal category members, Study III shows how the individual can form ideals from extracted information in the task environment, i.e., form notions of an extremely suitable and an extremely unsuitable candidate with which future candidates are compared. Although there is strong empirical support for exemplar memory accounts (e.g., e.g., Brooks, 1978; Estes, 1994; Hintzman, 1986; Medin & Schaffer, 1978; Nosofsky, 1986; Nosofsky & Johansen, 2000; Nosofsky & Zaki, 2002), the exemplar memory account has been criticized as being limited to tasks with few, distinct, and repeatedly presented, exemplars. Prototype-based models have instead been offered as alternatives to account for judgments on large sets of exemplars (e.g., Homa et al., 2008; Homa, et al., 1981; Minda & Smith, 2001; Smith & Minda, 1998; 2000). Prototype models have not been introduced to task structures where the criterion dimension is continuous, and the proposed PBM in Study III is an attempt to offer, for multiple-cue judgment research, a model that can stand up well in comparison with the cue abstraction model and exemplar memory accounts (e.g., Juslin et al., 2003; 2008).

Although statistical models, such as CAM, have been criticized for being paramorphic or "as if" models (e.g., Gigerenzer & Kurz, 2001; Hoffman, 1960), there are studies that have confirmed the rationale for cue abstraction (e.g., Brehmer, 1994; Einhorn et al., 1979; Juslin et al., 2003; 2008; Speekenbrink & Shanks, 2010). It is also long been known that the abstraction of cue directions is important for improved learning in multiple-cue tasks (e.g., Doherty & Balzer, 1988; Lindell, 1976; Newell et al., 2009; Rolison et al., 2012; von Helversen et al., 2013; von Helversen & Rieskamp, 2009), but the mechanism for detecting this has largely remained unknown. It is hypothesized in Study III that unsupervised observational training makes learners better at detecting such information across the flow of exploratory observations, in line with a direct perceptual account (e.g., Andersson & Runeson, 2008; Cohen, 2006; E. Gibson, 1969; J. Gibson, 1979; Runeson & Andersson, 2007; Runeson et al., 2000) and statistical learning (e.g., Fiser, 2009; Fizer & Aslin, 2001). The recurring difficulties in learning from supervised feedback on abstracting cue weights with hypothesis testing (e.g., Brehmer, 1980) also indicate that a receptive state of mind following observational training may be more effective. Operating from a receptive state of mind, observational training was therefore predicted to turn to abstraction of cue directions in the event of invited exemplar memory being obstructed, and the abstracted information was used to form ideal prototypes as reference points in subsequent similarity-based judgments. Feedback learning, operating from an inferential mode, was predicted to base abstraction on hypothesis testing of the cue-criterion relationship.

Study III replicates Henriksson (2012) and shows that the basis for abstraction differs for supervised and unsupervised learning. In a task that introduce stimulus confusion and triggers abstraction, abstraction based on hypothesis testing was shown to require a large sample of exemplars to test hypotheses on, while an abstraction basted on receptive bottom-up processes is not affected by the sample size, only by the saliency of cue directions for the formation of ideal prototypes. In line with the predictions, assessments of similarity to stored ideal prototypes are clearly favored by the unsupervised observational training mode, while cue abstraction is favored by the supervised feedback training mode. The residual effect of an exemplar memory process among those with the prototype response was not expected but may be reasonable, considering that the judgment policy was assumed to shift from exemplar memory to prototype processing when memory processes were obstructed. Thus, the memory of the exemplar may still impact the learner's judgments but this impact would presumably decrease in the course of the training trials.

The judgments assumed by PBM are expected not only to be fast; they are also assumed to be cost-effective, by exploiting natural reference points consisting of extreme or ideal prototypes carrying valid information from the task environment about the cue directions. The efficiency of using ideal prototypes representing categories has also been noted by Barsalou (1985), who argued that "ideal" prototypes facilitate for the individual to reach functional goals. Thus, instead of relying on a mean or median prototype representation of a category (e.g., Homa & Cultice, 1984; Minda & Smith, 2011; Posner & Keele, 1968; Rosch, 1975; Rosch & Mervis, 1975; Smith & Minda, 1998), the categorization can be based on similarity to an extreme or ideal prototype representation (e.g., Barsalou, 1985; Lynch et al., 2000; Massaro & Friedman, 1990; Palmeri & Nosofsky, 2001; Voorspoels et al., 2013). Research on preference and choice has also acknowledged the importance of ideals in decision-making (e.g., Coombs, 1958; De Soete et al., 1986; Kerimi et al., 2011; Mitchell & Beach, 1990; Zeleny, 1976). As Mitchell and Beach (1990) argue, "ideals" are important reference points with which options are compared in order to facilitate decision-making and increase judgment accuracy in a fast and cost-effective way.

Study III offers a prototype model that remains largely untested, and more studies are warranted in the future. One important implication of the proposed PBM is that the attributes of the ideal prototypes depend on the saliency of cue directions. Cues with little or no impact on the criterion also have low saliency concerning cue directions and would therefore go undetected. Consequently, the ideal prototypes may have varying numbers of defining attributes, with some environments possibly offering more complex ideals than others. Future research may need to take a closer look at the detection of cue directions and the formation of ideal prototypes as outlined in this thesis.

Supervised and Unsupervised Learning across the Life Span

The results of Studies II and III imply that the external environment may be tailored to facilitate learning for the individual, simply by changing the training mode. As has been shown in previous research, unsupervised observational training seems to offer a way to learn that does not affect neural regions normally involved in feedback learning (e.g., Cincotta & Seger, 2007; Poldrack et al., 2001). It has also been shown to be an efficient learning mode for patients with Parkinson's disease, a clinical group with known dysfunctions affecting set shifting abilities and executive functions governed by the frontal lobes (Shohamy et al., 2004; Smith & McDowall, 2006). Although the underlying neural basis has been discussed, there is evidence that elderly people in general are better off with an observational training mode, but have difficulties using a feedback training mode (Schmitt-Eliassen et al., 2007) and cannot efficiently use more taxing cue abstraction (Mata et al., 2012). Similarly, feedback training seems not to be suitable for children who cannot efficiently use cue abstraction despite facilitating instructions (von Helversen et al., 2010). Development and age-related decline in executive functions across the life span (e.g., Nyberg et al., 2010) indicate that a receptive bottom-up mode of processing in unsupervised observational training, primarily inviting exemplar encoding, may be an efficient alternative whenever top-down processes in supervised learning fail. As has been argued, exemplar memory processes can act as an efficient back-up process whenever rule-based processes fail (Juslin et al., 2008; Platzer & Bröder, 2013).

As numerous statistical learning studies have shown, the implicit abstraction of statistics from experience of the environment, provides the individual the important building blocks for higher cognition and may be a fundamental ability for human survival and adaptation (e.g., Fiser, 2009). Unsupervised observational learning, with a receptive bottom-up mode of processing, seems to be the mode of experiential learning that is present in infancy and continues through life, supporting basic cognitive functions (e.g., Barlow, 1989; Brady & Oliva, 2008; Fiser, 2009; Fiser & Aslin, 2001; 2002; Goldstein et al.,1983; Hasher & Zacks, 1979; 1984; Kirkham et al., 2002; Mundy et al., 2007; Saffran et al., 1996; Turk-Brown et al., 2009). Frequency processing is, for example, important for prediction and has been extensively investigated in JDM research (e.g., Sedlmeier & Betsch, 2002). Although many studies have shown that frequency processing is most often highly correct, which supports the idea that people are “intuitive statisticians” (e.g., Peterson & Beach, 1967), Study I shows fairly biased processing of frequencies. The determinants of the biased frequency of category members targeted were found in the constraints imposed by the external environment or from the individual sampling behavior. Experience from selective supervised learning can thus negatively affect frequency processing with a base-rate bias from storing pseudo-exemplars in memory. However, the less extreme bias and the better judgment accuracy for decision-contingent feedback suggest, at least in some respects, that the “intuitive statistician” is more likely to be an individual who is allowed to act on the environment, in line with the Gibsonian view (e.g., E. Gibson, 1969; J. Gibson, 1979). Consistent with statistical learning studies showing advantages for unsupervised observation in assessments of underlying statistical regularities in the environment (e.g., Brady & Oliva, 2008; Fiser, 2009; Fiser & Aslin, 2001; 2002; Hasher & Zacks, 1979; 1984; Kirkham et al., 2002; Turk-Brown et al., 2009), the results in Study II and III suggests that the term “intuitive statistician” may better capture an individual with an unsupervised observational training mode who exploits a receptive bottom-up mode of processing information.

Connecting Theories

The notion of rationality has been the focal point in JDM research since Paul Meehl’s (1954) influential work on inferior expert judgments in the early 1950s. The framework of the present thesis is highly influenced by Herbert Simon’s famous metaphor of scissors where the two blades describe the boundary conditions of human rationality (e.g., Simon, 1956; 1990). Rationality is thus bound by characteristics of the individual and of the external environment; and learning is a matter of adapting the process to the demands of the task environment (e.g., Anderson, 1991; Payne et al., 1993; Simon, 1955; 1956; 1990).

The main objective of this thesis was to study the efficiency of inferential top-down or receptive bottom-up mode of processing initiated by supervised and unsupervised learning, and the relationship between the two dominant approaches to human adaptation: the constructivist (Brunswik, 1955; Gregory, 1970; Hammond & Stewart, 2001) and the direct perceptual (E. Gibson, 1969; J. Gibson, 1979). The first assumes that people use top-down processes and infer the external environment, while the latter assumes that people use bottom-up processes and perceive the external environment as it is without mediating inferences (see Heft, 1981 for a theoretical distinction between a direct and indirect realism). The constructivist or inferential approach has a long tradition in cognitive psychology and JDM research, and has over the years received substantial theoretical support (e.g., Cooksey, 1996; Hammond & Stewart, 2001). Nevertheless, the constructivist approach has also introduced the concepts of intuition, intuitive processing, and dual-processing accounts of judgment and decision-making to account for rapid, automatic judgments (e.g., Gilovich et al., 2002), causing debates and controversies. Its proponents have also been accused of obstructing research by introducing ill-defined constructs that cannot be verified because the “intuitive system”, by definition, cannot be probed (e.g., Evans, 2008). Needless to say, insights into the processes occurring on a cellular or neural level may be unrealistic and the Gibsonian direct perceptual approach suggests that inferential mechanisms and external feedback are unnecessary to explain adaptative behavior and human experience (e.g., Gibson, 1979).

James Gibson rejected all forms of “mentalism” and would most likely have rejected the analyses of cognitive process, but the replicated interactions between learning mode and underlying task structure, would probably had been of concern and difficult explain from mainly one theoretical perspective. Both Gibson and Brunswik advocated the use of representative designs and stimuli sampled from natural environments (e.g., Brunswik, 1955; Dhami et al., 2004; Gibson, 1979). However, underlying structures in natural environments are rarely known and stimuli used for the investigation in this thesis were construed to manipulate the underlying characteristics and study their effect on achievement. The main argument in this thesis is that achievement and beliefs are affected by involved top-down or bottom-up processes instigated by the different learning modes. In addition, they were predicted to be differentially effective in different task environments. The relative effectiveness of top-down and bottom-up processing has also been noted in visual perception, for example, a transition from an inferential to a direct perceptual mode as a function of experience of a task (e.g., Andersson & Runeson, 2008; Runeson & Andersson, 2007; Runeson et al., 2000). Some have also suggested that there are separate neural systems supporting the different modes; the ventral constructivist system and the dorsal direct perceptual system (Norman, 2002). The two modes in perceptual estimation tasks have also been contrasted to an exemplar memory model. The exemplar memory model showed an impressive fit in certain subtasks but, overall, the direct perceptual or the invariant model provided a better fit for more experienced observers or when the individual was exposed to a large set of stimuli (Cohen, 2006). As has been argued by researchers in perception, there is a need for an integrative theory that can address the plethora of phenomena presented in research on perception over the years, and there are also proposals on how to reconcile the two ecological approaches (e.g., see reviews in Vicente, 2003 or Kirlik, 2009).

If a direct perceptual approach has mainly concerned how an individual handles a present situation, then a constructivist approach, especially in JDM research, concerns how the individual handles future, unknown, or uncertain situations (e.g., Vicente, 2003). Information in natural environments may often be fragmented or incomplete, and the results in Study 1 suggest that selective sampling of information and selective information imposed by external forces, are two important sources to biased beliefs and inferior performance that research needs to address more thoroughly. Handling the present and predicting the future are also important aspects of human adaptation and pose a challenge for an integrative approach to address. Lawrence Barsalou's integrative approach is an example of an embodied or situated account of human adaptation that connects cognitive and behavioral aspects to the ongoing interaction with the external environment, where the re-enactment of situated and multimodal sensory experiences stored in long term memory (cf. affordances; Gibson, 1979) is exploited for prediction and for preparing for future goal-relevant behaviors. For Barsalou, ideal prototypes are here important situated conceptualizations used to facilitate functional and goal-relevant behaviors (e.g., 2003; 2009; 2010).

As noted above, and is emphasized in Kurt Lewin's Field theory (1939), aging and individual differences are other factors that impact adaptive behavior and cognition. The relative efficiency of the learning modes among aging and clinical populations provide further support for the hypotheses in this thesis and suggest that to fully understand human adaptation it is necessary to take aging into the account. Previous findings and the results in this thesis provide support for the hypotheses that the learning modes engage those processes that the different theoretical and epistemological approaches assume. In addition, they were differently adaptive depending on underlying task structures, suggesting that both approaches may be important to understand the challenges human face in everyday life, in line with the claims for an integrative approach (e.g., Kirlik, 2009; Vicente, 2003). Needless to say, there are challenges with a general ecological framework that need to be overcome, but important scientific discoveries may be achieved if "scientific niche picking", searching for evidence in support for one theory and ignoring evidence for an opposing one, can be avoided.

Concluding Remarks

The ecological approach, as once proposed by Herbert Simon, has provided the overall framework for this investigation of human adaptation and (bounded) rationality. This thesis proposes that important scientific discoveries can be achieved by integrating two ecological and epistemological views on human adaptation: The Brunswik's constructivist view and the direct perceptual view outlined by Eleanor and James Gibson.

This thesis raises the possibility that people can adaptively shift between a "Gibsonian mode" and a "Brunswikian mode", and that these epistemological views, in fact, can be represented in the very same task, and even have different impact across the life span. The aim of this thesis is not to formulate a comprehensive theory. Rather, it is to show how supervised and unsupervised learning modes relate to the different theoretical accounts and are affected by underlying structures in task environments. In doing so, I seek to contribute to a better understanding of adaptive cognition: how complete and selective experience in everyday life, regardless of whether we are aware of it, modulates beliefs and influences our judgment and decision-making — for better and for worse.

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