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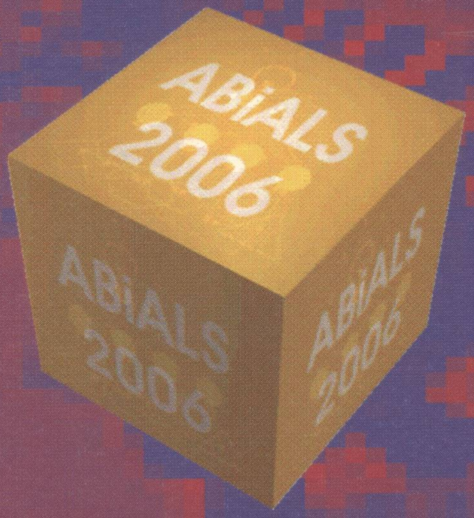
Anticipatory Behavior in Adaptive Learning Systems

From Brains to Individual and Social Behavior



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From Brains to Individual and Social Behavior

Springer

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Preface

Anticipatory behavior in adaptive learning systems is steadily gaining the interest of scientists, although many researchers still do not explicitly consider the actual anticipatory capabilities of their systems. Similarly to the previous two workshops, the third workshop on anticipatory behavior in adaptive learning systems (ABiALS 2006) has shown yet again that the similarities between different anticipatory mechanisms in diverse cognitive systems are striking. The discussions and presentations on the workshop day of September 30th, 2006, during the Simulation of Adaptive Behavior Conference (SAB 2006), confirmed that the investigations into anticipatory cognitive mechanisms for behavior and learning strongly overlap among researchers from various disciplines, including the whole interdisciplinary cognitive science area.

Thus, further conceptualizations of anticipatory mechanisms seem mandatory. The introductory chapter of this volume therefore does not only provide an overview of the contributions included in this volume but also proposes a taxonomy of how anticipatory mechanisms can improve adaptive behavior and learning in cognitive systems. During the workshop it became clear that anticipations are involved in various cognitive processes that range from individual anticipatory mechanisms to social anticipatory behavior. This book reflects this structure by first providing neuroscientific as well as psychological evidence for anticipatory mechanisms involved in behavior, learning, language, and cognition. Next, individual predictive capabilities and anticipatory behavior capabilities are investigated. Finally, anticipation relevant in social interaction is studied.

Anticipatory behavior research on cognitive, adaptive systems aims at exploiting the insights gained from neuroscience, linguistics, and psychology for the improvement of behavior and learning in artificial cognitive systems. However, this knowledge exchange is expected to become increasingly bidirectional. That is, the insights gained during the design and evaluation of different anticipatory cognitive mechanisms and architectures may also provide insights into how anticipatory mechanisms can actually shape, guide, and control natural brain activity. This book reveals many interesting and thought-provoking connections between distinct cognitive science areas. We strongly hope that these connections do not only lead to a deeper understanding of the functioning of anticipatory processes but also enable a more effective, bidirectional knowledge exchange and consequently more effective scientific progress in the natural and artificial cognitive systems research disciplines.

April 2007

Martin V. Butz
Olivier Sigaud
Giovanni Pezzulo
Gianluca Baldassarre

Organization

The third workshop on Anticipatory Behavior in Adaptive Learning Systems (ABiALS 2006) was held during the Ninth International Conference on Simulation of Adaptive Behavior (SAB 2006) on September 30th, 2006 in Rome, Italy. We are grateful to the organizers of SAB 2006 for giving us the possibility to hold the third workshop during their conference. This volume is an enhanced compilation of the workshop contributions and discussions. The organizers of the conference were Stefano Nolfi (chair), Gianluca Baldassarre, Raffaele Calabretta, John Hallam, Davide Marocco, Orazio Miglino, Jean-Arcady Meyer, and Domenico Parisi.

We are also more than grateful to our program committee members for providing us with careful reviews of the diverse contributions and often additional helpful comments and suggestions. Due to their hard work, we were able to organize two reviewing processes, one to evaluate and improve the original workshop contributions and a second one to improve the contributions (including modified resubmissions of the workshop's contributions) for this enhanced post-workshop proceedings volume. We are convinced that all accepted contributions provide new, highly stimulating insights into the realm of anticipatory mechanisms for adaptive cognitive systems. We would also like to thank Marjorie Kinney for proofreading all the contributions in this volume. Finally, we would like to thank all our colleagues, friends, and families that helped us during the production of this book with discussions, comments, suggestions, and general support.

This work was supported by the EU funded projects *MindRACES – from Reactive to Anticipatory Cognitive Embodied Systems*, FP6-STREP-511931, and *ICEA – Integrating Cognition Emotion and Autonomy*, FP6-IP-027819.

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Anticipations, Brains, Individual and Social Behavior: An Introduction to Anticipatory Systems

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Abstract. Research on anticipatory behavior in adaptive learning systems continues to gain more recognition and appreciation in various research disciplines. This book provides an overarching view on anticipatory mechanisms in cognition, learning, and behavior. It connects the knowledge from cognitive psychology, neuroscience, and linguistics with that of artificial intelligence, machine learning, cognitive robotics, and others. This introduction offers an overview over the contributions in this volume highlighting their interconnections and interrelations from an anticipatory behavior perspective. We first clarify the main foci of anticipatory behavior research. Next, we present a taxonomy of how anticipatory mechanisms may be beneficially applied in cognitive systems. With relation to the taxonomy, we then give an overview over the book contributions. The first chapters provide surveys on currently known anticipatory brain mechanisms, anticipatory mechanisms in increasingly complex natural languages, and an intriguing challenge for artificial cognitive systems. Next, conceptualizations of anticipatory processes inspired by cognitive mechanisms are provided. The conceptualizations lead to individual, predictive challenges in vision and processing of event correlations over time. Next, anticipatory mechanisms in individual decision making and behavioral execution are studied. Finally, the book offers systems and conceptualizations of anticipatory processes related to social interaction.

1 Introduction

The presence of anticipatory mechanisms and representations in animal and human behavior is becoming more and more articulated in the general, interdisciplinary research realm of cognitive systems. Hereby, anticipatory processes receive different names or are not mentioned explicitly at all. Commonalities between these processes are often overlooked. The workshop series "Anticipatory

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Behavior in Adaptive Learning Systems" (ABiALS) is meant to uncover these commonalities, offering useful conceptualizations and thought-provoking interconnections between the research disciplines involved in cognitive systems research.

After the publication of the first enhanced post-workshop proceedings volume in 2003 [13], research has progressed in all involved areas. Somewhat unsurprisingly, neuroscience and cognitive psychology are continuously revealing new influences of anticipations in cognition and consequent behavior and learning. Individual and, even more strongly, social behavior seem to be guided by anticipatory mechanisms, in which predictions of the future serve as reference signals for efficient perceptual processing, behavioral control, goal-directed behavior, and social interaction.

In the previous volume we offered an encompassing definition of anticipatory behavior: "A process, or behavior, that does not only depend on the past and present but also on predictions, expectations, or beliefs about the future." [14, page 3]. While this definition might clarify anticipatory behavior, anticipatory mechanisms can clearly come in a variety of forms, influencing a variety of behavioral and cognitive mechanisms.

This introduction first provides an overview over the possible beneficial influences of anticipatory mechanisms and how these influences might be realized most efficiently. It then surveys the contributions included in this volume. First, known cognitive mechanisms involved in anticipatory processes in the brain and in language evolution are surveyed. Moreover, a fundamental challenge for artificial cognitive systems is identified. Next, individual anticipatory behavioral processing mechanisms are addressed, including several conceptualizations, frameworks, the effective generation of predictions, and effective behavior execution. Finally, the book moves on to interactive, social systems and investigates the utility of anticipatory processes within.

2 Potential Benefits of Anticipatory Behavior Mechanisms

During the discussion sessions at the workshop day in Rome in September 2006, it became clear that there are multiple facets and benefits of anticipatory mechanisms. These can be conceptualized by their nature of representation and general influence on cognitive processes, as proposed previously [15]. Additionally, representations of time-dependent information and consequent knowledge gain can be distinguished based on their respective benefits for behavior and learning. These aspects are re-considered in the following sections.

2.1 The General Nature of Anticipatory Mechanisms

In many cases, it has become clear that anticipation itself is often slightly misunderstood, particularly due to the non-rigorous usage in habitual language. Therefore, we have offered an explicit distinction of different processing aspects of anticipations and have focused the workshop effort more on explicitly anticipatory mechanisms in cognitive systems.

First of all, anticipations can very generally be divided into *implicit* and *explicit* anticipatory systems. In implicit anticipatory systems, very sophisticated but reactive control programs are evolved or designed—potentially leading to intelligent, implicitly anticipatory system behavior. That is, albeit these systems do not have any explicit knowledge about future consequences, their (reactive) control mechanisms are well-designed so that the systems appears to behave cleverly, that is, in implicit anticipation of behavioral consequences and the future in general. This workshop, however, focuses more on explicitly anticipatory systems, in which current system behavior depends on actual explicit representations of the future. Cognitive psychology and neuroscience have shown that explicit anticipatory representations exist in various forms in animals and humans [44,26]. Thus, we are interested in anticipatory programs that generate predictions and utilize knowledge about the future to control, guide, and trigger maximally suitable and efficient behavior and learning.

Explicit anticipatory systems may be divided further into systems that use:

- Payoff Anticipations;
- Sensory Anticipations;
- State Anticipations.

Payoff anticipations characterize systems that have knowledge of behaviorally-dependent payoff and can base action selection on that representation. That is, different payoff may be predicted for alternative actions, which allows the selection of the current best action, as done in model-free reinforcement learning [78]. Sensory anticipations can be characterized as anticipatory mechanisms that support perceptual processing. State anticipatory processes enhance behavior decision making and execution exploiting anticipatory representations [15].

2.2 How Anticipations Can Help

To conceptualize and distinguish different sensory and state anticipatory mechanisms further, it is worthwhile to consider the question of *how* anticipations may affect cognitive processes (cf. also [26]). Thus, we now discuss how anticipatory mechanisms may influence adaptive behavior and, particularly, how such mechanisms may be beneficial for adaptive behavior. From a computationally oriented perspective the question arises how predictions, predictive representations, or knowledge about the future can influence sensory processing, learning, decision making, and motor control. Several different "*how* aspects" may be distinguished, which are first listed and then discussed:

- Useful information can be made available sooner, stabilizing and speeding-up behavior.
- Predictions can be compared with actual consequences, improving sensory processing, enabling predictive attention, and focusing model learning.

- The possibility to execute internal simulations can improve learning and decision making.
- Goal-oriented behavior can be triggered by currently desirable and achievable future states, yielding more flexible decision making and control.
- Anticipatory representations of information over time can be behaviorally useful.
- Models and predictions of the behavior of other agents may be exploited to improve social interaction.

Information Availability. Cognitive systems often face a serious timing and time delay issue. Sensory information is simply too slow to be processed and to arrive in time at the relevant behavioral control centers of the brain to ensure system stability. Behavioral experiments and simulations confirm that humans must use forward model information to stabilize behavioral control [21,61]. In psychology, the *reafference principle* [83] conceptualizes the existence of a forward model, proposing that efferent motor activity also generates a reafference, which specifies the expected action-dependent sensory consequences. Advanced motor control uses predictive control approaches that can yield maximally effective control processes [16].

Thus, cognitive systems should use re-afferent predictions that depend on activated efferences. These predictions can be used to avoid system instabilities due to delayed or missing sensory feedback. Interestingly, such stabilization effects come into play even with stabilizing recursive mathematical equations, making them "incursive" [22]. In sum, since future information can be predicted and thus be made available before actual sensory information arrives, system control and stability can be optimized by incorporating predicted feedback information.

Predictions Compared with Actual Consequences. Once subsequent sensory information is available, though, the predicted information can be compared with the real information to determine information novelty and thus information significance. Hoffmann [43,44] provides various pieces of evidence from psychological research that suggest that many cognitive processes, and especially learning, rely on comparisons between predictions and actual observations. One fundamental premise of his anticipatory behavior control framework is the comparison of anticipated with actual sensory consequences. These comparisons may be based on Bayesian models [53,20], which suggest that information integration in the brain is dependent on certainty measures for each source of information, and thus also most likely for forms of predicted information.

The first benefit of such a comparison is the consequent, continuous adaption of behavior based on the difference between predicted and actual behavioral consequences, as was also proposed in the reafference principle [83]. Hereby, the difference measure gives immediate adaptive control information, in addition to the current sensory state information. Also control theory relies on such comparisons to improve system measurements and system control, most explicitly realized in the Kalman filtering principle [51,36].

The filtering principle can also be applied to detect unexpected changes in the environment and consequently trigger surprise mechanisms. For example, based on a novelty measure that depends on the reliability of current predictions and actual perceived sensory information [59], surprise may be triggered if the current observation significantly differers from the predicted information. Surprise-based behavioral mechanisms can then improve system behavior, enabling a faster and more appropriate reaction to surprising events.

Surprise-dependent processes can also be used to improve predictive model learning itself. For example, surprise-like mechanisms were shown to be useful to detect important substructures in the environment [9], which furthermore is useful to partition the environment into partially independent subspaces. This capability was used, for example, to efficiently solve hierarchical reinforcement learning problems [6,75]. Other mechanisms train hierarchical neural networks based on failed predictions or based on activity mismatch between predicted and perceived information [74,67].

Internal Simulations. Both aspects considered so far are mainly of the nature of sensory anticipations, that is, sensory processing is improved, enhanced, compared with, or substituted by anticipatory information. On the other hand, anticipatory information can also be used beyond the immediate prediction of sensory consequences to improve behavior and learning. Interactions with the experienced environment are often re-played or projected into the future by means of an internal predictive environmental model [18,32,40]. Two types of internal simulations can be distinguished: online and offline simulations. Online simulations depend on the current environmental circumstances and can improve immediate decision making. Offline simulations resemble reflective processes that re-play experienced environmental interactions to improve learning, memory, and future behavior.

Current decision making can be influenced by simulating the consequences of currently available alternatives. In its simplest but least computationally costly form, *preventive state anticipations* [19] may be employed, which simulate the usually occurring future events based on habitual behavior. The mechanism only triggers preventive actions if the habitual behavior is expected to lead to an undesirable event. In doing so, undesirable states can often be avoided with only linear additional computational effort—linearly predicting the future of what "normally" happens. Advanced stages of such anticipatory decision making leads to planning approaches that consider many possible future alternatives before making an actual decision [5,15,77].

In contrast to such online, situation-dependent simulation approaches for action decision making, offline simulation, that is, the simulation of events that are not necessarily related to the current situation, have been shown to be useful for memory consolidation as well as for behavioral improvement. An example for memory consolidation is the wake-sleep algorithm [41], which switches between online learning phases, in which data inputs are stored in internal activation patterns, and offline learning phases, in which internally generated memory traces lead to memory generalization and consolidation. A similar structure is exhibited in bidirectional neural networks, originally applied to visual structuring tasks [67] where the emergent activity patterns resembled neuronal receptive fields in the visual cortex.

However, there are also behaviorally-relevant types of simulation, as exemplified in the DYNA-Q system in model-based reinforcement learning [77,78] and related sub-symbolic generalizing implementations of the same principle [5,10,76]. Hereby, an internal environmental model is exploited to execute internal "as if" actions and to update internal reinforcement estimates. Interestingly, from the behavior observation alone, it is often hard to determine if behavior is anticipatory due to previous offline simulations and resulting memory consolidation or due to online, situation-dependent planning simulations [12].

In summary, internal environmental simulations can help to make better immediate decisions, improve action decision making in general, and to learn and generalize the predictive environmental model itself.

Goal-initiated Behavior. Internal simulations, however, do not appear to be the whole story in the realization of efficient, flexible, adaptive behavior. Rather, behavior appears to be generally goal-directed, or rather goal-initiated [43,44,82]. That is, the activation of a desired goal state precedes and triggers actual behavioral initiation and execution. Cognitive psychological research confirms that an image of a goal, which is currently achievable, such as some immediate action consequences, is present before actual action execution is initiated [56]. Moreover, concurrently executed actions interfere mainly due to goal representation interferences, as shown in various bimanual behavioral tasks [60,55].

Thus, goal representations appear to trigger behavior, which is thus never reactive but always anticipatory. This is essentially the tenet of the *ideomotor principle*, proposed over 150 years ago [37,81,48]. This principle is now most directly used in inverse modeling for control, in which a goal state and the current state trigger suitable motor commands as output [50,57,62,80]. To further tune the inverse model capabilities, coupled forward-inverse modules can enable the choice of the currently most suitable inverse models amongst alternatives [84,34].

Additionally, it has been shown that goal-initiated behavior can efficiently resolve and exploit redundancies in the activated goal representation(s). For example, concrete goal states may be chosen based on redundant alternatives [72]. Also motor paths may be chosen based on current alternatives dependent on anticipated movement effort [8]. In this architecture, additional task constraints can be easily accounted for, for example, realizing efficient obstacle avoidance or compensating for inhibited joints [8,38]. A recent combination with reinforcement learning mechanisms enables the motivation-dependent goal activation, effectively unifying payoff with state anticipations [39].

Predictive Representations. Besides immediate influences on sensory processing and behavior, predictive representations need to be considered in more detail,