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. Subsequent chapters address predictive challenges in vision and the 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 involved in 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 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 past and present but also on predictions, expectations, or beliefs about the future." [14, page 3]. While this definition might clarify anticipatory behavior, the involved anticipatory mechanisms can clearly come in a variety of forms, influencing a variety of 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 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 appear to behave in (implicit) anticipation of behavioral consequences or some other future properties, 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 adaptivity, enabling surprise mechanisms, and focusing predictive model learning.

- The possibility to execute internal simulations can improve learning, memory, 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 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, which are often neglected in current adaptive behavior research. Representations need to be generated that identify dependencies in time rather than in space or between current input dimensions.

Recurrent neural networks have been applied in this respect, beginning with the famous Elman networks [23]. Recently, successful motor control patterns were published not only for hierarchical, self-organizing forward-inverse control structures [35] but also for the generation of believable behavioral patterns in real robot applications [46, 45]. Additionally, the LSTM network approach [42, 30] proved to be able to efficiently relate regular recurring patterns over time. Echo-state networks [47], on the other hand, are able to efficiently detect dynamic patterns over time.

Applications of predictive representations in artificial cognitive systems appear imminent. Hierarchical clusters of captured dynamics to, for example, cluster linguistic structures into recurring phonemes, syllables, words, and sentences appear demanding. In this respect, a hierarchical sequence learning architecture was shown to exhibit interesting, dynamically growing characteristics [11]. Current performance of various recurrent neural network approaches and hierarchical approaches on typical sequential tasks can be found elsewhere [31, 24].

Social Anticipations The final beneficial influences of the considered anticipatory mechanisms lie in social interaction. Recently, there has been increasing evidence that social beings show strong capabilities to represent the behavior of other animals by means of mirror neurons [71]. Hereby, neural activity is shown to represent not only one's own behavioral patterns, such as a grasping action, but also similar behavioral patterns executed by other animals.

Studies show that the animals hereby not only mirror the actual action but also the purpose (that is, the goal) of the action [29]. Gallese strongly suggests that mirror neurons are the key component to develop mutually beneficial interpersonal relations and empathy mechanisms [28, 27]. Arbib relates the mirror system and consequent imitative capabilities to language evolution [1].

Regardless of the representation used, it seems obvious that, in order to effectively interact with conspecifics, avoid betrayal, but exploit mutual possible benefit, it is necessary both to be able to individuate the conspecifics with which interaction takes place and to be able to predict the behavior and current goals of the other individuals. Only then seems trust and mutually beneficial behavior possible beyond evolutionary determined self-less behavior [69].

3 Overview of the Book

The taxonomy presented in the last section is reflected in the workshop contributions. Additionally, as the title suggests, the book moves from brain and cognitive evidence for anticipatory mechanisms to individual and social anticipatory behavior systems. This general train of thought, however, is reflected not only in the paper distribution in this volume, but also in the structure of various contributions themselves.

3.1 Anticipations in Brains, Language, and Cognition

In the next chapter, Jason Fleischer [26] surveys neural correlates of anticipatory processes in the brain, linking neural activity patterns identified in neuroscience research to anticipatory processes and research in adaptive behavior. First, he gives an overview of neuroscientific research paradigms and points out the difficulty in the different methodologies. He then focuses on three important brain areas: (1) the cerebellum, which is mainly involved in motor learning and control, (2) the basal ganglia, which is involved in reward-based learning, sequential action selection, and timing issues, and (3) the hippocampus, which is involved in sequential representations and memory formation. All three areas are known to also represent anticipatory aspects of behavior and learning. Fleischer concludes that the insights gained with respect to the distinct structures of the three regions as well as their involvement in anticipatory processes should provide helpful guidelines to design future anticipatory, brain-inspired artificial cognitive systems.

Samarth Swarup and Les Gasser [79] survey anticipatory aspects in language. They suggest that the more complex the language, the more anticipatory and social components are involved in it. They take an evolutionary approach and first identify the minimal conditions for the emergence of a proto-language. Then they analyze various languages in animals and identify the complexity of the structure of a language and the symbolic character of a language as the two main criteria for overall language complexity. Finally, they propose that overall language complexity increases along an anticipation axis from implicit over payoff and sensory, to state, and to social anticipations. Theories of natural and artificial language evolution are surveyed from this perspective. In conclusion, the paper proposes that the study of the minimal conditions for the emergence of language and the anticipatory component within may lead towards the design of artificial social agents that are able to learn to interact by a form of communication that emerges within the agent society itself.

Alexander Riegler [70] then provides a slightly controversial but thought-provoking essay on the potential problem of superstitious machines. He points out that an artificial system that attempts to process all information available is destined to start believing in non-existing correlations. Such false beliefs about interdependencies in the world may then lead to superstition and potentially mental illness in the machine. The solution is not to follow an information processing paradigm for the design of artificial cognitive agents, but rather an anticipatory constructivist approach, which focuses on the validation of internally generated, relevant anticipatory representations. Thus, instead of constructing artificial cognitive systems as datamining machines, we should focus on machines that construct an internal reality that represents only relevant interactions and dependencies of the environment.

3.2 Individual Anticipatory Frameworks

The subsequent contributions focus on anticipatory mechanisms and artificial cognitive system frameworks that include anticipatory components.

Giovanni Pezzulo et al. [65] compare the ideomotor principle from the field of psychology with the test operate test exit (TOTE) system from cybernetics. Both principles have a goal-directed nature with an emphasis on behavior and learning. Studies of a visual search system, a developmental arm control system, and a motivational model-based reinforcement learning system show that the ideomotor principle and the TOTE specify very similar behavioral principles. Moreover, the comparisons point out that both principles are rather underspecified and highlight additional mechanisms necessary to realize actual implementations.

Vladimir Red'ko et al. [68] then propose the "animat brain" framework for the design of artificial cognitive control systems. The framework is based on functional systems that contain a coupled system of a forward model predictor and an inverse model actor. Comparisons with other approaches highlight the potentially high flexibility of the "animat brain" approach due to the combination of reinforcement learning with hierarchically linked functional systems.

Aregahegn Negatu et al. [64] introduce an autonomous agent architecture termed the "learning intelligent distribution agent (LIDA) system", which is also inspired by cognitive processes. Their system incorporates payoff, sensory, and state anticipatory mechanisms. It it able to build associative and procedural memory structures based on schema mechanisms, it realizes selective attention based on global workshop theory [3, 4], and it is able to select actions based on its current internal drives and reinforcement learning principles. Simulations of the system show competent behavioral and adaptive capabilities illustrating automation and deautomation due to an anticipatory measure of prediction failure and consequent allocation of attentional resources.

Giovanni Pezzulo and Gianguglielmo Calvi [66] introduce a framework that can be used to simulate and evaluate schema-based anticipatory behavior mechanisms. Schema-based design, which is inspired by cognitive psychology research, is theoretically analyzed emphasizing goal-orientedness, flexibility of application, selectivity of information, and excitability, which depends on current drives and contextual input. Moreover, cooperative competition between schemas as well as pragmatic and epistemic (that is, information seeking) aspects of schema activity are investigated. Pezzulo and Calvi then introduce the computational platform "AKIRA Schema Language (AKSL)", which allows the implementation of concurrent resource-competitive schema systems. Exemplars show that the system masters action selection, attentional mechanisms, category formation, the simulation of future behavior, grounding schema activity in behavioral patterns, and hierarchical action control. The paper concludes with a proposal to use AKSL to shed further light on the question *when* anticipatory mechanisms are really beneficial for the improvement of cognitive process and behavior.

3.3 Learning Predictions and Anticipations

The next section of the book introduces several approaches to learning predictions and correlations in time. Often, it is proposed that sensorimotor contingencies are learned, that is, action-dependent sensory changes.

Wolfram Schenck and Ralf Möller [73] teach a moving camera head to predict sensory changes dependent on self-induced camera movements. They distinguish between two learning tasks: learning to predict future visual input and learning to predict the predictable visual areas in the input. To do so, their algorithms learn an action-dependent mapping of visual input rather than to predict the visual input directly. The task is successfully accomplished with a real camera head plus simulated fovea image (a retinal mapping), showing impressive learning and consequent action-dependent image mapping capabilities. The anticipatory component comes in handy here both for learning the mapping as well as for identifying predictable sensory input, working on the direct comparison of anticipated and consequently perceived actual input.

Jérémy Fix et al. [25] move higher up in the visual processing realm and tackle the task of memorizing the location of stimuli, which were previously focused upon. The task to maintain a coherent internal memory of stimulus locations despite the drastic perceptual changes due to saccadic eye movements is certainly non-trivial. To solve the problem, the authors introduce an interactive model of working memory, which maintains currently perceived inputs dependent on focus and predictions, and long-term memory, which predicts perceived inputs and is updated by working memory activity. Hereby, simulations show that anticipations are mandatory to be able to maintain a coherent memory of stimuli locations in the environment, independent of current eye focus. A complete and coherent memory can only be maintained when anticipatory mechanisms are applied.

Stefano Zappacosta et al. [85] propose a testbed for recurrent neural networks and related systems to integrate information in time. The task is to scan an object or a wall while moving around it or along it, respectively. The recurrent network is trained to classify the object scanned, investigating prediction robustness, noise-robustness, and different aspects of generalization capabilities of the network in question. Elman networks, echo state networks, leaky integrator networks, and LSTM networks are introduced exemplarily as suitable neural network candidates. An Elman network is then evaluated on two testbed instances: a wall task in which two different wall patterns need to be distinguished, and an object task in which three different objects are perceived. The testbed, possibly with additional action-information of movement type and speed in the future, seems to be a valuable tool to test and compare the capabilities of different time-series classification algorithms on somewhat real-world robotic classification tasks.

Philippe Capdepuy et al. [17] investigate the more symbolic challenge of event anticipation. The information-theoretic measures based on constant and consistent time delays as well as on contingency, that is, proximity in time, are used to automatically detect interesting event dependencies. Although only the predictive capabilities are investigated, the authors discuss the importance of such capabilities for anticipatory action decision making and propose also the involvement of epistemic verification actions that could be triggered for the verification of hypothesized event dependencies. Despite currently unresolved scalability as well as subsymbolic issues, the paper shows that the employed information-theoretic measures are highly capable of detecting consistent event contingencies and time-delay relationships.

3.4 Anticipatory Processes in Behavioral Control

Predictive capabilities alone are only one facet of anticipatory behavior, though. The following papers address different goal representations and predictions that directly influence actual behavior.

Kiril Kiryazov et al. [52] present an integrated behavioral architecture that uses symbolic analogical reasoning to make action decisions. The system is mounted onto the Aibo real-robot platform and solves the task of finding interesting objects in a house-like environment. Besides the anticipatory decision making capabilities based on analogy, the system applies selective attention mechanisms as well as top-down anticipatory perception mechanisms to filter out relevant information in the environment. Although it is hard to compare the current capabilities of the platform with other architectures due to the many hardware and setup dependent factors, the resulting anticipatory behavior aspects realized on an integrated real-robot platform are highly promising.

Toshiyuki Kondo and Koji Ito [54] present a recurrent neural network architecture with neuromodulatory biases that shows to be able to reach targets under various force fields. The network weights and connectivity evolve by means of a genetic algorithm. It is shown that the anticipatory biases are beneficial to achieve more robust reaching behavior under novel force fields. The results suggest that recurrent self-stabilization mechanisms can be highly beneficial for adaptation in gradually changing environmental circumstances. Future evaluations appear necessary to further shed light on the emergent representations and control components in such evolved recurrent neural network structures.

Arnaud Blanchard and Lola Cañamero [7] study how positive and negative goal states can be efficiently remembered in order to enable optimal behavioral control. They use a developmental approach that learns to classify goals based on a reinforcement learning derived scheme. Their aim is to use a minimal amount of memory by remembering only maximally suitable and unsuitable states in the environment—leaving the task to reach these states to a goal-directed control architecture. Their real robot implementation of the system is able to identify suitable goals as well as undesirable goals efficiently with a very low demand for memory. Future work intends to enhance the goal identification mechanism to be able to identify multiple and more distinct goals. Moreover, the goal generation mechanism will be interfaced with a motivational component, which will generate drives and correspondingly desired goal states as well as goal-directed motor control mechanism, which will be able to reach currently desirable goal states.

Arshia Cont et al. [2] use predictive system capabilities for the generation and improvisation of music. The paper provides a thorough overview of anticipatory cognition identified in music theory, suggesting that musical processing is highly anticipatory based on veridical expectations, schematic expectations, dynamic adaptive expectations, and conscious expectations. All four types interact concurrently and competitively. The remainder of the paper then focuses on the integration of payoff and state anticipations into a music generating and improvisation architecture, working either in self listening mode or in interaction mode, respectively. The provided results of the imitation of a Bach piece are impressive and promise fruitful future integrations of anticipatory mechanisms for automatized music generation and improvisation.

3.5 Anticipatory Social Behavior

After the study of different aspects of individual anticipatory behavior, the last chapters of this book address the importance of anticipatory mechanisms for efficient social interaction.

Mario Gómez et al. [33] introduce an anticipatory trust model in open distributed systems. A theoretical taxonomy of trust distinguishes between direct trust, which is about previously experienced service quality of another agent, and advertisement- and recommendation-based forms of trust, which are about the suggested service quality of another agent by yet other agents. The different measures are combined into a global trust measure—essentially the weighted average of the individual measures. Experiments are carried out in a simulated market environment with trading agents. The results stress the importance of stability and the capability to identify properties of other individuals, in order to be able to develop effective notions of trust. Moreover, they show that if the system is able to predict the behavior of other agents, the agent is able to adapt to changes in the environment more effectively.

Gerben Meyer and Nick Szirbik [63] study anticipatory alignment mechanisms in multi agent systems with petri nets. Conceptualizations are carried out within belief propagating networks, studying three types of alignment policies: on-the-fly alignment, pre-interaction alignment, and alignment induced by a third party. The mechanisms are illustrated within a business information system, sketching out constraint transactions of goods and money between multiple agents. It is shown that the state anticipatory mechanism is able to yield more efficient agent interaction executions. The integration of trust mechanisms for more efficient agent communication appears imminent. Moreover, the proposition of actual simulations in real-world game-like scenarios with other artificial agents, but also with expert players, promises to be highly revealing for future applications.

Emilian Lalev and Maurice Grinberg [58] study two recurrent neural network architectures playing the iterated prisoner's dilemma. While the first model used backward-oriented reinforcement learning methods, the second network basis its move decisions on generated predictions about future games. Thus, the latter network anticipates the behavior of the opponent player. The results suggest that human players use anticipatory capabilities to guide their decision process within the game. As with actual human participants, the cooperation rate of the latter network depended on a so-called cooperation index, which quantifies the likelihood that the opponent player cooperates. Thus, the results suggest that anticipatory connections are mandatory for efficient human-like network interaction within the iterated prisoner's dilemma game.

The final paper in this series studies the benefits of anticipating the behavior of another robot agent. Birger Johansson and Christian Balkenius [49] placed two real robots in differently complex arenas with the task of switching places with each other. The results show that in very simple environments without obstacles, a goal-directed behavioral strategy without any consideration of the opponent player, except for a reactive hard-coded obstacle avoidance mechanism, yielded the most efficient behavior. However, in more complex environments, in which robot interference is inevitable and harder to resolve, anticipatory mechanisms yielded the fastest behavior. In this case, the anticipatory mechanism predicted the behavior of the opponent robot and resolved possible trajectory conflicts online. Thus, it is shown that higher complex environments can make more complex, cooperative, anticipatory mechanisms beneficial. In very simple interactive environments, on the other hand, ignorance of the opponent or cooperative player can also be more effective, since no expensive contemplations or communicative interactions are necessary.

4 Conclusions

Research on anticipatory behavior mechanisms can be found in a variety of research areas. Indications for anticipatory mechanisms in the brain, and their influences on cognition and resulting individual and social behavior, continue to accumulate. It is hoped that anticipatory research in general, and this enhanced and re-reviewed post-workshop proceedings volume in particular, will contribute to a general understanding of anticipatory mechanisms in cognitive systems.

This introduction conceptualized different anticipatory mechanisms providing a taxonomy of how anticipatory mechanisms may improve adaptive behavior and learning. The overview of the contributions of this volume exposes important correlations of anticipatory behavior mechanisms between different research disciplines. These include neuroscience, cognitive psychology, linguistics, individual and social adaptive behavior research, music theory, business research with trading agents, and research in cognitive modeling.

The book can certainly only provide a glimpse at the different aspects of anticipations in these various disciplines. However, we believe that the contributions reveal and develop many highly correlated recurring anticipatory mechanisms and they identify many anticipatory principles that are highly beneficial to improve individual and social adaptive behavior. Thus, we hope that the articles in this volume will be inspiring for researchers in the cognitive systems area and lead to the offspring of many fruitful future research projects and interdisciplinary collaborations amongst scientists interested in both a deeper understanding of natural cognitive systems and the further development, design, and application of adaptive, flexible, and efficient artificial cognitive systems.

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