

**Anticipation for Learning, Cognition,
and Education**

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IlliGAL Report No. 2004027
May, 2004**

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Abstract

Predictions, desires, or intentions have recently shown to strongly influence behavior, adaptation, and learning. These anticipations influence behavior mediating decision making and action execution as well as attention. Although it is not the future itself that influences the present but the anticipated future states or future properties, the difference to purely stimulus driven behavior and learning is highly significant. Most recent analyses investigate when and where anticipations are helpful to improve behavior. The discovery of environmental properties that favor anticipatory behavior are crucial to understand when and where which adaptive mechanisms work best. The impact on the understanding of the world, social systems, human learning and understanding, as well as education principles might be immense. The perspective of purpose as part of the cause in the general case might have been underestimated and requires further investigations and considerations.

Anticipatory Behavior

Anticipations mediate behavior. Purpose directs attention. Predictions influence learning. Expectations predispose the mind and body. Desires bias or cause motivations. Intentions initiate behavior execution.

All these influences express a certain *anticipatory behavior*—behavior, or some cognitive process, that does not only depend on current sensory input but also predicted, desired, or intended future states or future properties. This definition was put forward in (Butz, Sigaud, & Gérard, 2003) stressing the importance of an interdisciplinary approach to anticipatory behavior and learning.

In fact, many disciplines have realized the importance of anticipations over the last decades. In the realm of control theory, the Kalman filter is among the most advanced filtering and control techniques predicting system behavior to optimize and stabilize the system (Haykin, 2001). In psychology, the experimental evidence of anticipatory behavior is continuously increasing (Rescorla, 1991; Rescorla, 1995; Hoffmann, 1993; Hoffmann, 2003). In neuroscience, neural activity hints towards anticipatory mechanisms in many subregions of the brain (Wolpert, Ghahramani, & Flanagan, 2001; Blakemore & Decety, 2001; Blakemore, Frith, & Wolpert, 2001; Schubotz & von Cramon, 2001). Linguistics realizes the strong task dependence of word production as well as understanding. Finally, computer science and particularly machine learning suggests the need for an internal model to improve adaptive behavior and learning (Sutton & Barto, 1998; Sutton, Precup, & Singh, 1999; Butz & Hoffmann, 2002).

All these aspects of anticipatory behavior can be combined in a general framework. Distinctions need to be drawn between different anticipatory mechanisms their applicative time frame, their purpose, and their possible benefit. The interdisciplinary approach to anticipatory behavior allows the gathering and analysis of different anticipatory phenomena from for example psychology, linguistics, or neuroscience. The gathered data allows then conclusions on structure and general purpose of anticipatory behavior. Computer science helps to validate the emerging theories using facet-wise analysis. Finally, the knowledge about different aspects of anticipatory behavior and learning may influence our general comprehension of learning and thus lead to a new more directed form of education.

Continuing on this path, the remainder of this article will provide some stunning evidence of anticipatory behavior from psychology and linguistics. Next, we provide some background from the computer science perspective and the machine learning realm in particular to show how important it is to understand the structure underlying any learning problem and any learning mechanism. Consequently, we suggest an approach to categorize and analyze different aspects of anticipatory behavior. In conclusion, we suggest possible impacts on future education and learning principles.

Experimental Evidence of Anticipatory Behavior

After the rise of behaviorism in the early 20th century (Watson, 1913; Skinner, 1971), the last decades have shown that there is more to behavior and learning than reward and punishment. Psychological experiments have proven that behavior is continuously mediated by current predictions, desires and intentions. Initially, Tolman and others (Tolman, 1932; Thistlethwaite, 1951) have conducted experiments with rats in simple mazes in which the rat behavior was only explainable when adding an anticipatory part. Thus, Tolman proposed the formation of expectancy units (Tolman, 1959). More recently, also experiments on humans showed anticipatory behavior influences. The following examples reveal influences on action initiation and execution, guidance of environmental exploration, and the influence on attention and incoming sensory processing.

The first experiment measures behavior in terms of reaction times and action execution. The experiment, conducted by (Kunde, 2001), shows that simple actions, such as a button press, can be initialized faster when the effect of the button press is somewhat compatible to the button press itself. Subjects were instructed to press one of four buttons as fast as possible. Dependent on a color stimulus a left or a right button was to be pressed. Only after the button was pressed and reaction times were measured, a visual spatial effect was presented on the screen either compatible with the side of the button press or incompatible. It was shown that subjects were able to press the button faster if the consequent effect is compatible. Note that the effect influenced the time until the correct button press was initialized although the effect was presented strictly after the button press. Thus, some sort of anticipation or preparation for the visual effect influenced the button press. Similar compatibility effects were found in the realm of length and intensity. It was also shown that not only the key press initialization was affected but also its execution (Kunde, Koch, & Hoffmann, 2004). Thus, anticipatory mechanisms influence behavior initiation and execution.

Another example illustrates anticipatory behavior mediated by current motivations. Using an eye-tracking device, which is regarded as a general indicator of cognition, subjects were presented a little cartoon picture in which, for example, a kangaroo figure shoots Mickey Mouse with a water gun. The gun is located in the middle of the picture so that the subjects naturally look at the gun first. With a memory task in mind (remember the scene and write down what was seen afterwards) people tend to look first at the character that is shot (after looking at the gun) and only then at the character that shoots. However, with the task of telling as fast as possible what is seen, the behavior of the people changes. Apparently due to the typical subject-verb-object structure

of the English language, people tend to look now first at the subject (that is, the character that shoots the gun) and already start speaking while the eyes move to the object (Griffin & Bock, 2000). Similar language-dependent eye behavior can be found when telling the time (Bock, Irwin, Davidson, & Levelt, 2003). The example clearly shows how the task biases eye movement. The need for a subject to phrase a proper sentence guides the eyes to the actor and thus allows a faster sentence production. Anticipatory behavior thus can speed-up the accomplishment of a task mediating attention and sensory processing.

The final example comes from the phenomenon of inattention blindness in psychology. The phenomenon suggests that attention might be even more powerful than previously thought and that especially the anticipatory component in attention is most crucial for successful processing of important sensory input. The experiment shows a short video clip in which a white team and a black team of three people each pass a ball to each other (Simons & Chabris, 1999). The task consists in counting how often the white (or black) team passes the ball to each other. However, the counting is not really the difficulty. Surprisingly, during the video a person in a black gorilla costume slowly walks through the scene even stopping in the middle hitting its fists on its chest. Hardly any subject actually notices the gorilla while watching the video (carefully counting the passes). Most subjects are even very surprised when the gorilla is shown afterwards (often suspecting that a different video was shown). In this case, the task strongly influenced attention and sensory processing. The knowledge of ball behavior and passing options enables the attentional focus to narrow down to the current task possibly overlooking very significant (but task irrelevant) events.

These three examples show that anticipations can influence behavior in many forms including behavior initiation and execution, behavior decision making, and attentional processing. Although the experiments were of rather different nature and were conducted in rather different realms, all behaviors were influenced by predictions, desires, or intentions about the future. (Hoffmann, 1993; Hoffmann, 2003) proposes an anticipatory behavioral control framework in which the comparison between the predicted and actual (sensory) input is the crucial factor for learning. Due to the feedback signal provided by the environment, the hypothesized internal predictive model can be directly learned and adapted.

Understanding Structure

Stepping back for a moment it needs to be noticed that any learning mechanism needs to have some sort of structure or proper *bias* to be effective. In fact, it can be proven that given a particular problem space in which all constructible problem solutions are equally likely any learning mechanism performs as well as any other learning mechanism (c.f. No Free Lunch (NFL) theorem (Wolpert & Macready, 1995)) and essentially as good as a random search mechanism. The reason why our natural learning and adaptive mechanisms do not work as poorly as a random search mechanism is because there is structure in our world. Due to this structure, not all problem solutions are equally likely and thus the No Free Lunch theorem does not hold usually. In fact, the evolutionary evolved learning predispositions (as imprinted in our genes) efficiently exploit previously encountered structures in the world to enable effective adaptation and learning.

However, what No Free Lunch tells us is that in order to construct an effective learning mechanism it is necessary to understand the underlying general structure of the learning task. Or, going one step further, if addressing problems in our environment bound by the three-dimensional space, time, and the consequent neighborhood relationships and constrained interactions of matter, the general structure of our environment needs to be understood to design efficient (and quite universal) learning mechanisms. Might there be a general principle underlying all evolution and learning that works better than random search? Has the world an underlying structure that can be exploited by

smart algorithms? Which structures are there to exploit?

(Goldberg, 2002) suggests that the identification and proper recombination of building block structures (complexity units) are at the core of such an intelligent or even innovative learning mechanism. If this is true, it would be necessary that structure in the world itself would be only possible to consist out of substructures and collections of such substructures which form new substructures in a hierarchical way. Many examples in our world suggest that any structure in our world is in fact composed of smaller substructures that somewhat hold together overcoming the general tendency to diffuse or increase entropy.

While the spatial dimensions are usually the predominant dimensions in object or structural formations, time results in another kind of neighborhood relationship and again essentially restricts influence and interaction. However, time is continuously flowing making the present reality, the past history, and the future full of options. Anticipations are the processes that consider the most probable and/or most desired options. Anticipatory behavior directs activity towards this subset of options and somewhat restricts cognitive processing to this subset. The focus however is not only a restriction but more importantly an enhancement enabling the organism to process the information in the subset in more detail allowing better understanding and vice versa again, more detailed focusing.

Thus, in order to understand or create effective behavioral (or cognitive) learning mechanisms, it is necessary to understand the underlying structure or principles of the environment in which the behavior is applied. For anticipatory behavior, several principles can be identified in our world and the effective corresponding anticipatory mechanism can be characterized and evaluated. The next section outlines the current approach to this endeavor.

Structure for Anticipation

While the above examples from psychology and linguistics suggest that anticipatory behavior is present in at least humans and higher animals, the structure as well as the benefit of these mechanisms is subtle. The question remains when and where which anticipatory mechanism is beneficial. While a complete answer to this question still does not exist, several hints and facet-wise answers can be found.

For example, in (Butz & Hoffmann, 2002) we showed that anticipatory behavior is beneficial in a partially dynamic environment. The conducted simulations were based on a previously conducted rat experiment (Colwill & Rescorla, 1985). The rat experiment consisted of three phases. In the first phase, rats received food or sucrose dependent on if they pressed a lever or pulled a chain. In the second phase, one of the reinforcers was devaluated by pairing it with a mild nausea (in this phase, neither lever nor chain were present). Finally, the rats were then tested, if they prefer to press the lever or pull the chain once back in the original setup but without providing any reinforcer. Significantly more actions were monitored (pressing or pulling) that previously led to the non-devaluated reinforcer.

Our simulations showed that in order to successfully simulate the observed rat behavior, the system needs to learn an online generalized internal model of the encountered interactions and the system needs to exploit the learned model to adjust behavior appropriately (somewhat reasoning for example that since the pulling previously led to food which I don't like anymore, I rather push to get sucrose). Purely stimulus driven behavior cannot account for the behavior since the lever (or chain) was never directly associated with the devaluation. Without generalization or encapsulation of the task and essentially the pairing of action to the reinforcer type no conclusion is possible. Finally, without a lookahead or anticipatory mechanism (expecting the food that is now avoided) the behavior again would not be possible.

In a more abstract sense, it was basically shown that in an environment in which causal relations are encountered and in which these causal relations are partially dynamic, better adaptivity can be reached if anticipatory behavior is available. That is, the encountered change or novelty in the environment is spread to other related scenarios guiding action decision making.

In the general case, we can distinguish several facets of anticipatory processing, outline their behavioral influences, and characterize their expected benefits and drawbacks. The following distinctions focus on the time aspect and on the direction of the influence:

- Anticipatory Behavior Execution
- Anticipatory Sensory Processing
- Anticipatory Internal Processing
- Anticipatory Planning and Decision Making

Anticipatory behavior execution is the factor closest related to adaptive control theory such as model predictive control (Camacho & Bordons, 1999) and the related Kalman filtering technique. The system learns and adapts an internal forward model of its environment and consequently relies less on sensory input for execution control. Advantages can be found in the speed-up of activity, the independence of faulty sensors, as well as the improved stability of the action execution due to the advanced filtering mechanism. Disadvantages might include the ignorance to possibly relevant disturbances or the premature convergence to suboptimal behavioral execution patterns.

Anticipatory sensory processing strongly addresses the attention side of our cognitive apparatus. The bias does not cause actual motor activity but rather the internal direction of cognitive activity. Essentially, the mind is predisposed to process only certain parts of the sensory input, as observed in the experiment with the gorilla above in which the direction of the attention towards team and ball filters the appearance of the gorilla. Again, advantages can be found in the processing speed-up and the task-dependent more detailed processing of the selected sensory input. Disadvantages are over-focusing possibly causing to overlook important situations.

Anticipatory internal processing results in the drawing of internal conclusions, connections, and notions of relatedness and relevancy. Internal means connections and conclusions that are made independent of the outside sensory influence. These mechanisms strongly relate to the proposed offline memory processing purpose of sleep (Stickgold, 1998) but might also be extended to related awake processing methods such as internal reinforcement learning techniques (Kaelbling, Littman, & Moore, 1996; Sutton & Barto, 1998) originally suggested in the Dyna framework (Sutton, 1990). The power of such internal processing lies in its independence of current sensory input and the general preparation of the system to future possible connections. Drawbacks can be imagined in the drawing of false conclusions and false associations due to misleading events or sensory data.

Finally, the most computationally expensive method is anticipatory planning and decision making. Behavior decision making is certainly influenced by many factors and includes the whole field of decision making. Essential for the anticipatory component is that behavior is influenced not only by the current sensory stimuli but also by the desired future stimuli. Incorrect expectations may lead to incorrect biases and inappropriate behavior decisions. For example, when crossing a road and getting hit by a car the expectation of still getting past is violated leading to the faulty decision of crossing the road in the first place. Hereby, the major drawback is the exponential nature of a general planning technique. However, the system can only plan as much ahead as the internal model seems reliable as a predictor. The advantage is faster adaptivity in dynamic environments and, given that the model is generalized and can be reapplied in different scenarios, faster adaptivity to new (but similar) environments.

These distinctions are for now only sketched out and are rather meant to emphasize the different aspects of anticipatory behavior than to make clear distinctions between the different types of anticipatory behavior. In general, the distinctions are made among the lines of the extend of future considerations (anticipatory action execution vs. planning) and impact on these considerations (immediate motor control vs. motor initiation vs. sensory processing). More important than those distinctions are their impact on actual behavior and learning. The simulation of such anticipatory processes and consequent analysis of different anticipatory techniques is on the way. Our final section focuses on the above considerations and tries to conclude with a novel perspective on learning and education.

Anticipations Guide Learning

In summary, we have seen that there are many aspects to anticipatory behavior, many benefits but also possible drawbacks. It is clear that most cognitive processes have an explicit anticipatory component that is shaped and evolved interacting with the environment and also interacting with itself. The usual benefit of anticipatory behavior is a more focused, goal directed behavior mediated by attention and action decision making.

Conclusions can be drawn towards learning and consequent education techniques. From the No Free Lunch theorem we know that it is necessary to understand the underlying structure of the subject at hand to decide on the appropriate education technique used. For example, associative memory such as vocabulary needs to be taught by providing as many and as significant associations as possible. Other more science-related subjects might require a more anticipatory way of teaching. Due to the underlying causal structure and the required internal model to understand the subject, the subject should be taught in an inductive way to facilitate learning of the structure.

Particularly, a student needs to be predisposed to have a general idea about the addressed subject and the current topic in mind. The clear provision and understanding of the current goal and the current scientific question at hand will be very helpful to enable the proper build-up of the student's scientific theory and its embedding in the broader perspective of the student. The revision of the underlying basics as well as the essential keywords and key concepts of the current topic will prepare the student for extension and refinement of its current understanding.

The student's predisposition should essentially lead to the capability of forming basic predictions about the next steps with respect to the topic. These predictions trigger anticipatory processing in the student allowing expectations about the outcome of a particular question. Exactly those expectations are then subject to further modifications and revisions due to the consequent further information provided by the teacher. Thus, the acquisition of scientific understanding might be viewed more as an interactive process in which students form theories in their mind and the teacher guides the theory formation. Questions are essential and might be asked by the teacher or interactively by the students to eliminate incorrect theory formations such as incorrectly assumed relations or hypothesized interactions.

As a final concern for future investigations it might be emphasized that in order to understand and promote learning, the understanding of the general underlying structure of the addressed topic is crucial. Learning can be seen as the interactive process of modifying, refining, and restructuring the so-far build knowledge representation. These refinement and restructuring processes strongly depend on the interaction between teacher and student. The best way essentially for the formation of predictive models (such as scientific theories) appears to be that the student continuously forms hypothesis and the teacher provides the actual correct conclusion. The resulting error signal then is most suitable to adjust and enhance the student's theory in mind.

Acknowledgments

I would like to thank Prof. David E. Goldberg for his continuous encouragement and his suggestions for this work. I would also like to thank Prof. Joachim Hoffmann for his continuous support and his suggestions for this work. Additionally, I would like to thank Marjorie Kinney, Pier-Luca Lanzi, and Stefan Merz for the fruitful discussions, opinions, and suggestions. Finally, I am grateful to all my fellows at the Illinois Genetic Algorithms Laboratory (IlligAL) at the University of Illinois at Urbana-Champaign as well as at the Department of Cognitive Psychology at the University of Würzburg. This work was partially supported by grant DFG HO1301/4-3 from the German research foundation (DFG). Additionally support is acknowledged from the Computational Science and Engineering graduate option program (CSE) at the University of Illinois at Urbana-Champaign.

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