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Enabling cognitive behavior of humans, animals, and machines: A situation model framework

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Abstract

The central goal of the ZiF Research Group "Cognitive behavior of humans, animals, and machines: Situation model perspectives" is to understand how cognitive behavior of humans, animals, and machines with its key features of flexibility and context-sensitivity are realized at the functional and mechanistic level. Findings, theories, models, and implementations of cognitive neuroscience (e.g., humans, rodents, and non-human primates) and artificial intelligence (e.g., autonomous robots) guide this endeavor. Despite recent and accelerated progress in these research domains (e.g., navigation in mental space or deep learning architectures), central issues are still unresolved. The following focus perspectives guide our ZiF think tank for understanding cognitive behavior: *"two*

systems" approaches to thought and action (e.g., model-based vs. model-free reinforcement learning), *capacity-limited working memory and attentional control* (e.g., levels-of-accessibility approach), and *cognitive maps* (e.g., in TOLMAN's goal-directed behavior perspective). Furthermore, we argue for the central importance of action control approaches to explain flexible and context-sensitive behavior. Considering this, we introduce the concept of a behavioral episode linking perceptual, long-term memory, and motor elements (objects, actions, scenes, outcomes). Within our overarching framework of "situation models", we view flexible set-up, testing (e.g., simulation), and fast learning of such episodes as key abilities for cognitive behavior of humans, animals, and machines.

1. The mission of the ZiF Research Group "Cognitive behavior of humans, animals, and machines: Situation model perspectives"

Everyday behavior can be decomposed into two modes or classes, namely habit- or routine-based behavior vs. deliberate or cognitive behavior. Imagine you are driving a car, after many years of practice. Driving can be considered as mostly habit-driven if you are confronted with an empty and straight road in the countryside. If you have to drive during rush hour in an inner-city area with many lanes, other cars, or bicycles, then a habit-based mode alone will not be sufficient. In this case, you have to act flexibly, especially in challenging situations such as when the usual traffic light signals at a busy intersection with many lines are not working anymore. Furthermore, you may also act in a context-sensitive manner, e.g., when you are listening to the radio and get informed that in the next street speed is measured. These features of behavior, flexibility and context-sensitivity—the combination of which we call cognitive behavior—are the key explanatory targets of our research group. Decisively, we are not only interested in identifying key questions, major insights, and controversies of empirically based theories and models of how cognitive behavior might be realized in humans and various animal species (e.g., rodents and non-human primates) but are also interested in cognitive behavior of intelligent machines such as autonomous robots (e.g., self-driving cars). In terms of humans and animals, a vast amount of scientific knowledge from various subfields of cognitive neuroscience (the combination of psychology and the brain sciences, e.g., POSTLE, 2015) exists. It is not evident which experimental phenomena from these subfields belong to key mechanisms underlying flexible and context-sensitive actions. In other words, we are at the beginning of understanding cognitive behavior of natural intelligent systems. A similar situation exists for artificial intelligence. Here, deep learning approaches have enabled the solution of long-standing mile-stone challenges such as high-quality language translation (SUTSKEVER et al., 2014), recognizing objects in images on par with humans (HE et al., 2015), or reaching or even surpassing human performance in advanced games, such as Chess, Go (SILVER et al., 2018), or Poker (MORAVČÍK et al., 2017). However, generalizing these skills to broader domains is still an open challenge (for a recent review with regard to driving, see, e.g., YURTSEVER et al., 2019). The currently generated deep learning solutions lack the degree of flexibility and context-sensitivity that we can observe not only in humans (e.g., HASSABIS et al., 2017; LAKE et al., 2017) but also in many animal species (e.g., including insects, CHITTKA, 2017). Moreover, the solutions created "emerge" to a high degree from data and are hardly penetrable for human analysis (SZEGEDY et al., 2013), are plagued by pathologies such as vulnerability through adversarial examples (MOOSAVI-DEZFOOLI et al., 2016), and often require learning times that would be equivalent to several thousand years of real-world interaction (AKKAYA et al., 2019). This has triggered new research lines that no longer primarily focus on a scaling of performance in demanding, but narrow domains, but instead try to identify principles that enable a broader flexibility of acting (for the domain of robotics see, e.g., SÜNDERHAUF et al., 2018).

Due to this analysis of the current research landscape, our international and multidisciplinary ZiF Research Group (https://www.uni-bielefeld.de/(en)/ZiF/FG/2019Behavior/)—a think tank for cognitive

neuroscience and artificial intelligence research—pursues the goal of bringing these research strands in psychology, brain science, and AI more closely together to trigger new insights into the mechanisms underlying cognitive behavior of humans, animals, and machines. For its endeavor, the group has identified three focus perspectives that will be explicated more fully in the following sections of this position paper: *"two systems" approaches to thought and action* (Section 3), *working memory and attention* (Section 4), and *cognitive maps* (Section 5), along with their integration in an overarching *framework of situation models* (Section 6).

This choice of focus perspectives is not only based on a necessarily highly selective review of the current state of the art of research on cognitive behavior but is also strongly inspired by the achievements of former ZiF Research Groups. First, in 1984/85, a Research Group under the guidance of WOLFGANG PRINZ and colleagues worked together on the at that time hardly recognized tight interaction of perception and action (e.g., PRINZ et al., 2013; PRINZ & SANDERS, 1984). Second, in 1994/95, HOLK CRUSE, JEFFREY DEAN, and HELGE RITTER headed a group focusing on "Prerational intelligence: Adaptive behavior and intelligent systems without symbols and logic" (CRUSE et al., 2000; RITTER et al., 2000). Achievements of this group were also important for the Excellence Cluster "Cognitive Interaction Technology" of Bielefeld University (https://www.cit-ec.de/en). Third, in 2012/13, WERNER SCHNEIDER and WOLFGANG EINHÄUSER implemented a ZiF Research Group on "Competition and priority control in mind and brain: New perspectives from task-driven vision" (SCHNEIDER et al., 2013b, 2015; https://www.uni-bielefeld.de/(en)/ZiF/FG/2012Priority/). Key ingredients from these three earlier ZiF groups play a prominent role for our current ZiF group that attempts to tackle the topic of cognitive behavior, namely, first, action control as an overarching integrative function of diverse "modules" of natural and artificial intelligent systems, second, computations of seemingly simple "brains" as a solid basis for intelligent behavior, and third, the task-driven linkage of perception, memory, and action by priority control mechanisms (attention).

Decisively, this ZiF group, as well as the earlier groups, does not attempt to put forward and promote specific theories or computational models on the subject of interest. Instead, the key goal is to establish new frameworks for tackling multidisciplinary and field-crossing topics. We call our framework for understanding cognitive behavior a "situation model" framework—a term that will be explained in Section 3.

2. Cognitive behavior: Computational constraints and abilities enabling its flexibility and context-sensitivity

Given our choice of two key facets of cognitive behavior, namely flexibility and context-sensitivity, we now ask what the underlying computational constraints and abilities might be—relating to MARR's (1982) computational level of analysis and explanation.

First, controlling behavior in a cognitive manner implies the ability to represent relevant environmental entities at a level that is sufficiently abstracted from the sensory-based information (e.g., eyes, ears) and motor-related information (e.g., muscle-related control; see, e.g, HOMMEL et al., 2001). We suggest that these internal environmental entities for enabling flexible and context-sensitive behavior consist of the following basic elements: information about objects (non-living and living), scenes (types, layouts), and actions (types, outcomes)—for a similar suggestion, see, e.g., KOERNER et al. (2015). Crucially, we assume that the element "intended behavioral outcome" (e.g., driving home safely)—which might act as an index or pointer—is bound to the various other types of information (objects, scenes, actions) in form of entities that we call "behavioral episodes" (e.g., KOERNER et al., 2015; see, also, SCHNEIDER, 2006). Each episode is defined by a unique combination of basic elements, that is, certain action outcomes, objects, actions, and scene parameters. The crucial role of action outcomes in controlling behavior and structuring action-related processing is emphasized by

ideomotor approaches (e.g., HOMMEL et al., 2001; PFISTER, 2019) and here serves as a key assumption. For habitual behavior, following the general logic of the NORMAN & SHALLICE (1986) model, we assume that several behavioral episodes might be retrieved from long-term memory (LTM), compete and that the strongest episode wins ("contention scheduling"). This episode is in charge of controlling behavior by filling the open parameters of the current episode (object, scene, action, outcome) with adequate sensory and memory information in a task-driven way (see, e.g., NEUMANN, 1984, 1987), resulting in "automatized" actions. For habit-based behavior that can be called strongly stimulus-driven (e.g., addictive behavior), just one episode might be retrieved. In case of cognitive behavior, we suggest that such stored behavioral episodes with fixed combinations of basic elements (parameters) are insufficient for attaining the intended action outcome.

Second, if stored episodes are insufficient for cognitive behavior what else might be required? We suggest that three basic computational abilities should be involved in enabling the flexibility aspect of cognitive behavior. Namely, these are (1) the ability to set-up novel episodes that are not yet available in LTM, (2) the ability to predict (e.g., simulate) the behavioral outcome of the new episodes covertly (in TOLMAN's (1948) terms "vicarious behavior", or by the German term *Probehandeln*, e.g., CRUSE & SCHILLING, 2013), or to test the outcome of the episode with overt behavior (e.g., THORNDIKE's trial, error, and accidental success form of learning; THORNDIKE, 1898), and, (3) the ability to use fast learning to rapidly improve the executed novel behavior over successive behavioral attempts. These abilities should also be involved in other types of action decision making and action planning processes (e.g., GALLIVAN et al., 2018). In terms of the example of the multilane intersection without functioning traffic lights, this might mean for you, e.g., to slow down, carefully observe the other cars, and find a path across the intersection based on the predicted behavior of other cars. Given you handled such a situation successfully for the first time, then better and safer handling is already likely the next time you will encounter a similar situation—a case of fast learning. There is a tremendous amount of literature on how each of the three computational abilities—setting up entities for controlling overt behavior (e.g., behavioral episodes) or purely covert behavior (called "thinking", e.g., KAHNEMAN, 2011), simulating the outcome, and fast learning—might be realized in human and various animal brains (e.g., BELLMUND et al., 2018; HASSABIS et al., 2017; KOERNER et al., 2015; OBERAUER, 2009; PTAK et al., 2017; RANGANATH & RITCHEY, 2012; RICHMOND & ZACKS, 2017; TOLMAN, 1948; WHITTINGTON et al., 2019). For robots, implementing human and animal flexibility is still a major challenge despite the grand recent achievements of artificial intelligence (e.g., HASSABIS et al., 2017; LAKE et al., 2017).

Third, in our view, cognitive behavior implies—in addition to a machinery for flexible behavior— the ability to retrieve the relevant information from massive amounts of knowledge available in LTM to support context-sensitive actions. In the case of driving, slowing down when knowing about speed measurements seems to be a relatively easy computational task. However, it is easy only when the knowledge about the speed measurement has already been obtained. But obtaining this knowledge may proceed along different routes (e.g., remembering that for the next street such measurements are frequent, or having read some pertinent announcement in the local newspaper, or noticing blinking lights in approaching vehicles, etc.) and being prepared for a rich range of such possibilities requires the ability to rapidly activate items in a potentially very large data base. Human behavior and behavior of many animal species display many such rich forms of context-sensitive behavior, enabled through a flexible task-mediated combination of selected knowledge sources. Unfortunately, a shared working definition of context is missing (e.g., STARK et al., 2018). Nevertheless, numerous findings, models, and theories about context are available from cognitive neuroscience research, in part dispersed across separate and hardly related research fields (e.g., AMINOFF et al., 2013; CHIU & EGNER, 2019; EKSTROM & RANGANATH, 2018; HOWARD & KAHANA, 2002; WIKENHEISER & SCHOENBAUM,

2016). Besides the challenge of linking these diverse findings and concepts into a lower-dimensional space, a crucial question to us is how mechanisms of context- and task-guided efficient selection (attention) from the massive LTM might look like (e.g., CHUN et al., 2011; SCHNEIDER et al., 2015).

3. Habit- and cognitive-based processing for thought and action: "Two systems" approaches and a working definition of a situation model

So far the argumentation in this paper relied on the assumption that compared to habit-based behavior, cognitive behavior requires an additional computational machinery—allowing, e.g., the set-up, testing (e.g., simulation), and fast learning of novel behavioral episodes. Early on in the history of empirical research in psychology and the brain sciences, suggestions about this additional machinery have been made in terms of two-systems-types of processes or computational architectures. Habit-based and cognitive behavior (covert in the form of thinking or problem solving or overt) have been claimed to rely on automatic vs. controlled processing modes (NEUMANN, 1984; SCHNEIDER & SHIFFRIN, 1977), or on non-executive vs. executive control (sometimes also called cognitive control, e.g., EGNER, 2017; MILLER & COHEN, 2001), or on fast vs. slow thinking (KAHNEMAN, 2011), or on model-free vs. model-based forms of learning and behavioral control, a recently very influential distinction (e.g., DAW et al., 2005; DAYAN & BERRIDGE, 2014; O'DOHERTY et al., 2017; WIKENHEISER & SCHOENBAUM, 2016). The characteristics of both types of processes/systems/computational machineries and their relationship to each other are subject to an ongoing debate. Especially promising to us seems an "old" paper by NORMAN and SHALLICE (1986) on two systems of action control. It contains the crucial idea that novel behavior—corresponding to what we call cognitive behavior—not only implies processing within a second, advanced cognitive control system which the authors call "supervisory attentional system", but often also requires the simultaneous activity of the more elementary first system for controlling habits, regulated by a process called "contention scheduling". In other words, according to this theory, the more elementary processes for habit-based behavior are selectively recruited by an advanced second system for cognitive behavior. In this position paper, we refer to the more elementary system as "system 1" and to the more advanced system as "system 2" (in line with, e.g., KAHNEMAN, 2011). Surely, system 2 has to bring in—in addition to top-down biasing and selection within the system 1—new types of operations and representational qualities within system 2, enabling flexible and context-sensitive thought and action.

On the basis of the conceptual landscape introduced so far, we suggest a tentative working definition of a key term of the ZiF group: A *situation model* refers to the computational space that enables set-up, testing (e.g. simulation), and fast learning of behavioral episodes consisting of novel combinations of elements (objects, scenes, actions, outcomes) as well as novel elements. This computational space (system 2), whose key function is to enable flexibility and context-sensitivity of behavior, should exist in addition to the standard machinery (system 1) that underlies habit-based behavior.

4. A capacity-limited computational machinery for cognitive behavior: Working memory and attention

If cognitive behavior, especially its flexibility aspect, requires the capability of setting-up (binding) and testing by simulation new behavioral episodes—units for controlling behavior within a situation model—then research on working memory should be highly relevant. The term has been introduced by MILLER, GALANTER and PRIBRAM (1960) as a "quick-access memory" that is used for the execution of plans. Later, BADDELEY and HITCH (1974) in their seminal paper defined working memory as the ability that allows short-term retention (e.g., of sensory-based speech or visual information) and, crucially, also allows the manipulation of the retained information (e.g., mental imagery). This line

of research emphasized different types of stores (phonological loop, visuo-spatial sketchpad, episodic buffer, see, for an update, BADDELEY, 2012) and their control processes (executive control), enabling the manipulation of briefly retained information. A different approach views working memory in terms of different levels of accessibility of LTM information (e.g., COWAN, 1999, 2017; OBERAUER, 2009; OBERAUER & LIN, 2017). "Activated long-term memory" refers to recently activated (e.g., primed) codes in LTM, while the "region of direct access" (OBERAUER, 2009) refers to the computational space of working memory, in which information can be manipulated (e.g., mental arithmetic or imagery)— an (cognitive control) operation that should be performed by the "focus of attention" (OBERAUER, 2009). Important for understanding cognitive behavior is the ability of this type of working memory to flexibly bind elements to contexts (OBERAUER, 2009; OBERAUER & LIN, 2017)—the first ingredient to enable cognitive behavior. Recent neural network models of visual working memory (e.g., MANOHAR et al., 2019) offered explicit ways of how flexible binding of elements—these could also be elements of behavioral episodes!—could be achieved in neuro-scientifically plausible ways.

Besides setting up flexible bindings of elements and manipulating entities of memory-derived "perceptual" contents (e.g., visual imagery, LOGIE, 1986), working memory should also be the space for simulating on the fly configured entities of cognitive behavior that we here call behavioral episodes (e.g., PTAK et al., 2017). A key question to us is how recent computational models (e.g., MANOHAR et al., 2019; OBERAUER & LIN, 2017) could be modified in order to cover flexible configuration and simulation of behavioral episodes. While the aforementioned models seek solutions closely in terms of computations that attempt to explain key behavioral and neural data patterns, a number of other models seek solutions in terms of suitable extensions of deep learning approaches. Here, a shared idea is to learn a fast, recurrent dynamics that exhibits the required, short-timescale and information-parsimonious behavioral flexibility, while the learning of this fast dynamics itself is implemented as a slow supervised (GRAVES et al., 2016) or reinforcement learning process (BOTVINICK et al., 2019). This realizes a form of meta-learning or "learning to learn", since the slow learning process creates a second dynamics that can rapidly adapt the system to a range of different contexts (SANTORO et al., 2016; SCHILLING et al., 2019).

The function of working memory for controlling action has been neglected until recently, when seminal reviews on the cognitive neuroscience of working memory brought action back to the focus of attention (e.g., D'ESPOSITO & POSTLE, 2015; MYERS et al., 2017; NOBRE & STOKES, 2019) , and thus substantially modifying and extending earlier suggestions (e.g., SCHNEIDER, 2013). Likewise, the deep learning approaches to shape fast adapting, recurrent dynamics through slow learning have revealed that the inclusion of suitably specialized memory subsystems can tremendously facilitate this process (BOTVINICK et al., 2019; GRAVES et al., 2016; SANTORO et al., 2016). Furthermore, working memory (e.g., COWAN, 1999; OBERAUER, 2009) can also be regarded as the computational space by which selected LTM knowledge creates flexible and context-sensitive behavior. Setting a threshold for access of LTM information to working memory (e.g., OBERAUER, 2009) might not be sufficient for this purpose. Internal attentional control processes (e.g., CHUN et al., 2011) might be required for task-specific forms of context-driven behavior.

The operations that perform all types of manipulations within working memory have sometimes been called "cognitive control" (e.g., EGNER, 2017), "executive control" (e.g., BADDELEY & DELLA SALA, 1996), "executive attention" (e.g., ENGLE, 2002), or "focus of attention" (OBERAUER, 2009) operations. These forms of attention have to be distinguished from other more elementary forms (e.g., visual attention, e.g., ALLPORT, 1993; DUNCAN, 2006). How executive attention or cognitive control in working memory might realize the setting-up of novel behavioral episodes (or other flexible entities for action control) and how they might be tested by simulation has not been subject of intensive research (for exceptions, see, e.g., HYUN & LUCK, 2007). In line with current views on multi-tasking

limitations (e.g., KOCH et al., 2018), the task-driven executive operations of setting up and testing behavioral episodes might simply be restricted to one operation at a time, allowing to revise the old structural "bottleneck idea" by a flexible task-dependent component (KOCH et al., 2018) within more recent working memory architectures (e.g., MANOHAR et al., 2019; OBERAUER, 2009).

5. Environmental models for cognitive behavior: Cognitive maps

During the area of behaviorism—a school of psychology viewing animals and humans as stimulus-response machines without meaningful internal states and processes—TOLMAN (1948) argued, first, for the idea that behavior has a purpose, is goal-directed and, second, crucial for our topic, claimed that behavior with challenging components—we here call it cognitive behavior—relies on cognitive maps. Crucially, a cognitive map in the Tolmian sense "captures relationships between cues, actions, outcomes, and other features of the environment" (WIKENHEISER & SCHOENBAUM, 2016; see, also BEHRENS et al., 2018). Such a map does not simply represent spatial relationships between objects—it in addition allows cognitive behavior.

Due to substantial advances not only in studying human behavior, mind, and brain in "cognitive maps" tasks (e.g., BELLMUND et al., 2018; SCHUCK & NIV, 2019) but also and mainly in studying freely behaving rats (e.g., EICHENBAUM, 2012; MOSER et al., 2017; SCHILLER et al., 2015), sophisticated neuro-computational models of cognitive maps (e.g., WHITTINGTON et al., 2019) have been postulated that explain how rats and humans master relatively complex problem-solving tasks and how they make cognitive decisions. For instance, various types of neurons and neural networks involving the hippocampus (e.g., "place cells"), entorhinal cortex (e.g., grid cells), or the orbitofrontal cortex have been identified as key players in how structural map knowledge might be used for generalization and fast learning (BEHRENS et al., 2018; BELLMUND et al., 2018; GARVERT et al., 2017; WIKENHEISER & SCHOENBAUM, 2016)—key ingredients for cognitive behavior. An early computational model of self-organizing maps (KOHONEN, 1982) has been shown to be able to form semantic maps (RITTER & KOHONEN, 1989) and support navigation in semantic spaces (ONTRUP & RITTER, 2002). Crucial action and memory control abilities such as navigation in real or imagined spaces as well as episodic memory and fast learning have been linked within the research tradition of cognitive maps (e.g., EKSTROM & RANGANATH, 2018; SCHILLER et al., 2015), and conversely, an integration of topographically organized memory subsystems has been found to be highly useful for learning flexible context-dependent behavior in complex computer games (PARISOTTO & SALAKHUTDINOV, 2017). Related to this, model-based reinforcement learning (e.g., O'DOHERTY et al., 2017)—considered as allowing fast learning (see, e.g., BOTVINICK et al., 2019)—is a decisive concept of many current cognitive map theories and models (e.g., BEHRENS et al., 2018; WIKENHEISER & SCHOENBAUM, 2016).

Complementary to this focus on spatial action and cognition as well as on various memory systems, in our ZiF Research Group approach, we emphasize cognitive action control issues such as how novel behavioral episodes are set up and simulated, and how they benefit from fast learning in a computational space that we call situation model. It will be crucial to clarify the relationships between these episodes as units of real and imagined behavior on the one hand, and cognitive maps, models of the environment (in the sense of reinforcement learning theories, e.g., WHITTINGTON et al., 2019; WIKENHEISER & SCHOENBAUM, 2016) on the other hand. Rich and in part flexible forms of structural knowledge, organized in real and conceptual spaces are key features of such maps (e.g., BELLMUND et al., 2018). Truly cognitive behavior is sometimes linked to the ability of intelligence (e.g., DUNCAN, 2010; for current robotics-directed approach, see www.scienceofintelligence.de) and understanding intelligence might require to also deal with the nature of mechanisms of habit-based behavior and how they interact with the machinery at the cognitive level (see, e.g., NORMAN & SHALLICE, 1986).

6. Putting all perspectives together: The situation model framework

The key explanatory goal of our ZiF Research Group is to understand cognitive behavior of humans, animals, and machines, its flexibility and context-sensitivity, at the functional (computational) and mechanistic (algorithmic & implementational, MARR, 1982) level. In order to tackle this ambitious challenge, we suggested the following three focus perspectives, namely "two systems" approaches for explaining habit-based vs. cognitive behavior, the capacity-limited computational space of working memory and of its attentional operations (cognitive control), as well as cognitive maps for specification of situation models. For making progress, we think that these selected but up to now barely related focus perspectives have to be combined in novel ways. Especially rewarding seems to us to link current research on cognitive maps to those on working memory—a territory as yet unknown and a first unique key feature of our ZiF Research Group. Research on working memory brings in a large data base and detailed computational models of "cognitive control" (executive attentional) operations relying on representations within LTM (e.g., COWAN, 2017; OBERAUER, 2009) as well as on representations within perception (LUCK & VOGEL, 2013; e.g., MANOHAR et al., 2019; SCHNEIDER, 2013). Complementary, cognitive map research usually focuses on more complex activities with often longer time scales in real and conceptual spaces (e.g., BEHRENS et al., 2018; BELLMUND et al., 2018).

The new linkage of working memory and cognitive maps might also offer interesting perspectives on the nature of "activated" contents (representations, operations) of a situation model. Within such a model, we assume that an "executive subspace" of the currently selected cognitive map (e.g., EKSTROM & RANGANATH, 2018) should exist enabling the attentional or cognitive control operations that are crucial for cognitive behavior (e.g., setting up and testing new behavioral episodes). In our view, this subspace might be best characterized as the highly capacity-limited part of working memory (e.g., the "region of direct access", OBERAUER, 2009). Up to now, some proposals have been made on how information from (activated) LTM is selected for this limited executive space (COWAN, 1999; e.g., OBERAUER, 2009), while other proposals attempted to specify the attentional mechanisms for selecting input from perception for access to working (short-term) memory (e.g., BUNDESEN, 1990; SPERLING, 1963), including access to the executive space for working memory operations (e.g., SCHNEIDER, 2013). It is not clear how these forms of "attentional" selection—from perception or LTM—are related. Based on the influential attention frameworks of biased competition (DESIMONE & DUNCAN, 1995) and possibly also of priority maps (e.g., BISLEY & MIRPOUR, 2019; FECTAU & MUNOZ, 2006; SCHNEIDER et al., 2013a), both forms of selection might rely on the same computational selection principles (see, also, CHUN et al., 2011).

A further key issue in working memory and attention research regarding cognitive behavior refers to the question of how contents currently present in capacity-limited working memory (derived from perception and/or LTM) might be related to newly incoming input from perception and/or LTM. For solving this dilemma, a decision has to be made which new input is allowed to enter the highly limited executive subspace and which already present contents of this space (e.g., used for fast binding operations) will be protected against replacements by new input (e.g., SCHNEIDER, 2013). Up to now, not much research has tackled this updating vs. maintenance issue (NAU et al., 2018; NEUMANN, 1990; O'REILLY & FRANK, 2006; POTH & SCHNEIDER, 2018).

Besides selecting these three focus perspectives and arguing for more conceptual and empirical research on their relationships, the second key feature of our ZiF Research Group is the emphasis on understanding the mechanistic basis of controlling cognitive actions (e.g., GALLIVAN et al., 2018; LAND & TATLER, 2009; NEUMANN, 1987; PEZZULO & CISEK, 2016; PRINZ et al., 2013; SCHNEIDER, 1995). This emphasis requires clarifying which computational entities (e.g., behavioral episodes?) are most promising for understanding the mechanistic basis of habit-based as well as cognitive behavior. Given our focus on cognitive behavior and the suggestion of behavioral episodes as key entities,
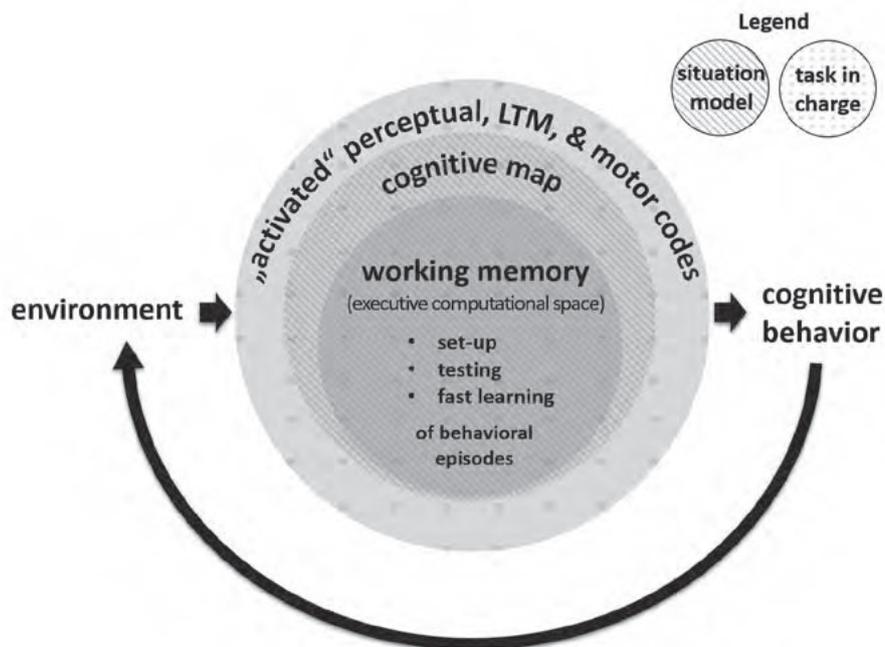
central empirical questions refer to candidate mechanisms that might underlie abilities such as flexible set-up, testing, and fast learning of such episodes. A major challenge is that the instant perception usually only provides state information about the situation that is uncertain and partial. For instance, in autonomic driving, the sensors can provide the current motions of all visible cars but fail to provide information about vehicles or pedestrians that are occluded—even if such information may be relevant. However, part of such "hidden" state information and expectations about likely actions can be inferred from past observations—e.g., having observed a pedestrian disappear behind a parking car, while other parts, such as inferring intentions of other traffic participants may require additional knowledge in the form of prior models (for a review, see, e.g., Schwarting et al., 2018). While in traffic situations the relevant history may be relatively short, in many everyday activities decisive information may depend on memorized observations days or even years ago (where do I have parked my car? Did I meet this person already?). Thus, an appropriate action policy typically needs to integrate context that is scattered across space, time, and further semantic dimensions (such as attributing knowledge or intentions to other). Therefore, the concept of a policy encapsulates a potentially very complex network of interacting mechanisms, each of them context-sensitive and dedicated to a subfunctionality, such as perception, localization, prediction, value estimation, progress monitoring, planning, and many more. This is to be expected, given the available insights from cognitive neuroscience. Remarkably, physics simulations and modern interactive computer games together with machine-learning approaches have turned out as a fertile study ground for creating, evaluating, and analyzing such networks of modules. While initial approaches of implementing all subfunctionalities in a single layered network that is trained through reinforcement learning worked unexpectedly well for small to medium-sized problems (e.g. Atari Games, Mnih et al., 2015), it turned out that a scaling of this approach to more complex situations faces a wall of extremely steeply rising computational demands. This has motivated a search for more structured architectures and by now several works have demonstrated that clever decompositions of the policy into suitable, modular constituents can lead to significant gains in efficiency (see, e.g., Graves et al., 2016; Melnik et al., 2019; Parisotto & Salakhutdinov, 2017; Santoro et al., 2016; Xu et al., 2019).

Given this exciting background and putting all key features of our ZiF group together, a framework can be formulated which was introduced above with the term situation model, following the way how Ranganath and Ritchey (2012) and Koerner et al. (2015) used the same term. The term had been introduced first in linguistic research in the context of mental models aiming to understand how text comprehension works (e.g., Johnson-Laird, 1983; Zwaan et al., 1998). Our use differs from this tradition and is line with what Ranganath and Ritchey (2012) and Koerner et al. (2015) mean. A framework specifies an overall field of research—here understanding cognitive behavior of humans, animals, and machines—, and specifies relevant key experiments and findings as well as relevant focus perspectives and theoretical concepts—here two systems, working memory, and cognitive maps, with their linkage to attention and action control. It is an open empirical question and a great challenge for our ZiF Research Group to demonstrate that the selection of these elements for the situation model framework opens a productive venue for a better understanding of cognitive behavior of humans, animals, and machines, for creating empirically testable theories and computational models as well as more cognitive robots.

Figure 1 gives a tentative graphical summary of our situation model framework. It consists of three nested layers inspired by the embedded process model of working memory (Cowan, 1999). The widest layer (system 1) refers to a computational space consisting of activated sensory (perceptual) codes, derived from the senses, activated LTM codes (e.g., declarative LTM), and activated motor codes that finally control overt behavior. The two narrower layers correspond to the situation model (system 2). The middle layer corresponds to the computational space of the cognitive map in charge

(see, e.g., EKSTROM & RANGANATH, 2018) as specified in currently prominent theories (e.g., BELLMUND et al., 2018; WHITTINGTON et al., 2019). In contrast to the activated codes of the widest layer, rich and flexible structural knowledge should be present there. The narrowest layer corresponds to working memory as an executive computational space allowing cognitive operations for setting-up, testing (e.g., simulation), and fast learning of behavioral episodes. Finally, it is important for us to emphasize the crucial role of the current task (behavioral demand) in shaping the representations and operations (e.g., DESIMONE & DUNCAN, 1995) within all three layers. This figure should serve as a first, very tentative attempt to identify possible key concepts of a situation model—with the prospect of initiating interdisciplinary and cross-field dialogue on the nature of this in many respects barely understood computational space. Even if key conceptual elements of our situation model framework turn out to be non-valid, but help to suggest novel experimental investigations on human and animal minds and brains, novel theories, and computational models as well as novel and more intelligent functioning robot architectures, then the key goal of the ZiF Research Group, namely a better understanding of cognitive behavior, would have been reached.

Figure 1: Cognitive behavior: a situation model framework.

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