A Motivational System for Cognitive AI

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Abstract. General Intelligence is not only characterized by the general representation and (relatively) general problem solving capabilities, but also by general motivation. Here, I sketch a framework for an extensible motivational system for cognitive agents, based on research in psychology. It draws on a finite set of pre-defined drives, which relate to needs of the system. Goals are established through reinforcement learning by interacting with an environment.

Keywords: Artificial General Intelligence, Cognitive AI, Synthetic Intelligence, Psi theory, Motivation, Motivational System, Cognitive Architectures.

1 Introduction: The Quest for General Intelligence

AGI (*Artificial General Intelligence*, or research into "strong Artificial Intelligence") as a discipline is fraught with difficulties. AI as a way of understanding and modeling the mind faces strong cultural opposition—many people, and even most scientists are deeply uncomfortable with treating the mind as an information processing machine (e.g., [1]). A large part of this opposition springs from a misunderstanding of the notion of *machine*, and the significance of computational models. These models constitute our best chance at understanding the mind and the nature of intelligence at all—and not because intelligence and mind constitute exceptions within the realm of nature. Natural sciences (unlike humanities) are largely concerned with the formulation of formal theories of their objects. Many objects of the sciences—like the formation of galaxies, stars and planets, the chemistry of biological cells, the changes of the planetary climate—require formal systemic theories of a complexity that goes beyond easy comprehension. Where these theories can not be broken down into individual, experimentally accessible questions, their coherence has to be tested by simulations, and any systemic theory that is specified to a degree of detail sufficient for simulation amounts to a computational model. A theory that wants to explain how the mind works will fall into this category.

The problems of AGI go much deeper than cultural opposition to computational modeling: even within the AI community, there is no clear agreement on what constitutes intelligence, and if it makes sense to define intelligence outside the context of human performance. For instance, purely mathematical approaches (for instance,

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the definition by Hutter and Legg [2], based on the ability of a system to achieve rewards), have not been universally agreed upon, because intelligence is not necessarily reward-seeking, and definitions based on problem solving ability are usually bound to individual classes of tasks. Consequently, there is no consensus and no single established methodology on how AGI's goals are to be reached.

Academic research into Artificial Intelligence has fragmented into a multitude of paradigms that eventually broke away and became sub-disciplines of computer science (such as machine learning, description logics, planning etc.), no longer concerned with understanding intelligence *per sé*. Even though AI has continuously spawned tremendously useful results, it arguably constitutes a string of failures with respect to attaining human-like intelligence. Every single paradigm of AI, such as symbolic models, connectionism, expert systems, and *Fifth Generation Computing* [3] has failed to produce breakthroughs with respect to this goal. But it should also be noted that AI has been consistently fruitful in advancing technology and computer science.

IBM's recent *Watson* system [4], which is able to outdo skilled humans in the question-answer game show *Jeopardy*, is a good example: While *Watson* constitutes an impressive engineering achievement, with useful applications in medicine and other fields, and may even affect the way people interact with computers, it is far from being "generally intelligent". *Watson's* architecture firmly constrains it into the territory of search engines, and will not scale towards an artificial mind [5].

One of the problems of the AGI label might be that it names a goal, but does not specify a methodology. AGI, taken as the *science of the mind as a computational system*, will have succeeded in its mission if its computer models are able to reproduce mental capabilities on at least a scope comparable to humans. However, this goal is not equivalent to an architectural paradigm. AGI is probably not best classed as a genuine sub-discipline of computer science. AGI might be seen as *cybernetic psychology*, as an attempt to formulate a general theory of psychology in terms of action regulating information processing systems. Indeed, AGI had been one of the original goals of cybernetics. Even after the decline of cybernetics as an independent field, AGI has been taken up by psychologists, under the label *cognitive architectures*. The influence of research into cognitive architectures on the psychological mainstream has been limited though—after all, models of general cognition are not the same thing as models of the human psyche. Most research in psychology is not interested in an overarching, unified theory of cognition. Instead, AGI relates to contemporary psychology in much the same way as the study of flight does to ornithology. And just as flight is not best understood as the movement of solid objects through a gaseous medium, AGI should limit its concern for general theories of representation, information processing, or control of robotic bodies, as long as they are not strictly relevant to its goal. AGI research will have to constrain its paradigms on suitable levels of description.

Even though AGI does not presume that mind and intelligence are inextricably linked to biological brains and human subjects (just as flight is not exclusively limited to feathered wings and avifauna), it will have to explain how the human mind is able to do what it does.

2 What Is Cognitive Artificial Intelligence?

What is the right frame for describing what a mind does? Within AI, we can discern at least the following camps:

1. *Symbolic ('classical') AI*. Newell and Simon's *Physical Symbol System Hypothesis* [6] states that symbolic computation is both necessary and sufficient for general intelligence. Since symbolic computation is Turing complete, this is trivially true, but criticism of symbolic (rule-based) AI maintains that a purely symbolic system does not constitute a feasible *practical* approach, either because discrete symbols are technically insufficient, or because it usually lacks grounding in a physical environment. This criticism gives rise to:
2. *Distributed (connectionist) AI,* which focuses on emergent behavior, dynamical systems and neural learning, and
3. *Embodied AI*, which focuses on solving the symbol grounding problem by environmental interaction.

The two latter paradigms are often subsumed under the 'New AI' label, and they are vitally important: Connectionism can provide models for neural computation, for learning and perceptual processing (but will also have to explain how sub-symbolic processing gives rise to symbolic cognition, such as planning and use of natural language). Embodiment situates a system in a dynamic environment and provides content for and relevance of cognitive processes.

Unfortunately, the paradigms do not get along very well: proponents of symbolic AI often ignored connectionism and symbol grounding, while connectionists frequently disregarded symbolic aspects of cognition. Most embodied AI focuses on controlling robots instead of modeling cognition; radical proponents of embodied AI even suggest that intelligence is an *emergent* phenomenon of the interaction between an embodied nervous system and a *physical* environment [7] and sometimes reject the notion of representation altogether. The success of AGI will largely be due to the right integration of symbolic cognition (language, planning, high-level deliberation) with sub-symbolic processing (perception, analogical reasoning, neural learning and classification, memory retrieval etc.) and action regulation in a *broad architecture*. We will have to aim for a *cognitive AI*, for the class of framework that combines the necessary and sufficient means for enabling the full breadth of cognitive capabilities.

Cognitive AI does not refer to abstract theorem provers and planners, nor does it focus on sensory-motor coupling. Instead, cognitive AI should process perceptual and conceptual information in much the same way as humans do. Cognitive AI has to combine distributed, dynamical representations with compositionality, has to handle analogy, ambiguity and error, must attribute motivational relevance and so on.

Such a framework will have to merge *general representations* (the capability to express arbitrary relationships, up to a certain complexity) with *general learning and problem solving* (the capability to acquire and manipulate these relationships in any necessary way, up to a certain complexity), a sufficiently interesting environment to operate upon, and a *general motivational system* (which supplies a polythematic, intrinsic motivation to direct action). Let us now look on some aspects of such a motivational system.

3 Prerequisites for Defining a Motivational System

Since we can not observe and verify most parts of the human motivational system directly, we will have to construct a model that can produce the desired behavior in simulations. Such a model will have to adhere to some constraints; it should provide:

- *conceptual soundness:* demonstrate a conceptual analysis of needs, motives, intentions and action regulation, and their place in a larger model of cognition,
- *functional adequacy:* the model should be sufficient to produce the desired range of behaviors and cognitive phenomena,
- *biological plausibility:* the model should be compatible with our knowledge of biological systems,
- *sparseness:* the model should aim for the minimum number of entities and relationships to produce the desired behavior,
- a *suitable level of detail for formalization:* all components and relationships have to be specified to a degree of detail that allows for implementation as a computational model,
- *avoidance of over-specialization:* where functional aspects or quantitative relationships are unknown, the model should not be unnecessarily constrained.

Also, the model should support an experimental paradigm, to be evaluated against competing approaches, so that progress can be measured. This could be a set of challenge problems, a competition between different solutions, or a suitable application.

A human-like intelligence could likely exist in a non-human body, and in a simulated world, as long as the internal architecture—the motivational and representational mechanisms and the structure of cognitive processes—are similar to the one of humans, and the environment provides sufficient stimulation. The desires and fears of humans correspond to their *needs*, such as environmental exploration, identification and avoidance of danger, and the attainment of food, shelter, cooperation, procreation, and intellectual growth. Since the best way to satisfy the individual needs varies with the environment, the motivational system is not aligned with particular *goal situations*, but with the needs themselves, through a set of *drives*.

Let us call events that satisfy a need of the system a *goal*, or an *appetitive event*, and one that frustrates a need an *aversive event* (for instance, a failure or an accident). Goals and aversive events are given by the environment, they are not be part of the architecture. Instead, the architecture specifies a set of drives according to the needs of the system. Drives are indicated as *urges*, as signals that make a need apparent. An example of a need would be nutrition, which relates to a drive for seeking out food. On the cognitive level of the system, the activity of the drive is indicated as *hunger*.

The connection between urges and events is established by *reinforcement learning*. In our example, that connection will have to establish a representational link between the indicator for food and a *consumptive action* (i.e., the act of ingesting food), which in turn must refer to an environmental situation that made the food available. Whenever the urge for food becomes active in the future, the system may use the link to retrieve the environmental situation from memory and establish it as a goal.

This defines some additional requirements to the architecture: The system needs:

- a set of suitable urges,
- a way of evaluating them to establish goals and identify adverse events,
- a world model that represents environmental situations and events,
- a protocol memory that makes past situations and events accessible,
- a reinforcement learning mechanism working on that protocol,
- a mechanism for anticipation, to recollect memory content according to the current environmental situation and needs,
- a decision making component, which pitches the current urges and the available ways to satisfy them against each other, and chooses a way of action,
- an action regulation component, so this way of action can be followed through.

A more advanced architecture will also require mechanisms for planning, classification and problem solving, to actively construct ways from a given situation to a goal situation (instead of just remembering a successful way from the past), and mechanisms for reflection, to reorganize and abstract existing memory content.

Note that many possible architectures may satisfy this set of requirements, and thus I will not specify an implementation here. Here, I will focus on the motivational side.

4 An Outline of a Motivational System, According to the Psi Theory

The Psi theory [8, 9] originates in the works of the psychologist Dietrich Dörner and has been transformed into a cognitive architecture by the author [10]. Unlike high-level descriptions of motivation as they are more common in psychology, such as the one by Maslov [11] or Kuhl [12], the motivational model lined out in the Psi theory is rigorous enough to be implemented as a computational model, and unlike narrow, physiological models (such as the one by Tyrell [13]), it also addresses cognitive and social behavior. A simulation model of the Psi theory has been demonstrated with MicroPsi[14]. In the following, I will identify the core components of the motivational system.

4.1 Needs

All urges of the agent stem from a fixed and finite number of 'hard-wired' needs, implemented as parameters that tend to deviate from a target value. Because the agent strives to maintain the target value by pursuing suitable behaviors, its activity can be described as an attempt to maintain a *dynamic homeostasis*.

All behavior of Psi agents is directed towards a goal situation, that is characterized by a *consumptive action* satisfying one of the needs. In addition to what the physical (or virtual) embodiment of the agent dictates, there are cognitive needs that direct the agents towards exploration and the avoidance of needless repetition. The needs of the agent should be weighted against each other, so differences in importance can be represented.

Physiological needs

Fuel and water: In our simulations, water and fuel are used whenever an agent executed an action, especially locomotion. Certain areas of the environment caused the agent to loose water quickly, which associated them with additional negative reinforcement signals.

Intactness: Environmental hazards may damage the body of the agent, creating an increased intactness need and leading to negative reinforcement signals (akin to *pain*). These simple needs can be extended at will, for instance by needs for shelter, for rest, for exercise, for certain types of nutrients etc.

Cognitive needs

Certainty: To direct agents towards the exploration of unknown objects and affairs, they possess an urge specifically for the reduction of uncertainty in their assessment of situations, knowledge about objects and processes and in their expectations. Because the need for certainty is implemented similar to the physiological urges, the agent reacts to uncertainty just as it would to pain signals and will display a tendency to remove this condition. This is done by triggering explorative behavior. Events leading to an urge for uncertainty reduction include:

- the agent meets unknown objects or events,
- for the recognized elements, there is no known connection to behavior—the agent has no knowledge what to do with them,
- there are problems to perceive the current situation at all,
- there has been a breach of expectations; some event has turned out differently as anticipated,
- over-complexity: the situation changes faster than the perceptual process can handle,
- the anticipated chain of events is either too short or branches too much. Both conditions make predictions difficult.

In each case, the uncertainty signal is weighted according to the relation to the appetitive or aversive relevance of the object of uncertainty. The urge for certainty may be satisfied by "certainty events"—the opposite of uncertainty events:

- the complete identification of objects and scenes,
- complete embedding of recognized elements into agent behaviors,
- fulfilled expectations (even negative ones),
- a long and non-branching chain of expected events.

Like all urge-satisfying events, certainty events create a positive reinforcment signal and reduce the respective need. Because the agent may anticipate the reward signals from successful uncertainty reduction, it can actively look for new uncertainties to explore ("diversive exploration).

Competence: When choosing an action, Psi agents weight the strength of the corresponding urge against the chance of success. The measure for the chance of success to satisfy a given urge using a known behavior program is called "specific competence". If the agent has no knowledge on how to satisfy an urge, it has to resort to “general competence” as an estimate. Thus, general competence amounts to something like self-confidence of the agent, and it is an urge on its own. (Specific competencies are not urges.) The general competence reflects the ability to overcome obstacles, which can be recognized as being sources of negative reinforcement signals, and to do that efficiently, which is represented by positive reinforcement signals. Thus, the general competence of an agent is estimated as a floating average over the reinforcement signals and the inverted displeasure signals. The general competence is a heuristics on how well the agent expects to perform in unknown situations.

As in the case of uncertainty, the agent learns to anticipate the positive reinforcement signals resulting from satisfying the competence urge. A main source of competence is the reduction of uncertainty. As a result, the agent actively aims for problems that allow gaining competence, but avoids overly demanding situations to escape the frustration of its competence urge. Ideally, this leads the agent into an environment of medium difficulty (measured by its current abilities to overcome obstacles).

Aesthetics: Environmental situations and relationships can be represented in infinitely many ways. Here ‘aesthetics’ corresponds to a need for improving representations, mainly by increasing their sparseness, while maintaining or increasing their descriptive qualities.

Social needs

Affiliation: Because the explorative and physiological desires of Psi agents are not sufficient to make them interested in each other, they have a need for positive social signals, so-called ‘*legitimacy signal*s’. With a legitimacy signal (or *l-signal* for short), agents may signal each other “okayness” with regard to the social group. Legitimacy signals are an expression of the sender’s belief in the social acceptability of the receiver. The need for l-signals needs frequent replenishment and thus amounts to an urge to affiliate with other agents. Agents can send l-signals to reward each other for cooperation. *Anti-l-signals* are the counterpart of l-signals. An anti-l-signal (which basically amounts to a frown) ‘punishes’ an agent by depleting its legitimacy reservoir.

Agents may also be extended by *internal l-signals*, which measure the conformance to internalized social norms.

Supplicative signals are ‘pleas for help’, i.e. promises to reward a cooperative action with l-signals or likewise cooperation in the future. Supplicative signals work like a specific kind of anti-l-signals, because they increase the legitimacy urge of the addressee when not answered. At the same time, they lead to (external and internal) l-signals when help is given. They can thus be used to trigger *altruistic behavior*.

The need for l-signals should adapt to the environment of the agent, and may also vary strongly between agents, thus creating a wide range of types of social behavior. By making the receivable amount of l-signals dependent of the priming towards particular other agents, Psi agents might be induced to display *‘jealous’ behavior*.

Social needs can be extended by romantic and sexual needs. However, there is no explicit need for social power, because the model already captures social power as a specific need for competence—the competence to satisfy social needs.

Even though the affiliation model is still fragmentary, we found that it provides a good handle on the agents during experiments. The experimenter can attempt to induce the agents to actions simply by the prospect of a smile or frown, which is sometimes a good alternative to a more solid reward or punishment.

4.2 Behavior Control and Action Selection

All goal-directed actions have their source in a motive that is connected to an urge, which in turn signals a physiological, cognitive or social need. Actions that are not directed immediately onto a goal are either carried out to serve an exploratory goal or to avoid an aversive event. When a positive goal is reached (a need is partially or completely fulfilled), a positive reinforcement signal is created, which is used for learning (by strengthening the associations of the goal with the actions and situations that have led to the fulfillment). In those cases in which a sub-goal does not yet lead to a consummative act, reaching it may still create a reinforcement via the competence it signals to the agent. After finally reaching a consumptive goal, the intermediate goals may receive further reinforcement by a retrogradient (backwards in time along the protocol) strengthening of the associations along the chain of events that has lead to the target situation.

Appetence and Aversion: For an urge to have an effect on the behavior on the agent, it does not matter whether it *really* has an effect on its (physical or simulated) body, but that it is represented in the proper way within the cognitive system. Whenever the agent performs an action or is subjected to an event that reduces one of its urges, a reinforcement signal with a strength that is proportional to this reduction is created by the agent's "pleasure center". The naming of the "pleasure" and "displeasure centers" does not necessarily imply that the agent experiences something like pleasure or displeasure. Like in humans, their purpose lies in signaling the reflexive evaluation of positive or harmful effects according to physiological, cognitive or social needs. (*Experiencing* these signals would require an observation of these signals at certain levels of the perceptual system of the agent.) Reinforcement signals create or strengthen an association between the urge indicator and the action/event. Whenever the respective urge of the agent becomes active in the future, it may activate the now connected behavior/episodic schema. If the agent pursues the chains of actions/events leading to the situation alleviating the urge, we are witnessing goal-oriented behavior.

Conversely, during events that increase a need (for instance by damaging the agent or frustrating one of its cognitive or social urges), the "displeasure center" creates a signal that causes an inverse link from the harmful situation to the urge indicator. When in future deliberation attempts (for instance, by extrapolating into the expectation horizon) the respective situation gets activated, it also activates the urge indicator and thus signals an aversion. An *aversion signal* is a predictor for aversive situations, and such aversive situations are avoided if possible.

Motives: A motive consists of an urge (that is, the value of an indicator for a need) and a goal that has been associated to this indicator. The goal is a situation schema characterized by an action or event that has successfully reduced the urge in the past, and the goal situation tends to be the end element of a behavior program. The situations leading to the goal situation—that is, earlier stages in the connected occurrence schema or behavior program—might become intermediate goals. To turn this sequence into an instance that may initiate a behavior, orient it towards a goal and keep it active, we need to add a connection to the pleasure/displeasure system. The result is a *motivator* and consists of:

- a need sensor, connected to the pleasure/displeasure system in such a way, that an increase in the deviation of the need from the target value creates a displeasure signal, and a decrease results in a pleasure signal. This reinforcement signal should be proportional to the strength of the increment or decrement.
- optionally, a feedback loop that attempts to normalize the need automatically
- an urge indicator that becomes active if there is no way of automatically adjusting the need to its target value. The urge should be proportional to the need.
- an associator (part of the pleasure/displeasure system) that creates a connection between the urge indicator and an episodic schema/behavior program, specifically to the aversive or appetitive goal situation. The strength of the connection should be proportional to the pleasure/displeasure signal. Note that usually, an urge gets connected with more than one goal over time, since there are often many ways to satisfy or increase a particular urge.

Motive selection: If a motive becomes active, it is not always selected immediately; sometimes it will not be selected at all, because it conflicts with a stronger motive or the chances of success when pursuing the motive are too low. In the terminology of *Belief-Desire-Intention agents* [15], motives amount to *desires*, selected motives give rise to goals and thus are *intentions*. Active motives can be selected at any time, for instance, an agent seeking fuel could satisfy a weaker urge for water on the way, just because the water is readily available, and thus, the active motives, together with their related goals, behavior programs and so on, are called *intention memory*. The selection of a motive takes place according to a *value* by *success probability* principle, where the value of a motive is given by its importance (indicated by the respective urge), and the success probability depends on the competence of the agent to reach the particular goal.

In some cases, the agent may not know a way to reach a goal (i.e., it has no epistemic competence related to that goal). If the agent performs well in general, that is, it has a high *general* competence, it should still consider selecting the related motive. The chance to reach a particular goal might be estimated using the sum of the general competence and the epistemic competence for that goal. Thus, the *motive strength* to satisfy a need d is calculated as $urge_d \cdot (generalCompetence + competence_d)$, i.e. the product of the strength of the urge and the combined competence.

If the window of opportunity is limited, the motive strength should be enhanced with a third factor: *urgency*. The rationale behind urgency lies in the aversive goal created by the anticipated failure of meeting the deadline. The urgency of a motive related to a time limit could be estimated by dividing the time needed through the time left, and the motive strength for a motive with a deadline can be calculated using $(urge_d + urgency_d) \cdot (generalCompetence + competence_d)$, i.e. as the combined urgency multiplied with the combined competence. The time the agent has left to reach the goal can be inferred from episodic schemas stored in the agent's current expectation horizon, while the necessary time to finish the goal oriented behavior can be determined from the behavior program. (Obviously, these estimates require a detailed anticipation of things to come, which may be difficult to obtain.)

At each time, only one motive is selected for the execution of its related behavior program. There is a continuous competition between motives, to reflect changes in the environment and the internal states of the agent. To avoid oscillations between motives, the switching between motives may be taxed with an additional cost: the *selection threshold*, a bonus that is added to the strength of the currently selected motive. The value of the selection threshold can be varied according to circumstances, rendering the agent 'opportunistic' or 'stubborn'.

Intentions: As explained above, intentions amount to selected motives, combined with a way to achieve the desired outcome. Within the Psi theory, an *intention* refers to the set of representations that initiates, controls and structures the execution of an action. (It is not required that an intention be conscious, that it is directed onto an object etc.—here, intentions are simply those things that make actions happen.)

Intentions may form *intention hierarchies*, i.e. to reach a goal it might be necessary to establish sub-goals and pursue these. An intention can be seen as a set of a goal state, an execution state, an intention history (the protocol of operations that took place in its context), a plan, the urge associated with the goal state (which delivers the relevance), the estimated specific competency to fulfill the intention (which is related to the probability of reaching the goal) and the time horizon during which the intention must be realized.

The dynamics of modulation: In the course of the action selection and execution, Psi agents are modulated by several parameters: The agent's *activation* or *arousal* (which resembles the *ascending reticular activation system* in humans) determines the action-readiness of an agent. It is proportional to the current strength of the urge signals. The perceptual and memory processes are influenced by the agent's *resolution level*, which is inversely related to the activation. A high resolution level increases the number of features examined during perception and memory retrieval, at the cost of processing speed and resulting ambiguity. The *selection threshold* determines how easily the agent switches between conflicting intentions, and the *sampling rate* or *securing threshold* controls the frequency of reflective and orientation behaviors. The values of the modulators of an agent at a given time, together with the status of the urges, define a cognitive configuration, a setup that may be interpreted as an *emergent emotional state*.

5 Summary

The Psi theory defines a possible solution for a drive-based, poly-thematic motivational system. It does not only explain how physiological needs can be pursued, but also addresses the establishment of cognitive and social goals.

Its straightforward integration of needs allows adapting it quickly to different environments and types of agents; a version of the model has been successfully evaluated against human performance in problem solving game [9].

The existing implementation of the Psi theory in the MicroPsi architecture [14] still restricts social signals to simple *l-signals* and *anti-l-signals*, and it does not cover a need for improving internal representations ('aesthetics'). Still, it may act as a qualitative demonstrator of an already quite broad computational model of motivation.

The suggested motivational model can be implemented in a variety of different ways, and we are currently working on transferring it to other cognitive architectures to obtain further scenarios and test-beds for criticizing and improving it.

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