Towards Modeling of Flow and Motivation: Exploring Affordances, Gamification, and Deep Hierarchical Reinforcement Learning

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This essay is an exploration of connected concepts around flow, motivation, gamification, neuroscience of affordances, and some technical models, which are computationally, descriptively, and/or normatively interesting, but are not tightly connected to humane cognition and behavior. The purpose of this work is twofold. First, to explore the literature across research fields and try to shed a little light to the cognitive architecture of motivation and its constituents. Second, to see how reinforcement (machine) learning framework parallels with motivation related literature and what of its aspects are poorly explicated, if one wanted to model motivation computationally. Modeling itself is, however, beyond the scope of this work.

Motivation is a multifaceted and ambiguous term, perhaps, best described here as an quantifiable inner state of mental energy or needs, that drives a person to choose and continue to do a particular activity. Better understanding of motivation through its constituents, could help to develop better tools to increase personal productivity and the meaningfulness of (working) life. After all, motivation is not static, it can change, and it can be changed (for regulation of motivation, see Wolters, 2003).

Below, I first summarize two motivation theories: self-determination theory (Deci & Ryan, 2012; Deterding, 2014; Ryan & Deci, 2000) and a temporal motivation theory (Steel, 2007; Steel & König, 2006). Self-determination theory (SDT) is chosen, because it is well known, has a long research history,is connected to flow theory (Nakamura & Csikszentmihalyi, 2014), and has been cherished as a psychological theory behind gamification (e.g. Deterding, 2011, 2014, p. 309). SDT breaks motivation down to three components: [1] *competence*, *autonomy*, and social *relatedness*. For autonomy, there exists a computational model and naturalization, although under a similar but differently labelled concept of *self-agency* (Kumar & Srinivasan, 2014), but this beyond the current scope. There is also a temporally hierarchical version of SDT, which expands STD to different (life) contexts, which clarifies its temporal aspects (Vallerand & Lalande, 2011; Vallerand & Ratelle, 2002). All this makes SDT relevant for modeling.

Temporal motivation theory is the other reviewed motivation theory (Steel & König, 2006; Steel, 2007, p. 71). It is derived from several fields and parametrizes motivation compactly into four factors: *value* of goal, *self-efficacy*, outcome-*delay* (time), and *sensitivity to delay* (subjective impulsiveness to distract from goal). Steel (2007)'s motivation theory (Steel & König, 2006) is specific enough to be described in a mathematical formula and it can therefore help in modeling motivation.

Some concepts first. Affordances are best described as potential action opportunities (Pezzulo & Cisek, 2016, p. 414) of an object or an item in the agents[2] proximal environment (Thill, Caligiore, Borghi, Ziemke, & Baldassarre, 2013, p. 492, Gibson, 1979/2014, 1977). Affordances play a central cognitive role in object and action related behavior. They provide connections to neuroscientific results, revealing how the brain represents objects and actions. They are essential factors in interaction feedback loop of behavior.

The interaction feedback loop is essential in understanding motivation and the "emergent motivation" (Nakamura & Csikszentmihalyi, 2014, p. 242) of flow. Namely, it portrays taken actions, environmental feedback, individual abilities, and action-options together as constituents of motivation and flow. With feedback loop, we can analyze motivation in terms of temporal hierarchy: how events on a smaller timescale affect motivation and action on larger timescale. I assume, motivation could be best understood, by reducing and describing its constituents upwards, from behaviorally and perceptually smallest timescale.

Temporal hierarchy perspective is supported by temporally hierarchical SDT (Vallerand & Lalande, 2011) and Pezzulo and Cisek (2016)'s neuroscientific view of affordances, as components in a multiple timescale hierarchical feedback loop. Feedback loops are best handled with reinforcement learning framework (Sutton & Barto, 1998/2017). This exploration will conclude with Kulkarni, Narasimhan, Saeedi, and Tenenbaum (2016)'s hierarchical deep reinforcement learning (see below). We evaluate briefly, whether it could be used as a computational model of motivation.

Schumacher and Hazeltine (2016)'s *task-file* model is neuroscientifically relevant to the current topic, alas, it is out of scope. "The task[-]file conceptualizes stimuli, responses, contexts, goals, and motivations" (Schumacher & Hazeltine, 2016, p. 453). It contests plausibly memory-schema based models (Norman & Shallice, 1986), where abstract affordances are "dissociated from goals and intentions of the organism" (Schumacher & Hazeltine, 2016, p. 453). The model would inform us about task-related representations in the brain (Schumacher & Hazeltine, 2016).

In the following, I go trough some background literature, which has interrelated concepts.

1 Background

In this section, I go trough motivation related literature from flow (Nakamura & Csikszentmihalyi, 2014), self-determination theory (Deci & Ryan,

[1] There are more elaborate components also. Reiss (2004) presents a multifaceted theory of intrinsic motivation and distinguishes 16 different basic motives. Talevich, Read, Walsh, Iyer, and Chopra (2017)'s recent meta-analysis presents a taxonomy of 161 motives.

[2] Agent here means either human, animal, or an artificial system.

2012; Ryan & Deci, 2000; Deterding, 2014), hierarchical model of intrinsic and extrinsic motivation (Vallerand & Lalande, 2011; Vallerand & Ratelle, 2002), temporal motivation theory (Steel, 2007; Steel & König, 2006), gamification (Deterding, 2014; Deterding, Sicart, Nacke, O'Hara, & Dixon, 2011; Hamari, Koivisto, & Sarsa, 2014), and affordances (Gibson, 1979/2014, 1977; Pezzulo & Cisek, 2016). This paves the way to view interactive feedback loop as an element of motivation, first through gamification (Deterding, 2015) and finally trough hierarchical (deep) reinforcement learning (Kulkarni et al., 2016; Sutton & Barto, 1998/2017).

1.1 Flow

Flow is a mental state of subjective optimal experience, where skills ("perceived action capabilities") and challenges ("perceived action opportunities") are in balance (quoting Nakamura & Csikszentmihalyi, 2014, p. 241, a recommended review).

In flow, continuous self-regulated interaction with the environment builds proximal goals, and using personal skills they are achieved. This creates positive feedback loop. "What happens at any moment is responsive to what happened immediately before" (ibid. p. 242). This "emergent motivation" (ibid.) mirrors directly two more specific accounts: hierarchical event-control "relationship between goal-level control (higher level) and perceptual-motor control (lower level) for sense of agency" (Kumar & Srinivasan, 2014, p. 1)[3] and reinforcement learning reviewed below (Sutton & Barto, 1998/2017; Kulkarni et al., 2016).

1.2 Motivation

In self-determination theory (Deci & Ryan, 2012; Ryan & Deci, 2000), motivation is distinguished by two components: intrinsic motivation "refers to the pleasure and inherent satisfaction derived from a specific activity" and extrinsic motivation "emphasizes performing a behavior because it is perceived to be instrumental in achieving valued outcomes that are distinct from the activity" (Venkatesh & Speier, 1999, p. 2). The (higher valued) intrinsic motivation is fueled by three psychological needs: *competence*, *relatedness* (to other people and groups), and *autonomy* (of own behaviors and lives, Deci & Ryan, 2012, p. 87). Intrinsic motivation is contrasted with extrinsic motivation, which usually contradicts with at least one of those three psychological needs.

Autonomy is "acknowledged[ ]typically by an authority figure", in situations where self-control could vary and depend on external factors (ibid. p., 94; Deterding, 2014, p. 309[4]). Autonomy refers to person's degree of control, related to self-governance and independence. Autonomy is connected a broader concept of *agency* (or self-agency). Agency has a component *sense of authorship*, which is "the degree to which participants believe they have control over their actions" (Kumar & Srinivasan, 2014, p. 1). This connection enables us to see how autonomy could be naturalized and operationalized in a behavioral model, as Kumar and Srinivasan (2014) present one for agency.

There is also a hierarchical model of intrinsic and extrinsic motivation (Vallerand & Ratelle, 2002), but it is out of elaborate scope. In it, Vallerand and Lalande (2011) distinguishes *global*, *contextual*, and *situational* levels of social factors and hierarchical levels of intrinsic and extrinsic motivation. Global level refers to "a person's personality and usual way of functioning" and motivation is considered on trait level (ibid., p. 45).

> [*Context*] level represents specific life contexts, such as education (or work for adults), leisure, and interpersonal relationships. - - - [I]ntraindividual motivational orientations - - - may differ in different contexts. For instance, a given individual may engage in leisure activities in a more intrinsic way but partake in work-related activities out of extrinsic motivation. (ibid.)
>
> [T]he *situational* level is the most specific and refers to the here and now of motivation - - - when engaging in a specific activity at a given moment in time." (my emphasis, ibid.)

The second motivation theory is temporal motivation theory. It is an integrative theory, combining "fundamental features of picoeconomics [or hyberbolic discounting], expectancy theory, cumulative prospect theory, and need theory" (Steel & König, 2006, p. 889).

$$Motivation = \frac{Expectancy \times Value}{1 + Impulsiveness \times Delay} \quad (1)$$

It characterizes motivation compactly in four parameters, shown in Equation 1. The nominator is the product of *expectancy* (self-efficacy; "the probability, that this outcome is achieved", Steel & König, 2006, p. 893) and the *value* the goal ("how much is the expected outcome valued?", ibid.). Increasing the nominator increases the motivation. The denominator is the product of *impulsiveness* (sensitivity to distract from the goal) and *delay* (of the outcome, Steel, 2007, p. 71). Increasing the denominator decreases motivation.

[3] This was studied behaviorally with a novel (p. 7) gameplay paradigm, where participants controlled a yellow circle as a "wolf" and a blue disc as a "sheep" (Kumar & Srinivasan, 2014, p. 3, 5).

[4] A context example: "the supervisor is helping me see how I can improve" versus "the supervisor tells me what I ought to do".

The good thing is, that temporal motivation theory parametrizes goal and time (Steel & König, 2006, p. 907). These, and other parameters, can be used to connect them to the interaction feedback loops and computational models below.

There are also many disturbances of motivation. The temporal motivation theory can also help further here. For impulsiveness, one could refer to the behavioral descriptions by Stahl et al. (2014). Steel (2007) himself applies the theory to procrastination, describing it as self-handicapping: "Procrastinators may feel that their actions will not change their situation, and thus they concentrate instead on managing their emotional reactions to the situation" (ibid., p. 63). "Ideally, procrastination should be associated with distractibility, poor organization, low achievement motivation, and an intention–action gap." (ibid., p. 70) Procrastination is in total contrast to flow, in which the person's actions lead to proximal goals and feed back emotionally towards new proximal goals.

1.3 Gamificaiton

The standard definition for gamification is the use of game elements in non-game contexts (Deterding et al., 2011, p. 2). Gamification can be seen as an interaction design toolbox of industry practices and multidisciplinary set of theories of how to design and create applications, services, and systems, that are motivating (engaging, fun) to use, independent of the situation and interaction-state, for different kinds of individuals. Based on the game design connection, the game design practices offer a promising source of motivational narratives, interaction cultures, work practices, technologies, design frameworks, and designer-role specific skills, that can be adopted in desiging gamified systems. In essence, gamification offers a toolbox to engineer motivation.

Game industry has a decade long history and expertise, at least in the field of maximizing fun and pleasure (Schell, 2013). Earlier gamification was chritisized by making a poor distinction: while game design maximizes pleasure, gamification maximizes efficiency (ibid.). Instead, according to Deterding (2014), the design goal of gamification should be good life. Gamification should not be considered as a mere decoration of services with motivational affordances. Instead, designed from ground up, considering the "key emotional benefits" for the usage (Schell, 2013).

Historically, between Schell (2013) and (Schell, 2010), many companies stared to offer gamification services Schell (2013). Some succeed, most not (ibid.), which meant, that the motivation had yet to be understood thoroghly and applied correctly. From theoretical perspective, this was an interesting challenge: could the motivation theories have had helped to design better systems? Could these theories still be helpfully contextualized to particular design problems?

Since then, gamification has progressed as an scientific field also (Hamari et al., 2014). In their review, Hamari et al. (2014, p. 3029) found gamification applied on several fields: education/learning (9 papers), intra-organizational systems (4), work (4), innovation/ideation (2), commerce (1), health/exercise (1), sustainable consuption (1), and data gathering (1).

Although gamification is a comprehensive design-toolbox with many opportunities to engineer on motivation, in this work I will focus only on motivational affordances. Namely, they are essential part of any cognitive interaction and, as shown in the next section, they play a central role in gamification. There are some interesting neuroscientific results about them.

1.4 Affordances

In the classic sense, affordances are potential actions for an object by an particular agent (Gibson, 1979/2014, 1977). And the agent's embodiment and actuators dictate potential affordances (Thill et al., 2013, p. 492), in a particular situation, but excluding the subjective phenomenology (McGrenere & Ho, 2000).

> The concept of affordance was first introduced by Gibson (1966), who observed that the dynamical pattern of the optic flow can be used to guide navigation reactively through the environment. He used the term affordance to refer to the fact that visual perception of the environment is not just passive perception of objects as such, but direct perception of the *potential actions that the perceiver can carry out* with them without the need for high-level processes such as reasoning about object properties. In the realm of manipulation, for example, a person seeing an object would not necessarily only perceive colours, shapes and so on, but first and foremost also directly perceive the object's "graspability", "liftability" and so on. (my ephasis, Thill et al., 2013, p. 492)

For example, affordances in neuroscience of macaque monkeys are things like: *walkable branches, reachable objects, grasp types, gaze target* (Pezzulo & Cisek, 2016). Neurally they are represented by mirror neurons[5] (Pezzulo & Cisek, 2016; Thill et al., 2013).

In gamified systems, affordances are some combination of *points, leaderboards, achievements/badges, levels, story/theme, clear goals, feedback, rewards,*

[5] In comparison, canocical neurons represent the perception of objects.

progress, and *challenges* (Hamari et al., 2014, p. 3027, Table 2). For further examples in e-learning context, see Bower (2008, p. 6 – 7).

There are differences between the affordances in gamification and neuroscience. In gamification, motivational affordances are known, as they are in the game design culture, and they seem to be more or less a closed group, at least when filtered to the most popular ones in Hamari et al. (2014)'s review. But, i) can all motivational affordances be reduced to those mentioned or ii) could there be conceptually new affordances? Is any domain mechanism mappable to existing motivational affordances or could new mappings be conceptualized, that ii) are not reducable? iii) Are cognitively efficient (working) affordances effective, because they are familiar for subjects (because their amount is limited and they are encountered often) or is any easily learned affordance equally efficient, in the feedback loop?

The neuroscience examples, on the other hand, include potentially every object and their possible uses in the world, which suggests an uncountable amount of affordances. Instantiations of motivational affordance in gamification surely seem as numerous as potential applications and their uses. But the difference in the domains is, that the motivational affordances (labels thereof) are abstracted away from the direct application-domain manipulation, whereas the context-bound affordances in neuroscience (examples above) include actual objects from the environment.

Based on above, the definitions of affordances would need clarification. The concept of affordance would also benefit, if its domains specific senses would be connected to a unified cognitive architecture of motivation.

Understanding affordances is useful in understanding motivation. Motivational affordaces are essential in gamification, as shown above. In addition, affordances are essential in a sequence of actions towards a goal, because optimal individual actions depend on object selection and prioritization, which depend partly on their affordances. The sequence of actions is built up in an interactive feedback loop with the situational environment.

2 Interactive Feedback Loop

To describe the motivation related interactive feedback loop, we can start from a gamification design technique named skill-atom lens (Deterding, 2015, developed from Cook, 2007). A skill-atom consists of the smallest possible unit of one interaction cycle " without losing its systemic 'gaminess'." (Deterding, 2015, p. 313). It breaks down to "goals, actions and objects, rules, feedback, emergent challenge, and motivation - - -. [The] rules are rarely explicitly accessible: They are implied in what actions, objects, and feedback are offered to the user." (Deterding, 2015, p. 313). Here, *goals* are typically explicit final pursued system states; *actions* mean behavior with implicit prioritization; *objects* are perceived and they configure the system state; *rules* are anything that specify "what actions the user can take and how they affect the system state"; *feedback* is immediate sensory information on the effects of user actions to system state changes or autonomous system processes and accumulated progress towards subject's goals; *challenge* is "[t]he perceived challenge of achieving the user's current goal, posed by the current system state relative to the user's perceived current skill"; and *motivation* is "[t]he psychological needs energizing and directing the user to seek out and (continue to) engage with the system—typically competence." (quots from ibid. p. 314)

Deterding (2015)'s skill-atoms offer a description for interactive feedback process in gamification design context. Skill-atoms lens is partially useful for our purposes. It does describe relations with its components, but does not quantify them. Nor does it specify *rules* and how they prioritize particular *actions* to choose from. If one would like to model the interactive feedback loop, one would surely need more details.

The skill-atoms components are partially compatible with reinforcement learning. Although, reinforcement learning is primarily a computational machine learning platform, it could also be applied for cognitive and behavioral modeling of motivation related interactive feedback loop. At least its readily parametrized components and modeling dynamics would help us in operationalizing motivational behavior.

3 Reinforcement Learning as a Conceptualization of Motivation

Notwithstanding, that "any task with a computable description can be formulated in the RL framework (e.g., Hutter, 2005)" (Schmidhuber, 2015, p. 100), reinforcement learning seems[6] a promising parametrization for motivation and flow. Namely, it formalizes long term *goal* (*value function*) with situational *action prioritization and selection* (*policy*[7]), immediate *feedback* (*reward signal*, scalar), *learning* (of policy), and possibly a *model* of the situational environment, to an established machine learning framework (Sutton & Barto, 1998/2017) . Mathematically (as a *partially observed Markov decision process*), there exists an optimal set of

[6]Regardless of whether they might not be described computationally.

[7]Policy that maximizes expected future rewards (Kulkarni et al., 2016, p. 2)

consecutive actions, that lead to a given goal, and these actions are given by an optimal policy (Wikipedia, 2017).

Kulkarni et al. (2016) extend the classic reinforcement learning framework to policy-learning under temporally sparse feedback. Their *hierarchical deep Q-network* (h-DQN) is an extension of Mnih et al. (2015)'s work on deep Q-network model (DQN), which produces human-level learning in playing classic ATARI video games, except the game "Montezuma's Revenge", because this game has "sparse, delayed rewards" (Kulkarni et al., 2016, p. 6). The h-DQN model is able to learn to play "Montezuma's Revenge", unlike previous state of the art methods of human-level gameplay models (ibid. p. 1). In the "Montezuma's Revenge", the player needs to learn to navigate in a room, collect the key (earning +100 points), and go to the next room (earning +300 points; ibid. p. 6).

The h-DQN is a temporal extension of DQN, "over two levels of hierarchy" (Kulkarni et al., 2016, p. 2). h-DQN includes a lower-level *controller* and a top-level *meta-controller*, both on their respective timescale levels[8].

The *controller* cycles every time step (ibid. p. 5), inputs *states* and the *current goal* (called intrinsic goal g; ibid. p. 3), produces atomic *actions* by *policy*$_1$ (π_g), and learns the *policy*$_1$, "by maximizing expected future intrinsic reward (from *internal critic*" (ibid. p. 4).

The *meta-controller* cycles, not after every timestep as *controller*, but after *controller*'s situational *episode*. It inputs *raw states* of environment and learns and produces *policy*$_2$ (π_g), "maximiz[ing] expected future [delayed] extrinsic reward - - - (f from the environment)" (ibid. p. 3, 5). In sum, the model's (a) "top level module (meta-controller) takes in the state and picks a new goal, and (b) a lower-level module (controller) uses both the state and the chosen goal to select actions either until the goal is reached or the episode terminates. The meta-controller then chooses another goal and steps (a-b) repeat" (ibid. p. 2).

Kulkarni et al. (2016)'s work is novel, because it presents a coarse mechanism to learn individual low level actions (affordances) to higher level sequence of actions, that can be used to progress towards goals posed by the environment. This is done in a challenging video gameplay task, which a human enjoys to do, experiencing flow. Thus, one could claim, that this is a simulation of the flow experience. Here, as in flow, the skills ("perceived action capabilities") and the challenges ("perceived action opportunities") are in balance (quoting Nakamura & Csikszentmihalyi, 2014, p. 241) and flow can also be operationalized as heightened challenge and skill (cf., Hamari et al., 2016).

Could, then, the h-DQN be seen as a simulation of humane SDT-style intrinsic motivation, which was defined above as a result of competence, relatedness, and autonomy? – Not really, because the h-DQN only labels one computational module (the *controller*) as intrinsic motivation, but beyond labels there are no causal elements of competence, relatedness, and autonomy, to which intrinsic motivation would be reduced. Thus, the h-DQN in its current form is only a s shallow reminiscent of the humane flow and motivation.

The h-DQN's temporal abstraction is also more simplistic, with only two levels (*controller* and *meta-controller*), than the above mentioned Vallerand and Lalande (2011)'s temporally hierarchical version of SDT. It has three levels: *global*[9], *context* (of life, i.e. work, education), and *situation* (Vallerand & Lalande, 2011, p. 45). The h-DQN's *controller* might be mapped to the *situation* level, but it is hard to see, that the *meta-controller*, although capable of learning not only one but many video gameplay tasks, would as is extend to humane *contexts* of work and education.

Although the h-DQN does learn action-selection and the respective affordances, the ability to execute particular actions seems to be given (Kulkarni et al., 2016). And, for object selection, Kulkarni et al. (2016) must use "custom pipeline to provide plausible object candidates", as in general the "[u]nsupervised detection of objects in visual scenes is an open problem in computer vision, although there has been recent progress in obtaining objects directly from image or motion data (Eslami et al., 2016)" (ibid. p. 7).

Based on this, there is still work to do, if one wants to model flow and motivation in humane-cognitively plausible way.

In future work, it would be useful to detail, how flow and motivation could be operationalized with the reinforcement learning framework, as the dynamics of flow and motivation could be modeled with it. Different theories of motivation than SDT would give different amounts of component parameters; maybe a single parameter would be easier to operationalize, when there are 16 (Reiss, 2004) or 161 (Talevich et al., 2017), than just three of them (competence, relatedness, autonomy). More thorough investigation to task-files (Schumacher & Hazeltine, 2016), affordances (Pezzulo & Cisek, 2016), self-control and self-agency (Kumar & Srinivasan, 2014), and the social aspects of hierarchical SDT (Vallerand & Lalande, 2011; Vallerand & Ratelle, 2002) would bring the current topic forward.

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[8] Both levels include their own DQN's.

[9] "personality and usual way of functioning" (ibid., p. 45)

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