Modulation of viability signals for self-regulatory control

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Abstract. We revisit the role of instrumental value as a driver of adaptive behavior. In active inference, instrumental or extrinsic value is quantified by the information-theoretic surprisal of a set of observations measuring the extent to which those observations conform to prior beliefs or preferences. That is, an agent is expected to seek the type of evidence that is consistent with its own model of the world. For reinforcement learning tasks, the distribution of preferences replaces the notion of reward. We explore a scenario in which the agent learns this distribution in a self-supervised manner. In particular, we highlight the distinction between observations induced by the environment and those pertaining more directly to the continuity of an agent in time. We evaluate our methodology in a dynamic environment with discrete time and actions. First with a surprisal minimizing model-free agent (in the RL sense) and then expanding to the model-based case to minimize the expected free energy.

Keywords: perception-action loop · active inference · reinforcement learning · self-regulation · anticipatory systems · instrumental value.

1 Introduction

The continual interaction that exists between an organism and the environment requires an active form of regulation of the mechanisms safeguarding its integrity. There are several aspects an agent must consider, ranging from assessing various sources of information to anticipating changes in its surroundings. An agent deciding between different courses of action also factors in potential costs and benefits derived from its future behavior. This process of selection among different value-based choices can be formally described as an optimization problem. Depending on the formalism, the cost or utility functions being optimized assume different normative interpretations. In reinforcement learning (RL) for example, an agent maximizes expected reward guided by a signal provided externally by the environment in an oracular fashion. The reward in some cases is also complemented with an intrinsic contribution, generally corresponding to an epistemic dimension of the agent. In active inference, the optimization is framed in terms of the minimization of the variational free energy to reduce the difference between sensations and predictions. Instead of rewards, the agent holds a prior
over preferred future outcomes, thus an agent minimizing its free energy acts to maximize the occurrence of its preferences and to minimize its own surprisal. Value arises not as an external property of the environment and instead it is conferred by the agent as a product of the contextual interplay of its own current configuration and the interpretation of stimuli. Although for living processes we could think of the priors as emerging and being refined over evolutionary scales, translating this view into a detailed algorithmic characterization raises important considerations because there is no evolutionary prior to draw from. Within the context of learning and control tasks such as those used in RL, we can find in the literature recent successes where the tasks are reformulated under the active inference framework. The approaches to specify a distribution of preferences have included for instance, taking the reward an RL agent would receive and encoding it as the prior [6,7,11,13,14,15], connecting it to task objectives [11] or through expert demonstrations [2,3,12]. Nonetheless a deeper understanding is required on how to algorithmically model autonomous goal-driven behavior when there is no clear way to specify the desired states beforehand, or how can an agent develop its own in a self-supervised manner. We set to explore these concerns by considering the case of an agent, that we assume, has a measuring channel that captures a minimal correlation with the environment. While initially an ordinary measure, a signal may acquire functional significance as the agent identifies it as a condition necessary for its continuity in the environment and learns to associate sensorimotor events to specific outcomes.

2 Preliminaries

2.1 Model-free surprisal minimization

Consider an environment whose generative process produces a state $s_t \in S$ at each time step $t$ resulting in an agent observing $o_t \in O$. The agent acts on the environment with $a_t \in A$ according to a policy $\pi$, obtaining the next observation $o_{t+1}$. Suppose the agent performs density estimation on the last $t - k$ observations to obtain a current set of parameter(s) $\theta_t$ describing $p_\theta(o)$. As these sufficient statistics contain information about the agent-environment coupling, they are concatenated with the observations into an augmented state $x_t = (o_t, \theta_t)$. Every time step, the agent computes the surprisal generated by a new observation given its current estimate and then updates it accordingly. In order to minimize surprisal under this model-free RL setting, the agent should maximize the expected log of the model evidence $\mathbb{E}[\sum_t \gamma^t \log p_\theta(o_t)]$ [1]. Alternatively, we maintain consistency with active inference by expressing the optimal surprisal Q-function as,

$$Q_{\pi^*}(x, a) = \mathbb{E}_{\pi}[-\log p_\theta(o) + \gamma \min_{a'} Q_{\pi^*}(x', a')]$$

estimated via DQN [8] or any function approximator with parameters $\phi$ such that $Q_{\pi^*}(x, a) \approx Q(x, a; \phi)$. 
2.2 Expected free energy

The free energy principle (FEP) [5] has evolved from an account of message passing in the brain to propose a probabilistic interpretation of self-organizing phenomena [10]. Central to current discourse around the FEP is the notion of the Markov blanket to describe a causal separation between the internal states of a system from external states, as well as the interfacing blanket states (i.e. sensory and active states). The FEP advances the view that a system remains out of equilibrium by maintaining a low entropy distribution of states it occupies during its lifetime. Correspondingly, the system attempts to minimize the surprisal of an event at a particular point. For most situations estimating the actual marginal likelihood is intractable, thus a system can instead minimize the upper bound, namely the free energy \( F = \mathbb{E}_q(s) \log q(s) - \log p(o, s) \). Where \( p(o, s) \) is the generative model and \( q(s) \) the variational density approximating hidden causes.

It follows that over an extended temporal dimension, an agent acts according to a policy \( \pi \) to minimize the expected free energy (EFE) \( G \) for a future step \( \tau > t \). This is expressed as \( G_\tau(\pi) = \mathbb{E}_{q(o_\tau, s_\tau|\pi)} [\log q(s_\tau|\pi) - \log p(o_\tau, s_\tau|\pi)] \). Where \( p(o_\tau, s_\tau|\pi) = q(s_\tau|o_\tau, \pi)p(o_\tau) \) is the generative model of the future, thus \( G \) can be rearranged as

\[
G_\tau(\pi) = -\mathbb{E}_{q(o_\tau|\pi)}[\log p(o_\tau)] - \mathbb{E}_{q(o_\tau|\pi)}[D_{KL}[\log q(s_\tau|o_\tau, \pi) \| \log q(s_\tau|\pi)]] \tag{2}
\]

the first and second term represent the instrumental and the epistemic value respectively. An agent selects a policy with probability \( q(\pi) = \sigma(-\beta \sum \mathcal{G}_\tau(\pi)) \) where \( \sigma \) is the softmax function and \( \beta \) is the inverse temperature. Given this process, an agent that performs active inference can minimize its free energy in two ways: by changing its beliefs about the world or by acting to sample the regions of the space that conforms to its beliefs.

3 Adaptive control via self-regulation

The concept of homeostasis has played a crucial role in our understanding of physiological regulation. It describes the capacity of a system to maintain its internal variables within certain bounds. Recent developments in the FEP describing the behavior of self-organizing systems under the framework, can be interpreted as an attempt to provide a formalization of this concept [10]. From this point of view, homeostatic control in an organism refers to the actions necessary to minimize the surprisal of the values reported by interoceptive channels, constraining them to those favored by a viable set of states. Crucially, an issue that is less delineated is how these attracting states come into existence. That is, how do they emerge from the particular conditions surrounding the system and how are they discovered among the potential space of signals. It has been shown that complex behavior may arise by minimizing surprisal in observation space (i.e. sensory states) without pre-encoded fixed prior distributions [1]. Here we consider an alternative angle intended to remain closer to the homeostatic
characterization of a system. For our scenario, the dynamics of the environment makes it difficult for an agent equipped only with a basic density estimation capacity, to find the type of regularities in observation space that can sustain a system in time. In these situations with fast changing dynamics, rather than minimizing free energy over sensory signals, the agent may instead leverage them to maintain a low future surprisal of another target variable, implying that it should remain within a certain expected range. Defining what should constitute the artificial physiology in simulated agents is not well established. Therefore we assume the introduction of a channel representing in abstract terms, interoceptive signals informing the agent about its continuity in the environment.

3.1 Methods

We assess the behavior of an agent in the Flappy Bird environment (fig. 1 left). This is a task where a bird must navigate between obstacles (pipes) at different positions while stabilizing its flight. Despite the apparent simplicity, the environment offers a fundamental aspect present in the physical world. Namely, the inherent dynamics leads spontaneously to the functional disintegration of the agent. If the agent stops propelling, it succumbs to gravity and falls. At the same time the environment has a constant scrolling rate, which implies that the agent cannot remain floating at a single point and cannot survive simply by flying aimlessly. Originally the task provides a reward every time the bird traverses in between two pipes, however for our case study the information about the rewards is never propagated and therefore does not have any impact on the behavior of the agent. The agent receives a feature vector of observations indicating its location and those of the obstacles. In addition, the agent obtains a measurement indicating its presence in the task (i.e. 1 or 0). This measurement does not represent anything positive or negative by itself, it is simply another signal that we assume the agent is able to calculate. Similarly to what is outlined in 2.1, the agent monitors the last \( t-k \) values of this measurement and estimates the density to obtain \( \theta_t \). These become the statistics describing the current approximated distribution of preferences \( p_{\theta_t}(m) \) or \( p(m|\theta_t) \). They are also used to augment the observations to \( x_t = (o_t, \theta_t) \). When the agent takes a new measurement \( m_t \), it evaluates the surprisal against \( p_{\theta_{t-1}}(m_t) \). In this particular case it is evaluated via a Bernoulli density function such that 

\[
-\log p_{\theta_{t-1}}(m_t) = -(m_t \log \theta_{t-1} + (1 - m_t) \log(1 - \theta_{t-1})).
\]

First, we train a baseline model-free surprisal minimizing DQN as specified in 2.1 parameterized by a neural network (NN). Then we examine the behavior of a second agent that minimizes its expected free energy. Thus the agent learns an augmented state transition model of the world, parameterized by an ensemble of NNs, and a surprisal model, also parameterized by another NN. In order to identify an optimal policy we apply rolling horizon evolution [9] to generate trajectories and to associate them to an expected free energy by decomposing equation 2 [13]
Fig. 1. **Left**: The Flappy Bird environment. **Center**: Performance of an EFE agent. The left axis indicates the unobserved rewards as reported by the task and the right axis the number of time steps it survives in the environment. The dotted line shows the average performance of an SM-DQN after 1000 episodes. **Right**: Parameter $\theta$ in time, summarizing the intra-episode sufficient statistics of $p_{\theta}(m)$.

The expression unpacks further the epistemic contributions to the EFE. The second and third term refer to the expected reduction in uncertainty about hidden causes and parameters respectively. For this task $o = s$, thus only the first and third term are considered.

### 3.2 Evaluation

The plot on fig. 1 (center) tracks the performance of an EFE agent in the environment (averaged over 10 seeds). The dotted line represents the surprisal minimizing DQN agent after 1000 episodes. The left axis corresponds to the (unobserved) task reward while the right axis indicates the approximated number of time steps the agent survives. During the first trials and before the agent exhibits any form of competence, it was observed that the natural coupling between agent and environment grants the agent a life expectancy of roughly 19-62 time steps in the task. This is essential as it starts to populate the statistics of $m$. Measuring a specific quantity $m$, although initially representing just another signal, begins to acquire value due to the frequency that it occurs. In turn, this starts to dictate the preferences of the agent as it hints that measuring certain signal correlates with having a stable configuration for this particular environment. Right fig. 1 shows the evolution of parameter $\theta$ (averaged within an episode) corresponding to the distribution of preferred measurements $p_{\theta}(m)$ which determines the level of surprisal assigned when receiving the next $m$. As the agent reduces its uncertainty about the environment it also becomes more capable of associating sensorimotor events to specific measurements. The behavior becomes more consistent with seeking less surprising measurements, and as we observe, this reinforces its preferences, exhibiting the circular self-evidencing dynamics that characterize an agent minimizing its free energy.

### 4 Discussion

Our main concern was to explore in what conditions a stable set of attracting states arises, conferring value to observations and leading to the emergence of...
self-sustaining dynamics. The model assumed the capacity of an agent to measure its operational integrity as it occurs in an organism monitoring its bodily states. This raises the issue of establishing more principled protocols to define what should constitute the internal milieu of an agent. A matter of deeper analysis, also motivated by results in [1], is the role of the environment to provide structure to the behavior of the agent. For instance, in the environments in [1], a distribution of preferences is spontaneously built on the assumption that the initial set of visual observations correlates with good performance on the task. Here it is the initial set of internal measurements afforded by the environment that contributes to the formation of a steady state, with the visual features only informing the actions necessary to maintain it. Future work should also explore the acquisition of hierarchical behavioral policies when an agent holds preferences at different levels. For example continual steady states - as presented here, and as end-goal absorbing states such as those studied in [11].

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