Toward Sophisticated Agent-based Universes - Statements to Introduce Some Realistic Features into Classic AI/RL Problems

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Statements to introduce some realistic features into classic AI/RL problems

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Abstract: In this paper we analyze some common simplifications present in the traditional AI / RL problems. We argue that only facing particular conditions, often avoided in the classic statements, will allow the overcoming of the actual limits of the science, and the achievement of new advances in respect to realistic scenarios. This paper does not propose any paradigmatic revolution, but it presents a compilation of several different elements proposed more or less separately in recent AI research, unifying them by some theoretical reflections, experiments and computational solutions. Broadly, we are talking about scenarios where AI needs to deal with true situatedness agency, providing some kind of anticipatory learning mechanism to the agent in order to allow it to adapt itself to the environment.

1 INTRODUCTION

Every scientific discipline starts by addressing specific cases or simplified problems, and by introducing basic models, necessary to initiate the process of understanding into a new domain of knowledge; these basic models eventually evolve to a more complete theory, and little by little, the research attains important scientific achievements and applied solutions. Artificial Intelligence (AI) is a quite recent discipline, and this fact can be easily noticed by regarding its history in the course of the years. If in the 1950s and 1960s AI was the stage for optimistic discourses about the realization of intelligence in machine, the 1970s and 1980s reveal an evident reality: true AI is a feat very hard to accomplish. This movement led AI to plunge into a more pragmatic and less dreamy period, when visionary ideas have been replaced by a (necessary) search for concrete outcomes. Not by chance, several interesting results have been achieved in these recent years, and it is changing the skepticism by a (yet timid) revival of the general AI field.

If on one hand the AI discourse mood has changed like a sin wave, on the other hand the academic practice of AI shows a progressive increment of complexity with respect to the standard problems. When the solutions designed to some established problem become stable, known, and accepted, new problems and new models are proposed in order to push forward the frontier of the science, moving AI from toy problems to more realistic scenarios. Make a problem more realistic is not just increasing the number of variables involved (even if limiting the number of considered characteristics is one of the most recurrent simplifications). When trying to escape from AI classic maze problems toward more sophisticated (and therefore more complex) agent-based universes, we are led to consider several complicating conditions, like (a) the situatedness of the agent, which is immersed into an unknown universe, interacting with it through limited sensors and effectors, without any holistic perspective of the complete environment state, and (b) without any *a priori* model of the world dynamics, which forces it to incrementally discover the effect of its actions on the system in an on-line experimental way; to make matters worse, the universe where the agent is immersed can be populated by different kinds of objects and entities, including (c) other complex agents, which can have their own internal models, and in this case the task of learning a predictive model becomes considerably harder.

In this paper, we use the *Constructivist Anticipatory Learning Mechanism* (CALM), defined in (Perotto, 2010), to support our assumption. In other words, we shows that the strategies used by this method can represent a changing of directions in relation to classic and yet dominant ways. CALM is able to build a descriptive model of the system

where the agent is immersed, inducting, from the experience, the structure of a factored and partially observable Markov decision process (FPOMDP). Some positive results (Perotto, 2010), (Perotto et al. 2007), (Perotto; Alvares, 2007), (Perotto, 2011), have been achieved due to the use of 4 integrated strategies: (a) the mechanism takes advantage of the situated condition presented by the agent, constructing a description of the system regularities relatively to its own point of view, which allows to set a good behavior policy without the necessity of "mapping" the entire environment; (b) the learning process is anchored on the construction of an anticipatory model of the world, which could be more efficient and more powerful than traditional "model free" reinforcement learning methods, that directly learn a policy; (c) the mechanism uses some heuristics designed to *well structured* universes, where conditional dependencies between variables exist in a limited scale, and where most of the phenomena can be described in a deterministic way, even if the system as a whole is not (a partially deterministic environment); which seems to be widely common in real world problems; (d) the mechanism is prepared to discover the existence of hidden or non-observable properties of the universe, which enables it to explain a larger portion of the observed phenomena. Following the paper, section 2 overviews the MDP framework and the RL tradition, section 3 describes the CALM learning mechanism, section 4 shows some experiments and acquired results, and section 5 concludes the paper.

2 MDP+RL FRAMEWORK

The typical RL problem is inspired on the classic rat maze experiment; in this behaviorist test, a rat is placed in a kind of labyrinth, and it needs to find a piece of cheese (the reward) that is placed somewhere far from it, sometimes avoiding electric traps along the way (the punishment). The rat is forced to run the maze several times, and the experimental results show that it gradually discovers how to solve it. The computational version of this experiment corresponds to an artificial agent placed in a bi-dimensional grid, moving over it, and eventually receiving positive or negative reward signals. Exactly as in the rat maze, the agent must learn to coordinate its actions by trial and error, in order to avoid the negative and quickly achieve the positive rewards. This computational experiment is formally represented by a geographical MDP, where each position in the grid corresponds to a state of the process; the process starts in the initial state, equivalent to the agent start position in the maze, and it evolves until the agent reaches some final reward state; then the process is reset, and a new episode take place; the episodes are repeated, and the algorithm is expected to learn a policy to maximize the estimated discounted cumulative reward that will be received by the agent in subsequent episodes.

These classic RM maze configurations present at least two positive points, when comparing to realistic scenarios: the agent needs to learn actively and on-line, it means, there is no previous separated time to learn before the time of the life; the agent must perform and improve its behavior at the same time, without supervision, by "trial-and-error". However, this kind of experiment cannot be taken as a general scheme for learning: on the one hand, the simplifications adopted (in order to eliminate some uncomfortable elements) cannot be ignored when dealing with more complex or realistic problems; on the other hand, there are important features lacking on the classic RL maze, what makes difficult comparing it to other natural learning situations. Some of these simplifications and lacks are listed below:

Non-Situativity: in the classic RL maze configuration, the agent is not really situated in the environment; in fact, the little object moving on the screen (which is generally called agent) is dissociated from the "agent as the learner"; the information available to the algorithm comes from above, from an external point of view, in which this moving agent appears as a controllable object of the environment, among the others. In contrast, realistic scenarios impose the agent sensory function as an imprecise, local, and incomplete window of the underlying situation stated by the real situation.

Geographic Discrete Flat Representation: in classic mazes, the corresponding MDP is created by associating each grid cell to a process state; so, the problem stays confined in the same two dimensions of the grid space, and the system states represent nothing more than the agent geographic positions. In contrast, realistic problems introduce several new and different dimensions to the problem. The basic MDP model itself is conceived to represent a system by exhaustive enumeration of states (a flat representation), and it is not appropriated to represent multi-dimensional structured problems; the size of the state space grows exponentially up with the number of considered attributes (curse of dimensionality), which makes the use of this formalism only viable for simple or small scenarios.

Disembodiment: in the classic configuration, the agent does not present any internal property, it is like a loose mind directly living in the environment; in consequence, it can be only extrinsically motivated, i.e. the agent acts in order to attain (or to avoid) some determined positions into the space,

given from the exterior. In natural scenarios, the agent has a "body" playing the role of an intermediary between mind and external world; the body also represents an "internal environment", and the goals the agent needs to reach are given from this embodied perspective (in relation to the dynamics of some internal properties).

Complete Observation: the basic MDP design the agent as an omniscient entity; the learning algorithm observes the system in its totality, it knows all the possible states, and it can precisely perceive in what state the system is at every moment, it also knows the effect of its actions on the system, because in general it is the only source of perturbation in the world dynamics. These conditions are far from common in real-world problems.

Episodic Life and Behaviorist Solution: in the classic enunciation, the system presents initial and final states, and the agent lives by episodes; when it reaches a final state, the system restarts. Generally this is not the case in real-life problems, where agents live a unique continuous uninterrupted experience. Also, solving a MDP is often synonymous of finding an optimal (or near-optimal) policy, and in this way most of the algorithms proposed in the literature are model-free. However, in complex environments, the only way to define a good policy is "understanding" what is going on, and creating an explicative or predictive model of the world, which can then be used to establish the policy.

2.1 The Basic MDP

Markov Decision Process (MDP) and its extensions constitute a quite popular framework, largely used for modeling *decision-making* and *planning* problems (Feinberg, Shwartz, 2002). An MDP is typically represented as a discrete stochastic state machine; at each time cycle the machine is in some state s; the agent interacts with the process by choosing some action a to carry out; then, the machine changes into a new state s', and gives the agent a corresponding reward r; a given transition function δ defines the way the machine changes according to s and a. The flow of an MDP (the transition between states) depends only on the system current state and on the action taken by the agent at the time. After acting, the agent receives a reward signal, which can be positive or negative if certain particular transitions occur.

Solving an MDP is finding the optimal (or near-optimal) policy of actions in order to maximize the rewards received by the agent over time. When the MDP parameters are completely known, including the reward and the transition functions, it can be mathematically solved by *dynamic programming* (DP) methods. When these functions are unknown, the MDP can be solved by *reinforcement learning* (RL) methods, designed to learn a policy of actions on-line, i.e. at the same time the agent interacts with the system, by incrementally estimating the utility of state-actions pairs and then by mapping situations to actions (Sutton, Barto 1998).

However, for a wide range of complex (including real world) problems, the complete information about the exact state of the environment is not available. This kind of problem is often represented as a *Partially Observable MDP* (POMDP) (Kaelbling et al., 1998). The POMDP provides an elegant mathematical framework for modeling complex decision and planning problems in stochastic domains in which the system states are observable only indirectly, via a set of imperfect, incomplete or noisy perceptions. In a POMDP, the set of observations is different from the set of states, but related to them by an observation function, i.e. the underlying system state s cannot be directly perceived by the agent, which has access only to an observation o. We can represent a larger set of problems using POMDPs rather than MDPs, but the methods for solving them are computationally even more expensive (Hauskrecht, 2000).

The main bottleneck about the use of MDPs or POMDPs is that representing complex universes implies an exponential growing-up on the state space, and the problem quickly becomes intractable. Fortunately, most of real-world problems are quite well-structured; many large MDPs have significant internal structure, and can be modeled compactly; the factorization of states is an approach to exploit this characteristic (Boutilier et al., 2000). In the factored representation, a state is implicitly described by an assignment to some set of state variables. Thus, the complete state space enumeration is avoided, and the system can be described referring directly to its properties. The factorization of states enables to represent the system in a very compact way, even if the corresponding MDP is exponentially large (Guestrin et al. 2003). When the structure of the *Factored Markov Decision Process* (FMDP) is completely described, some known algorithms can be applied to find good policies in a quite efficient way (Guestrin et al., 2003). However, the research concerning the discovery of the structure of an underlying system from incomplete observation is still incipient (Degris, Sigaud, 2010).

2.2 FPOMDP

The classic MDP model can be extended to include both factorization of states and partial observation, then composing a *Factored Partially Observable*

Markov Decision Process (FPOMDP). In order to be factored, the atomic elements of the non-factored representation will be decomposed and replaced by a combined set of elements. A FPOMDP (Guestrin et al., 2001), (Hansen; Feng, 2000), (Poupart; Boutilier, 2004), (Shani et al., 2005), (Sim et al., 2008), can be formally defined as a 4-tuple $\{X, C, R, T\}$. The state space is factored and represented by a finite non-empty set of system properties or variables $X = \{X_1, X_2, ... X_n\}$, which is divided into two subsets, $X = P \cup H$, where the subset P contains the observable properties (those that can be accessed through the agent sensory perception), and the subset H contains the hidden or non-observable properties; each property X_i is associated to a specified domain, which defines the values the property can assume; $C = \{C_1, C_2, ... C_m\}$ represents the controllable variables, composing the agent actions; $R = \{R_1, R_2, ... R_k\}$ is a set of (factored) reward functions, in the form $R_i : P_i \rightarrow \mathbb{R}$, and $T = \{T_1, T_2, ... T_n\}$ is a set of transformation functions, as $T_i : X \times C \rightarrow X_i$, defining the system dynamics. Each transformation function can be represented by a *Dynamic Bayesien Network* (DBN), which is an acyclic, oriented, two-layers graph. The first layer nodes represent the environment state in time t, and the second layer nodes represent the next state, in $t+1$ (Boutilier et al. 2000). A stationary policy π is a mapping $X \rightarrow C$ where $\pi(x)$ defines the action to be taken in a given situation. The agent must learn a policy that optimizes the cumulative rewards received over a potentially infinite time horizon. Typically, the solution π^* is the policy that maximizes the expected discounted reward sum

In this paper, we consider the case where the agent does not have an *a priori* model of the universe where it is situated (i.e. it does not have any idea about the transformation function), and this condition forces it to be endowed with some capacity of learning, in order to be able to adapt itself to the system. Although it is possible directly learn a policy of actions, in this work we are interested in model-based methods, through which the agent must learn a descriptive and predictive model of the world, and so define a behavior strategy based on it. Learning a predictive model is often referred as learning the structure of the problem.

In this way, when the agent is immersed in a system represented as a FPOMDP, the complete task for its anticipatory learning mechanism is both to create a predictive model of the world dynamics (i.e. inducing the underlying transformation function of the system), and to define an optimal (or sufficiently good) policy of actions, in order to establish a behavioral strategy. Degris and Sigaud (2010) present a good overview of the use of this representation in artificial intelligence, referring algorithms designed to learn and solve FMDPs and FPOMDPs.

3 ANTICIPATORY LEARNING

In the artificial intelligence domain, *anticipatory learning mechanisms* refer to methods, algorithms, processes, machines, or any particular system that enables an autonomous agent to create an anticipatory model of the world in which it is situated. An *anticipatory model of the world* (also called *predictive environmental model*, or *forward model*) is an organized set of knowledge allowing inferring the events that are likely to happen. For cognitive sciences in general, the term *anticipatory learning mechanism* can be applied to humans or animals to describe the way these natural agents learn to anticipate the phenomena experienced in the real world, and to adapt their behavior to it (Perotto, 2012).

When immersed in a complex universe, an agent (natural or artificial) needs to be able to compose its actions with the other forces and movements of the environment. In most cases, the only way to do so is by understanding what is happening, and thus by anticipating what will (most likely) happen next. A predictive model can be very useful as a tool to guide the behavior; the agent has a perception of the current state of the world, and it decides what actions to perform according to the expectations it has about the way the situation will probably change. The necessity of being endowed with an anticipatory learning mechanism is more evident when the agent is fully situated and completely autonomous; that means, when the agent is by itself, interacting with an unknown, dynamic, and complex world, through limited sensors and effectors, which give it only a local point of view of the state of the universe and only partial control over it. Realistic scenarios can only be successfully faced by an agent capable of discovering the regularities that govern the universe, understanding the causes and the consequences of the phenomena, identifying the forces that influence the observed changes, and mastering the impact of its own actions over the ongoing events.

3.1 CALM Mechanism

The constructivist anticipatory learning mechanism (CALM), detailed in (Perotto, 2010), is a mechanism developed to enable an agent to learn the structure of an unknown environment where it is situated, trough observation and experimentation, creating an

anticipatory model of the world. CALM operates the learning process in an active and incremental way, and learn the world model as well as the policy at the same time it actuates. The agent has a single uninterrupted interactive experience into the system, over a theoretically infinite time horizon. It needs performing and learning at the same time.

The environment is only partially observable from the point of view of the agent. So, to be able to create a coherent world model, the agent needs, beyond discover the regularities of the phenomena, also discover the existence of non-observable variables that are important to understand the system evolution. In other words, learning a model of the world is beyond describing the environment dynamics, i.e. the rules that can explain and anticipate the observed transformations, it is also discovering the existence of hidden properties (once they influence the evolution of the observable ones), and also find a way to deduces the dynamics of these hidden properties. In short, the system as a whole is in fact a FPOMDP, and CALM is designed to discover the existence of non-observable properties, integrating them in its anticipatory model. In this way CALM induces a structure to represent the dynamics of the system in a form of a FMDP (because the hidden variables become known), and there are some algorithms able to efficiently calculate the optimal (or near-optimal) policy, when the FMDP is given (Guestrin et al., 2003).

CALM tries to reconstruct, by experience, each transformation function T_i, which will be represented by an anticipation tree. Each anticipation tree is composed by pieces of anticipatory knowledge called schemas, which represent some perceived regularity occurring in the environment, by associating context (sensory and abstract), actions and expectations (anticipations). Some elements in these vectors can undertake an "undefined value". For example, an element linked with a binary sensor must have one of three values: true, false or undefined (represented, respectively, by '1', '0' and '#'). The learning process happens through the refinement of the set of schemas. After each experienced situation, CALM updates a generalized episodic memory, and then it checks if the result (context perceived at the instant following the action) is in conformity to the expectation of the activated schema. If the anticipation fails, the error between the result and the expectation serves as parameter to correct the model. The context and action vectors are gradually specialized by differentiation, adding each time a new relevant feature to identify more precisely the situation class. The expectation vector can be seen as a label in each "leaf" schema, and it represents the predicted anticipation when the schema is activated. Initially all different expectations are considered as different classes, and they are gradually generalized and integrated with others. The agent has two alternatives when the expectation fails. In a way to make the knowledge compatible with the experience, the first alternative is to try to divide the scope of the schema, creating new schemas, with more specialized contexts. Sometimes it is not possible and the only way is to reduce the schema expectation.

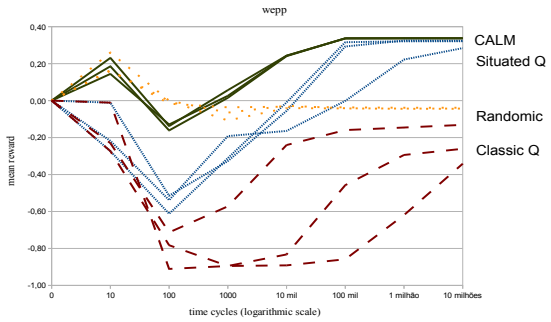
CALM creates one anticipation tree for each property it judges important to predict. Each tree is supposed to represent the compete dynamics of the property it represents. From this set of anticipation trees, CALM can construct a deliberation tree, which will define the policy of actions. In order to incrementally construct all these trees, CALM implements 5 methods: (a) *sensory differentiation*, to make the tree grow (by creating new specialized schemas); (b) *adjustment*, to abandon the prediction of non-deterministic events (and reduce the schemas expectations) (c) *integration*, to control the tree size, pruning and joining redundant schemas: (d) *abstract differentiation*, to induce the existence of non observable properties; and (e) abstract anticipation, to discover and integrate these non-observable properties in the dynamics of the model.

Sometimes some disequilibrating event can be explained by considering the existence of some abstract or hidden property in the environment, which could be able to differentiate the situation, but which is not directly perceived by the agent sensors. So, before adjusting, CALM supposes the existence of a non-sensory property in the environment, which it will represent as a abstract element. Abstract elements suppose the existence of something beyond the sensory perception, which can be useful to explain non-equilibrated situations. They have the function of amplifying the differentiation possibilities.

4 EXPERIMENTS

In (Perotto et al., 2007) the CALM mechanism is used to solve the *flip* problem, which creates a scenario where the discovery of underlying non-observable states are the key to solve the problem, and CALM is able to do it by creating a new abstract element to represent these states. In (Perotto, 2010) and (Perotto; Álvares, 2007) the CALM mechanism is used to solve the *wepp* problem, which is an interesting RL situated bi-dimensional grid problem, where it should learn how to behavior considering the interference of several dimensions of the environment, and of its body. Initially the agent does not know anything about the world or about its own

sensations, and it does not know what consequences its actions imply. Figure 1 shows the evolution of the mean reward comparing the CALM solution with a classic *Q-Learning* implementation (where the agent have the vision of the entire environment as flat state space), and with a situated version of the Q-Learning agent. We see exactly two levels of performance improvement. First, the non-situated implementation (Classic Q) takes much more time to start an incomplete convergence, and it is vulnerable to the growing of the board. Second, the CALM solution converges much earlier than Q-Learning, taken in its situated version, due to the fact that CALM quickly constructs a model to predict the environment dynamics, and it is able to define a good policy sooner.



5 CONCLUSIONS

Over the last twenty years, several anticipatory learning mechanisms have been proposed in the artificial intelligence scientific literature. Even if some of them are impressive in theoretical terms, having achieved recognition from the academic community, for real world problems (like robotics) no general learning mechanism has prevailed. Until now, the intelligent artifacts developed in universities and research laboratories are far less wondrous than those imagined by science fiction. However, the continuous progress in the AI field, combined with the progress of informatics itself, is leading us to a renewed increase of interest in the search for more general intelligent mechanism, able to face the challenge of complex and realistic problems.

A necessary changing of directions in relation to the traditional ways to state the problems in AI is needed. The CALM mechanism, presented in (Perotto, 2010) has been used as an exemple of it, because it provides autonomous adaptive capability to an agent, enabling it to incrementally construct knowledge to represent the regularities observed during its interaction with the system, even in non-deterministic and partially observable environments.

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