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Learning a Transferable World Model by Reinforcement Agent in Deterministic Observable Grid-World Environments

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Abstract. Reinforcement-based agents have difficulties in transferring their acquired knowledge into new different environments due to the common identities-based percept representation and the lack of appropriate generalization capabilities. In this paper, the problem of knowledge transferability is addressed by proposing an agent dotted with decision tree induction and constructive induction capabilities and relying on decomposable properties-based percept representation. The agent starts without any prior knowledge of its environment and of the effects of its actions. It learns a world model (the set of decision trees) that corresponds to the set of explicit action definitions predicting action effects in terms of agent's percepts. Agent's planning component uses predictions of the world model to chain actions via a breadth-first search. The proposed agent was compared to the Q-learning and Adaptive Dynamic Programming based agents and demonstrated better ability to achieve goals in static observable deterministic grid-world environments different from those in which it has learnt its world model.

Keywords: Adaptive agent; reinforcement learning; percept generalization; world model.

1. Introduction

Imagine a rat running in search for a food in lots of different mazes. An experimenter in animal cognition would be surprised to observe the rat perfectly navigating in one of the mazes but hitting walls and obstacles in the others. Otherwise stated, it seems that rats like other animals learn the effects of their basic actions in a way that is independent of their environment.

Imagine a comparable situation of an adaptive agent placed in an artificial grid-world environment. Every cell of a grid is labeled with some symbol. The agent can perform a few basic actions. If it goes left, the contents of all cells shift right (imitating the movement of its "view of sight"). If it goes up, cell contents shift down and so on[1]. The agent starts without any knowledge of its environment and of the effects of its own actions. Having operated in one environment for some time the agent is transferred to some another. This new environment has a completely different rearrangement of cell labels (assuming that labels retain their meanings). Do the regularities learned by the agent in the first environment have any sense in this second one? Should the agent continue learning or should it "reboot" and start learning from zero again?

Though adaptive agents are often thought as computational models of biological intelligence, these questions would be hard to many of them. In many agent designs, the knowledge learnt by an adaptive agent must be invalidated when the agent is confronted to a different environment (or even a different goal in the same environment) than that in which it has been learning. The transferability of learned knowledge to different environments is an important aspect of adaptive behavior. This aspect seemed to be underemphasized in the reinforcement learning research until very recently.

To address this challenge we have developed an adaptive agent called LEAD1[2] that is able to operate in a static observable deterministic grid-world environment roughly described above. The agent learns explicit action definitions in terms of its percepts and can predict the effects of its actions. This type of knowledge can be transferred and augmented in new environments that are different from those in which it has learnt its first experience.

[1] This environment is not subject to the perceptual reference frame assumption which requires that agent actions change only a small part of the agent's perceptual input, the remaining steady input providing a background or frame.

[2] Acronym for *Learning Explicit Action Definitions*.

2. Related work

An adaptive agent is the system that perceives and acts upon its environment and improves its performance by adjusting its internal configurations and actions in response to feedback from its environment. Figure 1 illustrates the agent-environment interaction. The agent starts without any knowledge of its environment and of the effects of its own actions. At every discrete time step t it receives percept information o^t through its sensors, processes this information, e. g. updates its internal world model, and selects some action a^t to be performed through its effectors. The action typically alters the state of the environment s^{t+1} resulting in new percepts o^{t+1} and a new percept-action cycle begins (Figure 1).

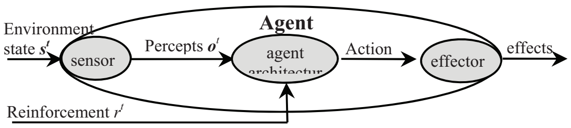


Figure 1. Illustration of an agent embedded into its environment

If agent's percepts are representing the complete environment state (e. g. $\boldsymbol{o}^t \equiv \boldsymbol{s}^t$), the environment is called observable. If the environment state is changed solely by the agent's actions, the environment is called static. If the same action performed in the same environment state but at two distinct time instants always results in the identical successor states, the environment is called deterministic. Otherwise the environment is called partially observable, dynamic and stochastic, respectively.

There are different agent architectures capable of associating agent's percepts to its actions. Detailed descriptions of many complete agent architectures can be found in A Survey of Cognitive and Agent Architectures [1]. We are mostly interested by the agents that learn some knowledge body from their experience and by the aspect of transferability of that knowledge.

First, agents are provided their goals in different ways. The most widespread approach is that of reinforcement [11] [12] [14]. It assumes that there exists a dedicated reinforcement channel into an agent (Figure 1). Reinforcement values coming through this channel tell the agent which environmental states are preferred to the others, thus indirectly describing its goal. Another approach is to assume the existence of a dedicated "goal channel" through which agent's goals are directly "injected"[3] into the system [10]. There are other more biologically inspired approaches where an agent is supposed to have motivations, innate behaviors or to be able to extract reinforcement values from the ordinary sensory input [3] [16].

[3] In humans, this would correspond to having mystical experiences such as unexplained visions and desires.

Second, agents make different architectural assumptions about their percepts. The most common assumption is to take percepts $\boldsymbol{o}^t$ as an atomic state identity label [15]. An alternative approach is to assume that perceptual information is decomposable and/or structured. In this latter case, percepts may be represented by a set of properties [5] [13] [16], described in propositional or the first-order logic [10]. The generalization capabilities of an agent have sense only if decomposable percept representation is used.

One of the most important dividing lines among agent architectures is the presence or absence of a world model. A world model is defined as a body of knowledge that tells the agent what are the expected outcomes of its actions in terms of its future percepts. The presence of a world model has clear architectural implications as only the world model makes an agent capable of planning, i. e. chaining sequences of its actions. We would distinguish three types of agent architectures: agents that learn utility values associated to percepts or the percept-action pairs (model-free agents), agents that learn both utility values and a world model (model-based agents) and agents that learn only a world model (model-rich agents).

An example of a model-free method is Q-learning [15]. The Q-learning based agent selects its actions on the basis of the percept-action utility values (Q-values). It improves its performance in terms of cumulative positive reinforcement. However the table of Q-values is a type of knowledge that bounds the agent to pursue a single goal in the same environment. Some extensions to Q-learning such as function approximation [2] and relational reinforcement learning [6] [7] aim to abstract from specific goals pursued and to exploit the results of previous learning phases in new situations. Function approximation approach uses properties-based percept representation [2] [7]. It generalizes over properties in order to approximate the Q-function. Relational reinforcement represents percepts as a set of ground facts stated in the first order logics [6]. It combines Q-learning and supervised learning by learning Q-function with relational regression tree algorithm [4]. These extensions to Q-learning make computationally intractable learning problems tractable, and increase the transferability of learned knowledge. However they do not compensate for the fact that an agent still lacks a world model and explicit definitions of its actions.

Examples of model-based architectures are Dyna [11], TD(λ) [12], and ADP [9]. Model-based agents also rely on the identity-based percept representation. Besides percept utility values they learn a world model consisting of a set of conditional transition probabilities of percept identities $p(\boldsymbol{o}^{t+1} \mid \boldsymbol{o}^t, a^t)$. Model-based agents, like model-free agents, select their actions on the basis of percept utility values. Thus, the probabilistic world model is seen not as a means for constructing explicit action plans but as a body of knowledge useful to the convergence of percept utility values to the optimal policy. Though model-based agents would be able to adapt to changing goals in the same environment, they would not be capable to predict the effects of their actions in new environments.

Among examples of model-rich agents are LIVE [10], the architecture proposed by Drescher [5], SRS/E [16], and CALM [13]. Model-rich agents learn their world model for the purpose of planning action sequences. Except for LIVE, model-rich agents rarely learn explicit action definitions. The world model of a model-rich agent often consists of the set of accumulated elementary experiences of the type <$\boldsymbol{o}^t$, a^t, $\boldsymbol{o}^{t+1}$>. Model-rich agents use properties-based percept representation. Thus, part of the world-model experiences can be generalized by omitting (e. g. replacing by a wildcard) some properties within $\boldsymbol{o}^t$, a^t, or $\boldsymbol{o}^{t+1}$ components. This capability of generalization is enough for pursuing different goals in the same environment, but not enough to solve the grid-world task outlined in the introductory section. On the other hand, SRS/E and CALM are advanced agent architectures in other respects. SRS/E can operate in stochastic environments, while CALM is designed to operate in deterministic but partially observable environments.

LIVE is model-rich agent that learns explicit action descriptions. It represents its percepts as a set of ground facts stated in the language of the first order logics[4]. States are generalized into a set of the action-defining STRIPS-like first-order logic rules. However, the LIVE approach relies on the perceptual frame hypothesis, which is not satisfied in the grid-world challenge outlined in the introductory section.

3. LEAD1 architecture

The underlying hypothesis of our approach is that the transferability of knowledge is intrinsically related to the generalization capabilities of an agent. An agent must learn to predict outcomes of its actions (a world model) on the basis of its percepts in such a way that regularities/laws establishing prediction hold for different unseen environments. This can be achieved only if decomposable percept representation is used and the agent is capable of extracting relevant properties and abstracting from irrelevant properties at the same time.

This kind of reasoning has driven us to design the LEAD1 agent. The life of the agent is organized in epochs each epoch consisting of a number of discrete time steps until it reaches the goal state. Agent recognizes that a goal state is reached at time t if it receives positive reinforcement $r^t = 1$. Otherwise it receives the reinforcement $r^t = 0$. The LEAD1 agent operates in a grid-world environment. Agent's percepts $\boldsymbol{o}^t = \{o^t_i\}$ correspond to the vector[5] of the grid-world cell labels called observations, where o^t_i denotes the observation of the i^{th} cell at time t.

LEAD1 architecture is outlined in Figure 2. Though the idea of integrating learning and planning in this way is not original but it is quite novel in the context of reinforcement learning (see subsection 3.2.). Each component of this architecture is explained in more detail in the following subsections.

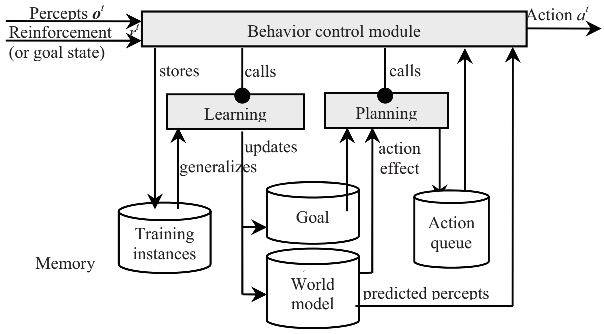


Figure 2. The architecture of the LEAD1 agent

3.1. Learning world model

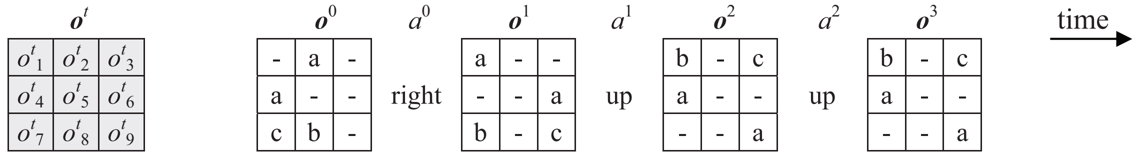
LEAD1 is based on Markov assumption. It assumes that any observation o^{t+1}_i is a function of the previous vector of observations $\boldsymbol{o}^t$ and of the action a^t. This functional relationship is expected to exist for every cell i and to hold for every time instant t.

$$\forall i \; \exists f_i \text{ such that } \forall t \; o^{t+1}_i = f_i(\boldsymbol{o}^t, a^t) \qquad (1)$$

If discovered, the functions $\{f_i,\}$ would predict future observations on the basis of past observations and agents actions. The entire set of functions $\{f_i,\}$ would make up the world model (one function per observation cell). The learner's task is to discover these functions through supervised learning. A supervised training set is continuously extended at every discrete time step t out of the triplets of agent's elementary experience <o^t, a^t, o^{t+1}>. Parts o^t, a^t of this experience are taken as attribute values and o^{t+1}_i (individual components of o^{t+1}) are taken as class-values (Figure 3).

[4] This means that LIVE, if making part of a real-world robotic application, would delegate a significant processing burden to its sensors. LIVE is not a reinforcement-based agent as it expects goals to be directly injected into the system.

[5] Though grid-world cells are organized in a two-dimensional matrix the observation vector $\boldsymbol{o}^t$ obfuscates spatial relationships among individual observations during the supervised learning of the world model.



	Attribute values (time = t)										Class values (time = t+1)								
	o^t_1	o^t_2	o^t_3	o^t_4	o^t_5	o^t_6	o^t_7	o^t_8	o^t_9	a^t	o^{t+1}_1	o^{t+1}_2	o^{t+1}_3	o^{t+1}_4	o^{t+1}_5	o^{t+1}_6	o^{t+1}_7	o^{t+1}_8	o^{t+1}_9
t=0	-	a	-	a	-	-	c	b	-	right	a	-	-	-	-	a	b	-	c
t=1	a	-	-	-	-	a	b	-	c	up	b	-	c	a	-	-	-	-	a
t=2	b	-	c	a	-	-	-	-	a	up	b	-	c	a	-	-	-	-	a
	…	…	…	…	…	…	…	…	…	…	…		…	…	…	…	…	…	…

Figure 3. The transformation of the agent's experience in a 3×3 grid world (top) into the set of training instances for supervised learning of a world model (bottom). Symbols {a, b, c, -} denote grid-world cell labels. The bottom training set is used for learning predictive functions $f_1, \ldots, f_9$ (9 learning tasks in total). The area in gray shows one particular training set used to learn the function f_3, such that $o^{t+1}_3 = f_3(\boldsymbol{o}^t, a^t)$

Many supervised learning techniques can be used to learn the set of functions $\{f_i\}$ satisfying (1). LEAD1 assumes it is operating in a deterministic and observable environment. This means that data noisiness problem can be neglected and suggests decision tree learner as a good candidate for solving this learning task. Pruning will not be required and decision trees built by the learner will always be consistent with all training instances stored in LEAD1's memory. The outline of LEAD1's decision tree learner algorithm is presented below:

```
BuildTree (Node, Inst, Depth)
   // Node  – DT Node being processed;
   // Inst  – set of training instances, associated to Node;
   // Depth – depth of Node.

   IF all members of Inst belong to the same Class THEN
      Label Node with Class
      return(success)

   FOR EACH attribute Attr_m
      IF Attr_m values match class values for every member of Inst THEN
         Label Node with Attr_m
         return(success)

   IF CurrentDepth = MaxDepth[6] THEN return(failure)

   FOR EACH attribute Attr_m
      Group the most scattered values of Attr_m, into the "other" value
      Estimate the utility of splitting Inst by Attr_m

   Sort attributes in the order of decreasing utility
   FOR EACH attribute Attr_m
      FOR EACH Attr_m value v_mi (including the value "other")
         Select instances Inst'∈Inst for which Attr_m = v_mi
         result = BuildTree(Successor(Node), Inst', Depth+1)
         IF result = failure THEN break
      IF result = success return(success)
END
```

The procedure outlined above and resulting decision trees have some differences with respect to decision trees built by other decision tree builders (e. g. C4.5).

[6] *MaxDepth* was set to 3 in our experiments.

1. **Terminal nodes**. Besides terminal nodes associated to the pure (in the sense of class labels) subsets of training instances, terminal nodes are created for mixed subsets of training instances if there is an attribute called predictive attribute such that its values match class values of every training instance in the mixed subset. In this case a terminal node is labeled with an attribute name. Labeling nodes with predictive attributes can be thought of as generalizing the structure of a decision tree at the terminal level (Figure 4).

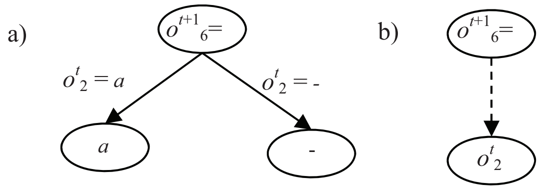


Figure 4. Decision tree predicting $o^{t+1}{}_6 = f_6(\boldsymbol{o}^t, a^t)$ (see Figure 3) by (a) the conventional decision tree builder and (b) by LEAD1. The second tree contains a single node that is labeled with the name of predictive attribute $o^t{}_2$

2. **Aggregating attribute values**. Sometimes the split over different values of an attribute results in a few identically labeled terminal nodes. In this case, the attribute values leading to the identically labeled terminal nodes are aggregated together under the "other" branch. If more than one group is present, the larger one is selected for aggregating. This procedure helps to deal with unseen attribute values during percept prediction step (Figure 5).

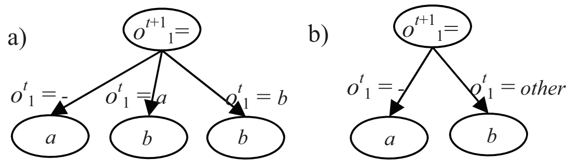


Figure 5. Decision tree predicting $o^{t+1}{}_1 = f_1(\boldsymbol{o}^t, a^t)$ (see Figure 3) by (a) the decision tree builder and (b) by LEAD1

3. **Search space and search strategy.** Decision tree builders usually follow a "divide and conquer" approach thus performing a hill-climbing, non-backtracking search in the space of possible decision trees. The learner component of LEAD1 performs a depth-first exhaustive search in the space of possible decision trees. The space of decision trees is constrained by the limit that is imposed on the depth of a tree. Failure to create a terminal node within a given depth limit under some branch of a tree causes backtracking. Then a different attribute is selected and sub-trees tied to neighboring branches are invalidated. This search strategy is more costly in computation time but helps in finding more compact decision trees.
4. **Node splitting criterion**. Node splitting criterion is used to measure the utility of an attribute for splitting a particular node. Decreasing order of utility is the order in which attributes are tested during the search. The utility $U(A)$ of the attribute A for splitting a particular node is given by (Figure 6):

$$U(A) = \sum_{k \in Classes} \frac{K_k + P_k}{K_k + P_k + N_k}, \text{ where} \qquad (2)$$

K_k, P_k, and N_k are the quantities of nodes resulting from the node split over A values such that:

K_k is the number of terminal nodes that would be labeled by the class k.

P_k is the number of terminal nodes that would be labeled with a predictive attribute and would cover at least one instance of class k.

N_k is the number of non-terminal nodes that would cover at least one instance of class k.

The node splitting criterion given by (2) avoids counting training instances in the sub-nodes of the node under investigation. The criterion is in favor of attributes that obtain as many "purely" separated and/or predicted classes as possible (Figure 6).

3.2. Learning goal test

LEAD1 can be provided with the goal either directly or indirectly. In the first case, the percepts corresponding to the goal state are directly "injected" into the agent. In the second case, the goal is specified indirectly by the signal coming through the reinforcement channel. The indirect case is more complicated as the planner requires goal percepts or the goal test to be known prior to planning. To address this problem LEAD1 is dotted with the capability of constructive induction[7] [8]. Having acted in its environment for some time, the agent accumulates a set of percept-reinforcement associations $\{<\boldsymbol{o}^t, r^t>\}$.Then it learns to discriminate positively and negatively reinforced percept subsets thus inducing a goal test. This goal test is not discarded but kept and refined across different environments thus implicitly assuming that there are universal laws explaining agent's reinforcement as a function of agent observations. Goal test induction may result in false generalizations especially if there are too few positive training instances. As a result, LEAD1 may pursue wrong goals during the initial epochs of its life.

3.3. Planning

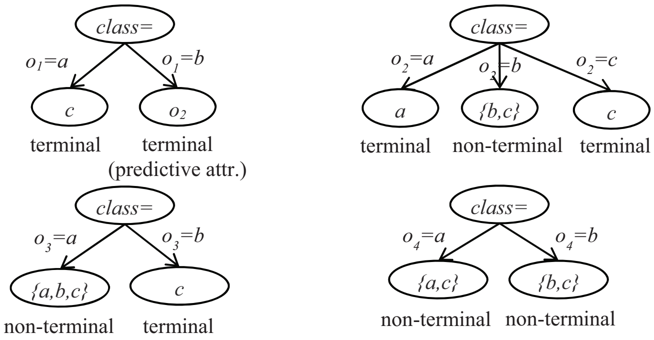
Planning component of the LEAD1 agent is responsible for finding the shortest action sequence that is expected to achieve agent's goal. It is based on the breadth-first depth-limited[8] search in the space of agent's percepts. The initial state is assumed to

[7] This capability is embedded into LEAD1's learner component but its details are not covered by this paper. Spatial relationships among individual observations of $\boldsymbol{o}^t$ are exploited in this type of learning.
[8] The depth limit was set to 15 in our experiments.

a) Sample training set

Attributes				Class
o_1	o_2	o_3	o_4	o_5
a	b	a	b	c
a	c	b	b	c
a	b	b	a	c
b	b	a	b	b
b	c	b	a	c
b	a	a	a	a

b) Candidate splits



$$U(o_1) = \sum_{k \in \{a,b,c\}} \frac{K_k + P_k}{K_k + P_k + N_k} = \frac{0+1}{0+1+0} + \frac{0+1}{0+1+0} + \frac{1+1}{1+1+0} = 3;$$

$$U(o_2) = 2; \quad U(o_3) = 0.5; \quad U(o_4) = 0;$$

Figure 6. Illustration of the node splitting utility function $U(A)$. a) Sample training set b) Four candidate splits based on attributes $\{o_1, o_2, o_3, o_4\}$. The best split is based on the attribute o_1 as it has the maximum estimated utility $U(o_1) = 3$.

correspond to the current percepts. Successor-states are generated on the basis of the world model to date.

3.4. Behavior control module

Behavior control module is responsible for organizing LEAD1's behavior at the highest level, i. e. it is responsible for the interaction of the learner and planner components, action selection, and exploitation vs. exploration trade-off. The outline of LEAD1's behavior control module for one time step is presented below:

```
Behavior control module (current percepts, reinforcement)
   static world model
   static InstWM       // training instances for learning world model
   static InstGT       // training instances for learning goal test
   static action queue // action set expected to achieve the goal
   static action       // last action taken
   static anticipated percepts

   action ← None
   InstWM ← Update(<previous percepts, action, current percepts>)
   InstGT ← Update(<current percepts, reinforcement>)
   IF anticipated percepts ≠ current percepts THEN
       world model ← Learner(world model, InstWM)
       action queue ← {}
   IF Satisfy(current percepts, goal test) THEN
      IF reinforcement = off THEN
         goal test ← Learner(InstGT)
         action queue ← {}
      ELSE return(action)
   IF action queue = {} THEN
      action queue ← Planner(world model, current percepts, goal test)
   IF action queue = {} THEN
      action ← random action
   ELSE // exploitation vs. exploration
      p ← random number, p∈[0,1]
      If p < p_rnd THEN
         action ← random action
         action queue ← {}
      ELSE
         action ← RemoveTopAction(action queue)
   anticipated percepts ← Predict(world model, current percepts, action)
   return(action)
END
```

LEAD1 invokes the learner component if anticipated percepts mismatch the current percepts, i. e. the real-world experience. The learner updates the world model and makes it consistent with the latest experience. Planning component is invoked if current percepts do not satisfy the goal test and there is no any action plan. Upon success, the planner returns the action sequence leading to the goal. Upon failure, it returns an empty sequence.

If the planner is unable to find an action plan LEAD1 selects a random action. Even if there is an action plan, a random action may be selected for the purposes of environment exploration. Probability p_{rnd} that LEAD1 will select a random action instead of an action suggested by the plan is given by:

$$p_{rnd} = \frac{2}{1+\exp\left(\frac{1}{\frac{inc_{rnd}}{all_{rnd}}+0.01}\right)}, \quad (3)$$

where *all_rnd* is the number of random actions within the sliding window of the most recent actions[9], and *inc_rnd* is the number of random actions among *all_rnd* actions that had their effects incorrectly predicted by the world model. The probability p_{rnd} decreases as the estimated reliability of the world model increases. If a random action is performed, any current action plan must be reset.

4. Experimental investigation

The objective of our experimental investigation was to demonstrate that an agent capable of learning its world model as well as its goal concept description is capable of solving an extended set of tasks, i. e. is capable of operating in a wider set of environments. For this reason, the LEAD1 agent was compared to other adaptive agents based on Q-learning and ADP reinforcement learning techniques. Though our experimental investigation included different experimental setups, comparisons were based on the experimental setup that is described below.

All agents were placed within an environment of the size of 9×9 cells. Every cell was assigned a label describing its content. There were 6 different cell content labels: *an agent*, *a box*, *an empty cell*, *a stump*, *a tree*, and *a wall*. Agents had an action set consisting of 8 elementary actions: four *go* actions and four *jump* actions, one action per possible direction [10]. If successful, actions *go* and *jump* displaced agents within their environment in the specified direction by 1 and 2 cells respectively. Any *go* action was successful if the destination cell was empty. Any *jump* action was successful if the destination cell was empty and the intermediate cell wasn't a tree or a wall. Agents remained in the same cell, if any action failed. The environment was considered to be spherical, meaning that having no obstacles it was possible for agents to reach the same cell after repeating the same *go* action 9 times.

The environment was completely observable to all agents through their percepts. However, sensors of the agents mapped the environment state into their subjective coordinates. As a result, for instance, the action *go left* caused the whole perceptual "view of sight" to shift right. Agents saw themselves in the center cell of their view at any time. Thus, this experimental setup could not benefit from the perceptual frame hypothesis[11] (Figure 7).

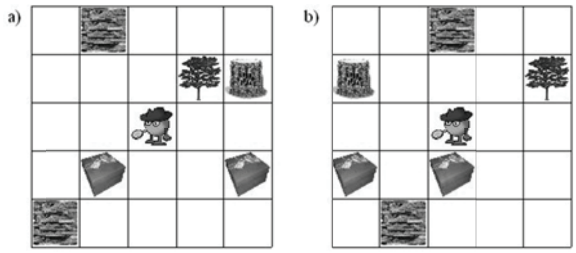


Figure 7. Grid-world environment of the reduced size 5×5. a) Initial percepts. b) Agent percepts after the action *go left* has been performed.

The life of all three agents was organized in epochs each epoch consisting of a number of discrete time steps. An epoch started by situating an agent in its environment. An epoch was terminated if an agent reached the goal or if maximum allowed number of time steps per epoch was exhausted [12]. Positive reinforcement was given only upon agent reaching the goal. Agents started the first epoch with blank memory, i. e. without any prior knowledge. The knowledge (world model, tables of stat utility values, Q-values) was accumulated from epoch to epoch.

Adaptive agents based on ADP and Q-learning techniques were implemented according to the schemes given by Russell and Norvig [14]. Both agents treated their percepts $\boldsymbol{o}^t$ as an atomic label defining state identity. Parameters of the exploitation vs. exploration trade-off function were optimized to yield the best performance.

All three adaptive agents were confronted to 10 tasks of gradually increasing complexity as summarized by Table 1.

[9] The width of the window was set to 20 in our experiments.

[10] In other experimental setups, the agent was given 2 actions: *go forward* and *turn right*.

[11] In other experimental setups, the agent was given an access to the environment state in its objective coordinates. As a result the agent saw himself moving around the environment (as if viewed from the top). Such an experimental setup could benefit from the perceptual frame hypothesis.

[12] The maximum duration of an epoch was set to 50 steps in our experiments.

Table 1. Experiment summary

Task No.	Environment type	Initial state	Goal state	Goal provision[13]
1, 2, 3	fixed	fixed	fixed	direct injection
4	fixed	random	fixed	direct injection
5	fixed	random	random	direct injection
6, 7	fixed	random	fixed	reinforcing "agent is next to the tree"
8	variable	random	random	direct injection
9, 10	variable	random	random	reinforcing "agent is next to the tree"

The environment type was denoted as *fixed* if contents of its cells were initialized in the same way at the beginning of every epoch. The environment was denoted as *variable* if its cells were initialized randomly using the same six possible cell content labels. The tasks 6-7 and 9-10 were characterized by the environments with more than one goal state. In these environments, all three adaptive agents where reinforced at any state where they found themselves next to some tree.

Agent performance was measured through their performance curves (Figure 8).

On the simplest tasks 1-4 all three agents converged to their optimum performance. Q-learning based agent exhibited a slower convergence with the increasing environment size (task 3). Q-learning based agent failed to solve tasks 5, 8-10, which correspond to the changing goal state. This confirms that model-free agents can learn to pursue a single goal. ADP based agent successfully solved the task 5 but failed to solve tasks 8-10. This means that ADP algorithm has mechanisms (world model) to adjust to new goals (the state utility values were cleared and recomputed on the basis of a world model at the beginning of each epoch). Variable type environment presented a challenge that went beyond the generalizing capabilities of both Q-learning and ADP. This challenge was solved by the LEAD1 agent that has learnt explicit action definitions in terms of its percepts.

LEAD1 solves even those tasks that Q-learning and ADP cannot cope, but it requires exponential time complexity compared with polynomial complexity of Q-learning and ADP.

5. Discussion and conclusions

The research presented in this paper has shown that it is possible to carry and re-use knowledge acquired in one environment to different environments thus extending the range of tasks solvable by the agent. It has also shown that the planning of action sequences may be a viable action selection policy of the reinforcement driven agents. This paper suggested that one of the ways to address the problem of knowledge transferability may be related to the appropriate selection of generalization capabilities of an agent.

The above conclusions are subject to certain limitations and assumptions. First of all, they apply to the class of static, observable and deterministic grid world environments. Second, they assume that meanings of cell labels and agent actions have a universal scope, i. e. that identical cell labels have identical meanings in both seen and unseen grid-world environments. Third, they were demonstrated only for the subset of environments that satisfy the first-order Markov property.

The concerns that LEAD1 that is developed for static, observable and deterministic environments could not be extended to stochastic, partially observable and dynamic ones are reasonable. However, we believe that there is a way of extending LEAD1's behavior to partially observable environments. The hidden variable approach similar to that used by CALM [13] may be one of the ways to follow. Stochastic perception of the environment (also known as perceptual aliasing) can be thought as a phenomenon arising in consequence to the partial observability of the world and approached by the same method as well.

The assumption of the universality of cell labels and agent actions doesn't seem to be very annoying. In real-world robotic systems, grid-world cell labels should normally by extracted by the frontend processing of sensory data. Though labels may become noisy, the labeling itself should remain consistent.

The agent architecture described in this paper was tested in the environments satisfying the first-order Markov property. It would be straightforward to extend the learning task defined by (1) to include more past percepts: $o^{t+1}_i = f_i(\boldsymbol{o}^{t-n}, \ldots, \boldsymbol{o}^{t-1}, \boldsymbol{o}^t, a^t)$. This would theoretically enable the agent to construct world model in the higher order Markov environments. However, the time complexity of learning is an exponential function of the number of parameters. Planning that is based on the breadth-first search is exponentially prohibitive as well. Giving-up the perceptual frame assumption does not allow the agent to use efficient search orienting heuristics like those derived from the means-ends analysis [10]. The limits imposed by the computational costs on the agents' architecture are still to be investigated.

Another interesting development of LEAD1 would be to carry it to the Block's World task [6] [7]. This environment is characterized by composite (parameterized) actions like PutOn(CubeA, CubeB) or PutOnTable(CubeA). It would be interesting to see how such an extension would impact the structure of LEAD1's world model.

[13] Only the LEAD1 agent described in this paper was provided its goal via direct injection. ADP and Q-learning based agents were always provided their goals via reinforcement.

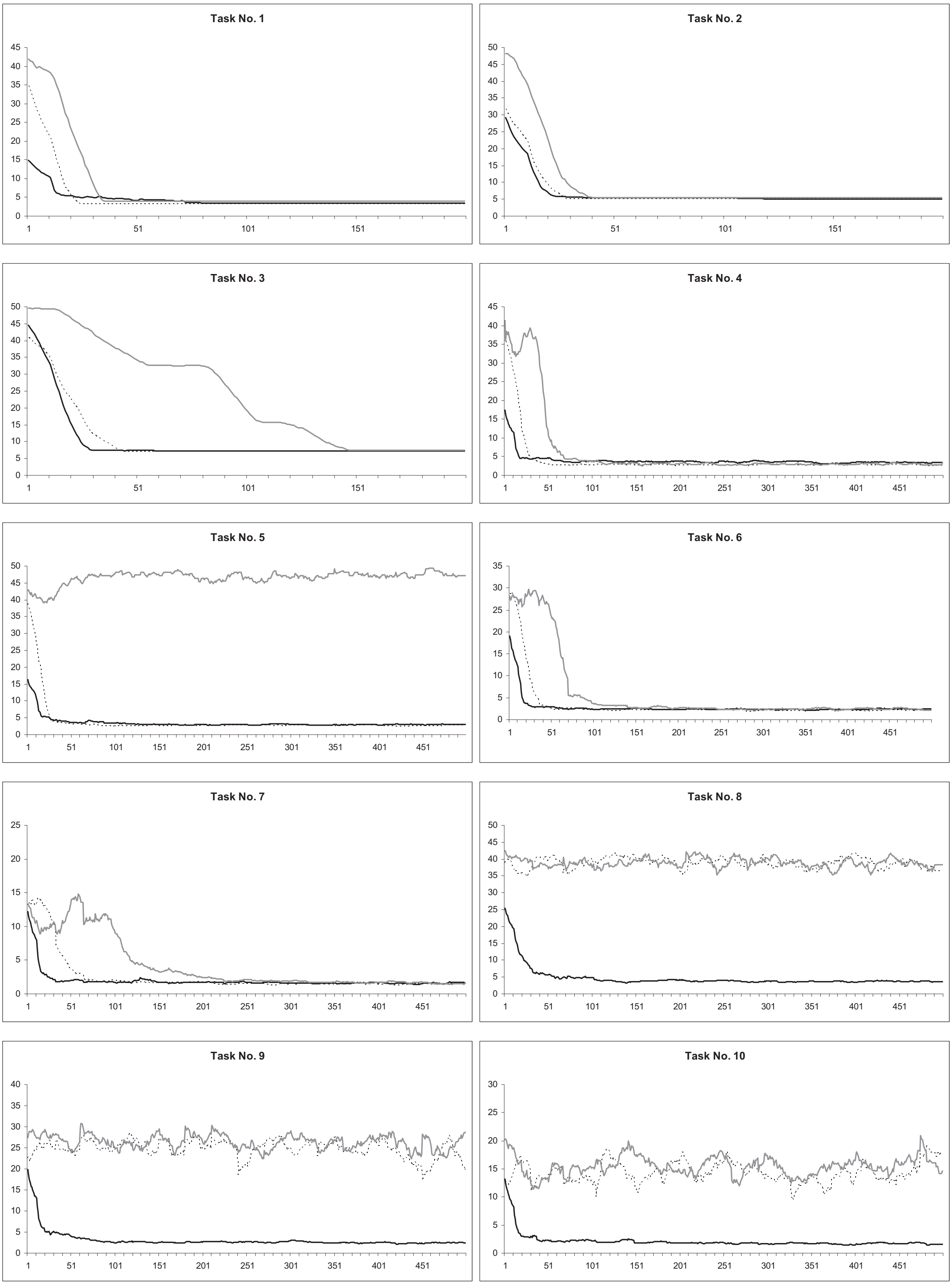


Figure 8. The performance curves of the LEAD1 (black solid), ADP (black dashed) and Q-learning (grey) based agents on the tasks 1-10. X axis shows the number of epochs and the Y axis shows the average number of actions to achieve the goal (performance). Y axis values have been averaged over epochs, using sliding window of size 20. In experiments presented results are averaged in 5 trials

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