Modeling Top-Down Perception and Analogical Transfer with Single Anticipatory Mechanism

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Abstract

A new approach to anticipations is proposed – anticipation by analogy. Firstly, the role of selective attention was explored both with simulation data and psychological experiment. After that, the AMBR model for analogy-making has been extended with a simple anticipatory mechanism and is demonstrated how top-down perception and analogical transfer can both be based on one and the same anticipatory mechanism. Finally, attention and action mechanisms were added to the model and AMBR was implemented in a real robot that behaves in a natural environment.

The Importance of Anticipations

Humans are anticipatory agents. They always have expectations about the world they live in (sometimes correct, sometimes wrong). Our everyday behavior is based on the implicit employment of predictive models. If, for example, we are looking for a certain book in an unknown room, we try to imagine where it could possibly be and then we go to look at this place. This is an example of anticipatory behavior as opposed to simple reactive behavior when we first see the object and then move towards it.

There are few attempts to implement anticipatory behavior in computational models or in real robots. Typically, the researchers from the neural network approach use learning as a main mechanism for generating implicit or explicit models of the environment. The learned network weights represent these models and the result could be considered an anticipatory system. Examples for this type of anticipations are the ALVIN model (Pomerleau, 1989), which learns not only to respond to the environment but also to predict the observations to be seen in the next step and the Anticipatory Learning Classifier Systems (Stolzmann, 1998, Butz at al, 2002), which combine online reinforcement learning and model learning methods and can learn several reward maps. The combination of online generalizing model learning and reinforcement learning allows the investigation of diverse anticipatory mechanisms including multi-objective goals integrating different motivations.

Another approach towards building anticipatory capacities is based on the DYNA-PI systems (Sutton, 1990). These systems are based on reinforcement learning systems that plan on the basis of a model of the world. Recently these models have been used to implement a neural network planner (Baldassarre, 2002) that is capable of finding efficient start – goal paths, and deciding to re-plan if "unexpected" states are encountered. Planning iteratively generates "chains of predictions" starting from the current state and using the model of the environment. This model is a neural network trained to predict the next input when an action is executed.

Anticipation by Analogy

The learning techniques based on generalization described above are based on the assumption that there is regularity in the input-output coupling. However, in some tasks, for example when searching for a hidden object, there will be no regularity. This paper describes an alternative approach towards anticipation based on analogical reasoning. The main idea is to generate predictions by analogy with a single episode from the past experience. We modeled anticipatory mechanisms and we tested them with simulations in environment that consists of rooms; some geometrical objects – cubes, pyramids, etc; one robot; and a bone-toy, which can be hidden behind a certain object. We used a simulated (Webots software) and real - Sony AIBO robot (ERS-7). The simplest scenarios we are working on involves the robot searching for a bone hidden somewhere behind some object in one of the rooms of a house. In some cases two episodes might be very close analogies, e.g. the bone is hidden behind the same object in another room, or behind the same "pattern of objects", however, in other cases the robot may need to build a more abstract analogy, e.g. the bone was behind the object with unique color, but now all objects have the same color and therefore the object might be behind the object with unique form.

Analogy-making is a very basic human ability that allows a novel situation to be seen as another already known one (Hofstadter, 1995). There are a number of cognitive models developed of this process or various parts of it. One of the first such models is the SMT developed by Dedre Gentner and her colleagues (Gentner, 1983). SMT assumes that analogy is transfer of a system of relations from one situation to another. It assumes that attributes are not important and thus are ignored in mapping. It also assumes that the two situations should share the *same* relations. Thus the above case of analogy between unique color and unique form relations is not possible in SMT unless a re-representation is performed (Yan, Forbus and Gentner, 2003), however, it is not clear how such a re-representation could be computed in this particular case. Other models of analogy-making such as ACME (Holyoak, Thagard, 1989), LISA (Hummel, Holyoak, 1997), and AMBR (Kokinov,

1994a) allow for mapping of relations with different names. Comparing these models we decided to use AMBR since ACME is psychologically unrealistic for making all possible pairing of possible correspondences and is based on a fixed thesaurus for finding synonyms, and LISA is still not capable of comparing complex enough structures that will be needed in the real-world applications of the robot scenarios. AMBR has also the advantage of integrating mapping and retrieval processes of analogy-making. However, none of these models has ever been used for anticipation; neither has been applied in robot scenarios.

Implementing Anticipations in the AMBR Model of Analogy-Making

AMBR is a decentralized model in which computations emerge from the interactions among numerous micro-agents (Kokinov, 1994a, 1994b, Kokinov & Petrov, 2001). All the micro-agents run in parallel and interact with each other and the macro-behavior of the system emerges from the local interactions and micro-behavior of the individual agents. These micro-agents run at individual speed each and this speed is dynamically computed depending on the relevance of this micro-agent to the context (Petrov & Kokinov, 1999, Kokinov & Petrov, 2001). Each of these micro-agents is hybrid – it has a symbolic part that represents the specific piece of knowledge that the agent is responsible for, and it has a connectionist part that computes the activation level which reflects the relevance of the agent to the context.

Thus in AMBR there are no separate steps in the analogy-making process: retrieval and mapping overlap and interact with each other. This allows for the structural constraint, which is important for the mapping process, to influence also on the retrieval process and thus it is possible remote and abstract analogies to be constructed.

AMBR does not separate semantic from episodic memory. Instead, the memory episodes are represented with a coalition of interconnected instance-agents that point to their respective concept-agents. The representation of the target situation and the representation of the environment serve as sources of activation that spreads to the relevant concepts, their super-classes and close associations, and then back to some instances from memory situations. Thus the Working Memory of the model is not a separate part but is defined as the part of the Long-Term Memory that consists of relevant enough items.

Each instance-agent that enters in the Working Memory emits a marker that spreads up-wards in the conceptual class-hierarchy. When two markers meet somewhere a hypothesis for correspondence between their origins is created. It represents the fact that there is something in common between the respective marker-origins, namely, they are both instances of a same class. Several mechanisms for structural correspondence create new hypotheses on the basis of existing ones – if two relations are analogous, their respective arguments should also be analogous; if two instances are analogous, their respective concepts should be analogous, etc.

Thus, gradually, many hypotheses for correspondence emerge and form a constraint satisfaction network that is interconnected with the main one. The final answer of the system emerges from the relaxation of this constraint satisfaction network.

Simulation Results

In the first series of simulations we used only the simulated version of the robot and the environment, thus excluding perception and exploring only the role of selective attention. The robot faces several objects in the room and has to build their representation in its mind. Then the task of the robot is to predict behind which object would the bone be and then finally to go to the chosen object and check behind it.

Thus there is a representation building part of the model, which target representation is then used for recalling an old episode which could be used as a base for analogy, a mapping between the base and the target is built, and the place of the hidden object in this old episode is used for predicting the place of the hidden bone in the current situation. Finally, a command to go to the chosen object is send. It is important to emphasize that all these processes emerge from the local interactions of the micro-agents, i.e. there is no central mechanism that calculates the mapping or retrieves the best matching base from memory.

In the simulations described here the AIBO robot had four specific past episodes encoded in its memory, presented in Figure 1. In all four cases the robot saw three balls and the bone was behind one of them. The episodes vary in terms of the colors of the balls involved and the position of the bone.
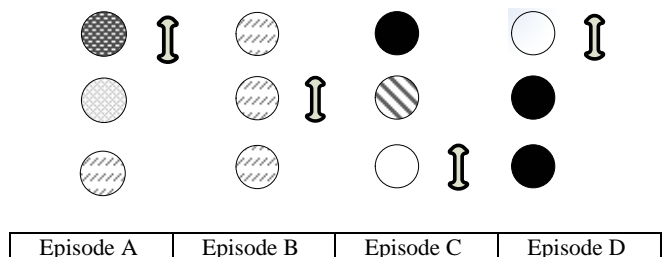

| Episode A | Episode B | Episode C | Episode D |

Figure 1: Old episodes in the memory of the robot (different colors are represented with different textures).

The robot was then confronted with eight different new situations in which it had to predict where the bone might be and to go and check whether the prediction was correct (Figure 2). The situations differ in terms of colors and shapes of the objects involved.
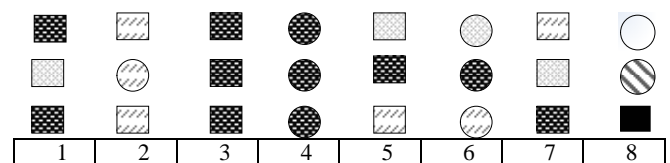

| 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |

Figure 2: New tasks that the robot faces.

In Figure 3 one can see the representation of the target situations that is extracted from the description of the simulated environment. Representation building for perceived real environment is described in the next section.

For the first series of simulations, however, the representation involves relations known to the robot such as **color-of (object-1-sit001, red1), same-color (object-1-sit001, object-3-sit001), unique-color (object-2-sit001), right-of (object-2-sit001, object-1-sit001), instance-of (object-1-sit001, cube),** etc. (see Figure 3 for some examples). The relations are in turn interconnected in a semantic network. For example, **same-color** and **same-form** are both sub-classes of the higher-order relation **same**.

In the simulations described above the attention of the robot was simulated by connecting only some of these descriptions to the input list which results that even though all relations, properties, and objects will be present in the Working Memory (WM) of the robot, only some of them will receive external activation and thus will be considered as more relevant. Thus different simulations with the same situation, but focusing the attention of the robot towards different aspects of the given situation, could result in different outcomes.
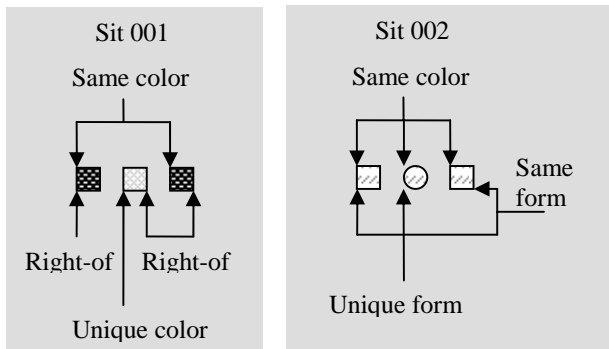

Figure 3: Representation of the target situations 1 and 2.

In each case there could be various solutions: different analogical bases could be used on different grounds and in some cases for the same base several different mappings could be established that will lead to different predictions (See Fugure 4 and Figure 5 for the specific mappings established and the predictions made).
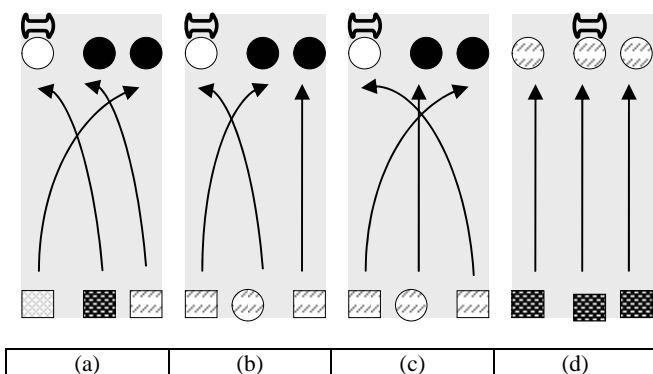

Figure 4: Examples of mappings established with changing the attention from form (a) and (b) to color (c) and (d).

In Figure 4 the mappings that the system has established for several situations are depicted: (a) Mapping established between target situation 1 and base D: unique colour goes to unique colour and the bone is predicted to be behind it. (b) and (c) Two different mappings established between situation 2 and base D: in (b) the focus of attention has been on the form of the objects and the mapping goes from unique form in the target to unique colour in the base, same form in the target to same colour in the base and the bone is predicted to be behind the object with unique form (namely behind the ball), in (c) the focus of attention is on the colours and therefore any mapping between the objects is possible, in this particular case the bone is predicted to be behind the right-most object. Finally, (d) presents the mapping between target situation 3 and base B where the focus of attention is on the colours: three objects of the same colour in both cases, independently of the difference in the form; the bone is predicted to be behind the middle object.
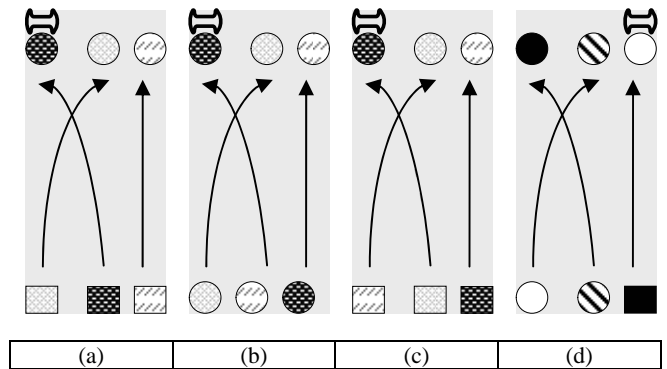

Figure 5: Examples of mappings based on the superficial color relations

The mappings that the system has established for several other target situations are shown on Figure.5. These are more superficial analogies where the color is dominating and where it is mapped on the same color in the old episode, i.e. if the bone was behind the red ball before then the robot would predict in these cases that the bone will be again behind the red object.

By varying the focus of attention on various aspects of the target situation one can get various results, thus figure 4b and 4c show two different mappings and therefore two different predictions will be generated by the system: 4b makes more sense, however, also humans do not produce always this specific mapping.

Evidently, situations 5, 6, 7, 8 (Figure.2) are more straight-forward – they require a rather superficial mapping of the specific colors. Situations 1, 2, 3, 4 are more interesting because they invite less obvious mappings. Thus in Figure 4a the mapping is between two objects having same color in the target and two objects (although different in form) having the same color in the base, although the colors themselves are different (red goes to black, and yellow to white). The most interesting case is 4b where a rather abstract mapping has been established: the two objects in the target which have the same form (cube) are mapped onto

the two objects in the base with the same color. Thus same-form goes to same-color as well as unique-form goes to unique-color. This mapping would be impossible with many other models of analogy-making (SMT maps only identical relations, ACME and LISA could not do it for different reasons – the pressure for mapping same-color onto same-color will be high). In AMBR this is possible because of the general knowledge that same-color and same-form are both special cases of the "sameness" relation and the markers starting from both episodes will cross in "same". In addition, focusing the attention on same-form would greatly help to find this mapping as demonstrated in the simulation.

Comparison with Human Data

After running the first series of simulations several times varying only the focus of attention to see whether the mapping changes; we conducted a psychological experiment. We showed the bases to the participants, changing the AIBO robot and the bone with a cover story about a child who has lost its bear-toy. We asked the participants to predict where the bear-toy would be in the given new situation.

The data from the human experiment are given in Figure 6a. As one can see there is a variety of answers for almost each target situation. Still there are some dominating responses. In order to be able to test the robot's behavior against the human data, 50 different knowledge bases have been created by a random generator that varies the weights of the links between the concepts and instances in the model. After that the simulation has been run with each of these knowledge bases in the "mind" of the robot. Figure 6b reflects the results. They show that the model has a behavior which is quite close to that of the participating human subjects in terms of the dominating response. The only major difference is in situation 2 where human subjects are "smarter" than AMBR: they choose an analogy with situation D (same-form goes onto same-color) much more often than AMBR. Still AMBR has produced this result in 25% of the cases. This means that AMBR is in principle able to produce this result, but it would require some tuning of the model in order to obtain exactly the same proportion of such responses.

Using Anticipation Mechanisms for Modeling Top-Down Perception and Analogical Transfer

The main disadvantage of the version described above is that AMBR lacked completely any perceptive mechanisms except for manual coding of a presented situation (target) and additionally perceived objects. In order to overcome this limitation we developed new mechanisms modeling top-down perception and attention. In addition, we used some modules of the IKAROS platform (http://www.ikaros-project.org/) to manage with the difficult task of bottom-up visual perception and object recognition. Thus we enriched our model AMBR with perception abilities. It gives us the possibility to extract the representations from real physical environment and not coding them manually inside the model. Thus, we tested AMBR with a real AIBO robot in a real environment. The newly built mechanism for

anticipation-creation is described briefly in the next subsections, as well as its usage both for top-down perception and for analogical transfer.
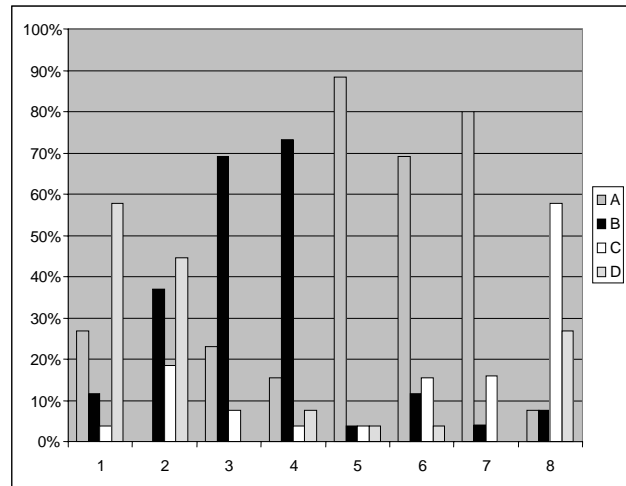
(a) Human data
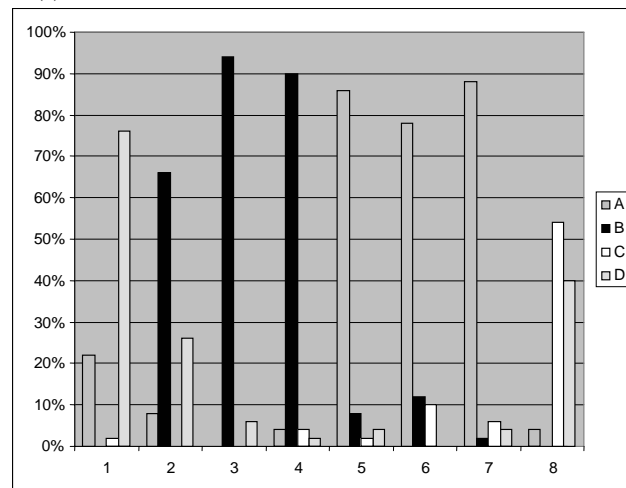
(b) AMBR simulation data

Figure 6: Comparing human and simulation data: which base has been used for analogy with each target situation and how many times.

Top-Down Perception as Anticipation

At the beginning, the robot is looking at a scene. In order for the model to "perceive" the scene, or parts of it, the scene must be represented as an episode, composed out of several agents standing for objects or relations, attached to the input or goal nodes of the architecture. It is assumed that the construction of such a representation is initially very poor. Usually, symbolic representations of only the objects from the scene without any descriptions are attached to the input of the model (for example, **cube-1, cube-2,** and **cube-3**). The representation of the goal is attached on the goal node (usually **find-t, Aibo-t,** and **bone-t**). During the run of the system, via the mechanisms of analogical mapping some

initial correspondence hypotheses between the input (target) elements and some elements of previously memorized episodes (bases) emerge. The connected elements from the bases activate the relations in which they are included. If it happens all arguments of a certain relation from a base episode to be mapped to elements from the target, than the respective relation is transferred from the base to the target. However, the new relation is considered as anticipation. Later on, the perceptual system should check whether it is really present in the environment or not. This dynamic *perceptual mechanism* creates anticipations about the existence of such relations between the corresponding objects in the scene. For example, suppose that **cube-T** from the scene representation has been mapped onto **cube-11** in a certain memorized situation. The activation retrieval mechanism adds to working memory some additional knowledge about **cube-11** – e.g. that it is yellow and is positioned to the left of **cube-22**, etc. The same relations become anticipated in the scene situation, i.e. the system anticipates that **cube-T** is may be also yellow and could be to the left of the element, which corresponds to **cube-22** (if any), etc. Thus, various anticipation-agents emerge during the run of the system.

Attention

The *attention* mechanism deals with the anticipations *generated by the dynamic perceptual mechanism*, described above. With a pre-specified frequency, the attention mechanism chooses the most active anticipation-agents and asks the low-level perceptual system to check whether the anticipation is correct (e.g. corresponds to an actual relation between the objects in the scene). The low-level perceptual system (based on IKAROS) receives requests from AMBR and simply returns an answer based on the available information from the scene. This information is received from the IKAROS system which extracts symbolic visual information from the real environment. There are three possible answers: 'Yes', 'No', or 'Unknown'. The answer 'Unknown' is returned very often because typically AMBR asks for a variety of relations. In addition to colors ('color-of' relations), spatial relations, positions, etc., it generates also anticipations like **"the bone is behind 'object-1'"**, or **"if I move to 'object-3', I will find the bone"**. Those relations play a very important role for the next mechanism – the *transfer of the solution* (i.e. making a prediction on which an action will be based) – as explained below.

After receiving the answers, AMBR manipulates the respective agent. If the answer is 'Yes', it transforms the anticipation-agent into instance-agent (i.e. *token*). In this way the representation of the scene is successfully extended with a new element, for which the system tries to establish correspondences with memorized episodes elements. If the answer is 'No', AMBR removes the respective anticipation-agent together with some connected to it additional anticipations. Finally, if the answer is 'Unknown', the respective agent remains anticipation-agent but behaves just like a real instance, waiting to be rejected or accepted in the future. In other words, the system behaves in the same way if the respective anticipation is true. However, the perceptual system or the transfer mechanism (see below)

can remove this anticipation. In this way AMBR gradually builds the representation of the scene.

Transfer of the Solution

The representation of the scene emerges dynamically, based on top-down processes of analogical mapping and associative retrieval and on the visual information from the environment. The system creates many hypotheses for correspondence that self-organize in a constraint-satisfaction network. Some hypotheses become winners as a result of the relaxation of that network and in this moment the next mechanism – the *transfer of the solution* is triggered. In fact, the transfer mechanism does not create the agents, which represent the solution. Actually, the perceptual mechanism has already transferred many possible relations but now the task is to remove most of them and to choose the best solution. For example, suppose the target situation consists of three red cylinders and let the task of the AIBO robot is to find the bone. Because of various mappings with different past situations the anticipation mechanism would create many anticipation-agents with the form: **"The bone is behind the left cylinder"** because in a certain old situation A the bone was behind the left cube and now the left cylinder and the left cube are analogically paired. Because of the analogy with another situation B, for example, the anticipation that **"the bone is behind the middle cylinder"** could be independently created. For a third reason, the right cylinder may also be considered as a candidate for searching the bone. Thus many alternative anticipation-agents co-exist. When some hypotheses win, it is time to disentangle the situation.

The winner-hypotheses take care to propagate their winning status to the consistent anticipation-agents. In addition, the inconsistent ones are removed. In the example above, suppose that situation A happens to be the best candidate for analogy. Thus, the hypothesis **left-cylinder<-->left-cube** would become a winner. The relation 'behind' from situation A would receive this information and take care to remove the anticipations that the bone can be behind the middle or behind the right cylinder.

As a final result of the transfer mechanism, some complex causal anticipation-relations like **"if I move to the object-3, this will cause finding the bone"** become connected to the respective cause-relations in the bases via winner-hypotheses.

Action Executing

In order to finish the whole cycle from perception to action and to test all mechanisms with a real robot, *sending an action command* has been modeled. The cause-relations that are close to the GOAL node trigger it. The node GOAL sends a special message to the agents that are attached to it, which is in turn propagated to all cause-relations. Thus, at certain moment, the established cause-relation **"if I move to object-3, this will cause finding the bone"** will receive such a message and when one of its hypotheses becomes winner, it will search in its antecedents for an action-agents. The final step is to request the respective action and this is done by sending a message to the action execution module

of the system. This module navigates the robot to the target object. The information for his/her position is updated from the IKAROS system. After arriving at the requested position the robot uncovers the object and takes his/her bone if it is there or stops.

Conclusions

This paper presents a new approach – we suggested that the analogy with previously experienced situations may be used for anticipation. Our attempt was to model these analogy-based anticipations with the AMBR model and to extend it with top-down perceptual and analogical transfer mechanisms. Finally, we used real AIBO robot to test the model in a natural environment.

Firstly, we explored the role of selective attention in the simulation and in a psychological experiment. After that, we implemented a simple anticipation mechanism in AMBR, namely transferring a relation from a memorized episode to the current situation if all arguments of the respective relation have been mapped. Thus, we actually extended AMBR both with top-down perceptual and with analogical transfer mechanisms, thus showing that may be one and the same basic mechanism underlie these seeming unrelated phenomena.

Finally, we added additional attention and action mechanisms in AMBR, and implemented it into a real AIBO robot that behaves in a natural environment.

However, this is just a small step in a larger project. We used the IKAROS system for bottom-up perception and for recognition of the objects. Further investigation and modeling of these processes should be made in order to achieve integrated active vision.

Now all the visual information for the environment is received from a global camera above the scene. The attention mechanism should be connected with the robot camera and particularly, with its gaze. Thus, both the salience maps from the environment and the top-down reasoning will influence the head-movement of the robot, and in turn, the order of checking of various anticipations.

This paper is an attempt to integrate high-level analogical reasoning with active attention and vision in a single model, based on a few main principles and in addition, to test this model with a robot in a real environment.

Acknowledgments

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