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Learning and Memory Processes in Autonomous Agents using an Intelligent System of Decision-making

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Abstract. This paper analyzes functions and structures of the memory that is an indispensable part of an Intelligent System of Decision-making (ISD), developed as a universal engine for autonomous robotics. A simplified way of processing and coding information in human cognitive processes is modelled and adopted for the use in autonomous systems. Based on such a knowledge structure, an artificial model of reality representation and a model of human memory (using, in particular, the concept of Long-Term Memory) are discussed. Finally, the paper presents a way of rearranging the system memory and modelling the processes of learning.

Keywords: Fuzzy systems, Cognitive robotics, Machine learning, Autonomous agents, Decision making, Knowledge representation.

1 Introduction

At any level of abstraction, in order to consider the learning processes designed for the use in autonomous agents, one should first conceive and implement a method of representing data/information (such as features, objects, etc.) in such systems. Within the contemporary learning processes, two principal stages can be distinguished. The first stage concerns the classical machine learning [30] or other new powerful methods, like the deep learning [2], used to initially recognize objects. The second stage of the learning process is founded on a dynamic organization of data representation of previously recognized objects, and is used to perceive and recognize new instances of the objects. Both above mentioned stages/areas are covered by a (complex/integrated) cognitive methodology which implements models of human information processing [19–22, 10]. Such pattern/feature recognition schemes make a powerful method for a great number of benchmark problems and different domain applications. Especially, the idea of feature creation and selection are important for the effectiveness of recognition problems [25].

Basically, with the use of great simplification and approximation, the methods of deep learning can be associated with the process of human cognition.

Using this point of view, in both domains, human and computer, there are the following two actions: feature recognition and analysis. Thus, in general, such a modus operandi can be applied in solving various engineering tasks ranging from arts and architecture to computer science and robotics [8].

In this paper, we present arguments and some solutions for data representation using the results of psychology. Such types of results were applied during the process of constructing ISD – an Intelligent System of Decision-making [19], as well as in one of its implementation in the form of an *xDriver* system [10], an extensively autonomous agent, controlling a model of a car on a virtual highway.

2 Coding Methods in Cognitive Perception

There is a belief that knowledge is represented in human minds analogously to a corresponding sector of reality (*realism* [37]). To cover multiplicity, however, the realism theory would need a large number of copies of a single object in mind. An opposite direction to the realism theory is called *constructivism* [17, 11], which assumes the possibility of the existing variety of possible interpretations (views) for any single object. Furthermore, constructivism also states that learning is an active & constructive process. The learner in those terms constructs information actively by creating its own representations of the objective reality. Any new piece of information is linked to prior knowledge (this means the mental representations are subjective).

On the other hand, it is clear that the early psychology was focused on handling images in human minds, which was only a pure theory, not verifiable. Later on, cognitive psychologists assumed that images are not appropriate representation in the case of problem solving, and created symbolic representations, like semantic networks [32]. The symbolic representation and its formal transformation ideas known as the symbol manipulation paradigm dominated in artificial intelligence for many years [16].

We thus assume suitability of constructivism and its applicability for agent or robotic purposes. This means that we are going to represent objects existing in reality, along with various view-points (use-cases, associations) and ref-

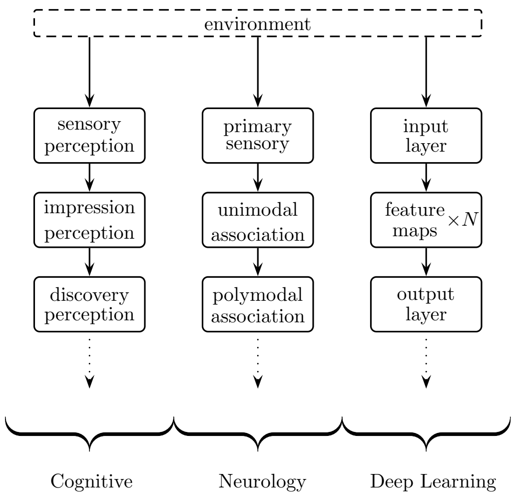


Fig. 1. Comparison of the cognitive, neurological and deep learning approaches to the stimuli processing

erences (relations, links, external-associations), which can be considered as generalized features (impressions, associations) in the semantic network approach. Note that such features play different roles in different contexts (emotions, locations, environment, etc.). It is thus clear that knowledge representation cannot be a pure projection of reality.

As already mentioned, cognitive science, especially the cognitive psychology provides a good basis for designing of learning mechanisms for autonomous agents. Cognitive psychology describes active processing of data (ranging from simple stimuli to a complex memory content) necessary in making decision concerning the issue of choosing an adequate practical reaction. Moreover, the cognitive science is based on a 'computational metaphor' that data processing in human minds may be partly, or completely [34], represented in a similar way as computational manipulations in computer systems.

From the neurology point of view the cognitive process may be seen as a perception-action cycle [13]. A crucial fact is that stimuli are processed in several layers of the system. A simplified schematic comparison of the discussed methods is presented in Fig. 1. The data/stimuli generated by the system's environment are passed over to the first stage of processing (sensory perception/primary sensory/input layer), where they are grouped and tentatively processing. Next, certain features are extracted: the impressions in the cognitive path (shapes, lines, spectrum), the features in the deep learning path, and straight features in the neurological path. The final stage is to merge those features into sensible groups (discoveries). Thereafter the decision concerning a desired reaction, can be worked out [2].

The above mentioned part of cognitive processes is referred to as cognitive perception. There are many works which intend to design a robotic system relying on cognitive perception, especially based on the perception-action cycle [9]. The system of perception appears to be the most crucial element for modern robotic systems. In this context, a *semantic* representation of the environment is very important, also [3]. An associated problem that also needs to be resolved, is the memory representation (*syntax*) of a single object.

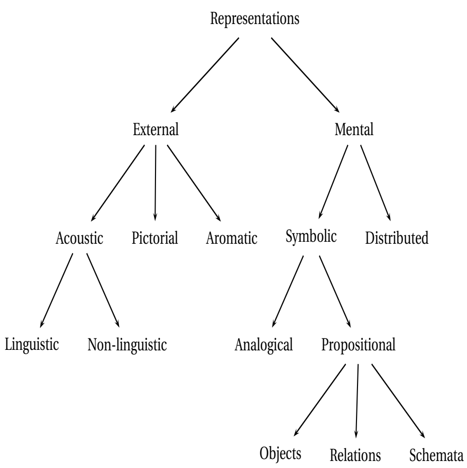
Note that constructivism and newer psychological studies lead to the following guidelines for the knowledge acquisition in humans:

– process the material semantically (as the knowledge is organized semantically, knowledge acquisition is optimized when the learner focuses on the meaning of new material)
– process and retrieve information frequently (retrieving or self-producing information can be contrasted with simply reading or copying it)
– connect new information to the prior knowledge
– create cognitive procedures (procedural knowledge is better retained and more easily accessed).

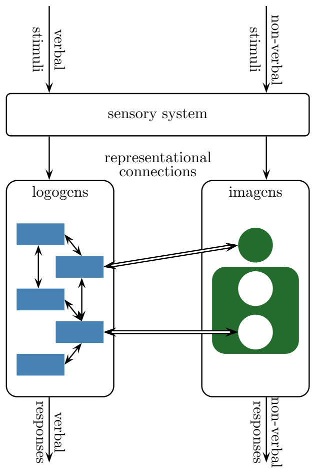
which also constitute a reasonable base both for the learner and for the learning applied in our developed ISD system.

2.1 Syntax of Memorized Objects

There are several theories categorizing mental representations of reality in cognitive psychology [33]. Allan Paivio [36] distinguishes *logogens*, memorized entities which can be put into words or labels (not displaceable or non-rotatable), and *imagens*, graphical items or other images of reality (which can have different placement or position and pose or view). In our interpretation such a label (logogen) will be equivalent to a notion (idea or concept). Imagens and logogens are appropriately connected using internal associations (references, links, or orderings). The theory of Paivio, also understood as dual-coding [39], is graphically interpreted in Fig. 2b.



(a) Types of representations in [12]



(b) The dual-coding theory [36]

Fig. 2. The models of data representation

In accordance with [12], generalized objects (both external or physical and mental or abstract) can be classified with the use of a tree (Fig. 2a). It is clear that with this representation only some aspects of the environment can be described. We consider the symbolic representations to be most important within the right ('mental') branch. In our treatment, the 'analogical' part concerns images and imagens, whereas 'propositional' objects are composed of relations, (sheer) objects and schemata (all of them can be logogens).

Another theory of memorizing objects is proposed by Stephen Kosslyn [18], who brings-up the fact that physical objects exists in 3D, and can be represented in a mental three-dimensional space by means of a 3D mental medium, where information takes the form of a cloud of points [5]. Such a medium has three most important properties of geometry:

- it may show spatial properties of an object, as well as some specific relation to other objects in the space (e.g. proportions)

– it may be zoomed, rotated and translated
– its details can blur in a time course.

According to Kosslyn, the long term memory (LTM) [19], used for keeping memorized objects (generalized: physical and abstract), is composed of only two basic types of elements: images and propositions, which take the form of *files*, describing object properties [12]. Image files contain all information necessary to visualize an image in the medium. In addition, in our solution, the points of the cloud (medium) can have additional features (like an individual color).

Experiments [41] show that spatial representation in human minds is in daily use. Moreover, this representation can be sufficiently accurate for many purposes, and can also be faster than pure semantic representation. Clearly, people quickly recognize pictures (without verbal interpretation), as compared to a virtual scene described by the text (with the use of free interpretation). There are several qualities which make the imageries special [40]:

– Effortless structure: Visual features are more important than the other sensations (see the methods of presentation, first impression, etc.), as a vital result of the human evolution. The structure of imagery results from visual perception (see the highly specialized decoders, like face detectors).
– Determinism: Basically, at any moment, there is only a single set of structures applied in visual perception. Sometimes, however rarely, there are pictures that can be interpreted in two ways (illusions). Nevertheless, the imagery is much more clear and deterministic than semantic (text) description.
– Perception-action coupling: Visual perception is inextricably linked with levels of reactions. This feature is very important in case of obtaining new data about the object of interest. Without vision, an agent, robot, or human cannot easily interfere with the surrounding space and objects.
– Pre-interpretation: A bottom-up process of perception, allows us to pre-interpret certain visual stimuli. This phenomena is very important in case of emergency (needing a fast reacting).

From the engineering point of view, there are also other issues to be solved. An important one is what to do with mathematics? Recall that the dual-coding theory states that all objects can be represented as imagens or logogens. The same concerns the representations of abstract operations (like square root). Another problem is how to evaluate them: In a most simple and practical case, some procedural techniques can be applied here. McCloskey & Macaruso [27] propose using numerical methods, based on the language of mathematics [7]. Today, this kind of representation allows also for a faster manipulation of numbers.

In summary, the system of human mind representation is triple coded (logogen, imagen and numerics). Any object may be described using a semantic verbal description (e.g. 'a horse has 4 legs'). Such a verbal representation is also connected to a non-verbal one, being a pack of 'graphical' features of this object (e.g. shape, color, texture, etc.). It is common that the non-verbal representation includes also a sample of this object (its image as a whole). Both verbal and non-verbal representations can also use numbers (simplifying the description).

Recently, a whole branch of knowledge representation and automatic extraction of knowledge, called data mining, has been developed within computer science. Structures called ontologies have been created in networks communication. They are defined as a formal explicit specification of a shared conceptualization [6]. In general, knowledge can be represented as the first-order logic and description logic [6], Minski's frames [29], or semantic networks [35]. There are also methods of uncertain knowledge representation, like neural networks, fuzzy systems, or Bayesian networks [44, 38].

3 Knowledge Representation in ISD

The Intelligent System of Decision-making (ISD), developed by Kowalczuk & Czubenko [19, 20] is based on human psychology. The ISD already includes some basic forms and elements taken from the representation theories. They result from cognitive psychology that deals with the process of perceiving (Fig. 4). On a similar basis, the ISD has elementary mechanisms of memory [22], especially the semantic one [28], suitably modelled and implemented. The semantic memory is responsible for storing abstract data, commonly known as knowledge. In a most simple view, the idea can be described in short as the stimuli coded into impressions, which are recoded into discoveries.

An impression is a simple feature of an object (like color, texture, etc.). Impression results from the activity of ascending paths, extending from receptors [14]. There are two groups of impressions [22]:

- primal: physical features, connected with real features of an object, and
- secondary: features associated with an object in the agent's memory, like feelings (sub-emotional context), certain composed impressions (like: 'this object may be friendly'), or associations to all kinds of needs.

Impressions (especially the primal ones) are recognized by several mechanisms of human mind [23] modelled in the resulting impressions-extraction diagram of ISD shown in Fig. 4. Those features describe the perceived objects written in using the mental system representations. According to the Kosslyn theory, impressions may be parts of the images *files* [18] mentioned before and corresponding to the discovery concept of ISD. The impressions, as primitives, are stored in a highly unwriteable piece of LTM (Long Term Memory). Thus, though new impressions may appear, it is a rare case.

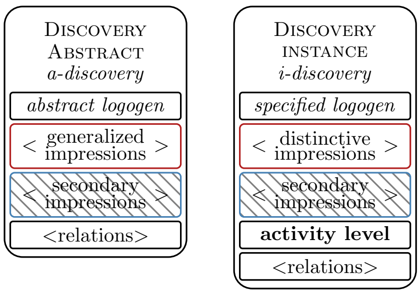


Fig. 3. Structures of discoveries [22]

New impressions of the secondary type can describe complex features of objects which are connected to the evaluative function of the human mind (for instance, something may be evaluated as 'awful'). Moreover, the secondary impressions may refer to some motivative factors – like emotions (a sub-emotional context) or 'objective' needs. Both motivational factors: emotions and needs, are interpreted, stored, and applied with the use of fuzzy representation [42]. They appear to be natural for the purpose of decision-making and communicating with human. The fuzzy-set approach to modelling emotions seems to be more natural than any crisp mathematical model.

Discovery is an abstract representation of an object. In most cases it can be imprecise, subjective and incomplete. It contains a list of impressions associated with the object (both primal and secondary), an object label (logogen), and connections to other discoveries (relations). Relations between discoveries can be presented in the form of propositions. For our robotic purposes the applied concept of discoveries and impressions covers the previously mentioned theories to a great extent.

The idea of discovery, in a certain sense, may be generalized to the concept of (abstract) *a-discoveries* [22]. Such a generalization allows the system to create an abstract part of semantic memory (a part of LTM) in a tree form. The roots of the tree represent most abstract objects (eg. 'animals'), whereas the leaves are usually certain instances of objects (e.g. a black horse). Consecutive instances of leaves are also possible (e.g. 'Black Star' can be a dark horse). They are called *i-discoveries* (discovery instances). The basic relationship between a-discovery is the relation of inheritance or succession (e.g. 'horse is an animal'), whereas the most common relationship between i-discoveries is the relation of belonging or affiliation (e.g. 'Silver Star belongs to Joe'). Moreover, the i-discovery also inherits from its parent (e.g. 'Silver Star is a horse'). The basic structure of the discoveries is shown in Fig. 3. To optimize the searching problem, an activity level or forgetting [24] has been added to the concept of i-discovery. In such a way most important discoveries can be recognized faster.

3.1 Path of Information

The path between the stimuli and a reaction proceeds through several stages [20]. The first stage of data gathering is sensory perception (Fig. 4), which receives the stimuli from certain receptors responsible for senses (sight, hearing, taste, smell, touch, balance, temperature, kinesthetic, pain) [33]. The sensory perception has two phases, related with proximal (an image on receptors) and distal (real objects represented as a stimulus) stimuli [26]. Proximal stimuli are written into a sensory memory, the receptors can focus on recognizing certain concrete features (impressions). The process of impression recognition is led according to some algorithms, which recognize shapes, colors, contours, textures, etc. This process is called the bottom-up recognition of impressions. Such a process can also have a top-down form, where some mechanisms can search the memory for the secondary impressions, and compare them with the current proximal stimuli.

3.2 Discoveries and Their Tecognition

Recognized impressions are grouped according to their localization in the space of performed perception. A sensible assembly of such impressions is called discovery. Grouping due to localization is not sufficient for the recognition. The process of discovery recognition involves searching the a-discoveries tree (a part of the semantic memory [28]), and matching the impressions. A discovery is recognized based on a best match performed using a certain threshold (e.g. 90% of agreement). Otherwise a signal FNO (Fetch New Object) is generated, and a new pack of discoveries is fetched and taken for comparison. After few trials the recognized discoveries are moved to a current scene memory, and the unrecognized ones are passed through to the second stage of searching and comparing.

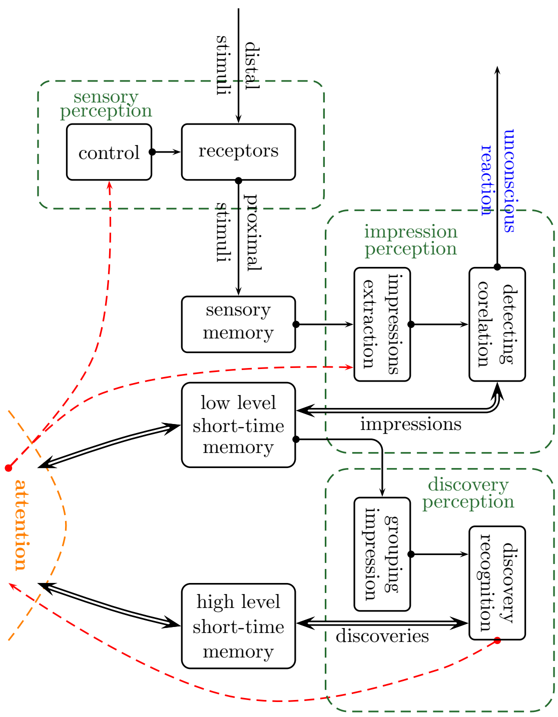


Fig. 4. The ISD perception process

In the second stage of the discovery recognition process, the agent compares unknown discoveries with some old, previously unrecognized objects (u-discoveries). In the case of matching (or similarity, in practice), the count number of this temporary discovery increases. When no match is found, the perception process generates a signal RNuO (Remember a New unrecognized Object) and creates a new unrecognized temporary discovery. At the end of this stage, when the count number of certain unrecognized discovery achieves a set level, this discovery is treated as an i-discovery and is moved to the semantic memory (yielding an associated signal of CNO, Create New Object). During this process, the analyzed discovery is consciously given a certain temporary name created by the thinking process. Presumably, some associated impressions of currently analyzed discoveries can be contradictory. In such cases, the discovery is dropped, issuing a respective signal DO, Drop the Object.

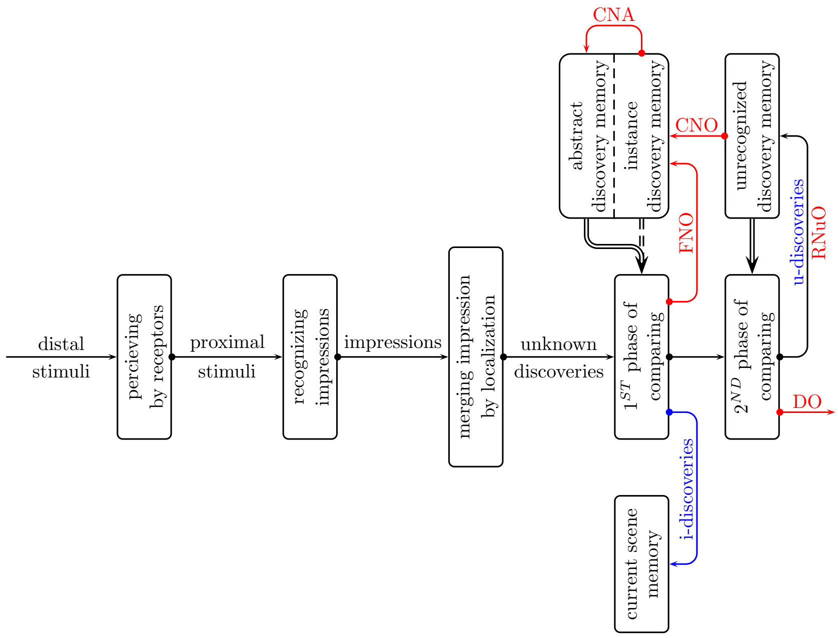


Fig. 5. Information path in the ISD system

4 Autistic Thinking and Learning

The cognitive process of thinking can be divided into two parts: realistic and autistic [4]. Realistic thinking is designed to achieve a particular goal, whereas autistic thinking is the formation of loose associations, imaginary hypotheses, etc. [33]. It also allows us to generalize the newly discovered i-objects, hence creating new a-discoveries (Create New Abstract on Fig. 5).

On the other hand, according to the Baron's theory [1], there are two groups of thinking: search and inference. The search group refers to the goal-directed (realistic) thinking, and may concern three classes of items: goals (using Pareto optimization, for instance), possibilities (considering various paths leading to the goal) and premisses (for gaining the goals). Inference consists in formulating conclusions on the basis of known prerequisites (e.g., generalization of the purposes, the formulation of proofs, etc). In addition, by inference, you can redefine poorly defined problems (or change of the goals), or close open problems [33]. Whereas the goals and possibilities refer to the goal-directed (active) thinking, the searching of evidences is rather associated to the autistic thinking.

Such a categorization allows us to present the autistic thinking as the one which manage the process of learning, especially its memorizing part. During autistic thinking, the mind can restructure the semantic memory (a part of Long Term Memory), add new relations, create new abstracts, and merge the old ones. Autistic thinking is also responsible for creating new impressions and accepting them to the set of the identified impressions, whereas realistic thinking allows, in the context of mental representation, to add new relations and impressions (from the accepted ones) to the currently known objects, as well as to name new discoveries.

4.1 Process of Restructuring the Memory

The process of restructuring the memory is concerned about both the abstract and the instance part of semantic memory. It performs the following four actions:

- creating a new a-discovery, by generalization of several i-discoveries, only when they are highly similar
- merging the old a-discoveries, in the case of high (fuzzy) similarity
- finding and evaluating new relations between the defined a-discoveries and i-discoveries
- creating new relation prototypes, based on a knowledge earlier obtained (e.g. a 'person' may be 'employee' of other 'person').

The best way to describe the relations taking place in the human mind and to implement them in computer science, lies in using linguistics, and fuzzy logic [43]. There are a lot of different relations grouped by their type [15]. Currently, in the ISD system, the relation prototypes includes only inheritance, possession, membership, instances (especially, the relations between the i-discovery and a-discovery), and feeling. This list can be further expanded in future.

5 Conclusions

The presented introduction to modeling of object representation in the memory of autonomous robots, is based on the psychological review of mental representations. The developed model uses the latest results from computer science, especially the ones concerning knowledge representation and fuzzy systems. As the experiments show [10], this combination seems appropriate for autonomous robot systems founded on cognitive models.

In future works we are going to implement the representation system described above on the ISD platform for new practical autonomous humanoid robot applications (like the NAO robot created by Aldebaran Robotics), which are to be based on the OWL-DL language and equipped with a number of mechanisms of reasoning (to mention the F-Logic system, and, especially, Flora-2).

Appendix: Memory Model in xDriver Simulations

This appendix presents a short note on an implementation of the ISD system, in which the memory model has been programmed in the language XML. Simulations were performed in JAVA, using several additional libraries (like guava, fuzzy110a, JFreeChart).

The aim of this study was to test the ISD system in the task of control of the car on a highway.

The *xDriver* system based on the ISD was used for the task of simulated car driving [10]. The principal aim of the *xDriver* simulation study was to test the ISD system (described partly here, and partly in our earlier publications [19–21]) in the task of autonomous driving.

Since the ISD system is a result of a thorough modelling of human psychology (generally known), there are concepts somehow similar to ISD which can be found in the literature (e.g. [31]). There are, however, no reports of a system which would model the human psychology for such practical purposes as autonomously driving, for instance. It is worth noting that our simulations have proven that the *xDriver* system may behave on the road as an inexperienced human driver [10].

The *xDriver* was tested only in virtual simulations, and real objects or images were not recognized. Nevertheless, it worked properly based on its own developed semantic memory. The applied concept of memory allowed the *xDriver* to 'understand' the traffic regulations, to make its own decisions, and, in consequence, to ride in accordance with the rules. In particular, the following types of abstract objects were applied in the *xDriver*: lane, horizontal road sign, vertical road sign, virtual static objects (trees, houses, etc.), and virtual dynamic objects (such as other cars, pedestrians, etc.).

In general, the semantic memory of the *xDriver* consists of abstract objects, which are represented as a-discoveries in the ISD system (Fig. 3), and instances of them (i-discoveries). Fig. 6 shows a sample of the semantic memory of the *xDriver* that consists of i-discoveries and a-discoveries. Boxes represent discoveries. The i-discoveries are marked by the encircled 'i' in the left corner of the box, the other discoveries are the a-discoveries. A-discoveries have generalized features (impressions, in the first sub-box, shown in red color), and their own labels (in italics). I-discoveries have distinctive impressions, which distinguish them from the a-discoveries, and allows us to process the impact of them on the cognitive decision making performed by ISD. The i-discoveries have a need context and contain also secondary impressions (marked with 'e:'), which are vital for the emotional context of the *xDriver*. The emotional context (as fuzzy membership functions) takes values between 0 and 1 and is applied in a procedure [20, 21] weighting all actually perceived objects. The need context of an object can also assume a normalized integer value (see the *pedestrian* object in Fig. 6), interpreted as a simple shift (increment or decrement) in a need unfulfilment function (or a more involved procedural estimation) for the indicated need of the analysed object. The value of the shift can change during the learning process, which allows for improvement of the semantic knowledge.

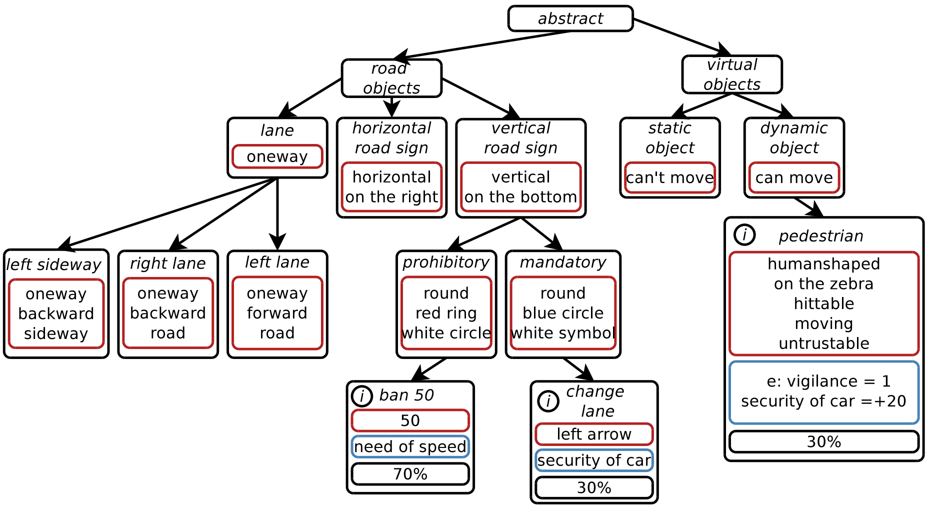


Fig. 6. Part of the semantic memory of the xDriver

The first sub-box (marked additionally in red color in Fig. 6) in each discovery definition describes here a single impression or a set of them (representing an object or discovery). The road signs (1-3) listed above (and defined as single impressions) can only trigger a kind of procedural evaluation of the actual needs of the *xDriver*. Whereas all the virtual objects (4-5) mentioned above can have their specific (not null) emotional or need contexts specified in the second sub-box (marked additionally in blue), that is, they can influence the needs and emotions of the xDriver. When the *xDriver* sees a sign 'speed limit 50' (in short 'ban 50' in Fig. 6, for instance, an evaluation of the indicated *xDriver*'s need starts, in which the *xDriver* re-estimates its *need of speed*, in a procedure which takes into account the resulting offset of the actual speed of the car over the imposed restriction (50 km/h). Note that, as compared to the road signs, the virtual objects have a number of defining impressions or features, including impressions like 'hittable' or 'accidentable', which point to certain possible consequences of interacting with these objects (for the composed driving system). The third sub-box (marked in black in Fig. 6) represents an activity level of the i-discovery (in terms of a currently updated relative frequency of its appearance).

Based on the above description of the characteristics of the ISD system, it is clear that the set of the presented objects can easily describe a straight road environment with which the *xDriver* is able to interact.

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