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proCog - a Biologically Motivated Relational Network

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Introduction

Most everyday activities heavily rely on the interaction of data driven bottom-up processing and category driven top-down information flow. This is especially true for perceptual tasks, for which high-level effects like current context, emotional state or generated expectations are well known. The proCog system we developed is an attempt to target this interaction within a simple graphical representation and a spreading activation algorithm.

Our approach avoids a strict separation between perceptual and conceptual representations as it has been proposed recently (see e.g. Barsalou, 1999), makes use of a joint bottom-up and top-down processing that follows biological principles (e.g. Ahissar & Hochstein, 2002) and confines on simple propagation of energies as inference rule (Collins & Loftus, 1975). As application domain a house scenario was selected for which knowledge about various rooms and objects typically located in them were fed into the system.

Network Architecture

Nodes

The domain knowledge is represented in a graph structure. There is only one type of node in the proCog network which is the representational entity of all concepts of the domain. Since these concepts are usually associated with different representational levels, a node in our network can be the representation of qualitative different concepts:

- representation of a sensory measurement, e.g. the color *color_FF0110* detected on some object
- representation of an instance of a concept, e.g. *cup1_kitchen1*
- representation of a category, e.g. *crockery*, as part of a classical ontology

The category nodes are taken mainly from the standard WordNet database and comprise not only knowledge about objects and locations, but also sensory categories like perceptual attributes, affordances or string representations. Instances thereof include specific views of objects and locations and can also be yet unclassified.

Links and Operators

Currently there are five relation types in use: *subclassOf* and *instanceOf*, which denote membership and set inclusion, *isLocatedIn*, which connects the subdomains of objects and locations and *isViewOf*, *hasRep* and *hasAttr* to ground the symbolic representations with perceptual entities. For the comparison of different sensory measurements and associated categories, operators were implemented for the domain of colors and shapes of objects.

Network Dynamics

Activation Algorithm

The dynamics of the relational network is based on a distributed activation radiating outward from some origin nodes. This idea of spreading activation dates back to the work of Quillian (1962) and has now many applications in various fields. The architecture described here is based on earlier work on brain-like information retrieval (Röhrbein, Artmann & Hirsch, 2004; for an overview see e.g. Crestani, 1997).

For the explicit modeling of different processing streams, the information spread is subdivided into several phases: The priming phase, which starts with a list L_1 of activated nodes and leads via top-down propagation of s_1 to an energy distribution which can be interpreted as the result of a fast “first guess” or as the result of a preceding classification. In the following activating phase, the energy (s_2) is spread along the entire network, originating from a second list of nodes (L_2) and constrained by damping factors p*. The final focusing phase acts top-down to perform a final filtering according to keywords specified in L_3 (with energy s_3) and results in a more precise energy distribution a_i of all nodes, which is considered as the system's output (see Equation 1).

The three phases are coupled straightforward by weighting the start values s_n of every phase with the resultant activation of the preceding phase. For nodes not in list L_n corresponding default activations d_n apply. The algorithm can handle several start nodes and for each a separate activation spread k_{ij} is performed. Since there can be multiple paths between nodes i and j, the maximum of all incoming energy values of a node is taken before the results of all spreads are summed:

$$a_i = \left\| d_2 + \sum_{j \in L_2} \max \kappa_{i,j} \right\| \cdot \left\| \sum_{\substack{j \in L_3 \\ (j,i) \in R^+_{onto}}} s_{3_j} + d_3 \right\| \qquad (1)$$

Information Flow

Each of these phases has its own view of the semantic network and can be customized separately. Whereas the priming and the focusing algorithm perform top-down processing by propagating energy only along the *instanceOf* and *subclassOf* links without any link or node damping (cf. transitive closure of R_{onto} in Equations 1 and 2), for the activating phase the whole semantic network is visible and the activation spread can be selectively constrained. In proCog, the nodes' energy values are calculated using separate dampings for the traversed links and nodes. These damping factors are specified as follows:

- For each node, the damping factor is the resultant activity of the priming phase
- For a link corresponding to a relation between instances of the knowledgebase and/or sensory measurements the factor is the product of a global damping factor and one specific for the horizontal direction, leading to a associative processing mode
- For an *instanceOf* or a *subclassOf* link, the factor is the product of a global damping factor and one selectively for the bottom-up direction. If the activation spreads in reverse direction a damping factor for the top-down direction applies.

Equation 2 recursively defines the spreading activation for all nodes i directly or indirectly connected to some origin nodes (case i=j) that have activation s_2:

$$\kappa_{i,j} = \begin{cases} s_2 \cdot \left\| \sum_{\substack{l \in L_1 \\ (l,j) \in R^+_{onto}}} s_{1_l} + d_1 \right\| & \text{if} \quad i = j \\ p^* \cdot \kappa_{k,j} \cdot \left\| \sum_{\substack{l \in L_1 \\ (l,i) \in R^+_{onto}}} s_{1_l} + d_1 \right\| & \text{else} \end{cases} \qquad (2)$$

Results

We obtained first results with situations that use ontological knowledge, with tasks that exploit prior knowledge about e.g. the default location of objects and with classification tasks. Table 1 summarizes the systems' behavior for 4 basic configurations. For simplification here no priming is used, L={}, and only the output nodes with highest ranking (a_i) are shown.

Table 1: Exemplary results with activated and focused nodes as input and different damping factors (p*).

processing mode (p*)	**activated nodes (L_2)**	**focused nodes (L_3)**	**resulting nodes (max. a_i)**
associative	color_EE0000 shape_of_cup	object	cup1_kitchen1
associative	cup1_kitchen1	room	kitchen1
bottom-up	cup1_kitchen1 plate1_kitchen1		tableware
bottom-up + top-down	cup1_kitchen1		cup1_kitchen1 cup1_kitchen2 cup2_kitchen2

The first two examples demonstrate associative activation spread starting from sensory measurements with different foci leading to a behavior, which has some classification and localization resemblance. The lower rows refer to situations in which the ontology is used. Pure bottom-up spread leads to the common category of the input nodes (L_2), but to all instances of the same category, if also top-down spreading is enabled.

Activation spreads can be easily piped by using high-ranking nodes as input for the next priming phase. Important aspects for further development include an analysis of robustness with respect to the initial values. Not shown here are further refinements due to individually weighting of activated nodes.

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