Language Acquisition from Neural and Sensorimotor Systems

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A fundamental learning problem in adaptive, embodied cognitive systems is how to learn discrete models of situated experience which can mediate between sensorimotoric experience and high-level cognitive processes (such as language and planning) [1]. Recent approaches include learning of discrete Hidden Markov Models for behaviour description [2] and active (curiosity driven) learning of perception prediction [3]. Through curiosity driven learning, also communication itself can be "discovered" among other actions as a source of rich information [4]. It can also be argued that in order to learn a situated form of language that takes into account the embodiment of the robot, there needs to be a close correspondence between the sensorimotor and linguistic capabilities. The robot should communicate about what it knows, and through active learning it could know how its actions will affect the environment.

In relation to situated language acquisition, the field of rule extraction from recurrent neural networks (RNN-RE) may seem to be a completely unrelated [5], [6]. There are, however, important connections between these fields that we suggest to exploit. RNN-RE is a form of automated discretization of dynamic systems, which is precisely what may be essential in mediating between sensorimotor control systems and higher-level cognition. Most earlier algorithms have, despite much progress, not been applied to very large complex RNNs trained on deep linguistic problems [7].

In recent work, however, many of the previous limitations have been surmounted through integrating previously separated components of RNN-RE algorithms [8]. Through the novel algorithm, `CrySSMEx`, extraction from RNNs is now possible for deep context-free grammars, for large RNNs (10^3 state nodes), chaotic systems and, for example, from echo state networks [9] predicting natural language sequences [10], [11]. A trained RNN in combination with `CrySSMEx` is a form of language acquisition. But there is no reason for only considering RNNs among the potentially broad set of dynamic systems that are susceptible to analysis of the kind that RNN-RE represents. We suggest that the dynamic system comprised of the sensorimotor-environment feedback loop of a situated robot is such a system.

We essentially want to view the learning of perceivable consequences of actions, in different situations (states), as a language acquisition problem. The goal is to find the "grammar" underlying the dynamics in the "dialogue" between the robot and its environment. `CrySSMEx` supports this by extracting a stochastic finite state machine description of the system. Moreover, accompanying the machine is a hierarchical description of how the continuous state space of the dynamic system is mapped to the extracted discrete states (i.e. grounding the grammar in the system). This hierarchical description can be considered `CrySSMEx`'s ontology of the state space.

The desired next step is to guide the active learning through social interaction [12]. This can involve guiding of exploratory curiosity driven behaviour ("dynamic scaffolding") as well as explicit labelling of the concepts acquired by `CrySSMEx`. This way we hope that a natural and transparent human robot interaction can be established as well as a means for establishing a common linguistic ground between the robot and its tutor.

We are implementing this under the EU FP6 IST Cognitive Systems Integrated project: "Cognitive Systems for Cognitive Assistants - CoSy" (`www.cognitivesystems.org`). Within the CoSy project a cognitive architecture is being constructed that facilitates integration of various subarchitectures (in C++, Java, Python). The architecture is already integrated with subarchitectures such as speech recognition and synthesis, natural language processing, planning, computer vision, visiual feature learnin, kinematics, etc.

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