08041 Abstracts Collection
Recurrent Neural Networks- Models, Capacities, and Applications
— Dagstuhl Seminar —

Luc De Raedt[1], Barbara Hammer[2], Pascal Hitzler[3] and Wolfgang Maass[4]

[1] Universität Freiburg, D
luc.deraedt@cs.kuleuven.be
[2] TU Clausthal, D
hammer@in.tu-clausthal.de
[3] Universität Karlsruhe, D
hitzler@aifb.uni-karlsruhe.de
[4] TU Graz, A
maass@igi.tu-graz.ac.at

Abstract. From January 20 to 25 2008, the Dagstuhl Seminar 08041 "Recurrent Neural Networks- Models, Capacities, and Applications" was held in the International Conference and Research Center (IBFI), Schloss Dagstuhl. During the seminar, several participants presented their current research, and ongoing work and open problems were discussed. Abstracts of the presentations given during the seminar as well as abstracts of seminar results and ideas are put together in this paper. The first section describes the seminar topics and goals in general. Links to extended abstracts or full papers are provided, if available.

Keywords. Recurrent Neural Networks, Neural-Symbolic Integration, Biological Models, Hybrid Models, Relational Learning Echo State Networks, Spike Prediction, Unsupervised Recurrent Networks

08041 Summary – Recurrent Neural Networks - Models, Capacities, and Applications

The seminar centered around recurrent information processing in neural systems and its connections to brain sciences, on the one hand, and higher symbolic reasoning, on the other side. The goal was to explore connections across the disciplines and to tackle important questions which arise in all sub-disciplines such as representation of temporal information, generalization ability, inference, and learning.

Joint work of: De Raedt, Luc; Hammer, Barbara; Hitzler, Pascal; Maass, Wolfgang

Full Paper: http://drops.dagstuhl.de/opus/volltexte/2008/1424

Neural-symbolic Integration: Constructive Aproaches for First-Order Logic Programs

Sebastian Bader (TU Dresden, D)

After a short introduction into the area of Neural-Symbolic Integration – from our perspective – and its state of the art, we will show how to construct neural networks approximating the consequence operator of a given first order logic program. This will include the construction of different network architectures. Furthermore, we will present some preliminary experimental results.

Keywords: Neural Symbolic Integration, First-Order Logic Programs

Joint work of: Bader, Sebastian; Hölldobler, Steffen; Hitzler, Pascal; Witzel, Andreas

Full Paper:
http://www.springer.com/engineering/book/978-3-540-73953-1

See also: Sebastian Bader, Pascal Hitzler, Steffen Hölldobler and Andreas Witzel, The Core Method: Connectionist Model Generation. In Perspectives of Neural-Symbolic Integration, Series: Studies in Computational Intelligence, Vol. 77, Barbara Hammer and Pascal Hitzler (Eds.), Springer, 2007, ISBN: 978-3-540-73953-1, pp. 205-232

Summary on the discussions on Neural Symbolic Integration

Sebastian Bader (TU Dresden, D)

While summarizing the discussion on Neural-Symbolic Integration, we found the following three questions to be of central importance: (1) How can we convince others to buy what we do? (2) What can be added to what we did so far? and (3) What can be gained from what we did so far? While trying to answer these questions, we listed a number of challenges. Those open problems can be grouped into five categories. (a) Application Scenarios, (b) Possible Extensions, (c) Relation to Biology and Cognitive Science, (d) Underlying Theory and (e) SyNe.

Of central importance is the identification of possible application scenarios (a). We expect to outperform conventional approaches within the areas of (natural) language processing and ontology learning from raw data. But this has to be shown on benchmark problems, on either already existing or on new ones. We also looked at possible extensions of our approach (b). These include the learning of the embedding function, the addition of probabilities and extensions to other logics. But we should also focus more on inferences and the learning of models and not only on representation aspect of logic. Finally we should study the relation of our systems to the area of inductive logic programming. Another open question is the relation to biology and cognitive science (c). Even though artificial neural networks were initially built to mimic the brain, little biology is left in present systems. The relation between neural-symbolic integration and those areas could lead to new insights for both. Unfortunately, a unfying theory (d) underlying all approaches in our area is still missing. This theory, should enable us to compare the approaches better and to understand their relation. Currently, neural-symbolic integration is about the embedding of logic into connectionist systems, but can we also take ideas from neural networks and integrate them into symbolic systems (e)? One option would be to introduce the concepts of gradient descent learning into logic.

We are now in a position to answer the initial questions. (1) We can convince other people, if we can outperform conventional systems. (2) There are many possible extensions, ranging from the adaptation to other logics to real inference procedures. (3) Even though we hope that our work will provide new insights for biologists or cognitive scientists, we expect more immediate advantages in the area of machine learning. But this needs to be shown by the successful application of a neural symbolic system to some real world problem.

Joint work of: Bader, Sebastian; Kühnberger, Kai-Uwe; Zaverucha, Gerson

The Core Method: Connectionist Model Generation

Sebastian Bader (TU Dresden, D)

Knowledge based artificial networks networks have been applied quite successfully to propositional knowledge representation and reasoning tasks. However, as soon as these tasks are extended to structured objects and structure-sensitive processes it is not obvious at all how neural symbolic systems should look like such that they are truly connectionist and allow for a declarative reading at the same time. The core method aims at such an integration. It is a method for connectionist model generation using recurrent networks with feed-forward core. After an introduction to the core method, this paper will focus on possible connectionist representations of structured objects and their use in structure-sensitive reasoning tasks.

Keywords: Artificial Neural Networks, Neural-Symbolic Integration, Logic Programs

Joint work of: Bader, Sebastian; Hitzler, Pascal; Hölldobler, Steffen; Witzel Andreas

Full Paper:
http://www.springer.com/engineering/book/978-3-540-73953-1

See also: Sebastian Bader, Pascal Hitzler, Steffen Hölldobler and Andreas Witzel, The Core Method: Connectionist Model Generation. In Perspectives of Neural-Symbolic Integration, Series: Studies in Computational Intelligence, Vol. 77, Barbara Hammer and Pascal Hitzler (Eds.), Springer, 2007, ISBN: 978-3-540-73953-1, pp. 205-232

Hybrid Dynamical Systems and Hybrid Differential Calculus

Howard Blair (Syracuse University, USA)

We set up differential calculi in the Cartesian-closed category of *convergence spaces*, and use these constructions to unify continuous, discrete, and hybrid differential calculi.

All topological spaces and directed graphs, together with hybrid amalgamations are convergence spaces. Some of the resulting differential calculi conservatively extend elementary differential calculus on Euclidean and Hilbert spaces. Some convergence spaces admit regular actions: Example: translations on a Euclidean space. These include topological vector spaces and modules over rings and lead to a unique maximum differential calculus that generalizes linear functions as differentials. Models of first-order logic expand to convergence spaces. This permits a differential operator to be added to .e.g. first-order logic. For X, Y topological spaces, X locally compact implies the space of continuous functions from X to Y, has the compact open topology as its convergence structure.

Keywords: Hybrid System, Convergence Space, Filter, First-Order Logic, Topology

Joint work of: Blair, Howard A.; Jakel, David W.; Rivera, Angel J.; Irwin, Robert J.

Full Paper:
http://www.cis.syr.edu/Hybrid_Calculus

Learning from relational databases using recurrent neural networks

Hendrik Blockeel (Katholieke Universiteit Leuven, B)

Learning from relational databases includes the problem of automatically constructing features that represent some form of aggregation over intentionally defined sets, where the aggregation function and the conditions defining the set are to be learned simultaneously. Recurrent neural networks can represent such features. In this talk we present "relational neural networks", an approach to relational learning that incorporates recurrent networks. Experimental results show that relatively complex aggregate features can be learned accurately using this approach.

Keywords: Relational Learning

Joint work of: Uwents, Werner; Blockeel, Hendrik

Probabilistic Logic Learning: An Introduction

Luc De Raedt (Katholieke Universiteit Leuven, B)

Statistical Relational Learning is a new subfield of artificial intelligence lying at the intersection of machine learning, reasoning about undertainty and relational and logical representations. It aims at developing models that can elegantly deal with objects as well as the relationships that hold amongst them. In this talk, I shall first motivate this research stream using a number of applications and then analyse its state-of-the-art taking a logical perspective.

More specifically, I shall explore the relationships between the traditional probabilistic models, which work essentially with a propositional representation, and their upgrades within statistical relational learning and introduce these using a number of examples. The examples used will include the upgrading of Bayesian or Markov networks (towards PRMs, BLPs or MLNs) and those of probabilistic Context Free Grammars and HMMs (towards SLPs, PRISM, ICL and LOHMMs) as well as our recent work on ProbLog and link mining in large biological networks.

Keywords: Probability, Logic, Learning, Inductive Logic Programming, Statistical Relational Learning

See also: De Raedt, Kersting, Probabilistic Logic Learning, SIGKDD Explorations 2003

Neural-Symbolic Learning Systems: from Non-Classical Reasoning to Relational Learning

Artur Garcez (City University - London, GB)

Three notable hallmarks of intelligent cognition are the ability to draw rational conclusions, the ability to make plausible assumptions, and the ability to generalise from experience. Although human cognition often involves the interaction of these three abilities, in artificial intelligence they are typically studied in isolation. In our research programme, we seek to integrate the three abilities within neural computation, offering a unified framework for learning and reasoning that exploits the parallelism and robustness of connectionism. A neural network can be the machine for computation, inductive learning, and effective reasoning, while logic provides rigour, modularity, and explanation capability to the network. We call such systems, combining a connectionist learning component with a logical reasoning component, "neural-symbolic learning systems". In this talk, I review the work on neural-symbolic learning systems, starting with logic programming, which has already provided contributions to problems in bioinformatics and engineering. I then look at how to represent modal logic and other forms of non-classical reasoning in neural networks. The model consists of a network ensemble, each network representing the knowledge of an agent (or possible world) in a particular time-point. Ensembles may be seen as in different levels of abstraction so that networks may be fibred onto (combined with) other networks to form a modular structure combining different logical systems or, for example, object-level and meta-level knowledge. Networks may also be combined to represent (and learn) relations between objects, with interesting applications in graph mining and link analysis in biology and social networks. We claim that this quite powerful yet simple structure offers a basis for an expressive yet computationally tractable cognitive model of integrated reasoning and robust learning. The material is part of the forthcoming book "neural-symbolic cognitive reasoning".

Modeling Spontaneous Activity and Stimulus-Response Relations of Biological Neural Networks

Tayfun Gürel (Albert- Ludwigs-Universität Freiburg, D)

Cultured mammalian cortical neurons can build small closed system living neural networks. Their activity can be monitored and electrically manipulated by Multi-Electrode Arrays. In this talk, I will present machine learning algorithms that can predict the upcoming activity in both cultured and simulated neural networks. The core of the algorithms consists of echo state networks that are adapted for neuronal spike activity, i.e. time series of point events. The experimental results show that upcoming spikes can be predicted with a good precision from the stimulus and the spike activity history.

Keywords: Neuronal Cultures, Echo State Networks, Spike Prediction

Unsupervised recurrent networks

Barbara Hammer (TU Clausthal, D)

Unsupervised data processing plays a particularly important role in the human brain simply because of the fact that no teacher is available. Despite this circumstance, technical models for unsupervised recurrent networks are still in its first stage, and a zoo of different architectures with very different capabilities exists. We will discuss some of these approaches and address the question of their capacity from a theoretical point of view.

Keywords: MSOM, Unsupervised Recurrent Networks

Logic Programs, Iterated Function Systems, and Recurrent Radial Basis Function Networks

Pascal Hitzler (Universität Karlsruhe (TH), D)

Graphs of the single-step operator for first-order logic programs - displayed in the real plane - exhibit self-similar structures known from topological dynamics, i.e. they appear to be fractals, or more precisely, attractors of iterated function systems. We show that this observation can be made mathematically precise. In particular, we give conditions which ensure that those graphs coincide with attractors of suitably chosen iterated function systems, and conditions which allow the approximation of such graphs by iterated function systems or by fractal interpolation. Since iterated function systems can easily be encoded using recurrent radial basis function networks, we eventually obtain connectionist systems which approximate logic programs in the presence of function symbols.

Joint work of: Hitzler, Pascal; Bader, Sebastian

Full Paper:
http://dx.doi.org/10.1016/j.jal.2004.03.003

See also: Sebastian Bader and Pascal Hitzler, Logic Programs, Iterated Function Systems, and Recurrent Radial Basis Function Networks, Journal of Applied Logic 2(3), 2004, 273-300

Computational properties of lamina-specific structure in cortical microcircuit models

Stefan Häusler (TU Graz, A)

The neocortex is composed of neurons on different laminae that form precisely structured microcircuits. We investigate if such stereotypical microcircuits, in particular their lamina-specific synaptic connection patterns, are distinguished by specific computational properties, which enable it to subserve the enormous computational and cognitive capabilities of the brain in a more efficient way.

For this purpose we analyzed the information processing capabilities of detailed cortical microcircuit models, that are based exclusively on empirical data with regard to their laminar connectivity pattern and consist of Hodgkin-Huxley neurons and dynamic synapses. More precisely we studied to what extent this cortical microcircuit template supports the accumulation and fusion of information contained in generic spike inputs into layer 4 and layers 2/3, and how well it makes this information accessible to the "generic neural users", i.e., to projection neurons in layers 2/3 and layer 5.

Our computer simulations demonstrate that these cortical microcircuit models exhibit specific computational advantages over various types of control circuits that have the same components and the same global statistics of neurons and synaptic connections, but are missing the lamina-specific structure of real cortical microcircuits. We arrived at the conclusion that their particular distribution of the total number of incoming and outgoing synapses of neurons (relative to circuit inputs and projection neurons) is primarily responsible for their better computational performance. Furthermore we showed that in terms of the properties of the dynamical system which is defined by such microcircuit models the dynamics of laminar circuits is less influenced by internal noise and noise in the generic spike input, thereby providing better generalization capabilities of projection neurons that were trained on various generic information processing tasks.

Joint work of: Häusler, Stefan; Maass, Wolfgang

The Core Method for Neural Symbolic Integration

Steffen Hölldobler (TU Dresden, D)

The core method provides a methodology for the generation of models for logic programs using recurrent connectionist networks with a feed- forward core. It combines the ideas that the semantics of logic programs can be obtained as fixed points of logical consequence operators, that contractions over a complete metric space have a unique fixed point and that continuous functions can be approximated arbitrary well by feed-forward neural networks. In the talk I will present examples of the core method for propositional as well as first- order logic programs.

Keywords: Neural-Symbolic Integration, Logic Programs

The Integration of Connectionism and First-Order Knowledge Representation and Reasoning as a Challenge for Artificial Intelligence

Steffen Hölldobler (TU Dresden, D)

Intelligent systems based on first-order logic on the one hand, and on artificial neural networks (also called connectionist systems) on the other, differ substantially. It would be very desirable to combine the robust neural networking machinery with symbolic knowledge representation and reasoning paradigms like logic programming in such a way that the strengths of either paradigm will be retained. Current state-of-the-art research, however, fails by far to achieve this ultimate goal. As one of the main obstacles to be overcome we perceive the question how symbolic knowledge can be encoded by means of connectionist systems: Satisfactory answers to this will naturally lead the way to knowledge extraction algorithms and to integrated neural-symbolic systems.

Keywords: Logic Programs, Neural Networks, Neural Symbolic Integration

Joint work of: Bader, Sebastian; Hitzler, Pascal; Hölldobler, Steffen; Witzel, Andreas

Full Paper:
http://www.wv.inf.tu-dresden.de/~borstel/pub/bhh06.pdf

See also: Sebastian Bader, Pascal Hitzler and Steffen Hölldobler, The Integration of Connectionism and First-Order Knowledge Representation and Reasoning as a Challenge for Artificial Intelligence, Journal of Information 9(1), Jan. 2006, 7–20

Boosting for Statistical Relational Learning

Kristian Kersting (MIT - Cambridge, USA)

Statistical Relational Learning (SRL) is a newly emerging research area that focuses on structured data. More precisely, it deals with machine learning and data mining in relational domains where entities may be latent, partially observed, and/or noisy. Although SRL methods show remarkable performances, the enormous number of possible models makes it difficult to select SRL models automatically from data.

In this talks, I will review our recent successes in applying boosting to leverage learning conditional SRL models. The key idea is to sacrifice comprehensibility by representing SRL models as weighted sums of relational regression models.

A Neural Approximation of Logical First-Order Models Using a Semi-Symbolic Level

Kai-Uwe Kühnberger (Universität Osnabrück, D)

There is an obvious tension between symbolic and subsymbolic theories, because both show complementary strengths and weaknesses in corresponding applications and underlying methodologies. The resulting gap in the foundations and the applicability of these approaches is theoretically unsatisfactory and practically undesirable. We present a theory that bridges this gap between symbolic and subsymbolic approaches by the introduction of a Topos-based semi-symbolic level used for coding logical first-order expressions in a homogeneous framework. This semi-symbolic level can be used for neural learning of logical first-order theories. Besides a presentation of the general idea of the framework some remarks are added concerning an evaluation of the theory and relevant open problems for future research.

Keywords: Neuro-Symbolic Integration, Topos Theory, First-Order Logic

Joint work of: Kühnberger, Kai-Uwe; Gust, Helmar; Geibel, Peter

Perspectives of Neuro–Symbolic Integration – Extended Abstract

Kai-Uwe Kühnberger (Universität Osnabrück, D)

There is an obvious tension between symbolic and subsymbolic theories, because both show complementary strengths and weaknesses in corresponding applications and underlying methodologies. The resulting gap in the foundations and the applicability of these approaches is theoretically unsatisfactory and practically undesirable. We sketch a theory that bridges this gap between symbolic and subsymbolic approaches by the introduction of a Topos-based semi-symbolic level used for coding logical first-order expressions in a homogeneous framework. This semi-symbolic level can be used for neural learning of logical first-order theories. Besides a presentation of the general idea of the framework, we sketch some challenges and important open problems for future research with respect to the presented approach and the field of neuro-symbolic integration, in general.

Keywords: Neuro-Symbolic Integration, Topos Theory, First-Order Logic

Joint work of: Kühnberger, Kai-Uwe; Gust, Helmar; Geibel, Peter

Extended Abstract: http://drops.dagstuhl.de/opus/volltexte/2008/1422

The Grand Challenges and Myths of Neural-Symbolic Computation

Luis Lamb (Federal University of Rio Grande do Sul, BR)

The construction of computational cognitive models integrating the connectionist and symbolic paradigms of artificial intelligence is a standing research issue in the field. The combination of logic-based inference and connectionist learning systems may lead to the construction of semantically sound computational cognitive models in artificial intelligence, computer and cognitive sciences. Over the last decades, results regarding the computation and learning of classical reasoning within neural networks have been promising. Nonetheless, there still remains much do be done. Artificial intelligence, cognitive and computer science are strongly based on several non-classical reasoning formalisms, methodologies and logics. In knowledge representation, distributed systems, hardware design, theorem proving, systems specification and verification classical and non-classical logics have had a great impact on theory and real-world applications. Several challenges for neural-symboli c computation are pointed out, in particular for classical and non-classical computation in connectionist systems. We also analyse myths about neural-symbolic computation and shed new light on them considering recent research advances.

Keywords: Connectionist Con-Classical Logics, Neural-Symbolic Computation, Non-Classical Reasoning, Computational Cognitive Models

Full Paper: http://drops.dagstuhl.de/opus/volltexte/2008/1423

On the Relationship between Biological and Artificial Neural Networks

Wolfgang Maass (TU Graz, A)

This review talk highlighted salient differences between biological and artificial neural networks. In particular the different role of time, as well as the diversity of neurons and synapses, and the substantial amount of spontaneous activity and trial-to-trial variability in biological networks of neurons was discussed. From these results, constraints and research goals were derived for artificial neural network models that aim at capturing essential aspects of inference in biological networks of neurons.

A Model for Bayesian Inference and Learning of Bayesian Inference in Neural Networks

Wolfgang Maass (TU Graz, A)

This talk sketched work in progress on a simple architecture for Bayesian inference in neural networks, as well as a new learning rule (the Bayesian Hebb rule) for learning correct Bayesian inference in such networks. It was shown that this learning rule is very fast (in fact, it beats the lower bound that is commonly derived through the VC-dimension), and can be shown to converge (with regard to expected weight changes) to the Bayes-optimal weight values.

Furthermore a new application of Bayesian inference for action selection in a reinforcement learning setup was discussed, as well as related data of biological experiments in the Lab of Shadlen.

Analysis and applications of bidirectional associative memories

Günther Palm (Universität Ulm, D)

Analysis will be in terms of memory capacity, applications concern pattern separation in vision and language understanding.

Keywords: Bidirectional Associative Memory

Language Learning in Neural Networks and Associative Memories

Günther Palm (Universität Ulm, D)

The actual talk merges three topics:

1)Bidirectional associative memories (as in the original title)

2) A general discussion of learning in recurrent networks

3) our recently developed system for language understanding and learning of new words (based on a recurrent combination of several associative memories).

Keywords: Bidirectional Associative Memories, Language Understanding, Learning, Disambiguation

Biological Neuronal Networks: Recurrent Neuronal Dynamics in the Mammalian Neocortex

Stefan Rotter (IGPP Freiburg, D)

The function of cortical networks depends on the collective interplay between neurons and neuronal populations, which is reflected in the correlation of signals that can be recorded at different levels. To correctly interpret these observations, it is important to understand the origin of neuronal correlations. Here we study how cells in large recurrent networks of excitatory and inhibitory neurons interact, and how the associated correlations affect the dynamic state, which has been termed "asynchronous-irregular". The main result is that the structure of the connectivity matrix of such networks induces considerable correlations between synaptic currents as well as between subthreshold membrane potentials. Although correlations are strongly attenuated when going from membrane potentials to action potentials (spikes), the resulting weak correlations in the spike output of the neurons nevertheless cause substantial fluctuations in the population activity, even in highly dilute d networks.

Joint work of: Rotter, Stefan; Kriener, B.; Tetzlaff, T.; Aertsen, A; Diesmann, M.

New RNNs for Challenging Tasks With and Without Teachers

Jürgen Schmidhuber (TU München, D)

The human brain is a recurrent neural net (RNN): a network of neurons with feedback connections. It can learn many behaviors / sequence processing tasks / algorithms / programs that are not learnable by traditional machine learning methods.

These capabilities explain the rapidly growing interest in artificial RNN for technical applications: general computers which can learn algorithms to map input sequences to output sequences, with or without a teacher. They are computationally more powerful and biologically more plausible than other adaptive approaches such as Hidden Markov Models (no continuous internal states), feedforward networks and Support Vector Machines (no internal states at all). RNN have recently given state-of-the-art results in time series prediction, adaptive robotics and control, connected handwriting recognition, image classification, speech recognition, protein analysis, stock market prediction, and other sequence learning problems. Today we cover the follo wing topics: 1. Multidirectional Supervised RNN for Handwriting and Vision. 2. Connectionist Temporal Classification: Combining Probabilistic Models and RNN, e.g., for Speech Labelling. 3. Co-Evolving Recurrent Neurons / Synapses for Control.

Keywords: Probabilistic Models, Multidimensional RNN, Co-Evolving Recurrent Neurons, Evolino

Full Paper:
http://www.idsia.ch/~juergen/rnn.html

Equilibria of Iterative Softmax and Critical Temperatures for Intermittent Search in Self-Organizing Neural Networks

Peter Tino (University of Birmingham, GB)

Optimization dynamics using self-organizing neural networks (SONN) driven by softmax weight renormalization has been shown to be capable of intermittent search for high-quality solutions in assignment optimization problems. However, the search is sensitive to temperature setting in the softmax renormalization step. The powerful search occurs only at the critical temperature that depends on the problem size.

So far the critical temperatures have been determined only by tedious trial-and-error numerical simulations. We offer a rigorous analysis of the search performed by SONN and derive analytical approximations to the critical temperatures.

We demonstrate on a set of N-queens problems for a wide range of problem sizes N that the analytically determined critical temperatures predict the optimal working temperatures for SONN intermittent search very well.

Keywords: Recurrent Self-Organizing Maps, Symmetry Breaking Bifurcation, N-Queens

Full Paper: http://drops.dagstuhl.de/opus/volltexte/2008/1420

Full Paper:
http://www.cs.bham.ac.uk/~pxt/PAPERS/ism.tr.pdf

See also: P. Tino: Equilibria of Iterative Softmax and Critical Temperatures for Intermittent Search in Self-Organizing Neural Networks. Neural Computation, 19(4), pp. 1056-1081, 2007.

The role of recurrent networks in neural architectures of grounded cognition: learning of control

Frank Van der Velde (Leiden University, NL)

A major difference between the brain and symbolic systems like the computer is the nature of representation. We argue that representations of words/concepts in the brain are grounded in a network structure, related to aspects of word meaning derived from perception, action, emotion and semantic information. Because representations are grounded, they cannot be copied and pasted to form combinatorial structures like sentences. To ensure that representations remain grounded, they cannot be encoded (encrypted) either, to form combinatorial structures. Recently, we presented a neural architecture that produces sentence structures based on grounded word representations. The architecture consists of neural 'binding' mechanisms that produces (novel) sentence structures on the fly. Here, we discuss how the control of this binding process can be learned. We trained a feedforward network (FFN) and a simple recurrent network (SRN) for this task. The results show that information from the architecture is needed as input for these networks to learn binding control. Thus, both control systems are recurrent. We show that the recurrent system consisting of the architecture and an FFN as a 'core' can learn basic (but recursive) sentence structures. After learning, the systems behaves well on a series of test sentences, including sentences with (unlimited) embeddings. However, for some of these sentences, difficulties arise due to dynamical binding conflicts in the architecture. In closing, we discuss potential future developments of the architecture presented here.

Keywords: Grounded Representations, Combinatorial Structures, Neural Architecture, Binding Control, Recurrent Network, Learning

Joint work of: van der Velde, Frank; de Kamps, Marc

The role of recurrent networks in neural architectures of grounded cognition: learning of control

Frank Van der Velde (Leiden University, NL)

Recurrent networks have been used as neural models of language processing, with mixed results. Here, we discuss the role of recurrent networks in a neural architecture of grounded cognition. In particular, we discuss how the control of binding in this architecture can be learned. We trained a simple recurrent

network (SRN) and a feedforward network (FFN) for this task. The results show that information from the architecture is needed as input for these networks to learn control of binding. Thus, both control systems are recurrent. We found that the recurrent system consisting of the architecture and an SRN or an FFN as a 'core' can learn basic (but recursive) sentence structures. Problems with control of binding arise when the system with the SRN is tested on number of new sentence structures. In contrast, control of binding for these structures succeeds with the FFN. Yet, for some structures with (unlimited) embeddings, difficulties arise due to dynamical binding conflicts i n the architecture itself. In closing, we discuss potential future developments of the architecture presented here.

Keywords: Grounded Representations, Binding Control, Combinatorial Structures, Neural Architecture, Recurrent Network, Learning

Joint work of: Van der Velde, Frank; de Kamps, Marc

Full Paper: http://drops.dagstuhl.de/opus/volltexte/2008/1421

Cognitive Vision for Humanoids

Heiko Wersing (Honda Research Europe - Offenbach, D)

In this presentation I will review recurrent neural network models for visual perception and their possible application in humanoid robotics. The first focus is a dynamic model of Gestalt-based perceptual grouping, the Competitive Layer Model.

I discuss the analysis and application of the model in the larger context of recurrent linear threshold dynamical systems. In the second part I will focus on structures for hierarchical feature decomposition and their application for the online learning of visual objects on a humanoid robot.

Keywords: Recurrent Networks, Gestalt Perception, Online Learning, Cognitive Vision

Probabilistic First-order Theory Revision From Examples as a Challenge for Connectionism

Gerson Zaverucha (Federal University of Rio de Janeiro, BR)

Recently, there has been a great interest in the Machine Learning community in the integration of relational representations with probabilistic reasoning, the so-called Statistical Relational Learning (SRL) also called Probabilistic Logic Learning (PLL). The probabilistic relational formalisms developed in this new area are capable of representing multiple relationships of heterogeneous objects as well the uncertainty and noise inherent of real world datasets. In order to reduce the search space, our system Probabilistic First-order Theory Revision From Examples (PFORTE) applies theory revision techniques that improves an initial user-defined or automatically generated theory using a set of examples. Thus, the search space is reduced since only points of the theory which are identified to have some problem will be modified. Preliminary experimental results show the benefits of revising probabilistic relational theories. Currently, Stochastic Local Search techniques are being applied to PFORTE in order to further improve the effectiveness of the revision process. Previously, we have developed a knowledge-based neural network that integrates propositional logic programming with recurrent neural networks, the Connectionist Inductive Learning and Logic Programming System (C-ILP). There has been some attempts to extend it to relational learning. Since there are (propositional) Probabilistic Neural Networks, is it possible to do SRL/PLL in neural networks? What would be the advantages and disadvantages?

Time-delay Recurrent Neural Network Architectures

Hans-Georg Zimmermann (Siemens - München, D)

Time-delay recurrent neural networks are a realization of state space models for the identification of dynamical systems.

First, we will discuss the modeling of open dynamical systems with standard RNNs, normalized RNNs, and RNNs incorporating an error correction mechanism.

Second we discuss a way to embed the open system into a closed RNN.

This is a new way of formulating the dynamics in a time consistent way which is missing in standard RNNs. With this approach it is also feasible to model large systems with sub-dynamics on different time scales.

Keywords: Recurrent Neural Network Architectures