ICCL Summer School, TU Dresden

Dresden, 1-3 September 2010

Neural-Symbolic Cognitive Reasoning

Artur d'Avila Garcez

City University London

aag@soi.city.ac.uk

Motivation

- The need for:

learning from changes in the environment

reasoning about commonsense knowledge

- The need for robustness: controlling the accumulation of errors in uncertain environments
- Integrating reasoning and learning:

Symbolic systems too brittle (commonsense cannot be axiomatized)

Neural networks too complex (modularity, legacy systems, explanation)

- Combining the logical nature of reasoning and the statistical nature of learning

Outline

- Overview of Neural-Symbolic Cognitive Model
- Backpropagation:
  - worked example
  - evaluation: cross-validation/ embracing uncertainty
- CILP translation algorithm, extraction, applications
- Nonclassical CILP: modal, temporal, etc.
- Fibring networks (specializations)
- Relational / first-order CILP (propositionalization)
- Abductive reasoning, attention, emotions, creativity, etc.

Neuroymbolic Computation is...
...interdisciplinary

Cognitive Science

Logic

Machine Learning

Probability Theory

Computer Science

Neural Computation

Neuroscience

...related to SRL and ILP but underpinned by neural computation

IET/BCS Turing lecture 2010 (Chris Bishop)

1960s-1980s: Expert Systems (hand-crafted rules)
“Within a generation... the problem of creating 'artificial intelligence' will largely be solved” Marvin Minsky 1967

1990's-present: Neural networks, Support vector machines (difficult to include domain knowledge)

New AI: Bayesian learning, probabilistic graphical models, efficient inference

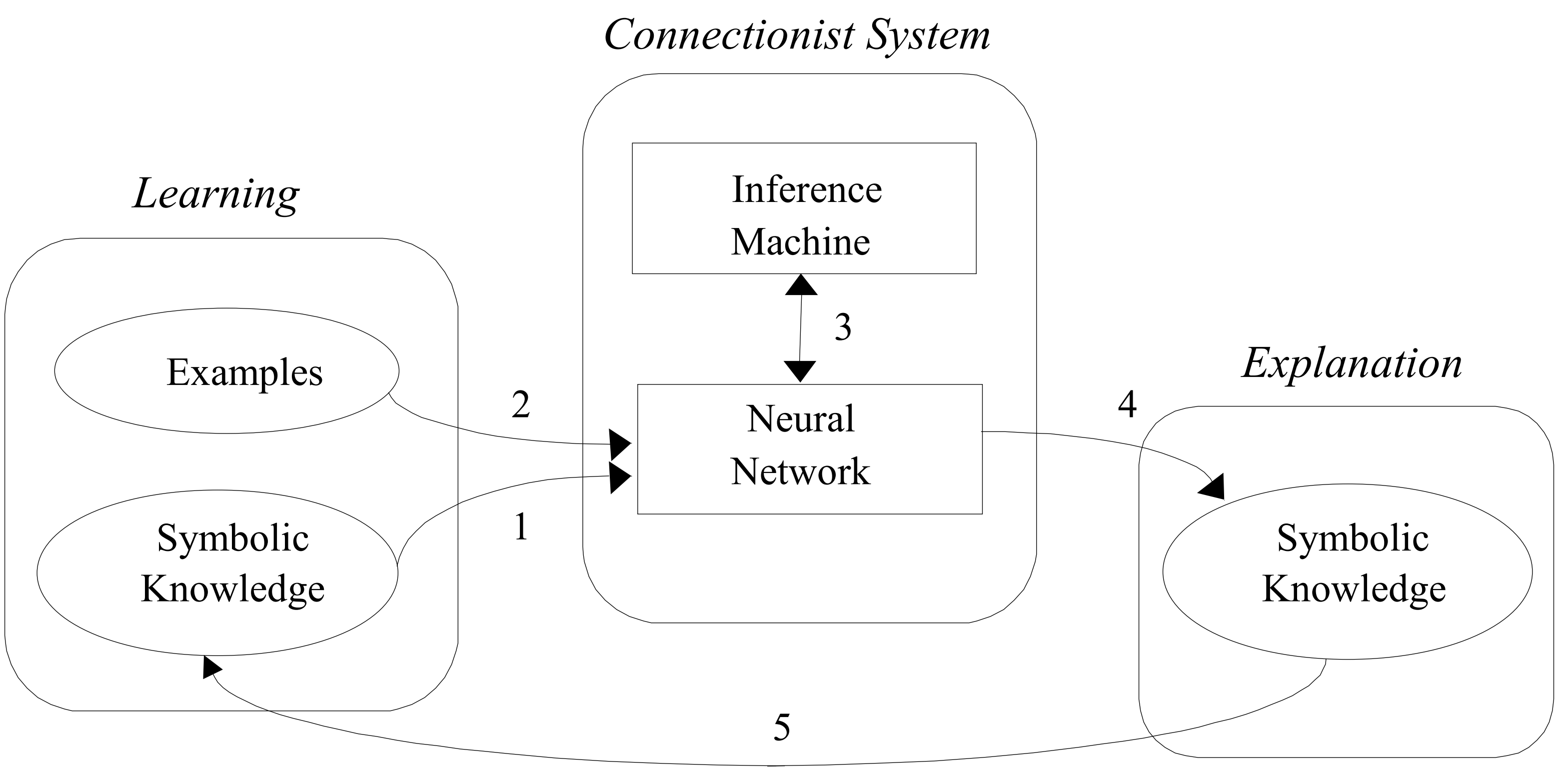
One Algorithm for Learning and Reasoning

high-level symbolic representations
(abstraction, recursion, relations)

translations

low level, efficient neural structures
(with the same, simple architecture throughout)

Neural-Symbolic Learning Systems



Connectionist Inductive Logic Programming (CILP) System

A Neural-Symbolic System for Integrated Reasoning and Learning

- Knowledge Insertion, Revision (Learning), Extraction

(based on Towell and Shavik, Knowledge-Based Artificial Neural Networks. Artificial Intelligence, 70:119-165, 1994)

- Real Applications: DNA Sequence Analysis, Power Systems Fault Diagnosis

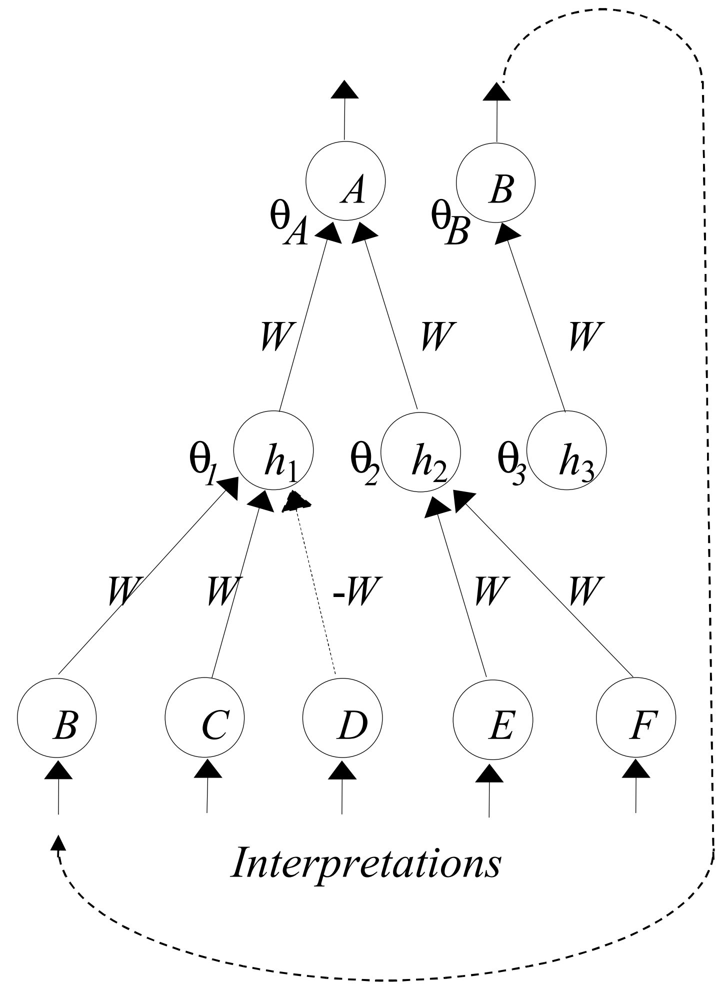
(using backpropagation with background knowledge; test set performance is comparable to backpropagation; test set performance on smaller training sets is comparable to KBANN; training set performance is superior than backpropagation and KBANN)

CILP Translation Algorithm

r_1: $A \leftarrow B, C, \sim D;$

r_2 : $A \leftarrow E, F;$

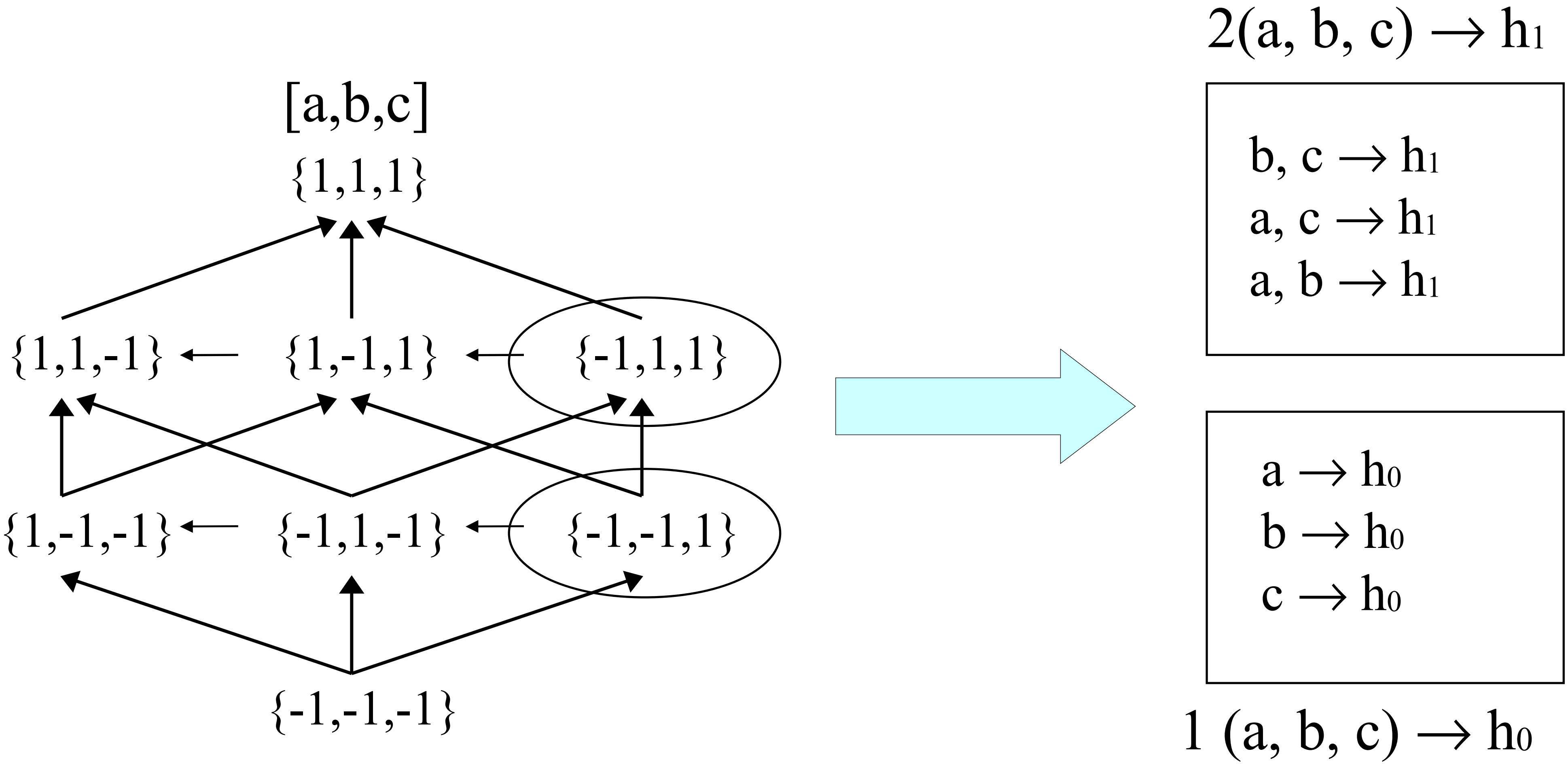
r_3 : $B \leftarrow$



based on Holldobler and Kalinke's translation, but extended to sigmoid neurons (backprop) and hetero-associative networks

Holldobler and Kalinke, Towards a Massively Parallel Computational Model for Logic Programming. ECAI Workshop Combining Symbolic and Connectionist Processing , 1994.

CILP Extraction Algorithm



<u>challenge</u>: efficient extraction of sound, comprehensible symbolic knowledge from large-scale neural networks

Publications

Garcez, Zaverucha. The CILP System. Applied Intelligence 11:59-77, 1999.

Garcez, Broda, Gabbay. Knowledge Extraction from Neural Nets. Artificial Intelligence 125:153-205, 2001.

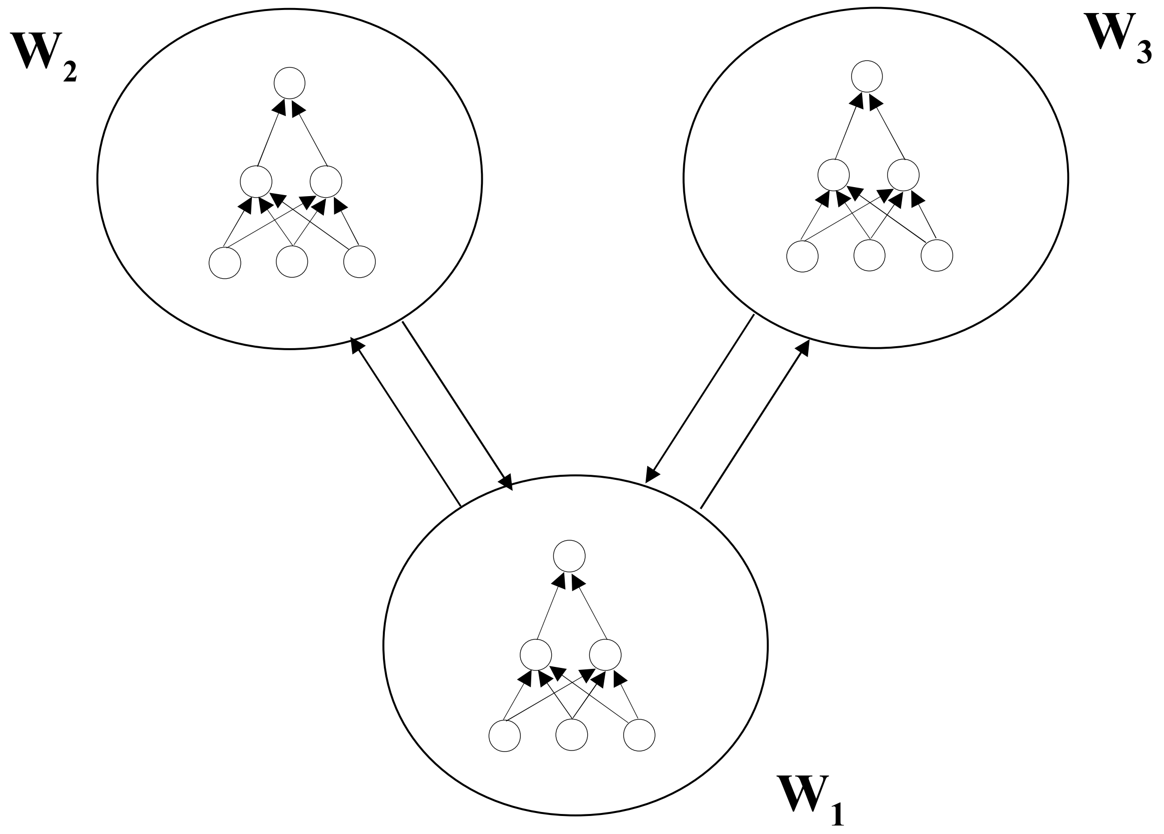
Garcez, Broda, Gabbay. Neural-Symbolic Learning Systems. Springer, 2002.

CILP extensions

- Non-Classical Reasoning
- Modal, Temporal, Epistemic, Intuitionistic, Abductive Reasoning, Value-based Argumentation.
- New potential applications including temporal logic learning, model checking, software engineering (requirements evolution), etc.

Connectionist Modal Logic (CML)

CILP network ensembles, modularity for learning, accessibility relations, disjunctive information

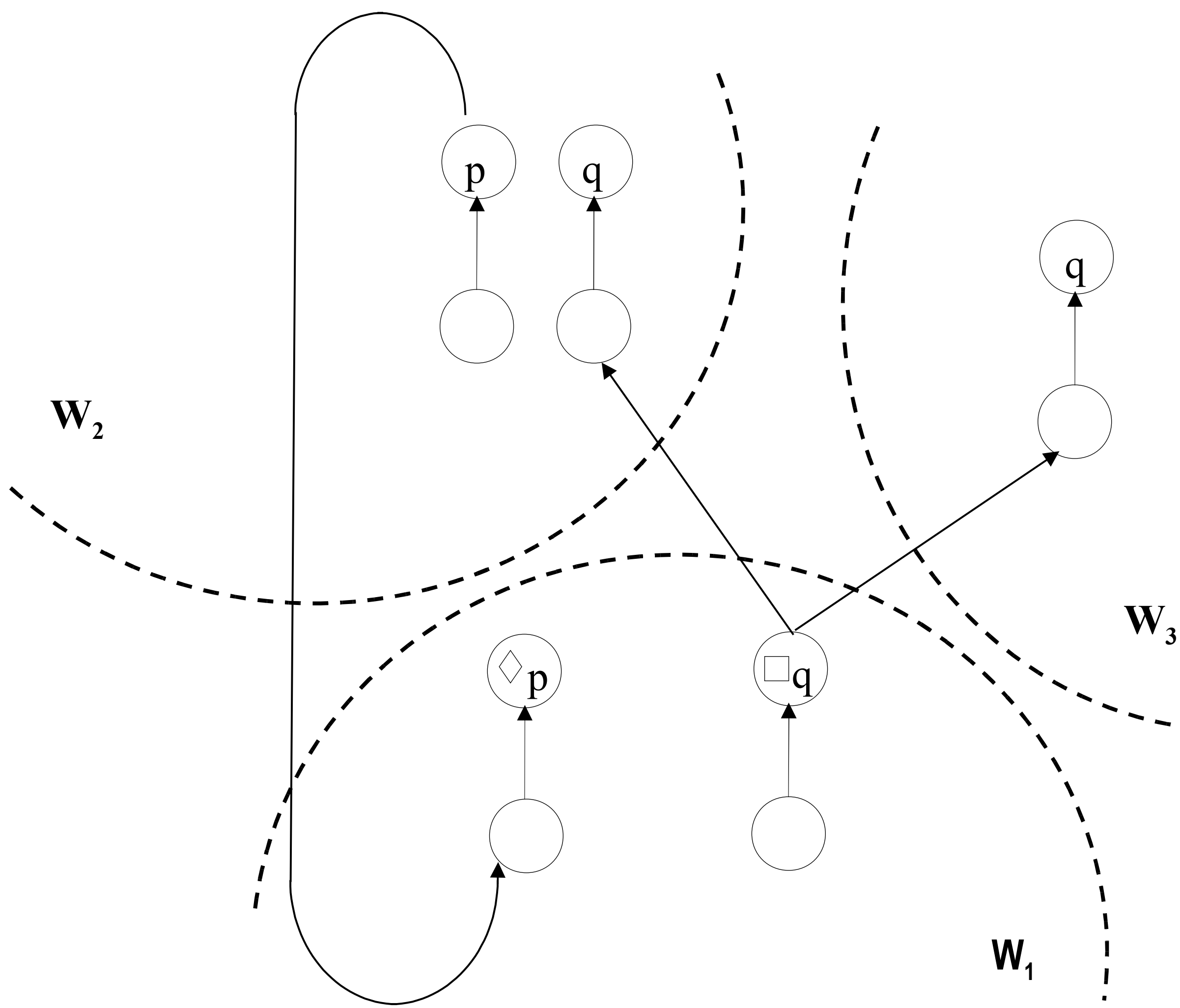


Semantics of   and ◊

A proposition is necessary (   ) in a world if it is true in all worlds which are possible in relation to that world.

A proposition is possible (◊) in a world if it is true in at least one world which is possible in relation to that same world.

Representing and ◊



CML Translation Algorithm

Translates modal programs into ensembles of CILP networks, i.e. clauses $W_i : ML_1,...,ML_n \rightarrow MA$ and relations $R(W_a,W_b)$ between worlds W_a and W_b, with M in { , ◊}.

Theorem: For any modal program *P* there exists an ensemble of simple neural networks *N* such that *N* computes *P*.

Learning in CML

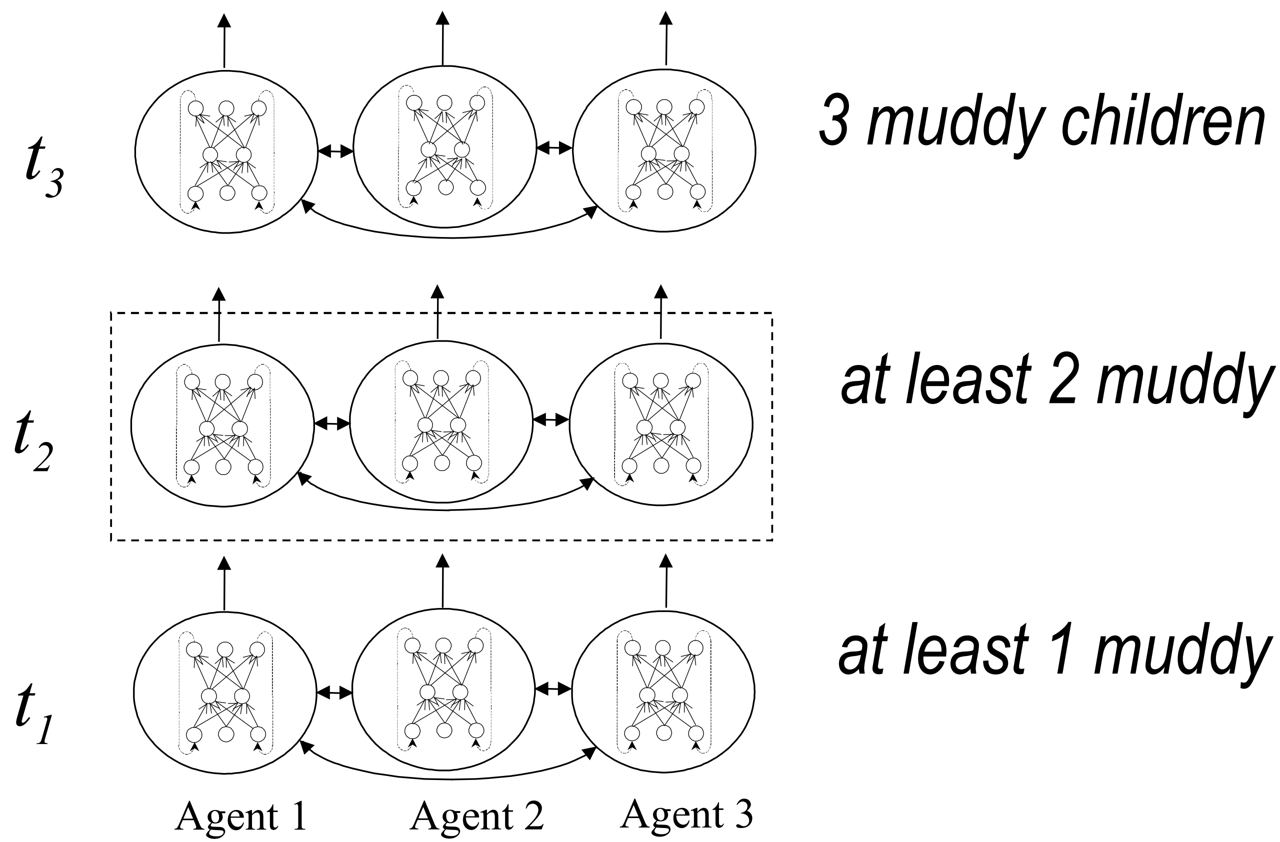
We have applied CML to a benchmark distributed knowledge representation problem: the muddy children puzzle

(children are playing in a garden; some have mud on their faces, some don't; they can see if the others are muddy, but not themselves; a caretaker asks: do you know if you're muddy? At least one of you is)

Learning with modal background knowledge offers better accuracy than learning by examples only (93% vs. 84% test set accuracy)

Connectionist Temporal Reasoning

A full solution to the muddy children puzzle can only be given by a two-dimensional network ensemble



Short-term and long-term memory

Publications

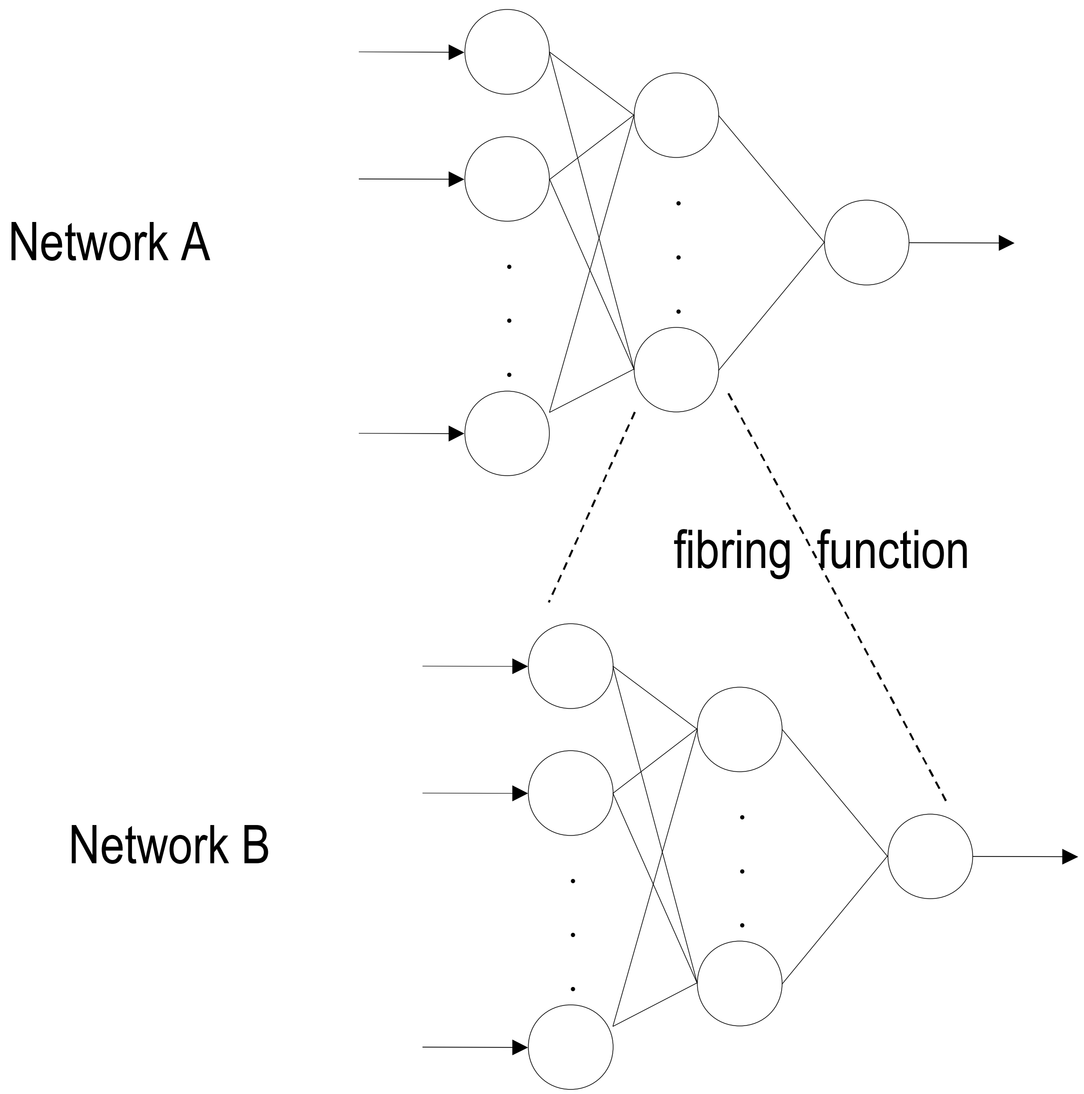
Garcez, Gabbay, Ray, Woods. Abductive Reasoning in Neural-Symbolic Learning Systems. Topoi 26:37-49, 2007.

Garcez, Lamb, Gabbay. Connectionist Modal Logic. TCS, 371: 34-53, 2007.

Garcez, Lamb, Gabbay. Connectionist Computations of Intuitionistic Reasoning. TCS, 358:34-55, 2006.

Garcez, Lamb. Connectionist Model for Epistemic and Temporal Reasoning. Neural Computation, 18:1711-1738, July 2006.

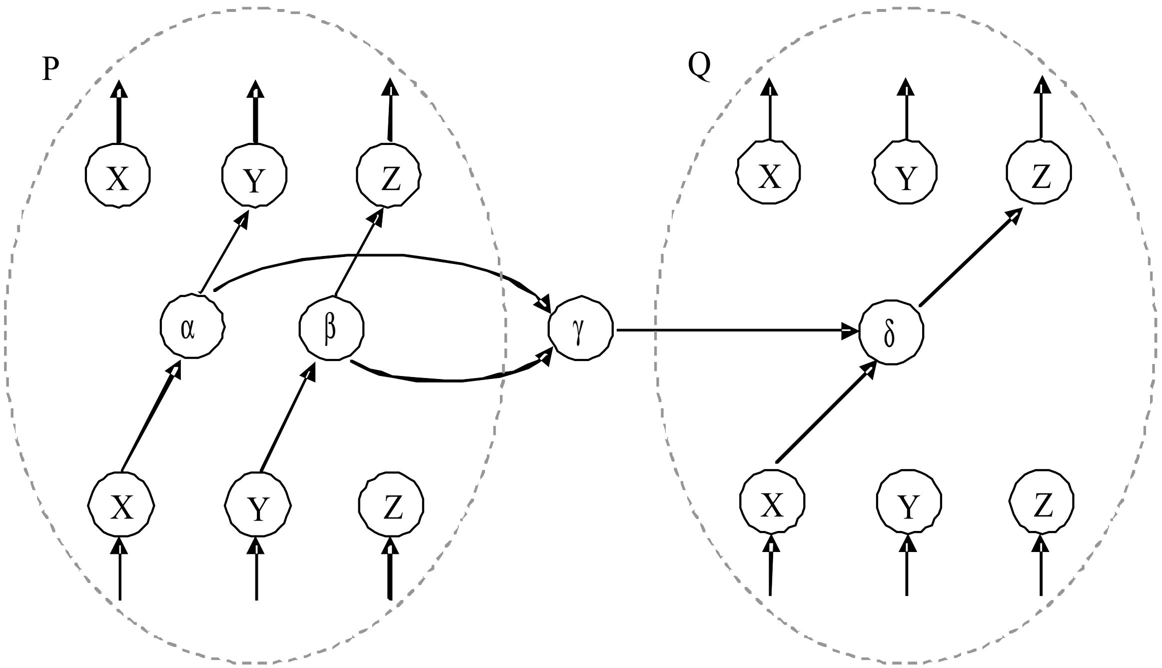
Combining (Fibring) Networks



Fibred networks approximate any polynomial function in unbounded domains

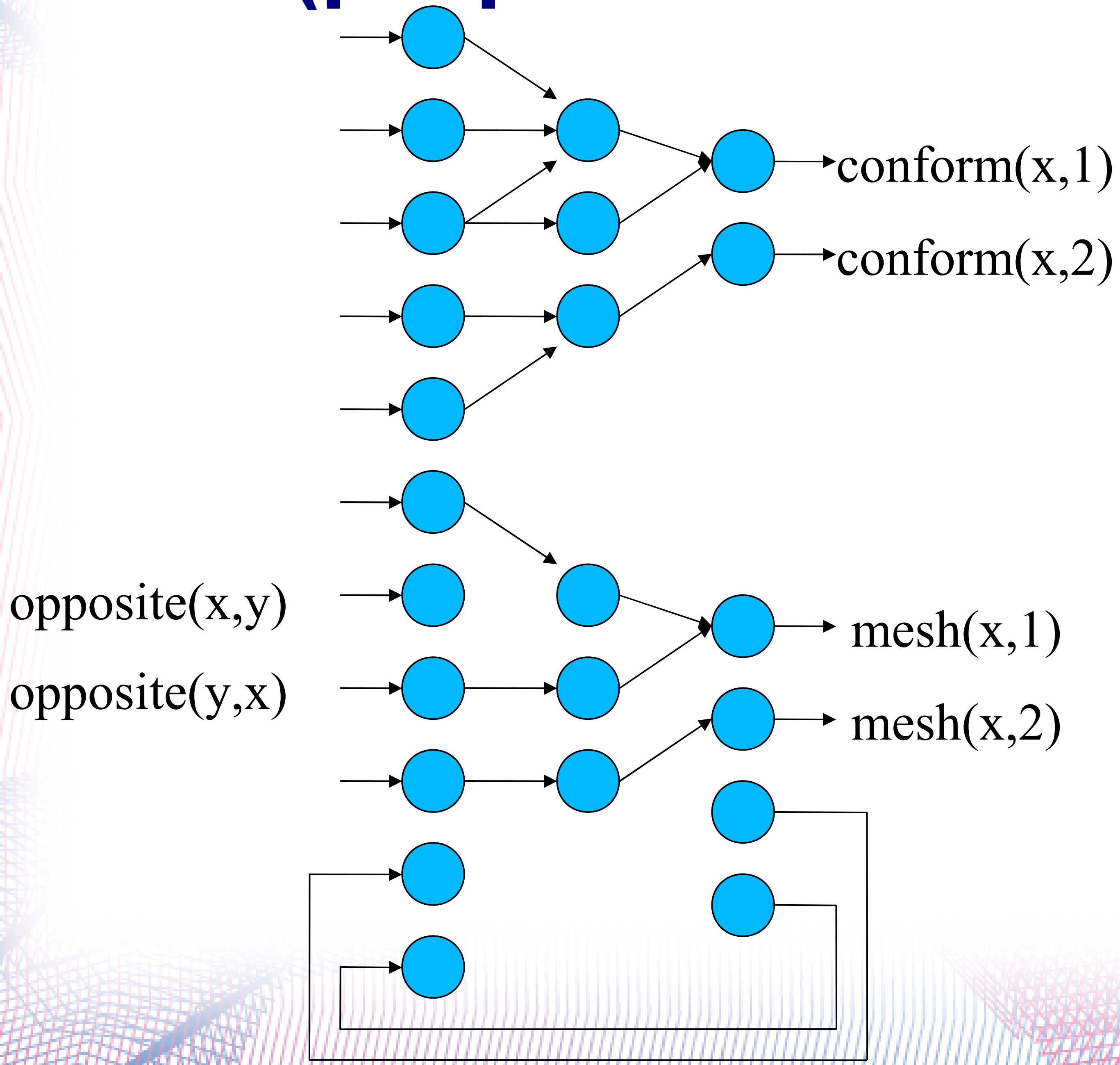
Relational Learning

Inputs presented to P and Q at the same time trigger the learning process in the meta-level

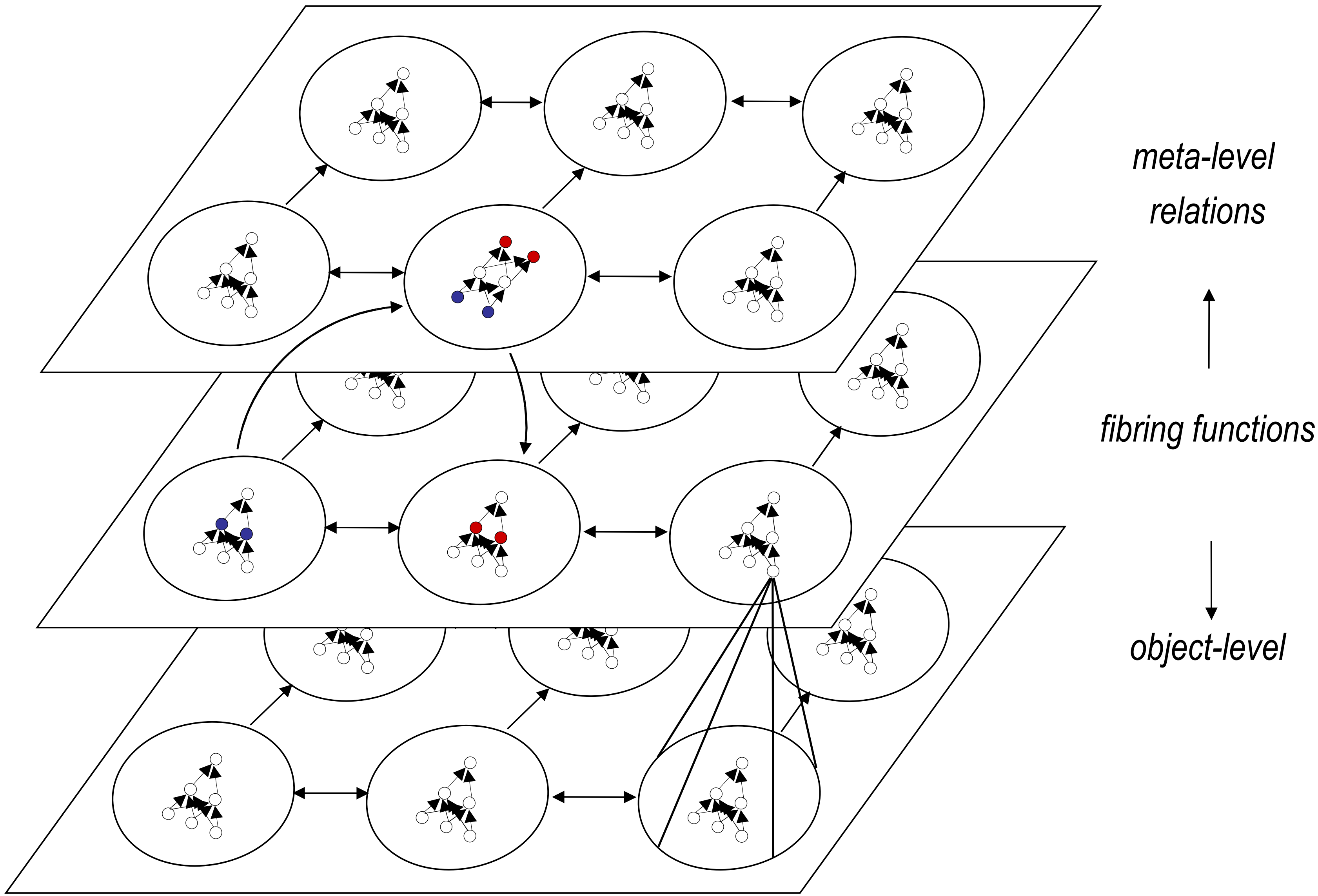


Experiments on the east-west trains dataset show an improvement from 62% (flat, propositional network) to 80% (metalevel network) on test set performance (leaving one out cross-validation)

FOL ANN (propositionalisation)



Cognitive Model: Fibred Network Ensembles



Publications

Garcez, Lamb, Gabbay. Neural-Symbolic Cognitive Reasoning. Springer, 2009.

Lamb, Borges, Garcez. Connectionist Model for Temporal Synchronisation and Learning. AAAI 2007, July 2007.

Borges, Garcez, Lamb. Integrating Model Verification and Self-Adaptation. ASE 2010, September 2010.

Garcez, Gabbay. Fibring Neural Networks. AAAI 2004, July 2004.

Current Work

- First Order Logic Learning: encoding vs. propositionalisation
- Neural Networks for Normative Systems: obligations, permissions, contrary to duty
- Adding domain knowledge to deep belief networks: higher order logic
- Neural Networks for Abductive Reasoning: creativity, emotions, attention
- Application in software engineering: model checking + adaptation
- Application in simulation environments: driving test, war games, robocup

Conclusion: Why Neurons and Symbols

To study the statistical nature of learning and the logical nature of reasoning.

To provide a unifying foundation for robust learning and efficient reasoning.

To develop effective computational systems for integrated reasoning and learning.