Neural-Symbolic Systems for Cognitive Reasoning

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Cognitive Neuroscience

The time is right for AI and Machine Learning informed by processes in the brain (evidence from neuropsychology, fMRI, etc.)

But computation has many desirable properties that are not present/hard to achieve in brain models:

- modularity (re-use)
- compositionality (vs. feedback in the brain)
- verification (model checking)
- variable binding (abstraction)
- explanation (reasoning)
- usability (human-computer interaction)
Representation precedes learning

“Logic is an attractive language of description because it has clear semantics and sound proof procedures. However, as a basis for large systems it leads to brittleness because consistent usage of the various predicate names cannot be guaranteed.

Brittleness can be overcome by using a new kind of logic in which each statement is learnable.

But there remains the question of how such a logic can be applied when building computer systems that perform computations of a cognitive nature.”

Les Valiant
2010 Turing Award Winner
Neural-Symbolic Systems

Cognitive Science

Logic
Learning
Neural Computation

Neuroscience
Neural-Symbolic Systems

“We need some language for describing the alternative algorithms that a network of neurons may be implementing” L. Valiant

(New) Logic + Neural Computation

GOAL: Learning from experience and reasoning about what has been learned in an uncertain environment in a computationally efficient way
Neural-Symbolic Methodology

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

translations

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

Analogy: low-level implementation (machine code) of high-level representations (e.g. java, requirements)
A Foundational Approach
(as opposed to the neuroscience or the engineering approach)

One Structure for Learning and Reasoning:

Take different tasks, consider what they have in common, formalize, evaluate and repeat.

KEY: controlling the inevitable accumulation of errors as part of a perception-action cycle

Applications: training in simulators, robocup, verification of software models, bioinformatics, power plant fault diagnosis, semantic web (ontology learning), general game playing, visual intelligence.
Neural-Symbolic Learning Systems

Connectionist System

Learning

Examples

Symbolic Knowledge

Explanation

Symbolic Knowledge

Inference Machine

Neural Network

1

2

3

4

5
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)

• Applications: DNA Sequence Analysis, Power Systems Fault Diagnosis
  (CILP using backpropagation with background knowledge:
  test set performance is comparable to backpropagation;
  test set performance on small training sets is comparable to KBANN;
  training set performance is superior than backpropagation and KBANN)
CILP Translation Algorithm

\[ r_1: A \leftarrow B, C, \neg D; \]
\[ r_2: A \leftarrow E, F; \]
\[ r_3: B \leftarrow \]

**THEOREM:** For any logic program \( P \) there exists a neural network \( N \) such that \( N \) computes \( P \) based on Holldobler and Kalinke’s translation, but extended to sigmoid neurons (backprop) and hetero-associative networks.

Power Plant Fault Diagnosis (real problem)

Mapping 23 alarms to 32 faults
Power Plant Fault Diagnosis

Background Knowledge (35 rules with noise)
278 examples of single and multiple faults

Fault(ground,close-up,line01,no-bypass) IF
Alarm(instantaneous,line01) AND
Alarm(ground,line01)

There is a fault at transmission line 01, close to the power plant generator, due to an over-current in the ground line of transmission line 01, which occurred when the system was not using the bypass circuit.
Promoter Recognition (bioinformatics)

Promoter = small DNA sequence at beginning of genes
Promoter Recognition (results)

Background Knowledge (14 rules):

Promoter IF Contact AND Conformation
Contact IF Minus10 AND Minus35
Minus35 IF @-36'ttgac'
Minus35 IF @-37'cttgac'
Conformation IF @-47'caat*ac' AND @-22'g*tc' AND @-8'gcgcc*cc'

10-fold cross-validation on set of 106 examples

CILP networks learn faster than backpropagation and KBANN, and perform slightly better than backpropagation and KBANN on small training sets. We attribute this to the soundness of the CILP translation (i.e. the above theorem).

We also ran experiments on the splice-junction determination problem obtaining similar results.
CILP Rule Extraction

• Knowledge is extracted by querying/sampling the trained network;
• A **partial ordering** helps guide the search, reducing complexity on the average case;
• A proof of soundness guarantees that the rules approximate the behaviour of the network;
• Rule simplification and visualization techniques help experts validate the rules;
• The rules can be visualized in the form of a **state transition diagram**
CILP Extraction Algorithm

THEOREM: CILP rule extraction is sound

Challenge: efficient extraction of sound, readable knowledge from large-scale networks
Publications on CILP


CILP extensions (deep networks)

• The importance of non-classical reasoning
• Preference, Modal, Temporal, Epistemic, Intuitionistic, Abductive Reasoning, Value-based Argumentation.
• New applications including normative reasoning (robocup), temporal logic learning (model checking), software model adaptation (business process evolution from text, e.g. email), training and assessment in simulators (driving test), visual intelligence (action classification in video).
Connectionist Modal Logic (CML)

CILP network ensembles, modularity for learning, accessibility relations, disjunctive information
Semantics of necessity and possibility

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

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

Modalities used for reasoning about uncertainty (following J. Halpern, MIT Press).
Representing box and diamond
CML Translation Algorithm

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

THEOREM: For any modal program \( P \) there exists an ensemble of 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 muddy)

Learning with modal background knowledge is faster and offers better accuracy than learning by examples only (93% vs. 84% average test set accuracy)
A full solution to the muddy children puzzle can only be given by a two-dimensional network ensemble.

THEOREM: For any temporal program $P$ there exists an ensemble of networks $N$ such that $N$ computes $P$. 
Publications on Nonclassical Computation


Combining (Fibring) Networks

A neuron that is a network! neuromodulation?

Expressiveness to represent first-order logic
Loosely-coupled integration: e.g. Network A and Legacy System B
Fibring Expressiveness

Fibred networks approximate any polynomial function in unbounded domains, e.g. $f(x)=x^2$, as opposed to each of A, B, C which are universal approximators in compact domains only.
Cognitive Model: Fibred Network Ensembles

- Meta-level relations
- Fibring functions
- Object-level
Publications on Fibring and Cognitive Model


Recent Applications

Training and Assessment in Simulators

Learning new information from observation of experts and trainees at task execution and reasoning about this information online to provide feedback to the user

Recent Applications (cont.)

Learning Normative Rules of the RoboCup Competition

Describing Actions in Video

A neural-symbolic deep network should allow the sharing of common features and the selective composition of features to produce efficient computation and generalisation.

Recent Applications (cont.)

- Hypotheses at t-1
- Video objects
- Pre-processing
- Hypotheses at time t
- Generate
- Reconstruct
- Ground truths

0.98: \( h_{48} \leftrightarrow fast\_moving \land direction\_vertical \land close\_distance \land bounce \land chase \land \bullet h_1 \land \bullet h_3 \land \bullet h_4 \land ... \)
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.
Current/Future Work

• Theory: how brains make mental models / abduction / argumentation
• Practice: systems and applications (training in simulators, visual intelligence, robotics)
• First Order Logic Learning: encoding vs. propositionalisation / binding problem
• Deep belief networks: adding and extracting domain knowledge / understanding multiple layer abstractions