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A Survey of Abduction in Neural Models and the Feasibility of a Neuroevolution Approach

Seminar Paper

Knowledge Processing

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Abstract

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1 Introduction

Motivation for Abductive Reasoning in Intelligent Systems

2 Fundamentals

2.1 Logical Reasoning

In [8] Minnameier logically analyses deduction, induction and abduction.

Deduction

Induction

Abduction

Four different abduction problems are characterized in [3] by Bylander et al.

Independent Abduction Problems This is what Bylander et al consider the simplest abduction problem. An abduction problem is called independent if "an individual hypothesis explains a specific set of data regardless of what other individual hypotheses are being considered.".

Monotonic Abduction Problems In these problems a composite hypothesis is capable of explaining data which cannot be explained by any single sub hypothesis of the composite hypothesis. It is important to note that the composite hypothesis is still able to explain any and all data which is explained by one of its sub hypotheses.

Incompatibility Abduction Problems Both monotonic and independent abduction problems cannot deal with a composite hypothesis including both a hypothesis and its negation, either needs to be excluded for the composite hypothesis to be acceptable. The necessity of both a hypothesis and its negation leads to incompatibility abduction problems.

Cancellation Abduction Problems Similar to incompatibility both monotonic and independent problems are not capable of is a composite hypthesis having a hypothesis which cancels a datum that another hypothesis would explain. Bylander et al give the example of one disease explaining an increased blood pH value while another disease decreases blood pH resulting in an overall normal blood pH.

Abduction, NP-hard Bylander et al further show in [3] that finding the most plausible combination of hypotheses which explains all data is an NP-hard problem.

2.2 Artificial Neural Networks

In [11] Rojas describes how natural neural networks compute and how artificial neural networks aim to model them. A generic neuron can be described by four different parts. The dendrites are its input channels and lead to synapses which connect to the axons (output channel) of other neurons, connecting them. Finally a neuron has a cell body from which the dendrites and axon emerge. A multitude of neurons are connected in this faction, forming a network in which the storage and processing of data is achieved by particular patterns of neural activity. A neuron which is excited sufficiently will fire an electric impulse along its axons exciting other neurons which are connected to its axons. Furthermore neurotransmitters are released, altering the excitement thresholds of neurons in the vicinity.

In [4] Cybenko has proven that neural networks are universal approximators; any function can be modeled by an artifical neural network, as long as its structure is suited for it concerning both the layout and the necessary complexity.

Problems When Dealing With Artificial Neural Networks A major problem when designing and exploring solutions via neural networks is that even in comparatively simple networks (relative to the billions of connections in natural neural networks) it is infeasible to debug them like classical computational solutions.

2.3 Neural-Symbolic Reasoning

In [6] Garcez et al give key challenges and contributions of a state of the art neural-symbolic computation. These are divided into four categories: Representation, consolidation, transfer and application.

Representation For this category they reference John McCarthy's claim of neural networks' propositional fixation which refers to most work on neural-symbolic learning and reasoning being focused on propositional logics. To advance in this regard the integration of further logics with more expressive capabilities should and are researched. How the brain is capable of symbolic reasoning via the means of distributed and sub-symbolic neural activations is a key challenge concerning representation.

Consolidation In order for a system to learn and adapt to new tasks it is crucial that learned, individual examples can be consolidated into an appropriate knowledge base to use for reasoning. A major challenge is the extraction of knowledge and a compact representation of it to allow for efficient processing for reasoning.

Transfer The transfer of knowledge between between domains allows for rapid learning and adaptation, giving the use of analogy in human learning and reasoning as an example of the importance. Garcez et al pose two questions which they deem to be two of the most important ones in this regard. One being how analogical transfer could be practically implemented in connectionist architectures. The other being on how possible analogies could be discovered on a sub-symbolic level.

Application In the last category Garcez et al look at how neural-symbolic systems are typically implemented, integrated and applied.

3 Neural Models for Abduction

3.1 Challenges in Abduction in Neural Models

3.2 Overview of Neural Models for Abduction

A Connectionist Approach to Cost-Based Abduction

In [1] Abdebal et al seek to apply high order recurrent networks to the cost-based abduction problem

Towards the integration of abduction and induction in artificial neural networks

In [9] Ray et al aim to translate abductive logic programs to artificial neural networks.

Abductive Reasoning in Neural-Symbolic Systems

In [7] Garcez et al research the ability of artificial neural networks, which are technically non-symbolic systems, to do massively parallel computations of abductive explanations to create a bridge between symbolic and non-symbolic approaches.

Neural Network Models for Abduction Problems Solving

[2]

A Neural Network Approach for First-Order Abductive Inference

[10]

4 Neuroevolution for Abductive Reasoning

4.1 Neuroevolution - Fundamentals

Artificial Evolution

In nature a constantly changing battle for survival and procreation determines the fate of existing species. An inherent trial and error process significantly alters the life forms and their behaviours to an amazing extent, and brings up novel and tricky solutions to all sorts of problems.

In artificial evolution the principle of natural occurring evolution is used under controlled laboratory circumstances. Computer simulations can model and predict the evolution of species (candidate solutions) over thousands of generations. Two crucial concepts in this approach are genetic encoding and the fitness function.

Genetic Encoding Genotype and Phenotype are the two sides of the genetic encoding of an organism. The genotype is what could be considered the source code for an individual as it determines how cells and parts of it are formed and placed. The phenotype is what the individual eventually ends up being, that is the sum of the relevant parts which have been encoded by the genotype; the genotype encodes the phenotype.

There are two basic forms for this encoding. In a direct encoding there is a one to one relationship between the two types. This is the easiest way to implement but is also inefficient as cells and parts which are fundamentally the same but occur in different locations are being encoded several times and thus redundantly. It furthermore does not take symmetry into account.

In an indirect encoding the genotype encodes in blocks of parts or cells which are only as small and diverse as they absolutely have to be. Instead of these blocks being encoded several times for each time they appear, they are encoded once and the genotype determines where they are activated.[12][5]

Fitness Function In natural evolution one could say that the relation between an individual and its environment implies a fitnessfunction, that is, a metric which determines the individual's capabilities of survival and procreation.

In artificial evolution the fitnessfunction is explicitly defined as a function to grade an individual's behaviour towards the solving of the problem at hand.

Benefit of Using Artificial Evolution The main benefit of using artificial evolution to find solutions is that it is not necessary to have any sort of explicit plan or vision of what the solution should look like. Instead, only a set of standards and constraints are needed to model the environment in which the candidate solution perform and evolve.

Neuroevolution

By combining artificial neural networks and artificial evolution the former cancels out the major drawback of the latter. In neuroevolution the "debugging" of the artificial neural networks is done implicitly by the evolution, as sufficiently functioning networks are allowed to survive and procreate while those that do not are culled. For

4.2 Advantages of Neuroevolution for Abductive Reasoning

4.3 Disadvantages of Neuroevolution for Abductive Reasoning

4.4 Proposal for Feasible Neurolutionary Approach

5 Conclusion

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