Universität Hamburg
Department Informatik
Knowledge Technology, WTM

Effects of encoding on the general learning ability of artificial neural networks

Seminar Paper

Bio-inspired Artificial Intelligence

Jan Fabian Schmid
Matr.Nr. 6440383
2schmid@informatik.uni-hamburg.de

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Abstract

TODO

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1 Introduction

One of the more prominent topics in bio-inspired artificial intelligence is the modelling of animal nervous systems using artificial neural networks (ANNs).
In contrast to artificial neural networks, that are used for function approximation in a variety of application fields nature-like neural networks should be larger, more organized and more plastic (cf. [6] p.1). The common approach to develope such networks, are evolutionary algorithms, since the evolution was responsible for developing the prototype.
Two aspects of creating nature-like ANNs, that research mainly focuses on, are:

- **Genetic encoding:** To use evolutionary algorithms for the developement of neural networks with specific behaviours, it is necessary to present the structure in some kind of encoding that can be handled by them. As in the genotype of animals, it is not desired to encode each neuron specifically, but rather to define rules for the network structure, that then lead to regular patterns (cf. [6] p.1).
  Algorithms that use a mapping of genotype to phenotype are called *artificial developmental systems.*

- **Synaptic plasticity:** The ability of an artificial neural network to change repeatedly during lifetime is called synaptic plasticity. A neural network with good plasticity is supposed to be able to adapt to different problems through a learning process, ideally even to situations that were not considered during the developement of the network.

Alongside a proper genetic encoding the fitness function has to be defined for evolutionary algorithms. Individuals that are newly developed during the application of the algorithm are adapted to the fitness function.
To obtain plastic ANNs the fitness function could check for fitness on many different test cases to ensure the general learning ability. It turns out however that this approach can hardly be feasible for more complex environments as the number of required test cases grows exponentially (cf. [6] p.2).In the studied paper [6] it is therefore suggested that genetic encoding and synaptic plasticity should be examined simultaneously (cf. [6] p. 1).

1.1 Suggested solution

Tonelli and Mouret say, that the use of artificial developmental systems leads to more regular network structures since it is easier to describe a more regular structure with repetitions and symmetries than to describe an irregular structure with seemingly no relations between the induvidual network parts using a general rule set like genetic encoding does.(cf. [6] p.2) Therefore their main hypothesis is: „We here propose that this bias towards regularity is critical to evolve plastic

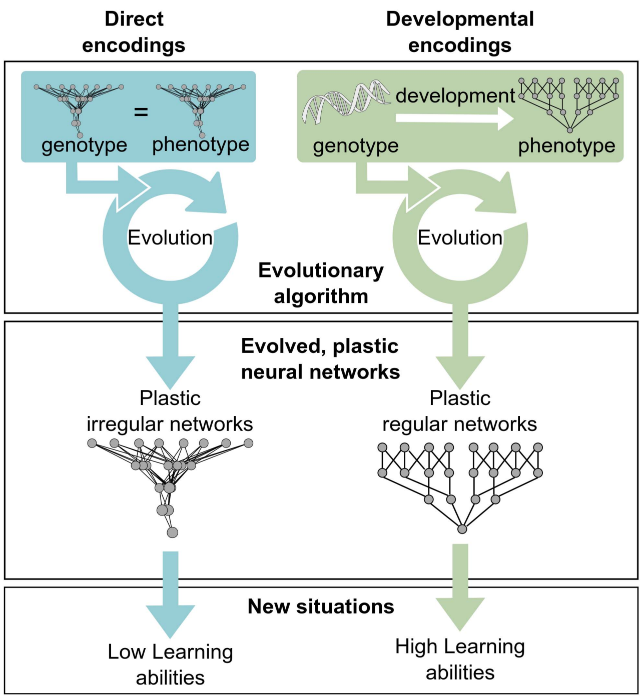

Figure 1: **Main hypothesis.** Using developmental encodings should facilitate the evolution of plastic ANNs with high learning abilities. doi:10.1371/journal.pone.0079138.g001 [2]

neural networks that can learn in a large variety of situations"([6] p.2). To visualize this idea they present the illustration in figure 1.1.

The higher general learning ability of more regular ANNs is supposed to stem from higher redundancies of network parts as the ANN can't be as specialized to the specific test cases used by the fitness function as a direct encoded network would be.

1.2 Goals and structure of this paper

This seminar paper is supposed to give an in-depth analysis of the presented paper [6] with focus on the effects of encoding on the general learning ability of artificial neural networks.

In chapter 2 some background information necessary to understand the concepts and the experimental setup used in the discussed paper will be given. Then in chapter 3 related publications that use artificial developmental systems for the developement of nature-like ANNs are presented. A description of how the proposed hypothesis was tested will be covered by chapter 4. Following, the results and conclusions are discussed in chapter 5. Then chapter 6 will conclude the paper by summarizing the main findings.

[2]Source: Tonelli, Paul and Mouret, Jean-Baptiste (2013), [6] p.3

2 Background Information

2.1 Regularity

Regularity measures the compressibility of a network. It is a characterization of the phenotype, not the genotype, of the ANN. Tonelli and Mouret compute the regularity by calculating the number of symmetry axes (cf. [6] p. 4). If two parts of the network can be interchanged without altering the graph they are called symmetric. It is only necessary to describe one of these parts and reference it for each additional occurance, therefore the description of a network with more symmetries is more compressable.
These symmetries are automorphisms and can be easily calculated for most graphs (actually it is an NP-complete problem).
A graph automorphism is a permutation σ of the vertex set V of the graph $G = (V, E)$, that maps an edge $(\sigma(u), \sigma(v))$ to the vertices u and v iff they formed an edge (u,v) already in G.
Since an automorphism of the graph to itself always exists, the number of symmetries is the number of automorphisms less one.

2.2 From genes to nervous systems

It is necessary to encode the structure of an ANN to a representation that can be modified easily if an evolutionary algorithm is to be used for its developement. Encodings can be divided into two groups:

- **Developemental encodings** use a genotype to phenotype mapping like DNA does. The code defines construction rules which if followed lead to a certain network structure. Small changes in the code can, if followed, have huge impacts on the resulting phenotype allowing a fast exploration of parameter space, but the fine tuning becomes difficult. Often similar and symmetric network structure parts arise in the phenotype since all neurons, and all connections, follow the same rules.
- For **direct encodings** the mapping from genotype to phenotype is immediate as the parameters to each neuron and each connection can be directly derived from the code. In the developemental encoding this is not possible since they depend on their relation to different network parts by the defined rules.

In the studied paper three different encodings are compared with each other, two of them are developemental encodings (HNN and map-based) and one direct encoding.

2.2.1 Direct encoding

The ANN is decribed by a directed graph. The networks of the first generation of the evolutionary algorithm are initiated as a simple feed-forward network without

hidden layers and random weights.
Seven different mutation operators are modifying the network during evolution while no cross over is implemented. Each mutation happens with a specific probability to the operation:

1. A connection is randomly added
2. A random connection is removed
3. Randomly choose a connection and change its target or source
4. Create a new neuron by randomly choosing a connection and creating a new target neuron with the same connection weight
5. Delete a random neuron and its connections
6. Randomly choose a connection and modify its weight
7. Activation function of a random neuron is changed

2.2.2 TODO: map-based encoding

[5]

2.2.3 TODO: HNN encoding

Different encodings to describe neural networks tested in this paper
- How do they work?
- What differentiates them?

2.3 TODO: Skinner-box

- Where and for what purpose can this experiment be used?

3 TODO: related work

Typical approaches from related work
- typically the two problems (1. encoding of nervous systems for evolution of large good neural networks and 2. synaptic plasticity in neural networks) are studied separately

About generative encodings:
- [3] → L-Systems
- [4] → neuroscience toolbox

About synaptic plasticity:
- [2] → importance of synaptic plasticity for learning
- [1] → synaptic plasticity in neural networks

4 TODO: Approach description

Proposal of the paper
- Bias towards regularity is critical to evolve plastic neural networks
Experiment in the paper to verify the proposal - design of analysis
- How is it structured?
- What is it able to show?
- Expected results?

5 TODO: Approach analysis

Results from the presented experiment
- Are the results according to the proposal?
Which effects did the different encodings have?
- Map-based encoding
- HNN
- Direct encoding
Critique
- Were the choosen encodings reasonable and sufficient?

6 TODO: Conclusion

How reasonable is the approach of the paper?
General conclusions about the effect of different encodings for neural networks

References

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