A Comparison of the Factors Affecting Brain Evolution and Computer Evolution

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Outline

• Background
• Network Encoding
• Inheritance of Learned Traits
• Embodiment
• Conclusion
BACKGROUND
Evolutionary Algorithms

- Initial Population
- Fitness Calculation
- Evolution Winner
- New Generation
- Selection
- Recombination, Mutation
Artificial Neural Networks (ANNs)
Evolving Neural Networks

(Figure from the OpenNERO wiki)
NETWORK ENCODING
Direct Encoding

Genotype

| 0.1 | -0.1 | 0.25 | 0.4 |

Phenotype

\[ w_{1,1} = 0.1 \]
\[ w_{2,1} = -0.1 \]
\[ w_{3,1} = 0.25 \]
\[ \eta = 0.4 \]
Direct Encoding Limitations

- Limited scalability
- Cannot capture morphogenesisis of neural systems
- Limited regularity

(Kitano 1990)

Irregular Structure

Regular Structure

ANN plots from (Huizinga, Mouret, and Clune 2014)
Developmental Encodings: Matrix Rewriting

Genome: $SABCDBaaaecedaaab\ldots$

Evolvable rules: $S \rightarrow AB, CD, A \rightarrow cp, ac, B \rightarrow aa, ae, C \rightarrow aa, ab, D \rightarrow aa, ab$

Fixed rules: $a \rightarrow 00, 00, b \rightarrow 00, 01, c \rightarrow 10, 00, e \rightarrow 01, 01, p \rightarrow 11, 11$

Development:

Initial State: $S \rightarrow AB, CD$

Cycle 1: $AB, cpa, aca, aae, aaaa, aaab$

Cycle 2: $AB, cpa, aca, aae, aaaa, aaab$

Cycle 3 (final): A Network Defined

Connectivity definition for a feed forward network

Figure from (Floreano, Dürr, and Mattiussi 2008), model suggested by (Kitano 1990)
Developmental Encodings: Cellular Encoding

- «Parent Cells» are replaced by «Child Cells»
- Genome specifies how each cell should be replaced:

(a) Initial graph  (b) Sequential Division ’S’  (c) Parallel Division ’P’

(Gruau 1994)
Developmental Encodings: «Axon» Growth

- Growth occurred *during* robot lifetime
- Genotype decided growth and branching patterns
- Phenotypic plasticity: Final connections depended also on *network activity*

From (Nolfi, Miglino, and Parisi 1994)
Developmental Encodings: «Axon» Growth

- The same individual displayed different behaviors in different environments:

From (Nolfi, Miglino, and Parisi 1994)
HyperNEAT: Exploits regularity without development

- Compositional Pattern Producing Networks (CPPNs) generate regularities:

(a) Mapping

(b) Composition

Picture from (Stanley, D’Ambrosio, and Gauci 2009)
HyperNEAT: Exploits regularity without development

- Compositional Pattern Producing Networks (CPPNs) generate regularities:

(a) Symmetry  (b) Imperfect Symmetry  (c) Repetition with Variation

Picture from (Stanley, D’Ambrosio, and Gauci 2009)
HyperNEAT: Exploits regularity without development

- Evolved CPPNs encode ANN weights:

1) Query each potential connection on substrate

2) Feed each coordinate pair into CPPN

3) Output is weight between \((x_1, y_1)\) and \((x_2, y_2)\)

Picture from (Stanley, D’Ambrosio, and Gauci 2009)
Exploiting Regularity

- Many real world problems display regularity. A regular encoding of networks can make them easier for evolution to solve.
- Example: Legged locomotion.

(Clune et al. 2009)
Indirect Encodings

• More closely reflect the generation of biological neural systems
  – For example, a human genome of 30,000 genes encodes a human brain with 100 trillion connections

(Stanley, D’Ambrosio, and Gauci 2009)

• Allow for the evolution of larger neural networks
• Allow for the evolution of regularities
• Help evolution find solutions *exploiting* regularity in the problem

(Stanley, D’Ambrosio, and Gauci 2009)
INHERITANCE OF LEARNED TRAITS
Lamarckian Evolution

• Traits acquired in parents’ lifetimes can be inherited by offspring  
  (Lamarck 1809)

• This type of direct inheritance of acquired traits is not possible, according to modern evolutionary theory  
  (Sasaki and Tokoro 1999)
Inheriting Learned Traits?
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\[
\begin{align*}
0.1 & \quad -0.1 & \quad 0.25 & \quad 0.4 \\
\end{align*}
\]

\[
\begin{align*}
w_{1,1} &= 0.1 \\
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w_{3,1} &= 0.25 \\
\eta &= 0.4
\end{align*}
\]
Inheriting Learned Traits?

| 0.1 | -0.1 | 0.25 | 0.4 |

\[ w_{1,1} = 0.4 \]
\[ w_{2,1} = -0.8 \]
\[ w_{3,1} = -0.2 \]
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Inheriting Learned Traits?

\[
\begin{align*}
\eta &= 0.4 \\
w_{1,1} &= 0.4 \\
w_{2,1} &= -0.8 \\
w_{3,1} &= -0.2
\end{align*}
\]
Is Lamarckian Evolution Beneficial?

- In *static environments*, it can be more efficient.
- But, what about in dynamic environments?

(Sasaki and Tokoro 2000)
Learned parent skill:

Inherited child skill:

**Static**

**Dynamic**
Optimal Heredity Rate in Dynamic Environments

(Figure from Sasaki and Tokoro 2000)
Varying the Heredity Rate, $\tau$

Chromosome Pool

Genetic Algorithm
- selection
- recombination
- mutation

(1) $w_0 = D(c_e)$

(2) Learning during the Life

(3) $c_i = D^{-1}(w_0 + \tau \cdot (w_L - w_0))$

(4) $c_i$

(Figure from Sasaki and Tokoro 2000)
### Experiment 1: A Static Environment

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<thead>
<tr>
<th></th>
<th>Food</th>
<th>Poison</th>
</tr>
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<tbody>
<tr>
<td>Generation 1</td>
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<td>X</td>
</tr>
<tr>
<td>Generation 2</td>
<td>X</td>
<td>X</td>
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<tr>
<td>Generation 3</td>
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<td>...</td>
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Experiment 1: A Static Environment

(Figure from Sasaki and Tokoro 2000)
## Experiment 2: Low Environmental Dynamism

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<td>...</td>
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</table>
Experiment 2:
Low Environmental Dynamism

(a) $\tau = 0.000$

(b) $\tau = 0.001$

(c) $\tau = 0.01$

(d) $\tau = 0.05$

(e) $\tau = 0.1$

(f) $\tau = 1.0$
## Experiment 4:
**High Environmental Dynamism**

<table>
<thead>
<tr>
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<th>Food</th>
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<th>Poison</th>
<th>Poison</th>
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<tbody>
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<tr>
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<tr>
<td>...</td>
<td></td>
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</tbody>
</table>
Experiment 4: High Environmental Dynamism

(a) $\tau = 0.000$

(b) $\tau = 0.001$

(c) $\tau = 0.01$

(d) $\tau = 0.02$

(e) $\tau = 0.05$

(f) $\tau = 1.0$
Performing vs. Learning

- Lamarckian evolution ($\tau > 0$) transmitted «the ability to perform something»
- Darwinian evolution ($\tau = 0$) transmitted «the ability to learn something»
Lamarckian Evolution

• Genetic inheritance of acquired traits is not biologically possible:

• This experiment showed that, even if it was possible, such inheritance may not be beneficial, because it generates *specialists* rather than *general* learners.
EVOLVING *EMBODIED* INTELLIGENCE
Non-Embodied Intelligence

Inputs → Brain → Outputs
Embodiment

“The embodied view suggests that the actual behavior emerges from the interaction dynamics of agent and environment through a continuous and dynamic interplay of physical and information processes.”

(Pfeifer, Lungarella, and Iida 2007)
Evolutionary Robotics

(Floreano et al. 2004)
Evolutionary Robotics - Motivations

1. Creating efficient robotic controllers, that exploit morphology and environment
2. Suggesting and testing hypotheses about the neural circuits found in nature

(Floreano et al. 2004)
Active Motion and Neural Development

- An essential part of embodiment is controlling ones’ body.
- Removing the ability to control ones’ body, changes neural development.

(Picture from Held and Hein 1963)
Active Motion and Neural Development

- «Passive» kittens showed decreased performance on visually guided tasks:
  - Descending a «hill» on the shallow or deep side.
  - Extending paws when approaching a surface.
- «Self-produced movement with its concurrent visual feedback is necessary for the development of visually-guided behavior»

(Held and Hein 1963)
Active Motion in Evolved Robots

(Suzuki, Floreano, and Di Paolo 2005)
Experimental Setup

1. Evolve robots to move around without colliding
   - Evolved robots *learn* to interpret visual stimuli

2. Train evolved robots in active and passive condition:
   - Active: Chooses its own movements
   - Passive: Preprogrammed movements.

3. Evaluate the behavior and neural structure of trained robots
   - In this phase, learning is disabled, to test the *previously learned* behaviors
Results – Performance Scores

«Active» learners perform better than «passive» learners

(Suzuki, Floreano, and Di Paolo 2005)
Results – Typical Behaviors

«Active» learner

«Passive» learner

(Suzuki, Floreano, and Di Paolo 2005)
Active Motion

- Animal studies show that active motion is essential to normal visual development
- Evolutionary robotics experiments show that the effect can be seen in simple neural controllers, and suggest hypotheses for the observed effect.
CONCLUSION
Conclusions

• Several factors influence the evolution of neural networks – in nature and in computers.
• Natural brains arise from a developmental process, are embodied and cannot transmit learned skills to offspring.
• Computer simulations frequently abstract away some of these factors.
References


Thank You