Trait-based Diversity Measurement in Genetic Algorithms using Artificial Neural Networks

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OVERVIEW

Introduction

Existing Diversity Measures

Neural Network Trait Diversity

Experiments

Conclusion

GENETIC ALGORITHMS USING NEURAL NETWORKS

- Population with individuals
- Individuals are candidate solutions
- Neural networks as candidate solutions
- Continuous procreation

FUN AND EXCITING

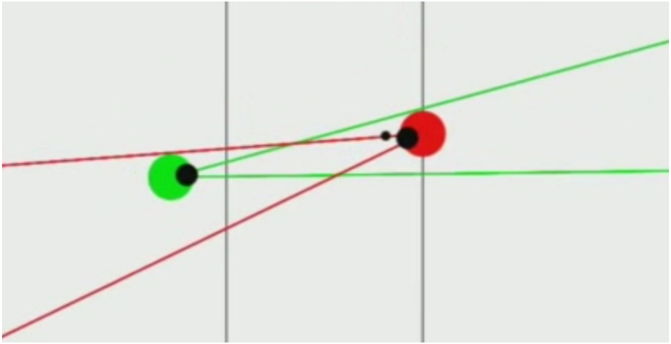


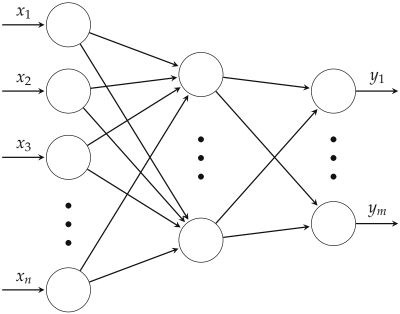
Figure: `youtube.com/watch?v=u2t77mQmJiY`

USEFUL AND SERIOUS

Figure: en.wikipedia.org/wiki/genetic_algorithm

- Measuring diversity?

REPRESENTING CANDIDATE SOLUTIONS



- Static network structure
- Weights represent the network as bit strings
- Straightforward manipulation

ASSESSING CANDIDATE SOLUTIONS

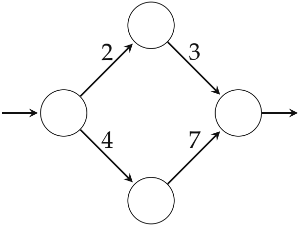
- How good is a candidate solution? How fit is it?
- Which conditions are important to observe?
- Defining a fitness function

Overview

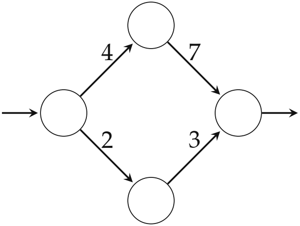
EXISTING DIVERSITY MEASURES

- Genotypic diversity measure (genetic make-up)
- Phenotypic diversity measure (behaviour/fitness)

GENOTYPIC MEASURES



0010 0100 0011 0111



0100 0010 0111 0011

- Hamming distance of 6
- Levenschtein distance of 6
- Genotypically diverse
- Phenotypically equal

FITNESS-BASED PHENOTYPIC MEASURE

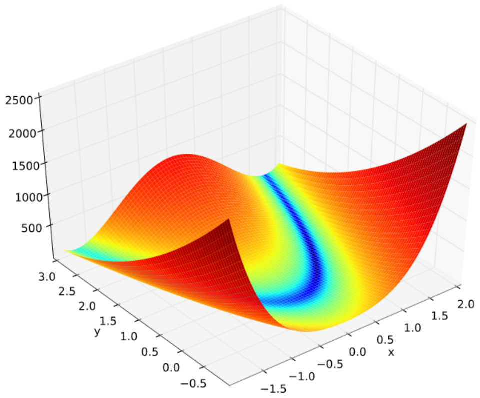


Figure: `en.wikipedia.org/wiki/rosenbrock_function`

WHAT SHOULD BE MEASURED?

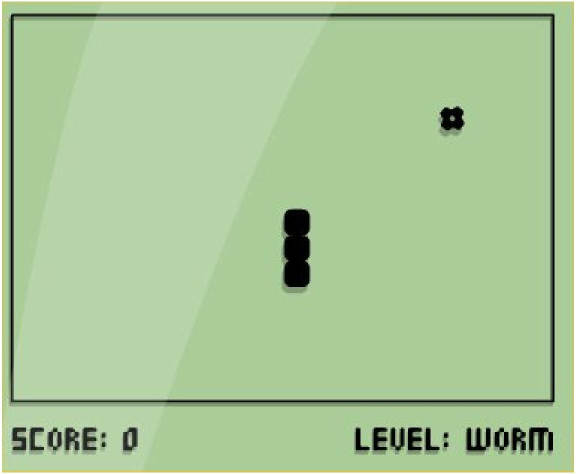
- What about the actual behaviour?
- Which behaviour do candidate solutions have?
- Categorize according to behaviour

OVERVIEW

IDEA

What difference could be nice to measure about two AI-players in the cell phone game Snake?

- Difference in traits.



Problem

Can we measure the traits of a neural network in general?

- Application dependent

Traits

Solution: break down traits further

- Two neural networks have different traits if they for some input produce a different output.

Easy to measure!

Traits

Solution: break down traits further

- Two neural networks have different traits if they for some input produce a different output.

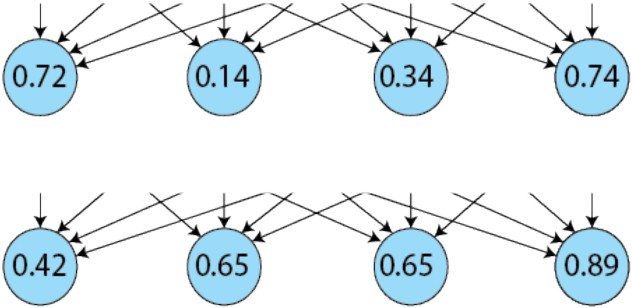
Problem: We cannot try all possible inputs.

- Solution?

TRAITS

Observation:

- Some neural networks produce different outputs, but behave the same!



- Classification problems
- Decision problems

How will this affect the design of NNTD?

NNTD

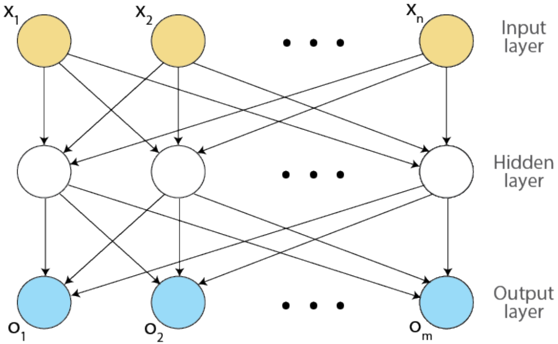
Input: A set of neural networks.
Output: A diversity measurement based on difference in *traits*

Method:

- Calculate a large amount of random inputs
- For each input r:
  - Assign each neural network a species based on its output on r.
  - Calculate a diversity based on the distribution of individuals into species.
- Return the average diversity for all random inputs.

NNTD

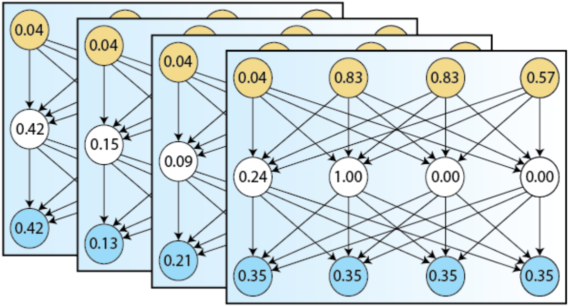
Calculate a large amount of random inputs (n-tuples) for the neural network architecture used



NNTD

For each input:

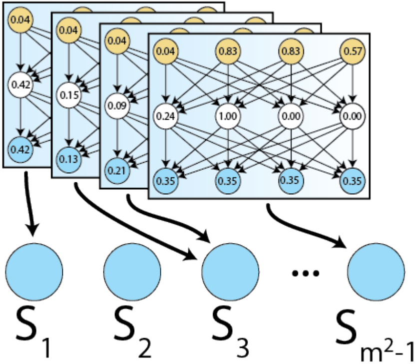
- Calculate the output of all neural networks.



NNTD

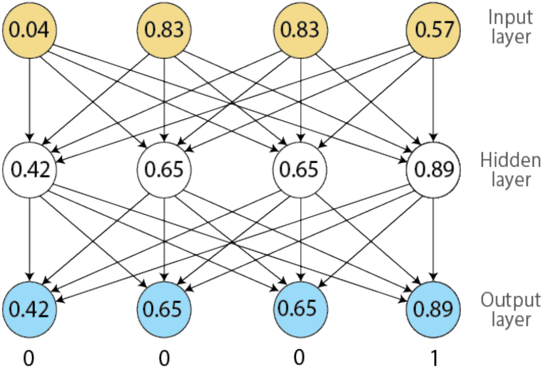
For each input:

- Distribute the neural networks into species based on their output.



Distribution of neural networks into species

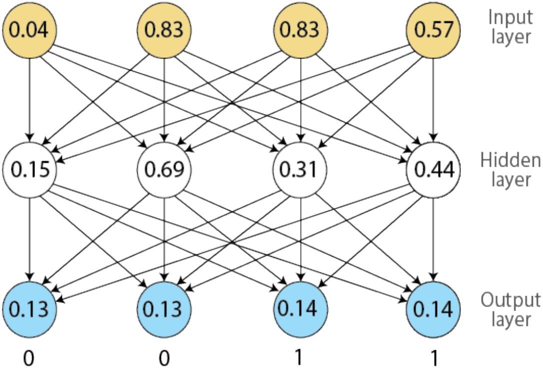
Given neural network f_1 and input $r = (0.04, 0.83, 0.83, 0.57)$



We say that $f_1 \in S_1(r)$, because binary `0001` is 1 in decimal.

Distribution of neural networks into species

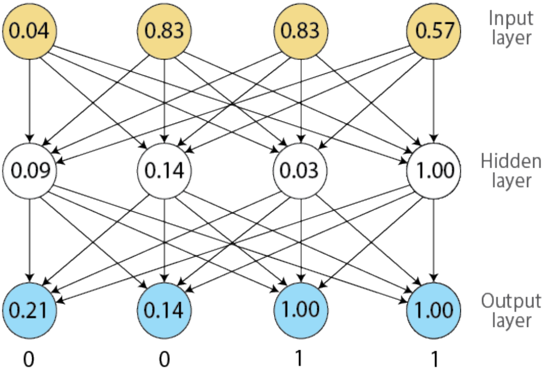
Given neural network f_2 and input $r = (0.04, 0.83, 0.83, 0.57)$



We say that $f_2 \in S_3(r)$, because binary `0011` is 3 in decimal.

DISTRIBUTION OF NEURAL NETWORKS INTO SPECIES

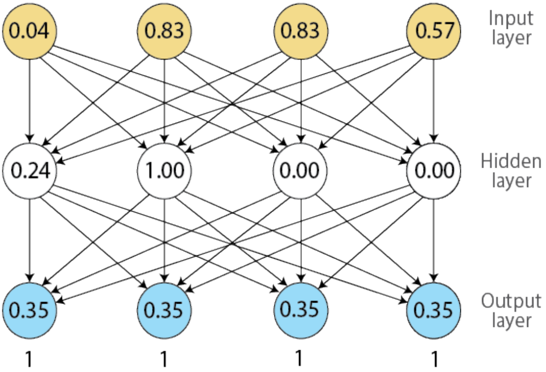
Given neural network f_3 and input $r = (0.04, 0.83, 0.83, 0.57)$



We say that $f_3 \in S_3(r)$, because binary `0011` is 3 in decimal.

DISTRIBUTION OF NEURAL NETWORKS INTO SPECIES

Given neural network f_4 and input $r = (0.04, 0.83, 0.83, 0.57)$



We say that $f_4 \in S_{15}(r)$, because binary `1111` is 15 in decimal.

FORMALLY

If $b_m b_{m-1} \dots b_1$ is the binary representation of a number i, we define the species $S_i(r)$ to contain any neural network $f \in F$, that given r as input satisfies

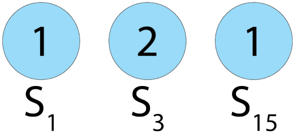
$$\forall j \in \{1, 2, \dots, m\} \left(b_j \rightarrow (o_j = h) \wedge \neg b_j \rightarrow (o_j < h)\right) \tag{1}$$

$$\text{where } h = \max\{o_1, o_2, \cdots, o_b\}$$

NNTD

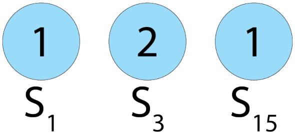
For each input:

- Calculate Simpson's Diversity Index based on the size of each species.



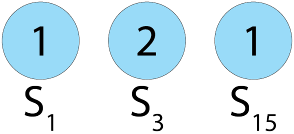
SIMPSON'S DIVERSITY INDEX

$$r = (0.04, 0.83, 0.83, 0.57)$$



SIMPSON'S DIVERSITY INDEX

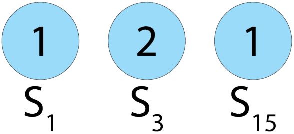
$$r = (0.04, 0.83, 0.83, 0.57)$$



$$D_r = 1 - \frac{\sum_{q \in Q_r} (|q| (|q| - 1))}{|F| (|F| - 1)} \tag{2}$$

Simpson's Diversity Index

$$r = (0.04, 0.83, 0.83, 0.57)$$



$$D_r = 1 - \frac{\sum_{q \in Q_r} \left(|q| \left(|q| - 1 \right) \right)}{|F| \left(|F| - 1 \right)} \tag{3}$$

$$D_r = 1 - \frac{1(1-1) + 2(2-1) + 1(1-1)}{4(4-1)} = \frac{5}{6} \tag{4}$$

NNTD

NNTD:
The average Simpson's Diversity Index for all random inputs.

Overview

STATIC & DYNAMIC EXPERIMENTS

- Diversity measures
  - NNTD ($100 \cdot 1000 \cdot t$ for snake)
  - Fitness-based (100 for snake)
  - Hamming distance ($450 \cdot 100^2 = 4.5$ million for snake)
  - Levenshtein distance ($450^2 \cdot 100^2 = 2$ billion for snake)
- Replacement rules
- Evaluation environments
  - Static
  - Dynamic
- Why did we choose this setup

INITIAL SIMILARITY EXAMPLE

- Population of five individuals
- Initially random

$$40\,\% \left\{ \begin{array}{l} \texttt{01010101} \\ \texttt{01010101} \\ \texttt{11000101} \\ \texttt{01101010} \\ \texttt{10101111} \end{array} \right. \qquad \left. \begin{array}{l} \texttt{01010101} \\ \texttt{01010101} \\ \texttt{01010101} \\ \texttt{11000010} \\ \texttt{10001000} \end{array} \right\} 60\,\%$$

Initial Mutation Example

- Again a population size of five
- Initial bitstring of `01010101`

$$5\,\%\left\{\begin{array}{l}\texttt{01010111}\\\texttt{01010101}\\\texttt{01010101}\\\texttt{11010101}\\\texttt{01010101}\end{array}\right.\qquad\qquad\left.\begin{array}{l}\texttt{01010101}\\\texttt{10010100}\\\texttt{00011100}\\\texttt{01010100}\\\texttt{01010101}\end{array}\right\}20\,\%$$

STATIC & DYNAMIC EXPERIMENTS

- Diversity measures
  - NNTD ($100 \cdot 1000 \cdot t$ for snake)
  - Fitness-based (100 for snake)
  - Hamming distance ($450 \cdot 100^2 = 4.5$ million for snake)
  - Levenshtein distance ($450^2 \cdot 100^2 = 2$ billion for snake)
- Replacement rules
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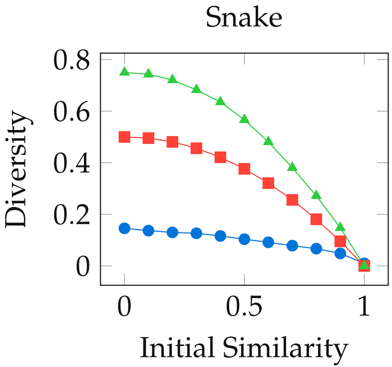
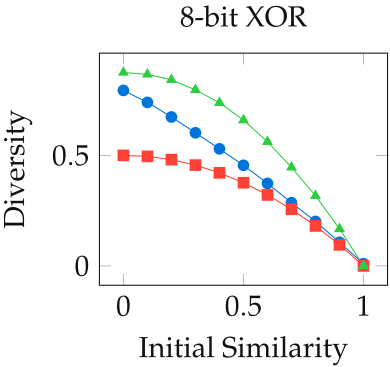
  - Static ✓
  - Dynamic
- Why did we choose this setup

Initial Similarity Results

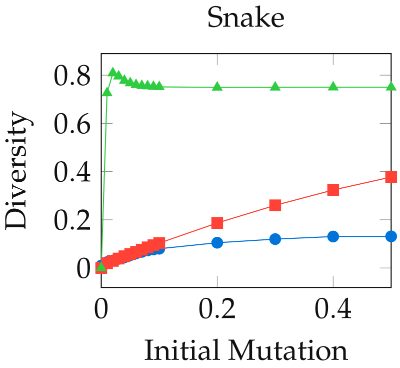
- The measures behave as expected
- Fitness-based, Hamming Distance, NNTD

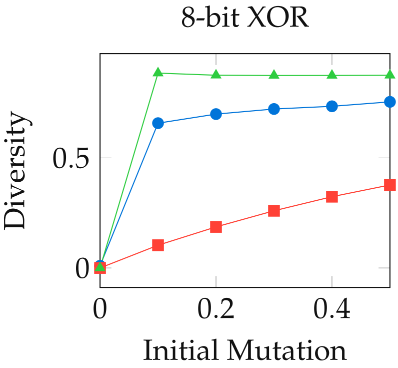




Initial Mutation Results

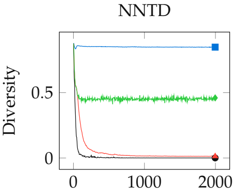
- NNTD jumps and levels out the fastest
- Fitness-based, Hamming distance gradually climb
- Fitness-based, Hamming Distance, NNTD

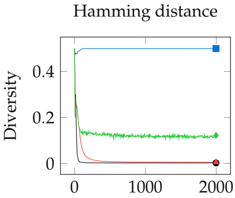


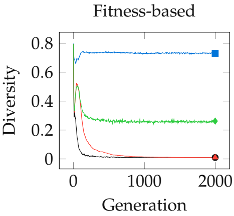


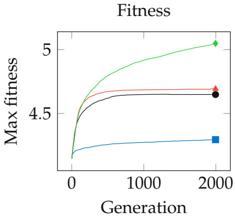
Dynamic Results, 8-bit XOR

- Greedy, Ancestor Elitism, Single Parent Elitism, MEEE









OVERVIEW

Conclusion

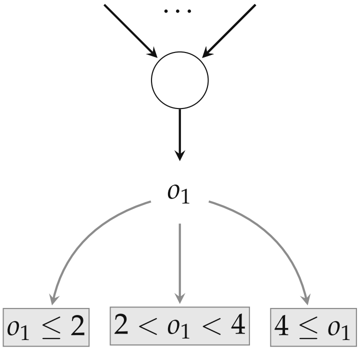
- The phenotypic fitness-based measure is unreliable
- Hamming distance seems oddly similar to NNTD
- Many, many factors and variables influence results
- Maximum diversity is not always desirable

FUTURE WORK

- Experiments, experiments, experiments
- Determining random inputs
- Understanding the difference between Hamming distance and NNTD
- Different species classification algorithms

SPECIES CLASSIFICATION

- NNTD classifies output neurons based on boolean output
- It's possible to classify by a singular output's range instead
- Such a method would expand the problem domain and data structures



Thank you!