# How Learning Can Guide Evolution [1]

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# Motivations: The Baldwin Effect

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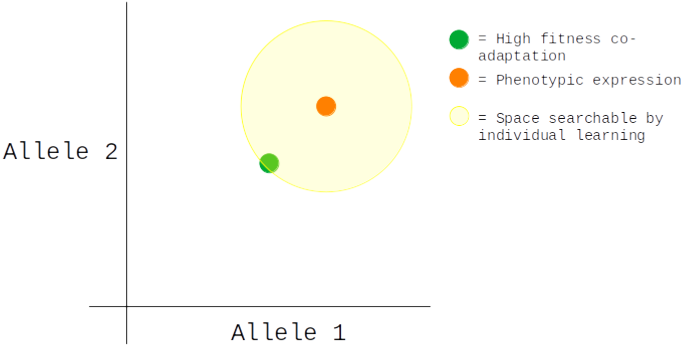
**What is the impact?**

By applying learning on top of genetic adaptation the search for a fitness increasing co-adaptation may become easier.

# The Baldwin Effect: Why?

Genotypes "nearby" to those which express successful traits may still yield greater fitness than their counterparts if individual learning is able to compensate for the gap.



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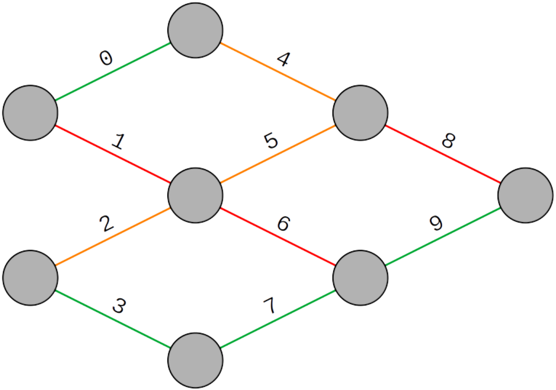
- An edge who's associated bit is ? may be either active or inactive.

So the task of an agent is to allocate their ? bits correctly.

# Genetic Model Cont.

| Index: | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|---|
| Value: | 1 | 0 | ? | 1 | ? | ? | 0 | 1 | 0 | 1 |



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- We suppose that there is some task for which the network configured with only active edges is the unique optimal solution.
- In each play cycle agents receive reward only if they submit the optimal network configuration. Thus with genetic search alone discovering the optima is difficult.

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| Index: | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|---|
| Value: | 1 | 0 | ? | 1 | ? | ? | 0 | 1 | 0 | 1 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Value: | 1 | 0 | 1 | 1 | 0 | 1 | 0 | 1 | 0 | 1 |

# Reproductive Dynamics, Mate Selection

The likelihood of an agent $a_i$ being selected as a parent is roughly proportional to $p(a_i)$:

$$p(a_i) = \frac{1 + U(a_i)}{\sum_{i'=0}^{n} 1 + U(a_{i'})} \tag{1}$$

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So if agent $a_1$ is twice as successful as $a_2$ we expect to produce about twice as many offspring for $a_1$.

# Reproductive Dynamics, Parental Composition

Offspring a produced by combining the genetic code of the two parents. A cutoff is chosen at random and determines which bits are drawn from which parent.

Parent 1

| Index: | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|---|
| Value: | 1 | 0 | ? | 1 | ? | ? | 0 | 1 | 0 | 1 |

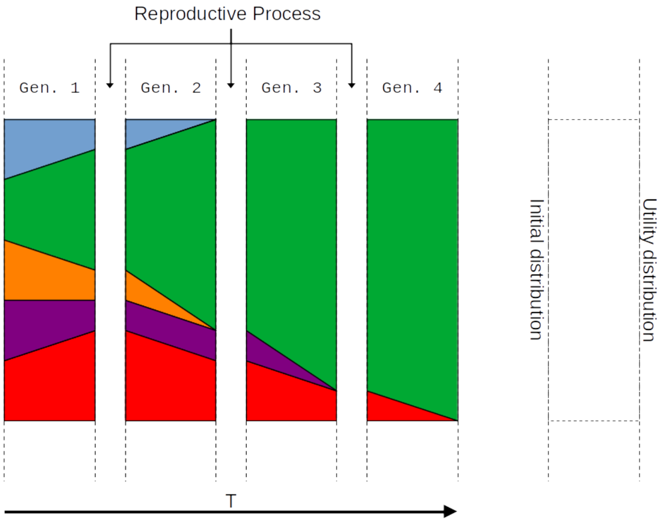
Parent 2

| Index: | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|---|
| Value: | 0 | 1 | 1 | ? | 0 | 0 | 1 | 1 | ? | 1 |

| Index: | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|---|
| Value: | 1 | 0 | ? | 1 | ? | ? | 1 | 1 | ? | 1 |

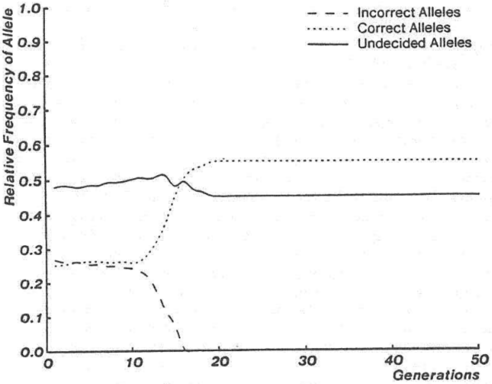
Offspring with cutoff=5

# Diagram Overview



# Results

Experiments using this model produced results supporting the idea that individual learning can drastically improve evolutionary searc hes.



G. E. Hinton and S. J. Nowlan, "How learning can guide evolution," 1987.
Classic/Keystone paper supporting the Baldwin effect via evolutionary simulations.