Population Size and the Extinction of Mammoths

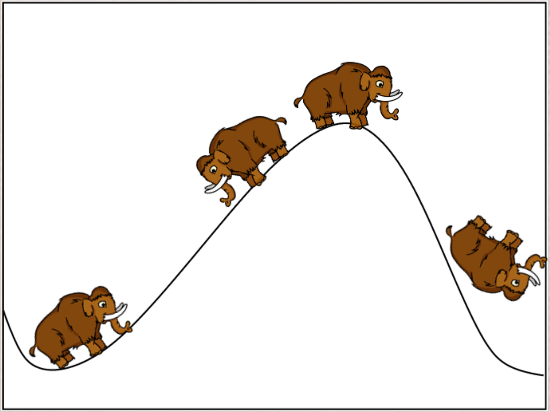
Daniel Ashlock, Senior Member IEEE

Abstract

This papers models the results of a comparison between populations of extinct mammoths. One population sample is from the heydey of mammoths and part of a large population, the other was from a survival at a time close to the species extinction on Wrangle island. The key issue is the impact of population size on the ability to hold position on an optima.

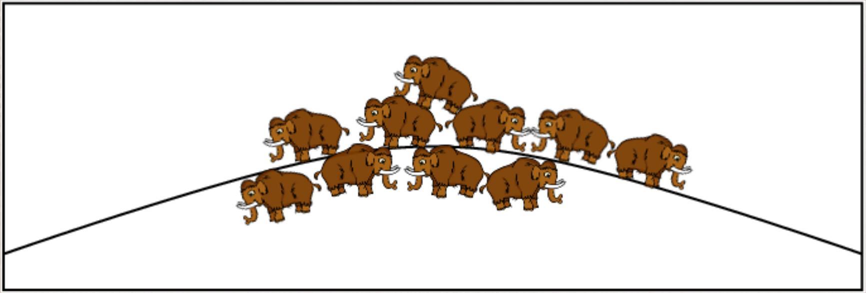
The Situation Being Modeled

The hypothesis of the biological paper that formed the basis for this work is that natural selection to not efficiently remove deleterious near-neutral mutations and does not effectively conserve beneficial near neutral mutations.



The Situation Being Modeled

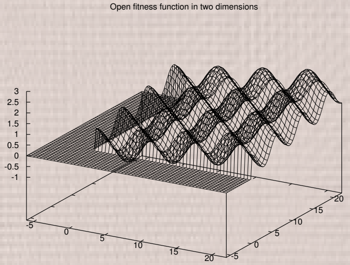
- Recast in fitness landscape context, this means that a small population has trouble staying on an optima while a large one can stay there.
- We also look at an additional factor: how does population size affect the ability to discover new hills?

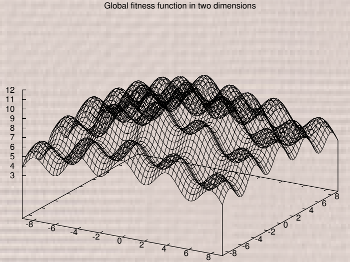


Bad Mammoth! Down!

The Two Functions

We use two fitness functions. The first one goes upward forever while the other has a global optima in the center.





The open fitness function.

$$\frac{1}{n}\sum_{k=1} n\cos(x_i) + \frac{x_i}{10}$$

The global fitness function.

$$\sum_{k=1}^{n} 2\cos\left(\frac{\pi}{2}x_i\right) + \frac{1000}{\sum_{k=1}^{n} x_i^2 + 100}$$

How are the experiments run?

The idea is to see how a population, initialized on an optima, behaves.

- For the open function the population is started at the top of the lowest hill.
- For the global function the population is started on top of the global optima.

For the **open function** the question is – how many new optima can the population discover? For the **global function** the question is can the population stay on the optima.

In addition to having **two functions** and **population sizes of 10, 32, 100, 320, and 1000** we use different sizes of mutations, scaled to be smaller that half a hill diameter. Finally **two evolutionary algorithms are used.**

The First Evolutionary Algorithm

The first algorithm is a **reaper queue algorithm**. The population is placed in a line. A population member is selected in proportion to fitness, cloned, mutated and the clone is placed at the back of the line. The character at the head of the line is then deleted. This algorithm is **not elitist** and so can only hold onto an optima by generating children that retain their parent's fitness. This algorithm is **more nearly biological** than most evolutionary algorithms and would typically be thought to be **a bad optimization algorithm**. The reaper queue is an idea from *Tierra:*

Reference

T. S. Ray, **An evolutionary approach to synthetic biology: Zen and the art of creating life.** Artificial Life, 1(1/2):179209, 1994.

The Second Evolutionary Algorithm

The second evolutionary algorithm uses a population of size one. A set of **k** mutants are generated and the best one replaces the current population member. The values **k**=2,5,8,11,14 are used. These simulate different size populations. This algorithm also uses different mutation sizes. The purpose of this mutation is to generate fitness trajectories – a single line of descent – traced across the hills of the fitness landscape.

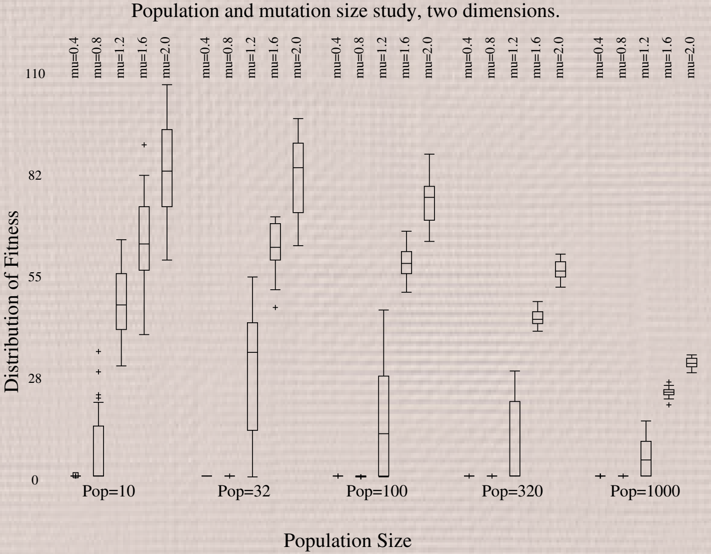
This algorithm is modeled on *evolution strategies:*

Reference

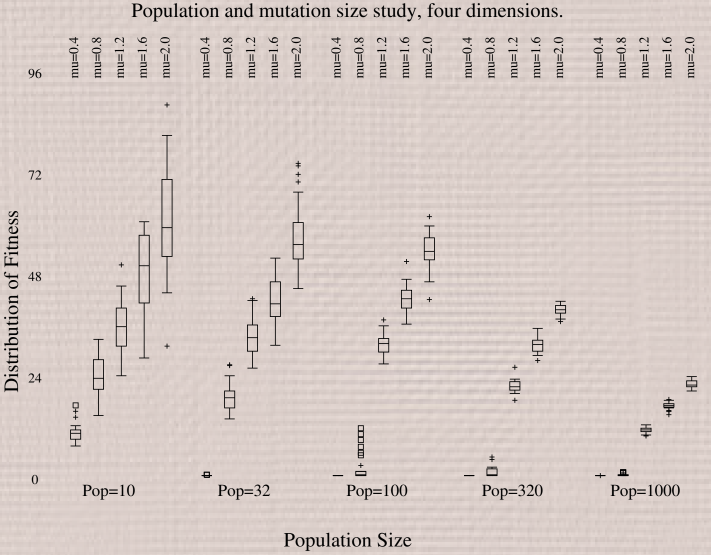
Hans-Georg Beyer, **The Theory of Evolution Strategies**, Springer, Berlin, 2001.

This algorithm is also **not elitist** and so can only hold onto an optima by generating children that retain their parent's fitness. The more mutants there are, the easier this is.

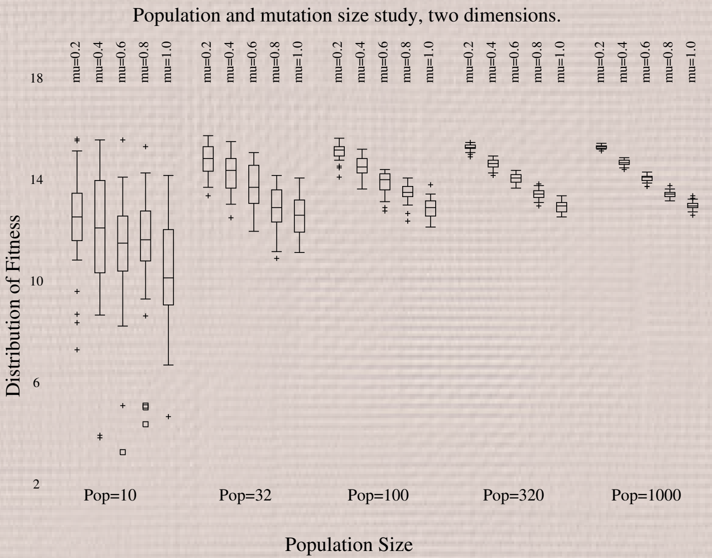
Open landscape, reaper algorithm, two dimensions.



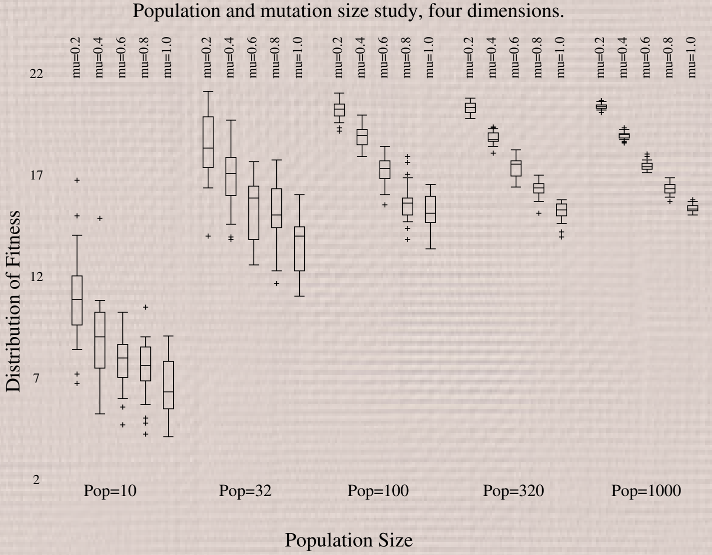
Open landscape, reaper algorithm, four dimensions.



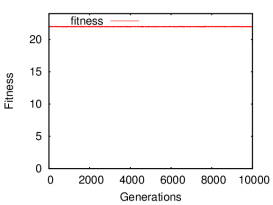
Global landscape, reaper algorithm, two dimensions.



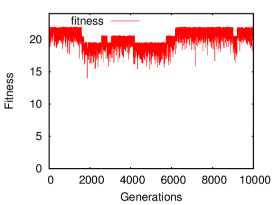
Global landscape, reaper algorithm, four dimensions.



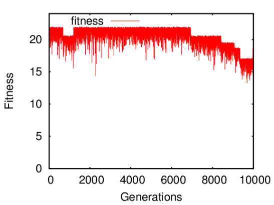
Global landscape, ES-like algorithm.



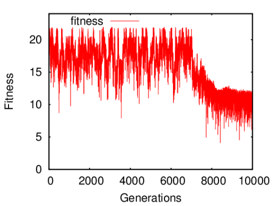
k=14 $\epsilon = 0.2$



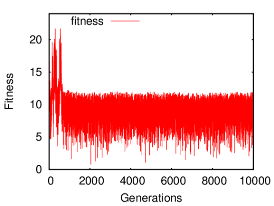
k=2 $\epsilon = 0.4$



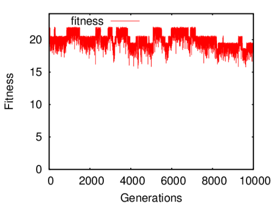
k=2 $\epsilon = 0.4$



k=2 $\epsilon = 0.6$



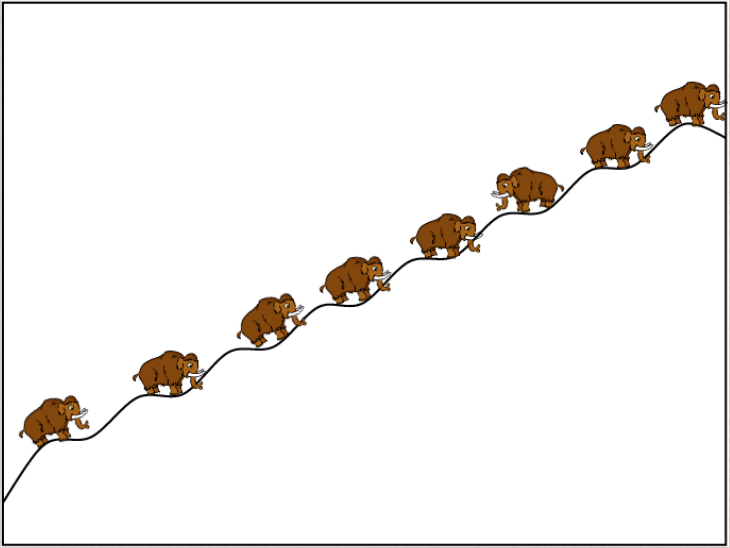
k=2 $\epsilon = 1.0$



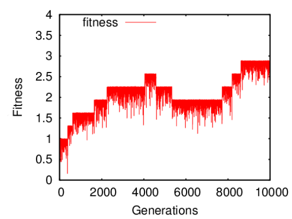
k=5 $\epsilon = 1.0$

Look at all the different ways a trajectory can vary on the open landscape.

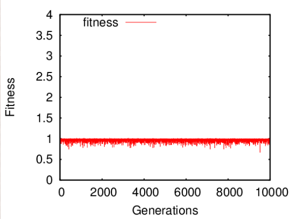
Mammoth Lineages on an Open Landscape



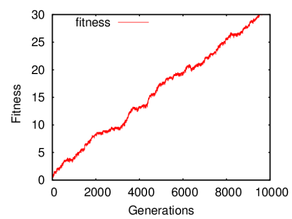
Open landscape, ES-like algorithm.



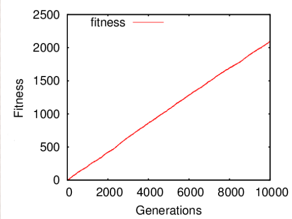
dim=2 k=2 $\epsilon = 0.2$



dim=4 k=2 $\epsilon = 0.2$



dim=4 k=2 $\epsilon = 1.0$



dim=4 k=14 $\epsilon = 1.0$

Look at all the possibilities!

Implications for Optimization

One of the major design issues in an evolutionary computation system is the trade-off between **exploration and exploitation**.

- Exploration can be thought of as searching for new hills in the adaptive landscape.
- Exploitation consists of finding the top of a hill that the population already occupies.

Another way to summarize the findings of this study are that **smaller populations favor exploration while larger ones favor exploitation**. Since small populations both discovered better hills in the simulation of adaptive radiation and fell off the global optima of the global fitness landscape, this tendency remains **in spite of the adaptive value of exploration or exploitation**.

What Next?

- These simulations use a single species, reproducing clonally. It would be very interesting to use multiple, interacting species. In this case we would replace the fitness landscapes with interactions between different species.
- One point where observation and theory diverge is that there are **more rare species that theory predicts**: a multi-species simulation would permit us to model the "natural" level of rare species.
- A myth is that rare species are endangered – in fact **recently rare** species are endangered. That means that species can probably *adapt* to being rare.
- **Ring optimization** has some of the qualities of a small population and some of those of a large population. This system night let us figure out what these qualities are.

Many Thanks

Thanks to the *National Science and Engineering Research Council of Canada* and the *University of Guelph* for support of this work.