TIEBREAKS AND DIVERSITY: ISOLATING EFFECTS IN LEXICASE SELECTION

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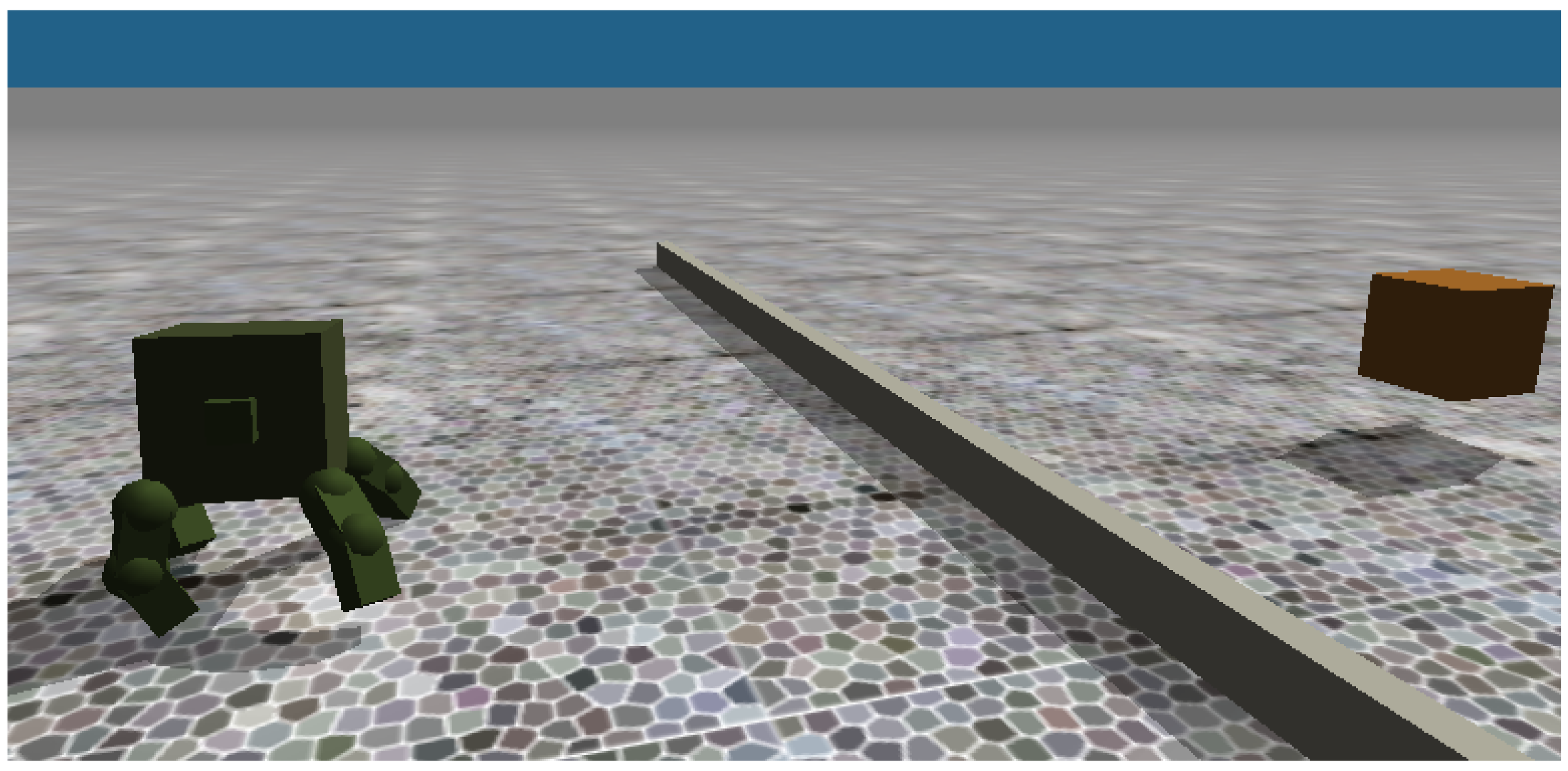
INTRODUCTION

A robot controller should be capable of solving a variety of tasks in a domain, rather than only addressing specific instances of a task (i.e. it should be a **general** controller). Prior work has shown that **Lexicase selection** is more effective than other evolutionary algorithms in a task where quadrupedal animats learn gaits that enable traversal of a barrier of varying height.

FIGURE 1



The simulated robot performing its task. The world contains a target (represented by the small box) and a barrier. A population of neural controllers is subjected to evolutionary pressure to find gaits able to move the robot across the obstacle, to the target. The barrier can be any height within a range, although it is always in the same position.

BACKGROUND

This work leads on from previous work where we compared different ways of exposing species (over evolutionary time) to barriers of different heights, to try to find the general solution.

In the earliest of this series (Stanton and Channon, 2013), we made comparisons between random height presentations, only the highest barrier, a gradual increase in height, and time-dependent sinusoidal changes in height. We found that properly tuned oscillatory presentation resulted in the best generalisation.

In the next contribution (Moore and Stanton, 2017), we examined *Lexicase* selection (Helmuth, Spector, and Matheson, 2014), and compared to these previous strategies. **In Lexicase, a number of objectives (in this case, barrier heights) are randomly chosen and ordered, and parents are selected based on winning a tournament over the ordered objectives.** We found that, when properly parametrised, Lexicase is superior to all other strategies.

CONTRIBUTIONS

In this paper we examine the reasons behind the superior performance of Lexicase selection in the barrier task. We explore a wide range of Lexicase parameters and investigate the hypothesis that the increased performance is a result of maintaining population diversity.

We characterise the relationships between the parameters (such as the number of Lexicase environments [objectives in a tournament] and the “fuzzing” of high-scoring individuals), the number of tie-breaks (where tournament objectives are exhausted without a clear winner), and the resulting diversity of evolving species.

ACKNOWLEDGEMENTS

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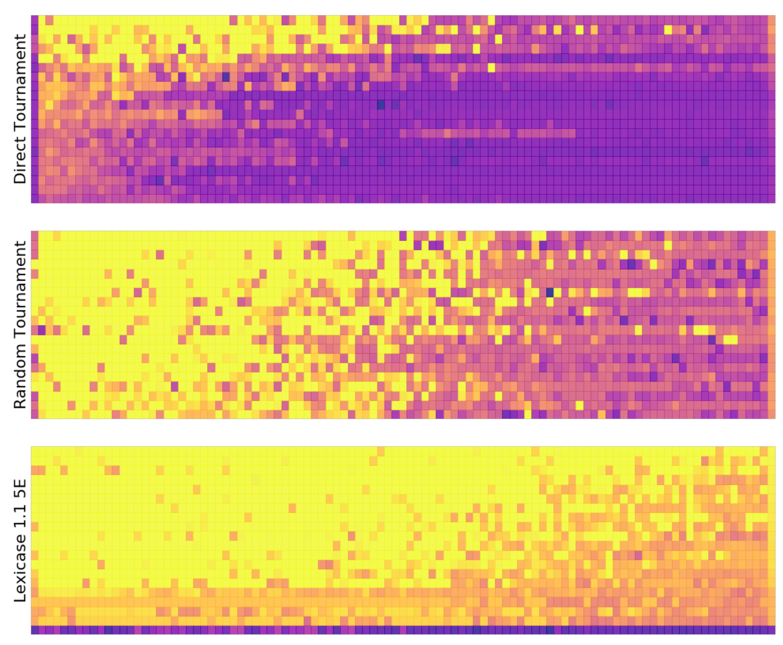
METHODS

- Feedforward neurocontroller with joint angle inputs, target direction inputs, $\sin(t)$ and $\cos(t)$ spontaneous inputs, and 12 hidden units. Outputs are target angles for joints, achieved with a proportional-derivative control mechanism.
- Simulation in ODE 0.15.2, evaluation lasts 20 seconds. 50 individuals per species; 20 replicates per treatment. Evolution of floating-point weights with crossover and Gaussian mutation takes place over 5000 generations, then final evaluation stage measures performance across 100 barrier heights.
- Fitness measure is proximity to the target; diversity measure is mean per-locus variance in the population.

RESULTS AND CONCLUSIONS

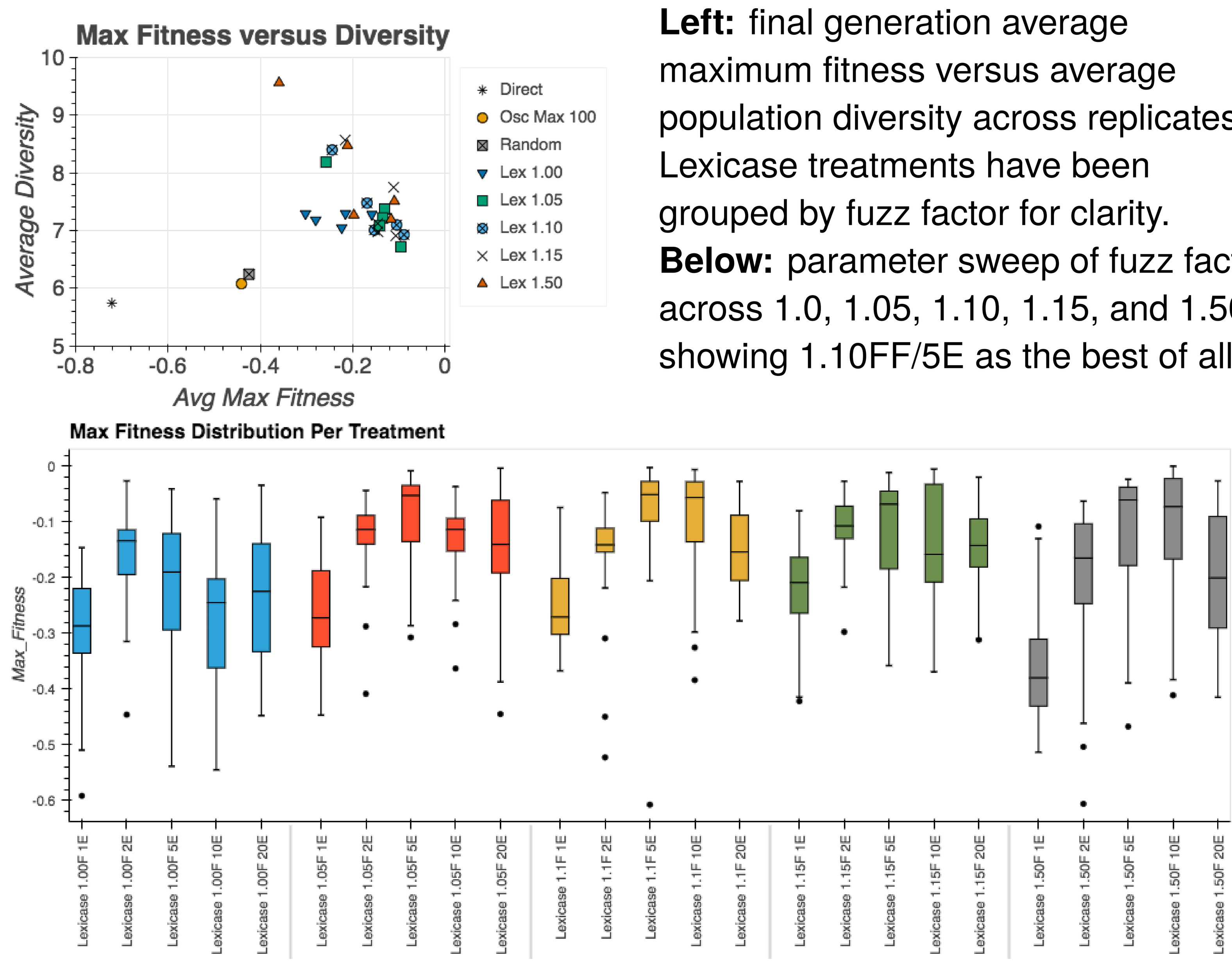
- **5 environments and 1.10 fuzz factor performs best.**
- **Performance is driven by diversity and the number of environments.**

FIGURE 2



Performance of the best individual per replicate across all 100 environments, in the post-evolution evaluation phase. Darker shades indicate poor performance, lighter shades indicate success. Wall heights increase from left to right. From top to bottom: highest wall only; random wall heights; and Lexicase 1.10FF/5E. The superiority of Lexicase is clear here from the lightness of the heatmap.

FIGURE 3



Left: final generation average maximum fitness versus average population diversity across replicates. Lexicase treatments have been grouped by fuzz factor for clarity. **Below:** parameter sweep of fuzz factor across 1.0, 1.05, 1.10, 1.15, and 1.50, showing 1.10FF/5E as the best of all.

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