

# Exploring the Heterotic Landscape with Genetic Algorithms and Reinforcement Learning

Thomas Harvey

Based on work in collaboration with: Steve Abel, Andrei Constantin and Andre Lukas

2103.04759, 2108.07316, 2110.14029, 2111.07333



# Outline

- Introduction - RL, GA and Monads
- Reinforcement Learning (RL) applied to Monads
- Genetic Algorithms (GA) applied to Monads
- Conclusion

# Introduction

# Introduction: ML (Specifically RL)

- There has been a focus on supervised ML in String Theory
  - For review see: F. Ruehle, Phys. Rep. 839, 1-117, 2020
- RL: “Mastering the game of Go with deep neural networks and tree search” - Silver et al.
- RL is more appropriate to search the string landscape
  - Halverson, Nelson, Ruehle, 1911.07835
  - Larfors, Schneider, 2003.04817
  - Constantin, Harvey, Lukas 2108.07316
  - Krippendorff, Kroepsch, Syvaeri, 2107.04039

# Introduction: GA

- GA dates back to the 1960s
  - J. Holland, “Adaption in Natural and Artificial Systems”, 1975
- Has been used in our field to search large environments
  - Abel, Rizos, 1404.7359
  - Abel, Cerdeno, Robles 1805.03615,
  - Cole, Schachner, Shiu, 1907.10072,
  - Abel, Constantin, Harvey, Lukas 2110.14029
  - Cole, Krippendorf, Schachner, Shiu, 2111.11466

# Introduction: GA and RL for String Model Building

- Our Aim: *“Can RL/GA construct string realisations of the standard model”*
- If so:
  - How do they compare?
  - Do they find any, until now, unknown models?
  - Do they give us model building insight?
- We focus heterotic models via Monad bundles
  - Very few promising models are known here!

# Introduction: Monad Bundles

- Heterotic Models are specified by
  - Smooth Calabi-Yau manifold  $X$
  - Vector Bundle  $V$  on  $X$ 
    - Will be  $SU(4)$  bundle for us  $\rightarrow SO(10)$  GUT Theory
- Monad bundles are constructed via a short exact sequence.

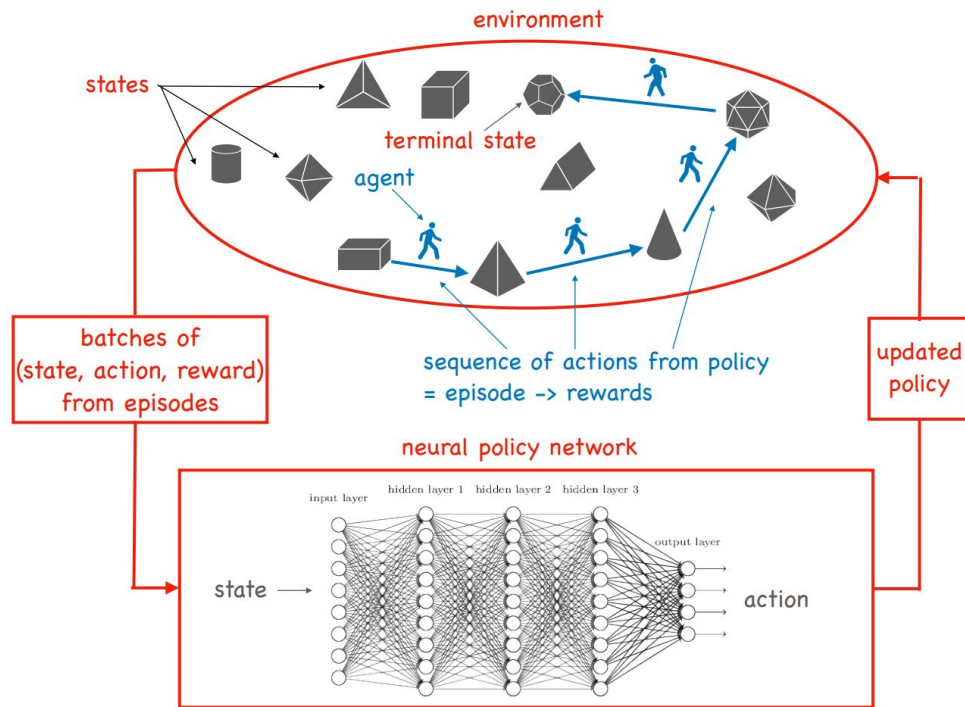
$$0 \rightarrow V \rightarrow B \xrightarrow{f} C \rightarrow 0 \qquad V \cong \text{Ker}(f) \qquad B = \bigoplus_{a=1}^{\bar{}} \mathcal{O}_X(\mathbf{b}_a) \qquad C = \bigoplus_{\alpha=1}^{\bar{}} \mathcal{O}_X(\mathbf{c}_\alpha)$$

- Such a bundle is called a “Monad”
  - Key Point: Specified by a large number of integers

# Reinforcement Learning (RL)

# RL: The Basics

- Agent explores environment collecting rewards
- We will specify rewards based on agreement with experiment
- Model building with RL:
  - String Theory - Here
  - Particle Physics - Harvey and Lukas 2103.04759
- Realised REINFORCE and Actor-Critic in Mathematica



# RL: Monads

<u>RL</u>	<u>Physics</u>
<b>Environment</b>	All Monads (B,C) on a fixed Calabi-Yau with entries: $b_{\min} \leq b_a^i \leq b_{\max}$ and $c_{\min} \leq c_a^i \leq c_{\max}$
<b>Actions</b>	For fixed (i, j, a): $b_a^i \rightarrow b_a^i \pm 1$ and $c_a^j \rightarrow c_b^j \pm 1$ simultaneously
<b>Reward</b>	Increase in State Value State Values $\sim$ -(Deviation from MSSM*) + (Big Bonus if Terminal)
<b>Terminal State</b>	The Standard Model spectrum*

\*All checks requiring cohomology calculations are done after training

# RL: Mon

## RL

### Environment

### Actions

### Reward

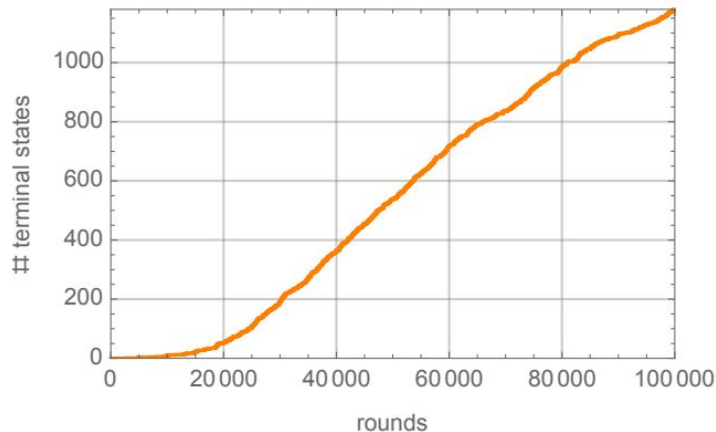
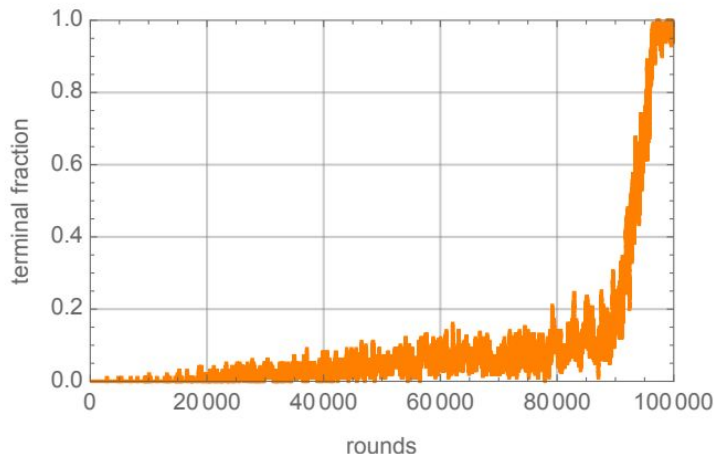
### Terminal Stat

property	term in $v(B, C)$	comment
index match	$-\frac{2 \text{ind}(V) - \tau }{hM^3}$	$\tau = -3 \Gamma $ is the target index, ind(V) computed from Eq. (2.20)
anomaly	$\frac{1}{hM^2} \sum_{i=1}^h \min(c_{2i}(TX) - c_{2i}(V), 0)$	no penalty if anomaly condition satisfied, $c_{2i}(V)$ computed from Eq. (2.20)
bundleness	$-(d_{\text{deg}} + 1)$	$d_{\text{deg}}$ = dimension of degeneracy locus as discussed in Sec. 2.4; if the degeneracy locus is empty, $d_{\text{deg}}$ is to be taken as $-1$
split bundle	$-n_{\text{split}}$	$n_{\text{split}}$ = number of splits in $V$
equivariance	$-\sum_{U \subset B, C} \text{mod}(\text{ind}(U),  \Gamma )$	$U$ runs over all line bundles in $B, C$ or blocks of same line bundles, as discussed in Sec. 2.4
trivial bundle	$-n_{\text{trivial}}$	$n_{\text{trivial}}$ = number of trivial line bundles
stability $V$	$-\frac{\max(0, h^0(X, B) - h^0(X, C))}{hM^3}$	tests Hoppe's criterion for $V$ , cohomologies from formulae in Sec. 2.3
stability $V^*$	$-\frac{\max(0, h^0(X, B^*) - h^0(X, C^*))}{hM^3}$	tests Hoppe's criterion for $V^*$ , cohomologies from formulae in Sec. 2.3

Table 2: Contributions to the intrinsic value for the monad environment. The intrinsic value  $v(B, C)$  is the sum of all eight terms and  $M = \max(b_{\text{max}}, c_{\text{max}})$ .

# RL: Bicubic

- SO(10) GUT From Monad on Bicubic, with Z3 X Z3 Wilson line
- $b_{\min} = -3, b_{\max} = 5, c_{\min} = 0, c_{\max} = 5, r_B = 6, r_c = 2$ 
  - $10^{12}$  states in total!
- Training ~1 hour on single CPU - Find ~15 models after extra checks

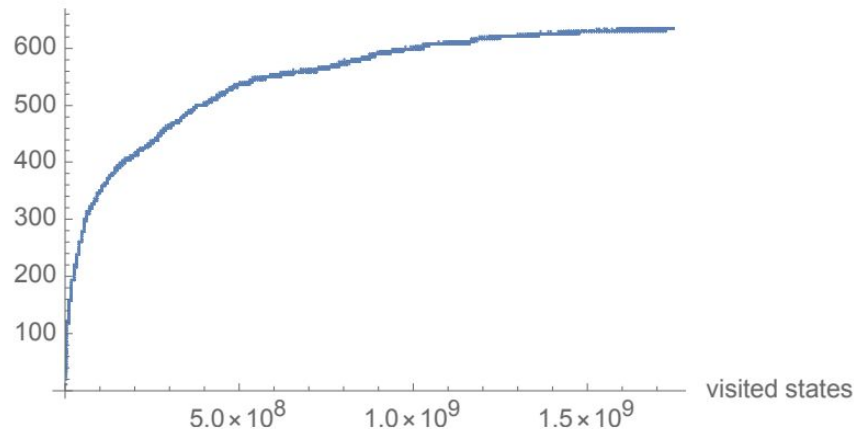


# RL: Bicubic

- Keep searching to saturation (35 core days)
- Suggests almost all models found
- Contains 27 genuine new (6,2) models, and the one known model!
  - Anderson, Gray, He, Lukas - 0911.1569
- Also have  $O(500)$  models on triple tri-linear

$$X \sim \left( \begin{array}{c|ccc} \mathbb{P}^2 & 1 & 1 & 1 \\ \mathbb{P}^2 & 1 & 1 & 1 \\ \mathbb{P}^2 & 1 & 1 & 1 \end{array} \right)$$

inequiv. perfect states



# RL: Bicubic

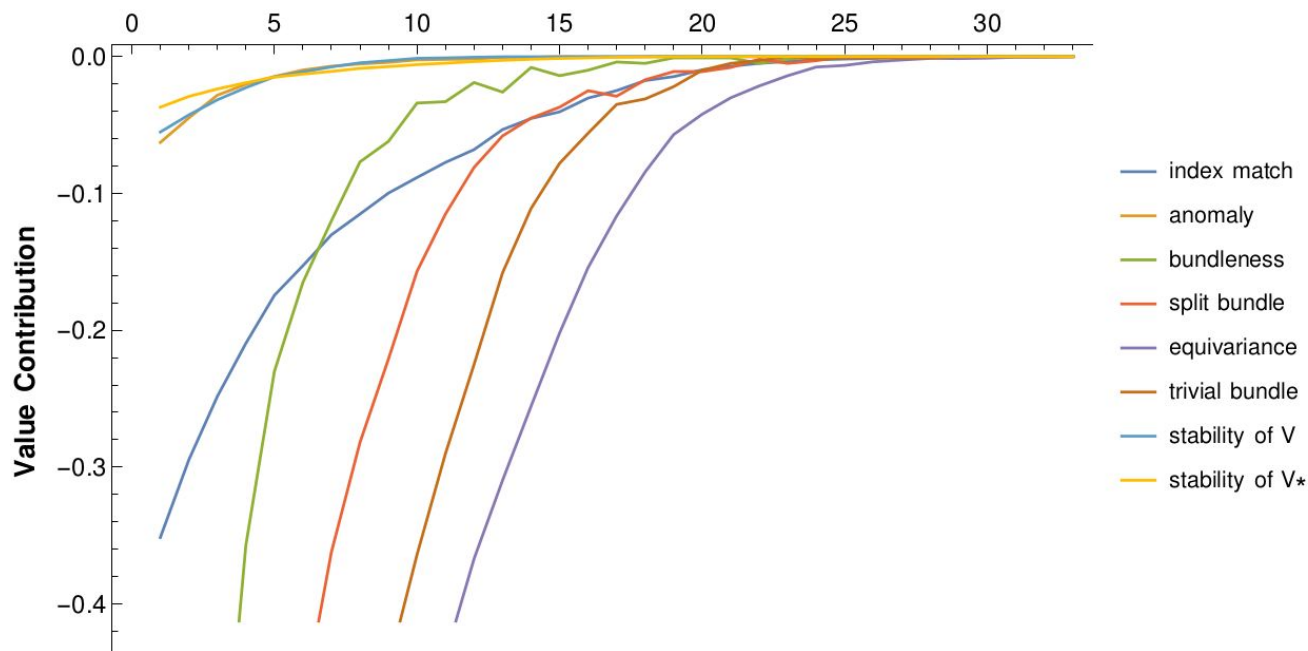


Figure 7: The different contributions to the intrinsic value for  $(r_b, r_c) = (6, 2)$  bicubic models. This data is averaged over 1000 terminal states using the trained network.

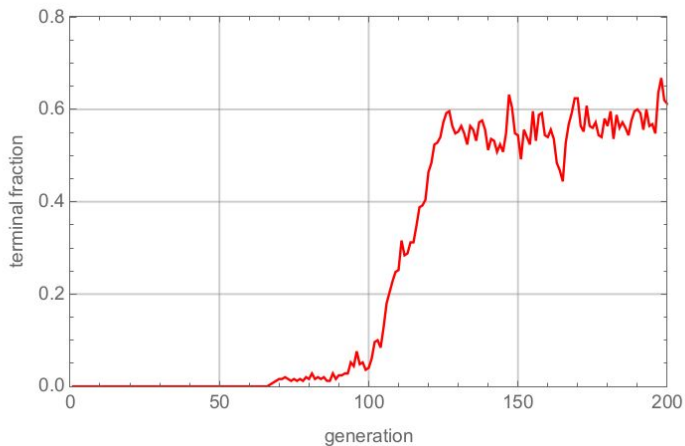
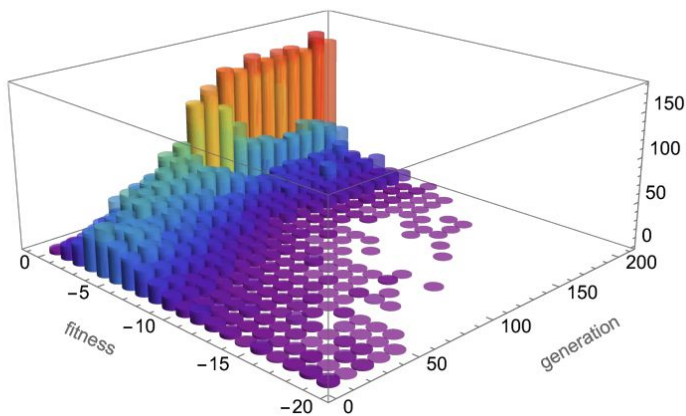
# Genetic Algorithms (GA)

# GA: The Basics

- Take integers specifying Monad and convert to binary
- Assign “fitness” (= state value in previous language) to each
- Create population (250 in our case)
- Evolve the population via crossing and mutation many times over
- After a number of generations the population has many terminal states
- Code for GA available:
  - <https://github.com/harveyThomas4692/GAMathematica>

# GA: Bicubic

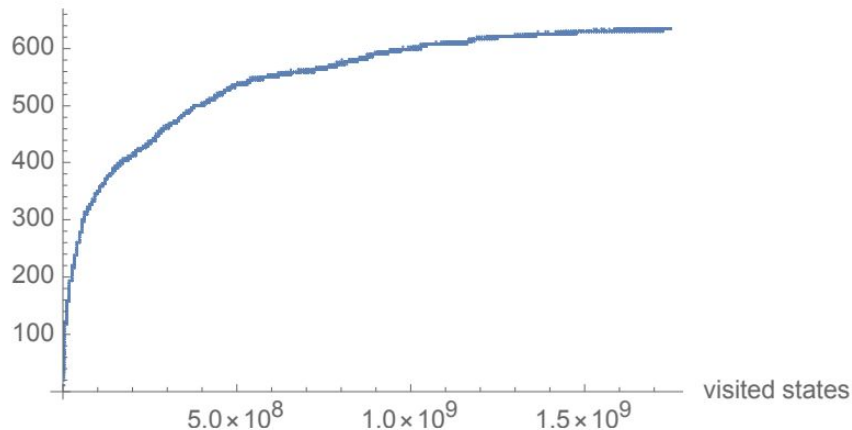
This produces terminal states in minutes



# GA: Bicubic RL vs GA

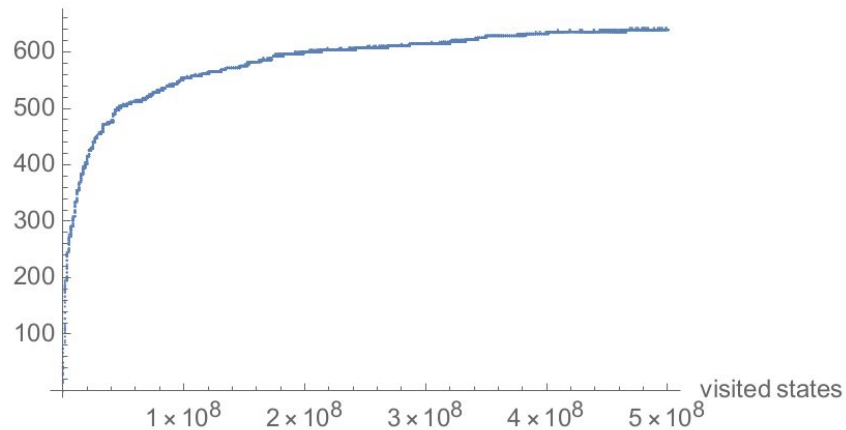
RL (35 Core days)

inequiv. perfect states



GA (10 Core days)

inequiv. perfect states



- Largely the same terminal states as found with RL
- GA appears faster than RL for this problem and our implementation
- GA tends to find more permutations (expected from implementation)

# Conclusion

- RL and GA are both efficient in engineering string models
- Many new models are discovered
  - Both methods give similar models, including many new models
- For our implementation GA was faster at finding terminal states
- Can this be extended to other manifolds? larger  $h^{11}$ ? Extra Constraints?
- Can this be used in other string constructions?