Particle Physics Model Building with Reinforcement Learning

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Reinforcement Learning

Agent, following a neural network called a policy, explores an environment

Rewards are gained as we move around the environment

In simplest algorithm (REINFORCE), the policy is updated at the end of episodes to gain more rewards in future episodes

We suggest that one should use the space of QFTs as an environment, rewards are then chosen to match “agreement with experiment”. The theories in best agreement are chosen to end the episodes

Froggatt-Nielsen Mechanism

- Extension to the Standard Model to explain Yukawa couplings
- Introduces a number of new scalars and symmetries
  - These scalars, and standard model fields, have a charge under these new symmetries
  - Scalar vevs generate Yukawa terms

$$\mathcal{L}_{\text{Yuk}} = Y^u_{ij}\bar{Q}^i H^c u^j + Y^d_{ij}\bar{Q}^i H d^j + \text{h.c.}$$

$$\mathcal{L}_{\text{Yuk}} = \sum_{i,j}\left(a_{ij}\phi_1^{n_{1,ij}}\cdots\phi_r^{n_{r,ij}}\bar{Q}^i H^c u^j + b_{ij}\phi_1^{m_{1,ij}}\cdots\phi_r^{m_{r,ij}}\bar{Q}^i H d^j\right) + \text{h.c.}$$

Learning the Froggatt-Nielsen Environment

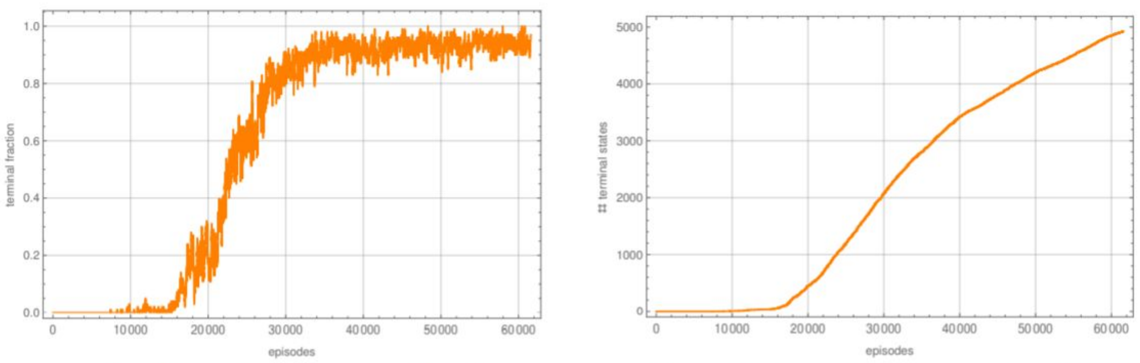
- Natural value, orders of magnitude in disagreement with quark masses and CKM matrix elements.
  - Ignore CP violating term
  - Terminal states have value > -5
- Only learn the charges
  - Sweep through possible vevs
  - Leave the O(1) coefficients fixed during training.
- Think of this as a proof of concept

$$\mathcal{V}(\mathcal{Q}) = -\min_{|v_a| \in I} \sum_{\mu} \left| \log_{10}\left(\frac{|\mu_{\mathcal{Q},v_a}|}{|\mu_{\exp}|} \right) \right| .$$

$$\mathcal{R}(\mathcal{Q},\alpha) = \begin{cases} \mathcal{V}(\mathcal{Q}') - \mathcal{V}(\mathcal{Q}) & \text{if} \quad \mathcal{V}(\mathcal{Q}') - \mathcal{V}(\mathcal{Q}) > 0 \\ \mathcal{R}_{\text{offset}} & \text{if} \quad \mathcal{V}(\mathcal{Q}') - \mathcal{V}(\mathcal{Q}) \leq 0 \end{cases} .$$

Learning the Froggatt-Nielsen Environment

- 1 scalar 1 symmetry ~1 hour on a PC
- 2 scalar 2 symmetry ~1 day on a PC
- 4630 unique 1 scalar 1 symmetry models found
  - At least 89 of which can have value > -1 by varying O(1) coefficients
- 57807 unique 2 scalar 2 symmetry models found
  - At least 2019 of which can have value >-1 by varying O(1) coefficients



(c) Fraction of terminal episodes vs episode number.

(d) Number of terminal states vs episode number.

Conclusions

Reinforcement Learning as a method of model building in particle physics

Reinforcement learning

Used Froggatt-Nielsen as an example environment

No reason to believe that this method can't be used more generally

More details in paper - **arXiv:2103.04759**