SOUTHWESTERN UNIVERSITY

Target-Based Image Evolution Using Quality Diversity Based Exclusively on Genome Complexity

Anna Wicker

Introduction

Target-based evolution using CPPN genotypes is difficult, but previous work [1] comes close to recreating a target image using the loss value generated by an autoencoder to bin images in a MAP-Elites archive. However, a closer approximation to the target can be recreated by binning the archive in a simpler way.

Evolving Images

- CPPNs [2] can generate images by setting a color for each pixel based on its position.
- MAP-Elites takes offspring, categorizes them into bins, and keeps the best image in each bin.
- Images were binned using two methods:
  - Using the number of neurons in the CPPN (Compositional Pattern Producing Network).
  - Using an autoencoder loss value and the number of neurons. The loss value indicates how well the produced image matches the target image and thus shows how distinct an image is from the rest of the archive.

Autoencoder Bin Labels

- An autoencoder periodically trains on the archive, so it can recreate those images well. A high loss value means an image is novel, since it is hard to recreate.
- Since loss provides a measure of novelty, loss values in different ranges are associated with different MAP-Elites bins to create interesting stepping stones.

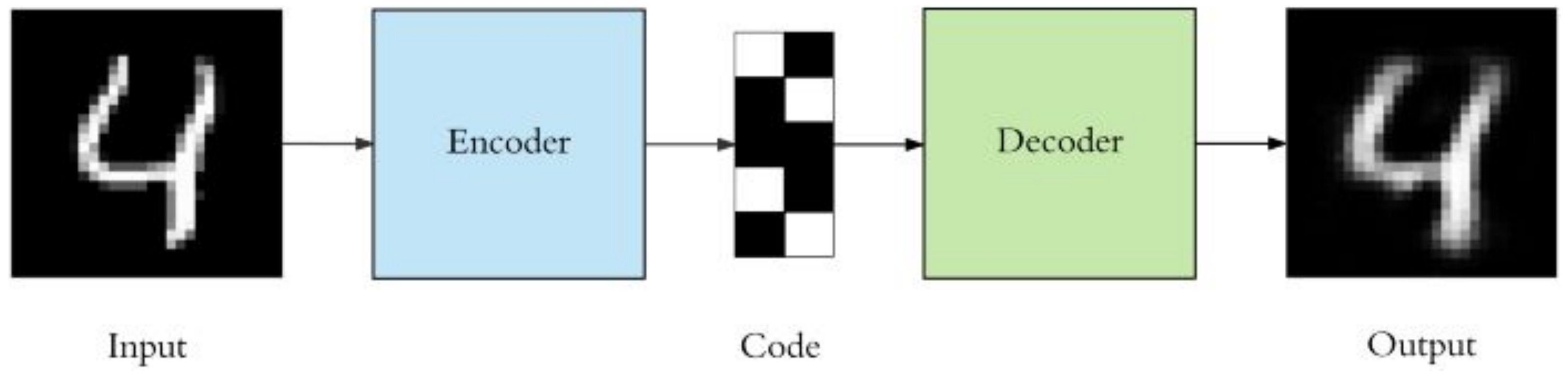

Figure 1: An example of an autoencoder reproducing a noisy image.

Figure 2: The original skull target image created by Picbreeder users. Difficult to recreate this specific image.

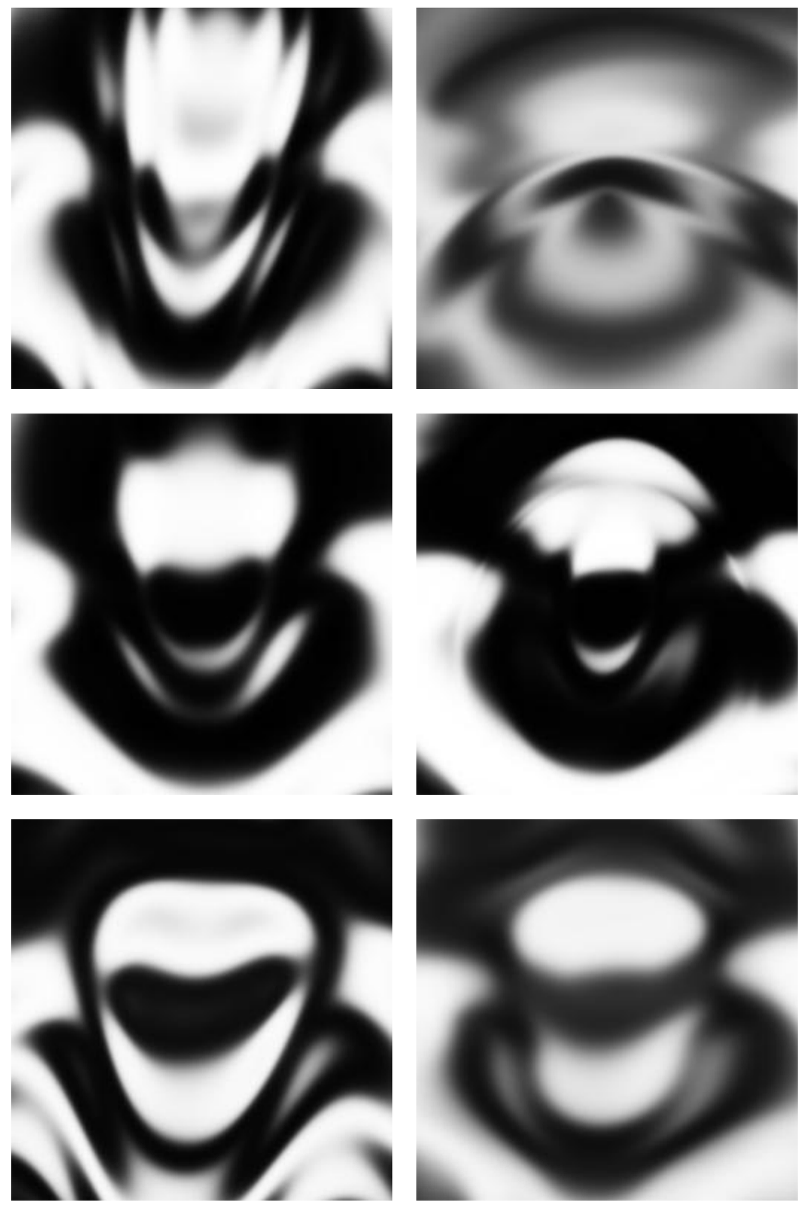

Figure 4: Images with highest fitness produced using the autoencoder scheme.

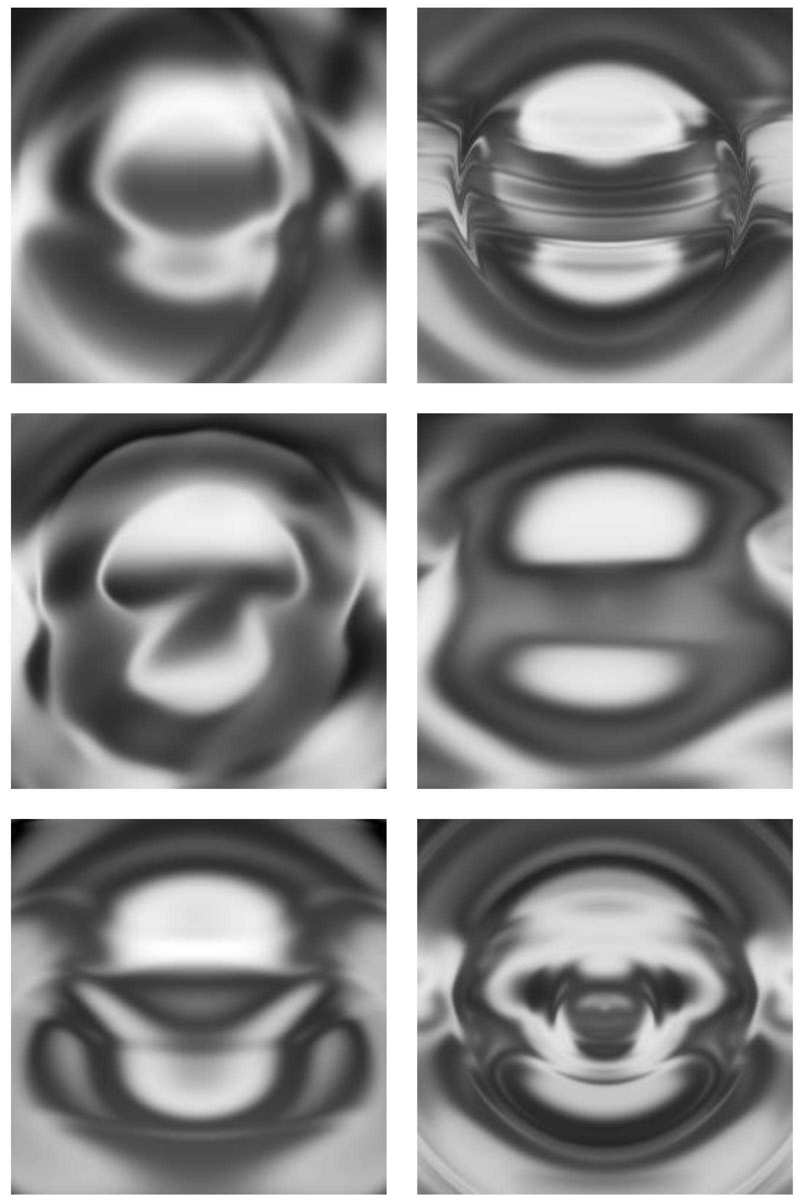

Figure 5: Images with highest fitness produced using just neurons for binning.

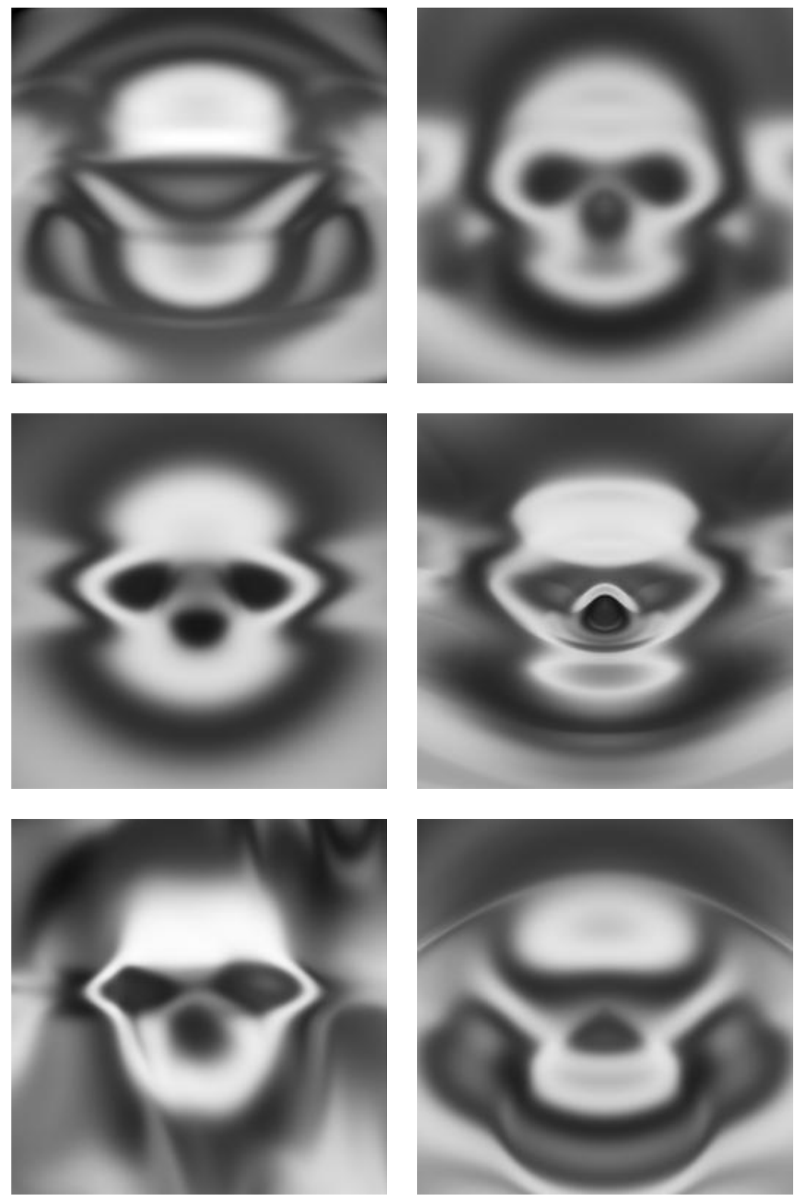

Figure 6: Images with lower fitness that look like skulls to humans.

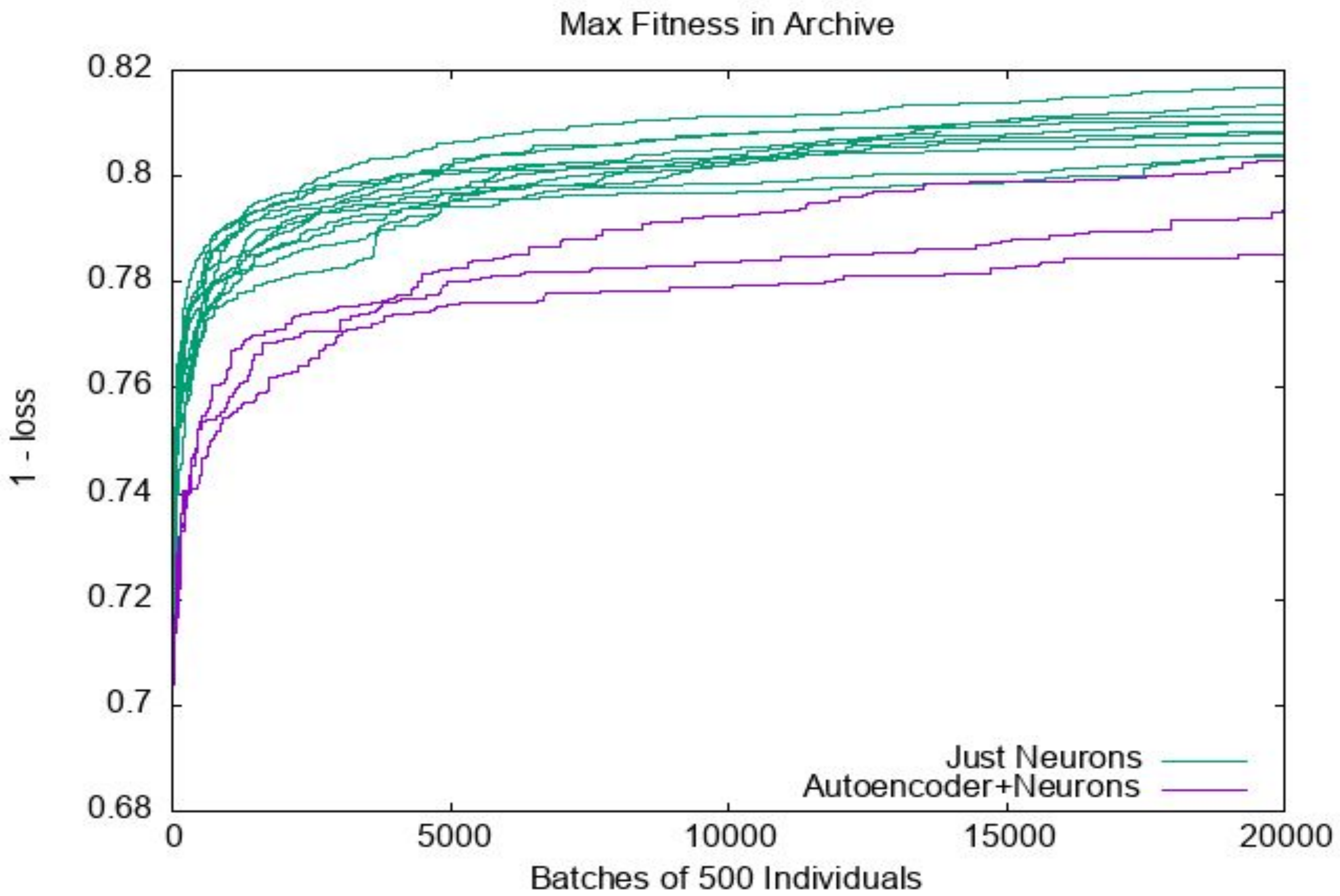

Figure 3: Measuring how close the evolved images are to the skull target image.

Conclusion

- When the archive is binned using only the number of neurons in the CPPN, the images more closely match the target and had a higher fitness score.
- Images saved in the archive when using the autoencoder bin labels are further from the target image and had a lower fitness score.
- Images with a high fitness have a higher percentage of pixels that match perfectly to this **specific** skull image. However, an image may look more skull-like in general to a human but have a lower fitness score.

References

[1] Adam Gaier, Alexander Asteroth, and Jean-Baptiste Mouret. 2019. Are Quality Diversity Algorithms Better at Generating Stepping Stones than Objective-based Search?. In Genetic and Evolutionary Computation Conference Companion, ACM.
[2] Stanley, K.O. Compositional pattern producing networks: A novel abstraction of development. Genetic Programming and Evolvable Machines 8, 131–162 (2007).