Simulating the Evolution of Writing Systems with Reinforcement Learning and Visual Selective Pressures

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This experiment was conducted in an attempt to better understand human writing systems. Specifically, whether or not the statistical similarities between them are a product of simple visual selective pressures. To achieve this, I used reinforcement learning to generate an artificial character set that will be compared to character sets of real languages. This paper will analyze quantitative measures of these character sets to determine if the limitations of visual recognition are sufficient to account for statistical uniformity in human character sets.

Quantitative Measures of Human Writing Systems and their Implications

In the paper "Character complexity and redundancy in writing systems over human history" (Changizi Mark A., 2005), methods and measures for comparing human writing systems are proposed. Primarily, *redundancy* and *length*. Chengizi reasons that the similarity in these measures is a result of selective pressures optimizing ease of writing and reading for humans. He created multiple measures with which to compare different human character sets. Following are the proposed equations for combinatorial degree (d) and redundancy (R):

$\beta \leq 1$:constant value representing the degree to which characters are composed of strokes from the set's repertoire

$L =$ Average stroke length of a character

$d = \beta L$

$R = 1 - (\frac{d}{L})$

Through the study of these measures across many writing systems, he sought to identify "fundamental properties of the human visuo–motor system". In the conclusion of this paper, Chengizi contends that reading is the principal pressure determining the selection of the writing system. This means that high stroke redundancy would be favored over low writing cost (i.e. more work for the writer, lower chance of nonrecognition for the reader). Additionally, he theorizes that the average character length across all writing systems may correspond to the "subitizing limit" of human short term visual memory (how many objects can be held in short term visual memory at a time). This value is often put at roughly 3 (Vogel E.K., 2001).

Hypothesis

Through the generation of a new artificial character set using reinforcement learning, Chengizi's correlations between human writing systems and "fundamental properties of the human visuo–motor system" can be put to the test. If our model mirrors the same quantitative findings of Chengizi, it would support the following hypotheses:

1. The average strokes per character across writing systems (3) is a feature of all character sets generated through the selective pressure of visual recognition
2. Stroke redundancy increases reader accuracy in all character sets generated through the selective pressure of visual recognition

Methods

The Unity game engine and the ML-Agents Unity package were used to generate the artificial character set with reinforcement leaning. Within this Unity environment, two agents with different capabilities and reward mechanisms were created. The first agent, the scribe, had access to a random integer ID at the start of each episode. During the scribe's turn, it was given the capability to create multiple lines on the surface in front of it using up to 25 vertices. The second agent, the reader, did not have access to the integer ID at the beginning of each episode. Instead, it was given a randomly offset position in front of the same wall that the scribe would draw on during the episode. For the reader's turn, a grayscale camera sensor with a resolution of $50x50_{px}$ would observe the wall in front of it. These two agents took their turns in sequence for each episode. Thus, the reader's visual observations would depend on the symbol created by the scribe. If the reader was able to correctly guess the ID given this information, both agents would receive a reward according to their reward function:

Scribe Reward $= 2 - \frac{\#ofLines}{13} - \frac{\#ofVertices}{25}$

Reader Reward $= 1$

Scribe Punishment $= -1$

Reader Punishment $= -1$

Given that the environment for this model has no additional constraints or mechanisms, the only way for the scribe agent to reliably relay the hidden ID to the reader agent is to develop a set of sufficiently distinct and symbols that can be identified by the reader agent through mild visual noise (see figure A4 for environment).

Results and Discussion

The training simulation was permitted to run for 3.25 million episodes (30 hours of training). The final accuracy of the reader agent averaged 80%, reaching a maximum of 83% accuracy (see figure A3). The scribe and reader agents finished training with mean rewards of 1.411 and 0.607, respectively. Given the accuracy of the reader agent, we can consider the generation of the artificial character set to be a success, since it has created symbols that are visually identifiable by their features.

The qualitative inspection of these artificial characters reveals a few key differences between this artificial character set and human character sets. It appears that the model has selected for characters showing great diversity in position and complexity. This diversity may help the reader agent correctly discern the symbols. Another distinct difference between this generated character set and human character sets is that some IDs are represented by multiple symbols (see figure A1). In order to calculate the average strokes per character for this set, multiple samples were collected for each stroke ($\approx$4) to get an average stroke count for each character. After this operation, the average stroke count per character in the set was calculated to be 7.735. This is well above the average stroke count in human character sets (3) (Changizi Mark A., 2005). However, symbols representing IDs 0 and 1 in the generated set highly skew this average, each containing the maximum of 24 strokes. If these symbols are omitted as outliers from the set of characters we obtain a new stroke count average of 3.67. This is much closer to the average stroke count of human character sets and would call into question the first hypothesis claim. Since our computer model's vision is not limited by a subitizing limit like the human brain, the similarity between average stroke count in human and artificial character sets would indicate another contributing factor (to stroke count) inherent to character recognition. However, Given the small size of the artificial character set, we cannot reject these points as outliers. Thus, we cannot support our first hypothesis. Qualitative analysis of the symbols do not appear to share any recurring stroke patterns. This indicates a very low value for combinatorial degree (d). Since no recurring strokes can be identified in the symbol set, we will use the lowest allowed value $d = 1$. This yields a redundancy value of $R = 1 - (\frac{1}{7.735}) = 0.87$. This value is higher than the value found by Changizi for human characters (0.5) (Changizi Mark A., 2005). This high value of redundancy is in spite of the fact that the scribe's reward is mitigated by a significant drawing cost (thus, it has incentive to minimize redundancy). Changizi supposes that redundancy is universally present in writing systems because the accuracy of human readers outweighs the cost of writing. Through the analysis of this artificial character set, we can see that the preference for redundancy is inherent for visual character recognition. This supports our second hypothesis.

The experiment conducted could be greatly improved upon given enough time to train models under various conditions and with various reward functions. Increasing the number of characters in the set to 30 would make the model more comparable to the average human character set. Additionally, building a "stroke-type-network" (the process for which is specified in Changizi's paper) for the generated character set could yield a more accurate combinatorial degree.

References

Changizi Mark A., S. S. (2005). Character complexity and redundancy in writing systems over human history. *Proc Biol Sci.*, 267–275.

Vogel E.K., L. S., Woodman G.F. (2001). Storage of features, conjunctions, and objects in visual working memory. *Exp. Pscyhol. Hum. Percept Perform*, 92–114.

Appendix

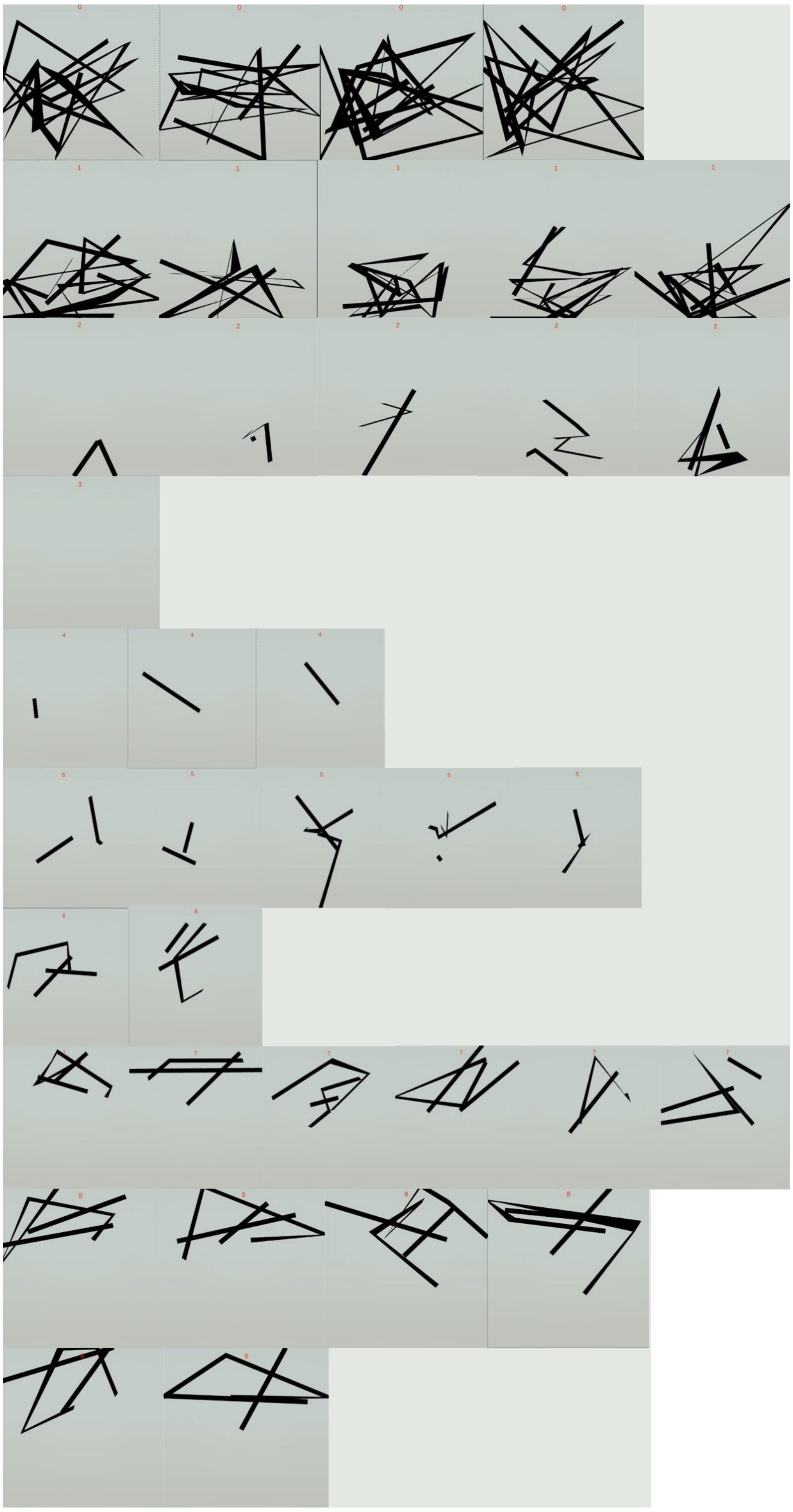

Figure A1. Samples of characters created by model

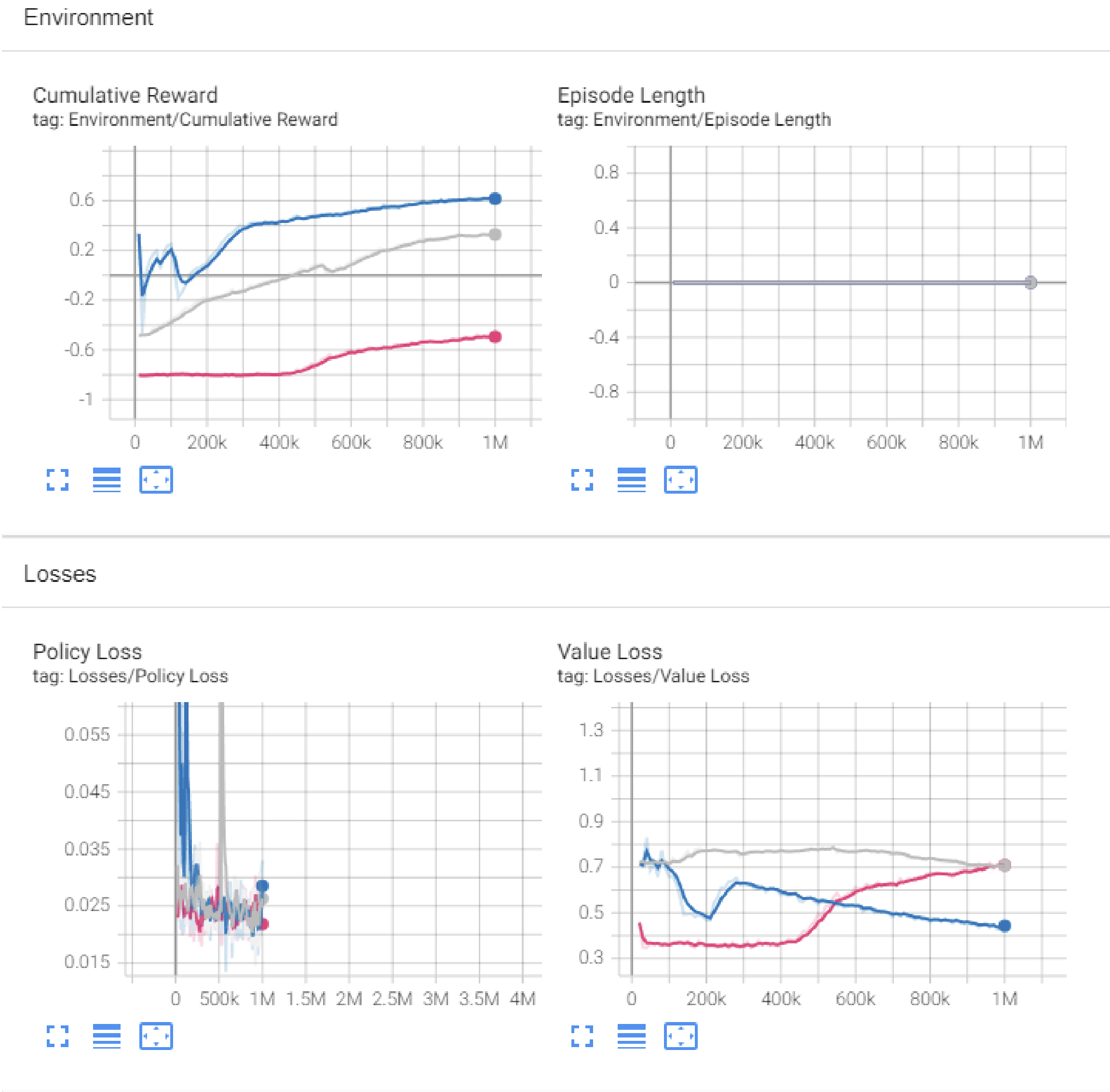

Figure A2. Graphs showing model training statistics. (red = first 1M episodes, grey = second 1M episodes, blue = third 1M episodes)

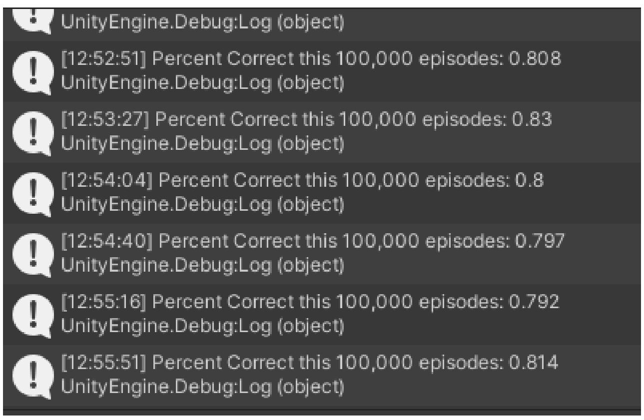

Figure A3. Average percent correct at end of training.

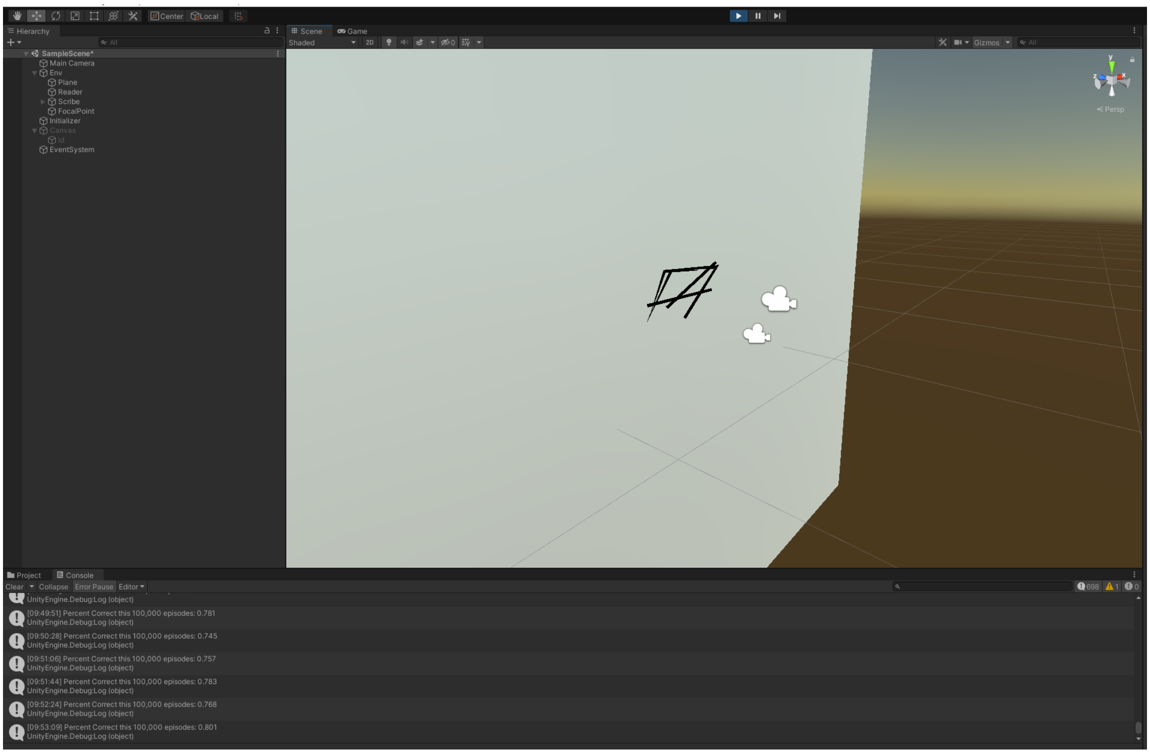

Figure A4. Unity training environment setup. The project can be pulled from the git repository https://github.iu.edu/gwaldow/CogSciProject