Generating Novel Glyph without Human Data by Learning to Communicate

Seung-won Park*
Seoul National University, MINDs Lab Inc.
yyyyy@snu.ac.kr

Abstract

In this paper, we present Neural Glyph, a system that generates novel glyph without any training data. The generator and the classifier are trained to communicate via visual symbols as a medium, which enforces the generator to come up with a set of distinctive symbols. Our method results in glyphs that resemble the human-made glyphs, which may imply that the visual appearances of existing glyphs can be attributed to constraints of communication via writing. Important tricks that enable this framework is described and the code is made available.

1 Introduction

The glyph is a visual representation of characters for writing, which is a medium of human communication along with speech. Throughout human history, hundreds of glyphs were created, and some of them are still in use today. Despite many of the glyphs were invented independently, some of the glyphs are known to resemble each other [2, 5]. But then, if artificial intelligence is given a task to generate the glyph for visual communication without any training data derived from human’s writing, will it resemble the existing glyphs? What will such ‘alien language’ look like?

In this paper, we propose Neural Glyph, a system that can generate novel glyph by training neural networks to communicate via visual symbols. We find that such ‘alien language’ looks visually similar to existing glyphs, even though any data from existing glyphs are used. We also propose a method for controlling the amount of variation of visual appearance within each symbol.

2 System Architecture

Our system aims to generate a novel set of symbols by jointly training a generator and classifier to transfer a message via visual symbols as a medium (channel), following the Shannon-Weaver model of communication [9]. The whole system is trained with only classification loss in an end-to-end manner, as shown in figure[1] The generator encodes the given message into a sequence of action spaces that define the brushstroke for a symbol. Then, the sequence of action space is rendered into a visual symbol with a pre-trained neural painter [7]. Finally, the classifier predicts the original message that the generator aimed to deliver via the symbol.

Generator. The generator aims to synthesize the sequence of action space that defines the visual appearance of the given index (message) of symbol. To generate the glyph consisted of \(N\) symbols, the embedding lookup table of size \(N\) is constructed to provide representation for each distinctive symbols. Then, a two-layer MLP transforms the representation into the sequence of action space. Considering the fact that handwriting produced by humans is different for every individual and time, we try to simulate the stochastic writing behavior by injecting random noise to the MLP.

*http://swpark.me

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Neural Painter. To propagate the gradients from prediction error to the whole system, it is critical for the renderer to be differentiable. In our system, we adopt a GAN-based neural painter [7], which was trained with a synthetic brushstroke dataset consisted of Bézier curves. We use the PyTorch implementation and the pre-trained weights produced by the author of the neural painter [7]. While training our system, the weights of neural painter are frozen. To make the generator focus on generating a set of symbols that have diverse shapes, we fix the brushstroke to have constant thickness and color (black) by setting the corresponding action parameters constant.

Classifier. The CNN-based classifier is trained to decipher the original message from the rendered symbol. The classifier is built with a pre-trained MobileNet V2 [8], where the last fully-connected layer is replaced with a randomly initialized projection layer to produce logits for symbol classification. We empirically observed that the system fails to generate the distinctive symbols when the classifier is trained from scratch or the weights from MobileNet V2 are frozen.

3 Experiments

Results. The resulting glyph is different for each run since it is possible to generate a limited number of distinctive symbols in various ways. One of the example results is shown in figure 2 and more results are shown in figure 3. We may observe that many of the results resemble the symbols from the existing glyphs; we encourage the readers to compare the results with glyphs shown in the Omniglot encyclopedia [1], since most of them are not in use for nowadays.

Effect of temperature. While running the system after training, the amount of variation of visual appearance within each symbol can be adjusted by controlling the temperature (magnitude) of the noise injected through the generator. The results are shown in figure 4.

4 Future Works

We have shown the preliminary results on generating novel glyphs without human data by learning to communicate. Our results are encouraging and numerous future works will be possible. First, constructing an action space that better represents the human brushstroke may lead to results that better resembles the human-made glyphs, where only three Bézier curves are used in this work. Furthermore, exploring the results with other types of medium for communication will be interesting; this might be possible by utilizing their corresponding neural renderers with appropriate constraints applied, such as an audio signal (DDSP [3]) or 3D object (Softras [4]).
Broader Impact

The emergence of the novel glyph from communication between neural networks may inspire artists, and benefit linguists or cognitive scientists on studying the underlying pattern of existing glyphs. However, we believe the amount of impact will be limited since the real-world application of our work does not seem to exist.

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*http://deepest.ai/*
A Related Works

Previous works on generating novel visual language that works with a communication objective include Cooperative Communication Networks [6], Dimension of Dialogue [10], and GlyphNet [11]. However, our work is the first to generate a visual language based on glyphs, which is directly interpretable by human vision.

B Reproducibility

To enhance the reproducibility of our work, we provide some detailed information about our system.

Code availability. A jupyter notebook script for training is available at the following Google Colab URL: https://colab.research.google.com/drive/1NDEdM7PjcS2ohKP39UnsX02hgyOpYX?usp=sharing

Hyperparameters. Along with open-source implementation of our system, we show the detailed hyperparameters:

- Number of symbol classes to form a glyph ($N$): 10
- Number of strokes (length of the sequence of action space): 3
- Batch size: 16
- Optimizer: Adam
- Learning rate: $1 \times 10^{-3}$
- Number of training steps: 10k (takes 5 minutes on Google Colab P100 GPU)
- Symbol embedding dimension: 16
- Generator noise vector dimension: 16
- Generator MLP dimension: 32
- Action space parameters that are controlled by the generator: pressure, control_x, control_y, end_x, end_y, start_x, start_y, entry_pressure
- Action space parameters that are fixed: size (brush size, set to 0), color_r, color_g, color_b (colors, set to -1)

Miscellaneous notes.

- Throughout the training iteration, the generated set of symbols do not tend to converge into constant visual appearance, and the loss with respect to the number of iteration spikes. The training should be stopped when the validation loss is reasonably low or the user gets satisfactory results. Failing to stop at the right time may lead to redundant symbols.
- With $N = 10$, the final classifier showed an accuracy higher than 99.0%.
- All experiments for this work are done with GPU available within Google Colab.
- Implementing our system does not require the data loader, since the input/target batches are constructed with random symbol indices.
Figure 3: Uncurated examples of generated glyph sampled with temperature $T = 1.0$, showing results of every independent run in each row. It can be observed that the system prefers to leave one of the symbols as the centered dot, which is the result of randomly initialized weights of the generator.
Figure 4: Examples illustrating the amount of variation of visual appearance within each generated symbol, which is adjusted by controlling the temperature. For each row, a figure on the right side shows the samples generated with different temperatures ($T = 0.0, 0.25, 0.5, 1.0, 1.5, 2.0, 4.0$ for each column) for the symbol shown in the left side. Higher temperatures yield more stochastic results.