Perceptual Font Manifold from Generative Model

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It is difficult to explore and design a favorite font type.
BACKGROUND:
Font Manifold [SIGGRAPH2014]

Variational Autoencoder [ICLR2014]

Motivation

Designing or editing fonts is difficult

Human perception on fonts is absent

Soft Kitty, Warm Kitty
Soft Kitty, Warm Kitty
Soft Kitty, Warm Kitty
Soft Kitty, Warm Kitty
Related Works

GAN

Multi-Content GAN, CVPR2018

Chinese Fonts Manifold, EG2018

Font Style Transfer, 2016

VAE

FontMatcher, IUI2018

Perception

How to introduce human perception into font deep generative models?
Contributions

1. Perceptual Study in Learning Process

2. UI for Perceptual Font Manifolds

\[ x_1 = 0.2 \]
\[ x_2 = 0.5 \]
Framework

Input \rightarrow Conv \rightarrow Conv \rightarrow Conv \rightarrow VAE Encoder \rightarrow Conv \rightarrow Conv \rightarrow Conv \rightarrow VAE Decoder \rightarrow Conv \rightarrow Conv \rightarrow Conv \rightarrow Output

Latent Variables

Perceptual Study \rightarrow Font Manifold \rightarrow User Interface
Training Data

2169 font images
Google Fonts

training dataset
Generative Model

Latent Space

Input

A

Latent Space

Decoder

Output

Lambda

Convolutional

Dense

Flatten

Convolutional

Output

(28, 28, 1)

(28, 28, 32)

(14, 14, 64)

(14, 14, 64)

(14, 14, 64)

(12544)

(32)

(5)

(14, 14, 64)

(14, 14, 64)

(28, 28, 32)

(28, 28, 1)

(12544)
Framework
UI for Perceptual Study

<table>
<thead>
<tr>
<th></th>
<th>POP</th>
<th>Formal</th>
<th>Casual</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>273</td>
<td>311</td>
<td>298</td>
<td>884</td>
</tr>
</tbody>
</table>

Soft Image
Round
Bold
(1) POP

Hard Image
Thesis
Symmetrical
(2) Formal

Freedom Image
Slant
Scratchy
(3) Casual
Perceptual Study
Manifold Learning

Purple: POP
Green: Formal
Yellow: Casual

Kernel density estimation

Perceptual Study

t-SNE*

dimensionality reduction

Perceptual Manifolds

*t-distributed Stochastic Neighbor Embedding
UI for Font Manifold
Results

Ubuntu 16.04 LTS,
Intel Core i7-7700 CPU 3.60GHz × 8,
GeForce GTX 1060 3GB GPU
Python 3.5
CUDA 8.0
CuDNN 6.0
Keras-gpu 2.1.6
Perceptual Font Manifold

POP

Formal

Casual
Comparison Study: font exploration

- Target Font Image
- Arranged in 10 columns and 160 rows

- Searching with a mouse

Conventional UI

Ours

20 graduate students, 2 groups

10 target fonts
Comparison Study: results

**exploration accuracy**

- **SSIM**

**time cost**

- **Time (s)**

<table>
<thead>
<tr>
<th>Method</th>
<th>Exploration Accuracy</th>
<th>Time Cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>Traditional</td>
<td>8.5 ± 0.5</td>
<td>97s</td>
</tr>
<tr>
<td>Ours</td>
<td>8.7 ± 0.3</td>
<td>54s</td>
</tr>
</tbody>
</table>

**structural similarity**

- **Similarity: S (SSIM score)**
  - $0 \leq S \leq 1$

**covariance**

$$SSIM(x, y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{\left(\mu_x^2 + \mu_y^2 + C_1\right)\left(\sigma_x^2 + \sigma_y^2 + C_2\right)}$$

(mean  standard deviations)
From A to Z

The quick brown fox jumps over the lazy dog

POP

The quick brown fox jumps over the lazy dog

Formal

The quick brown fox jumps over the lazy dog

Casual
Conclusions

1. Perceptual study in generative model

2. UI for perceptual font manifolds

Limitations

1. Only handles “A” fonts - Font Style Transfer

2. Not for TrueType Fonts

From A to Z: Supervised Transfer of Style and Content Using Deep Neural Network Generators, 2016
Thank You!

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