A Learned Representation for Scalable Vector Graphics

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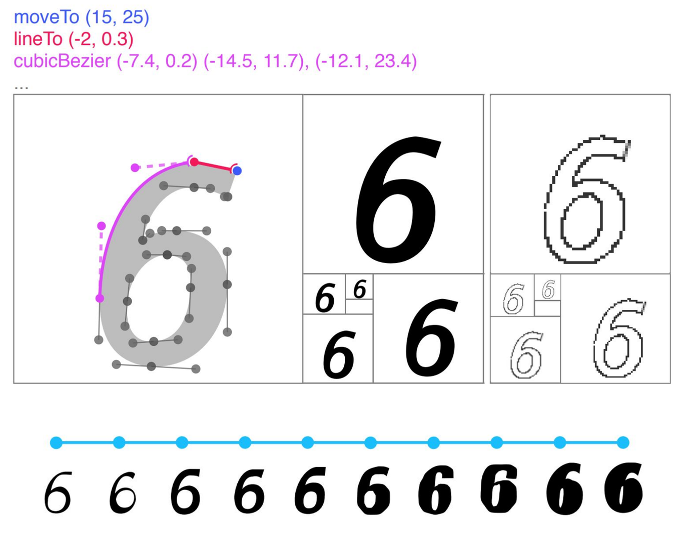
INTRODUCTION

Want to create a **generative model of scalable vector graphics** (SVGs), an image format with structured commands.

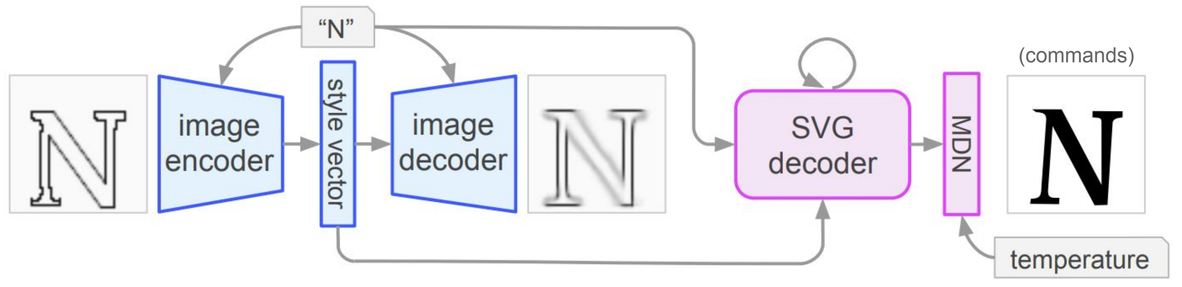
Structured image generation has been tackled [1,2] with unstable objectives [3,4] because it assumes the need for unsupervised learning.

We take advantage of the **free supervision** of the SVG format to show that modelling fonts can be done with simpler supervised methods.



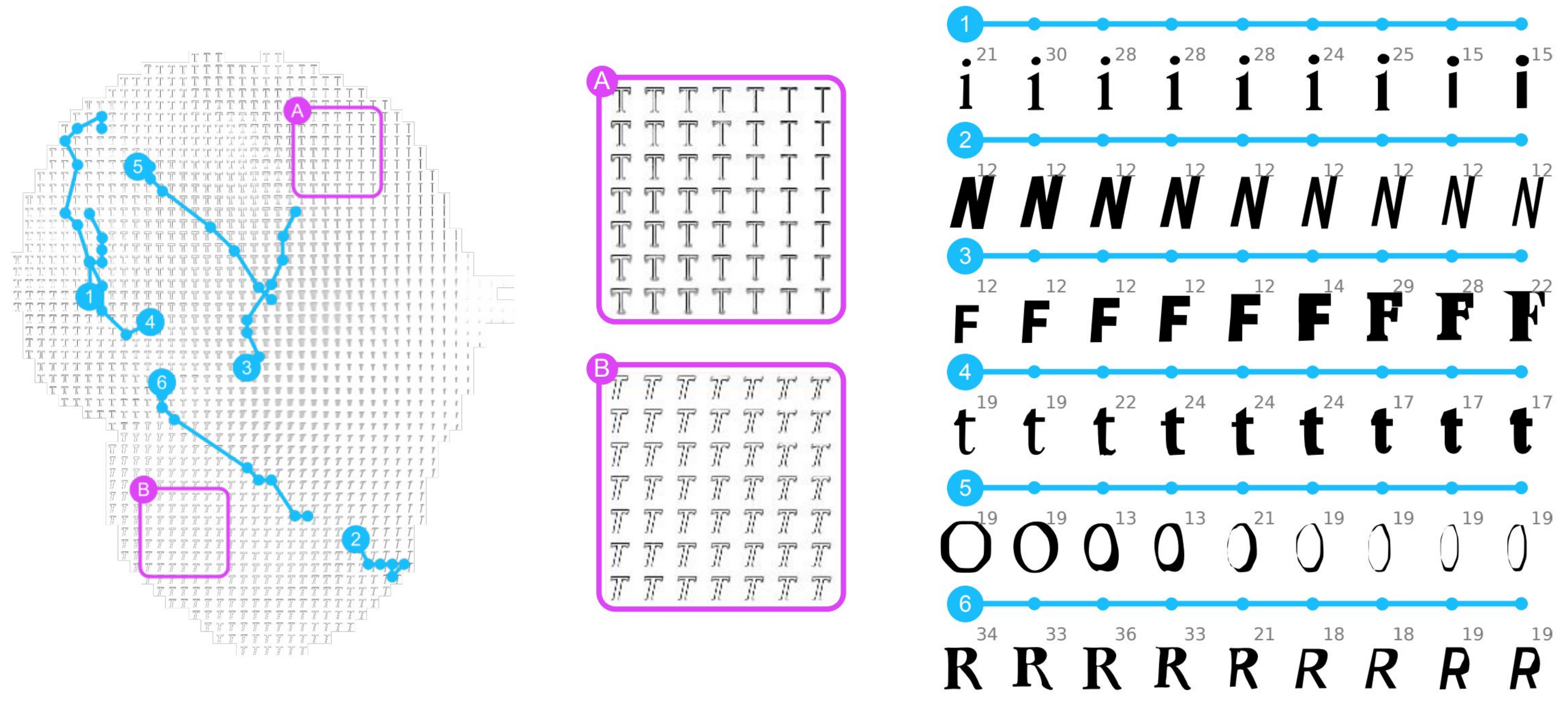
METHOD

- Learn a visually semantic representation z of icons (blue)
- Learn to decode SVG commands from z (purple)



RESULTS

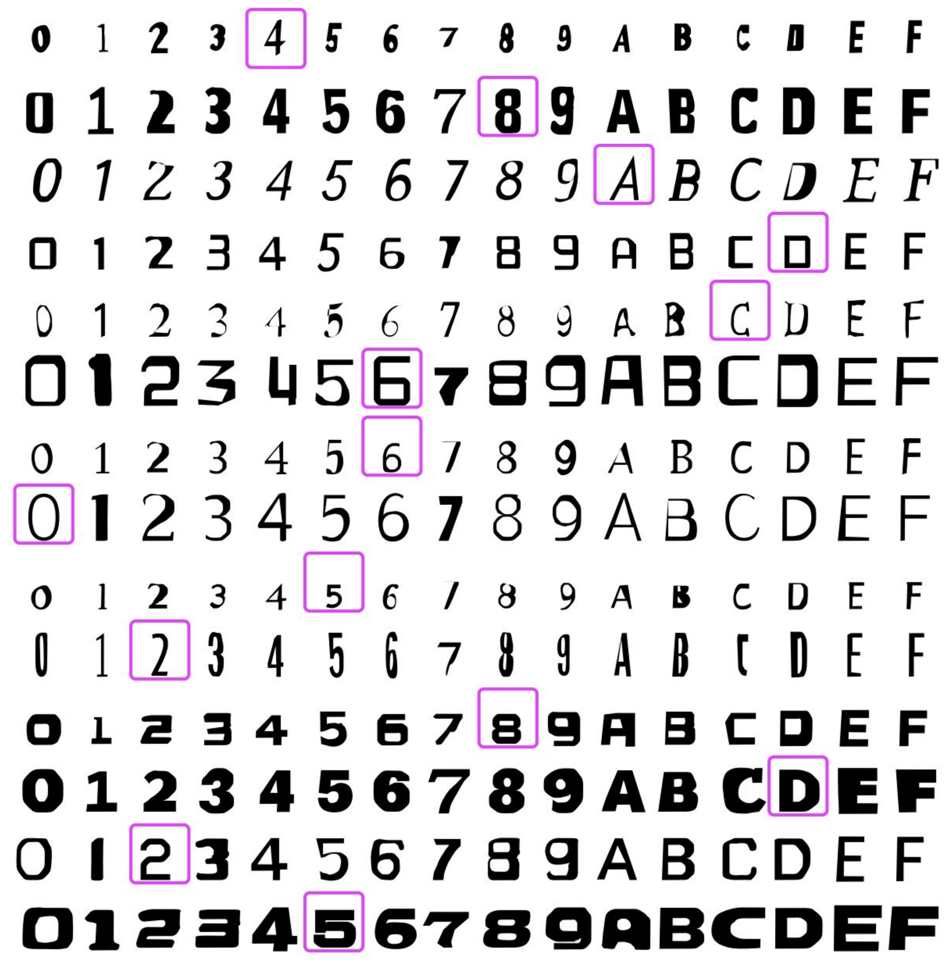
We learn a smooth latent representation z of font style



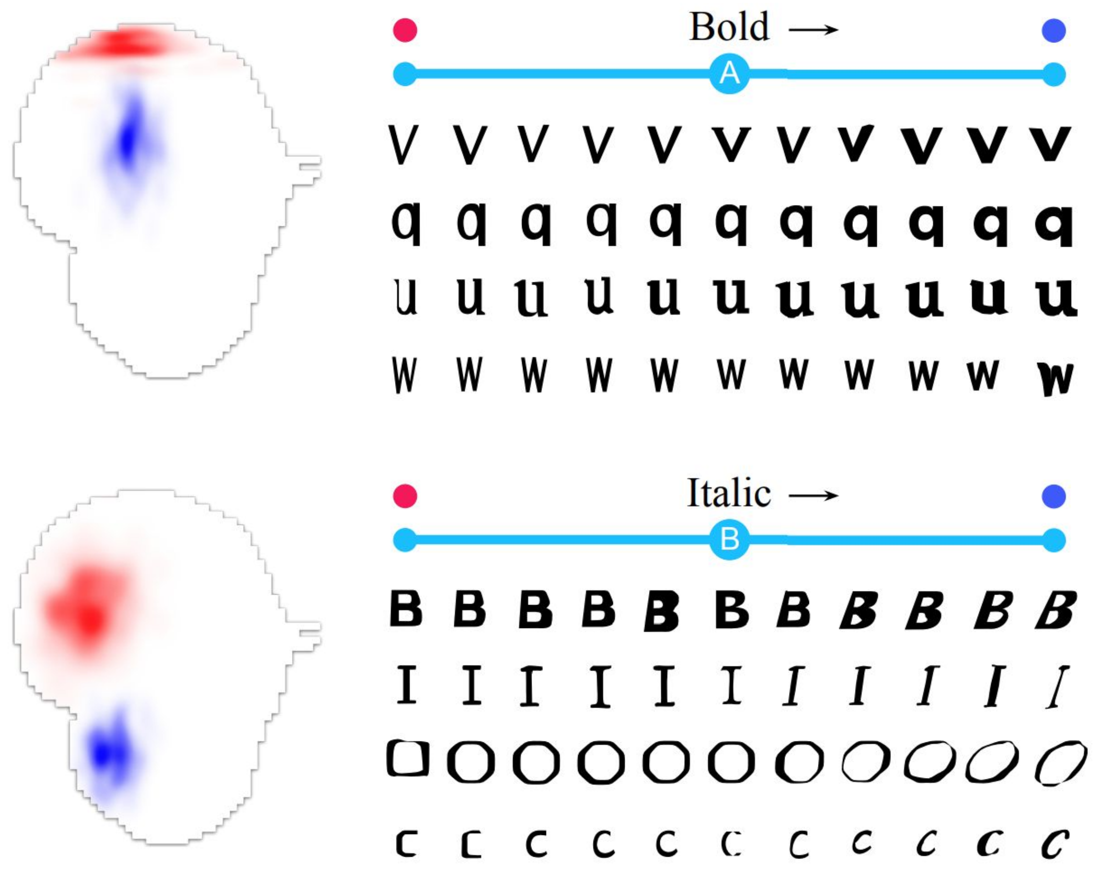
EXPLOITING THE STYLE z

The representation is class-agnostic

We can exploit this for propagating styles between classes



Similarly, we can find **style analogies**: directions of the space that correspond to high-level concepts.

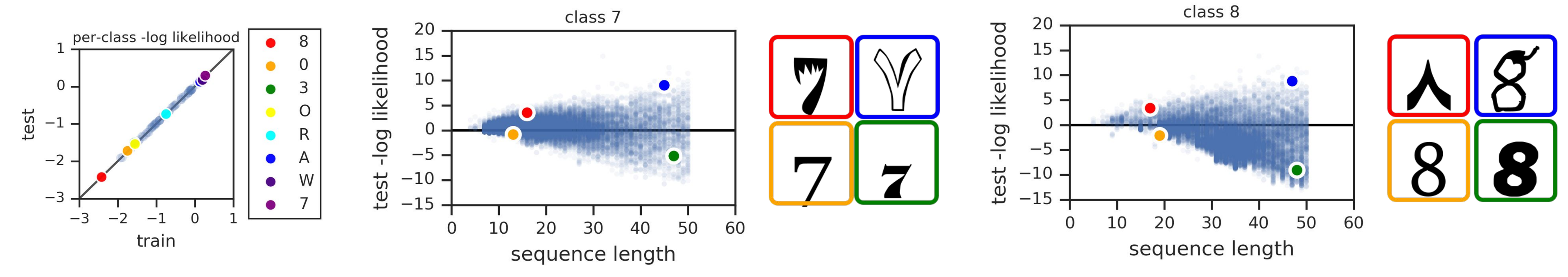


These attributes could allow designers to manipulate font design easily, especially when integrated with tools for manipulating them such as [5].

DISCUSSION

The model performs better on some classes than others. Classes with longer command sequences per glyph tend to provide more supervision of high quality outputs

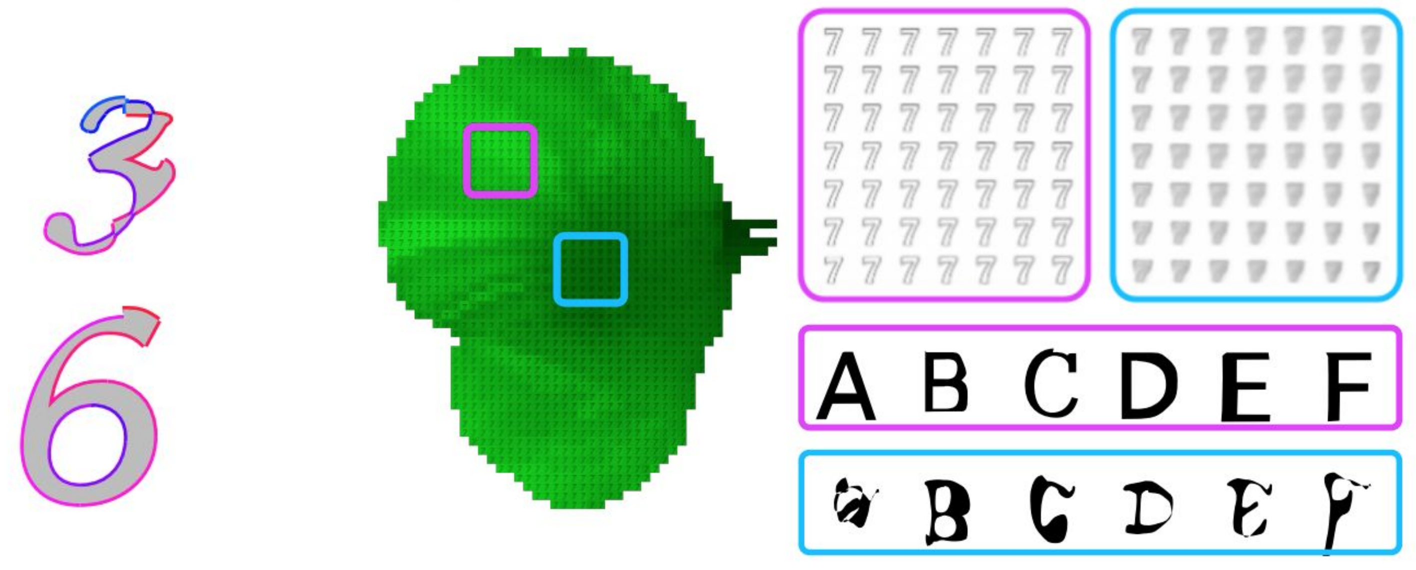
Yet, regardless of length or class, the failure modes are generally due to high variability of styles in the dataset.



Limitations include:

A. Modelling commands as sequences can compound errors
B. High-variability regions of latent z create uncertain predictions

Many of these can be mitigated with simple post-processing or by analysing model uncertainty.



REFERENCES

[1] Ganin, Yaroslav, et al. "Synthesizing programs for images using reinforced adversarial learning." arXiv preprint arXiv:1804.01118 (2018).
[2] Ellis, Kevin, et al. "Learning to infer graphics programs from hand-drawn images." Advances in Neural Information Processing Systems. 2018.
[3] Sutton, Richard S., et al. "Policy gradient methods for reinforcement learning with function approximation." Advances in neural information processing systems. 2000.
[4] Goodfellow, Ian, et al. "Generative adversarial nets." Advances in neural information processing systems. 2014.
[5] Loh, Bryan. "SpaceSheets: Design Experimentation in Latent Space." (2018).

magenta.tensorflow.org/svg-vae arxiv.org/abs/1904.02632