

Momentous Brands

Finding New Value in WPP's
Brand Asset Valuator (BAV)

LANDOR & FITCH

With design, the type we use can be as powerful as the words we chose.



IMPORTANCE OF TYPE

Type is the most time extensive thing to design

Creating custom typefaces is an activity commonly done for brands in the marketing world, with many desiring something unique to their brand or corporate identity. One major reason that brand design projects can garner 7-figure price tags is the development of a custom font.

The graphic consists of several letters in a sans-serif font, arranged in a cluster. The letters and their approximate colors are: 'a' (red), 'A' (white), 'B' (yellow), 'c' (white), 'e' (white), 'n' (yellow), 'o' (white), 'p' (white), 'S' (red), and 'z' (white). The background is a solid dark purple color.

IMPORTANCE OF TYPE

130,000 published fonts exist

For the Roman alphabet. And while that sounds like a lot compare that to the millions of apps in the app store; the billions of discernible colors; and



PROBLEM

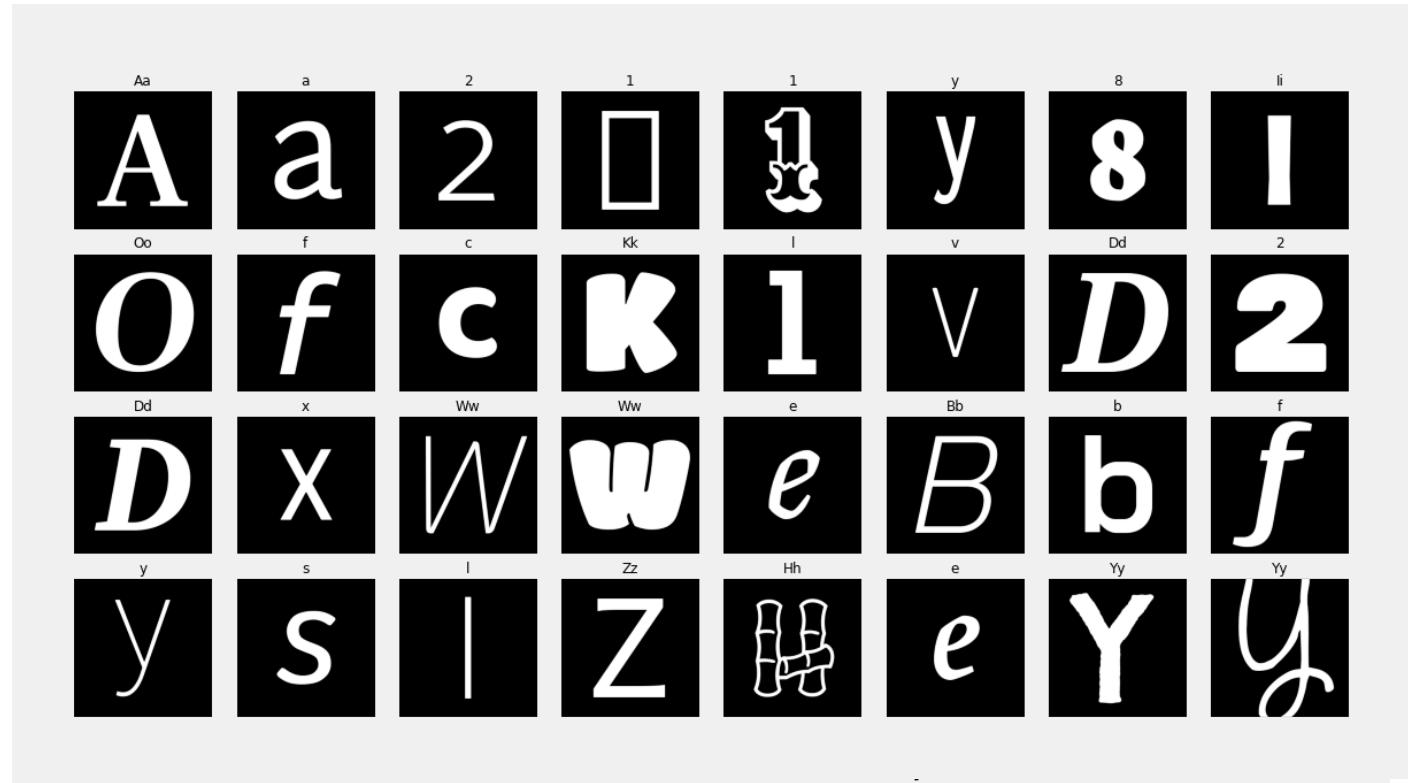
Though one of the oldest forms of media, Our type palette is relatively limited.



APPROACH

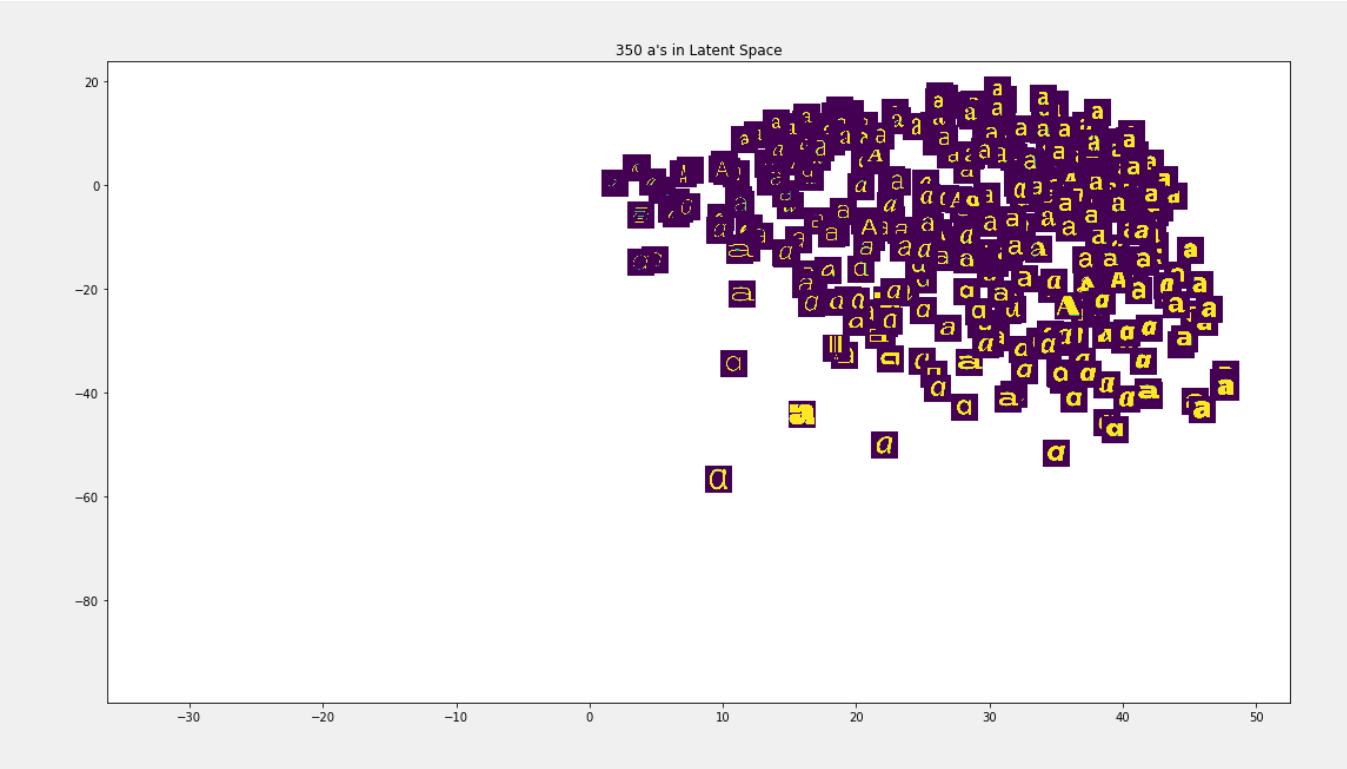
Exploring the world of type

1. Assemble



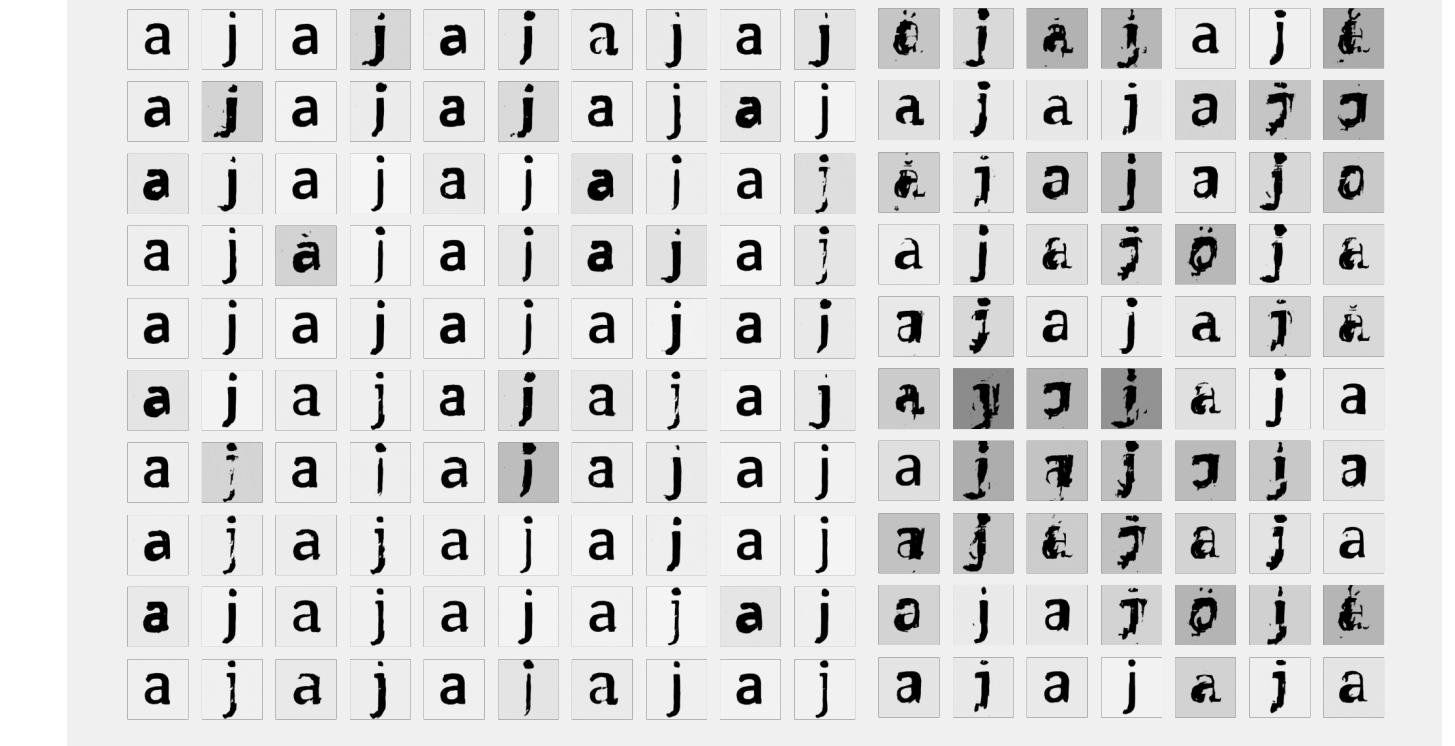
Unfortunately, no official dataset typeface or Roman character dataset existed prior to this work. A large part of this project included the construction of an image dataset from the available 3,500+ .ttf files

2. Project



Using a 2 dimensional Autoencoder to visualize all 'a' and 'j' characters onto the latent space to help visualize what the model learned about the representation of each.

3. Generate

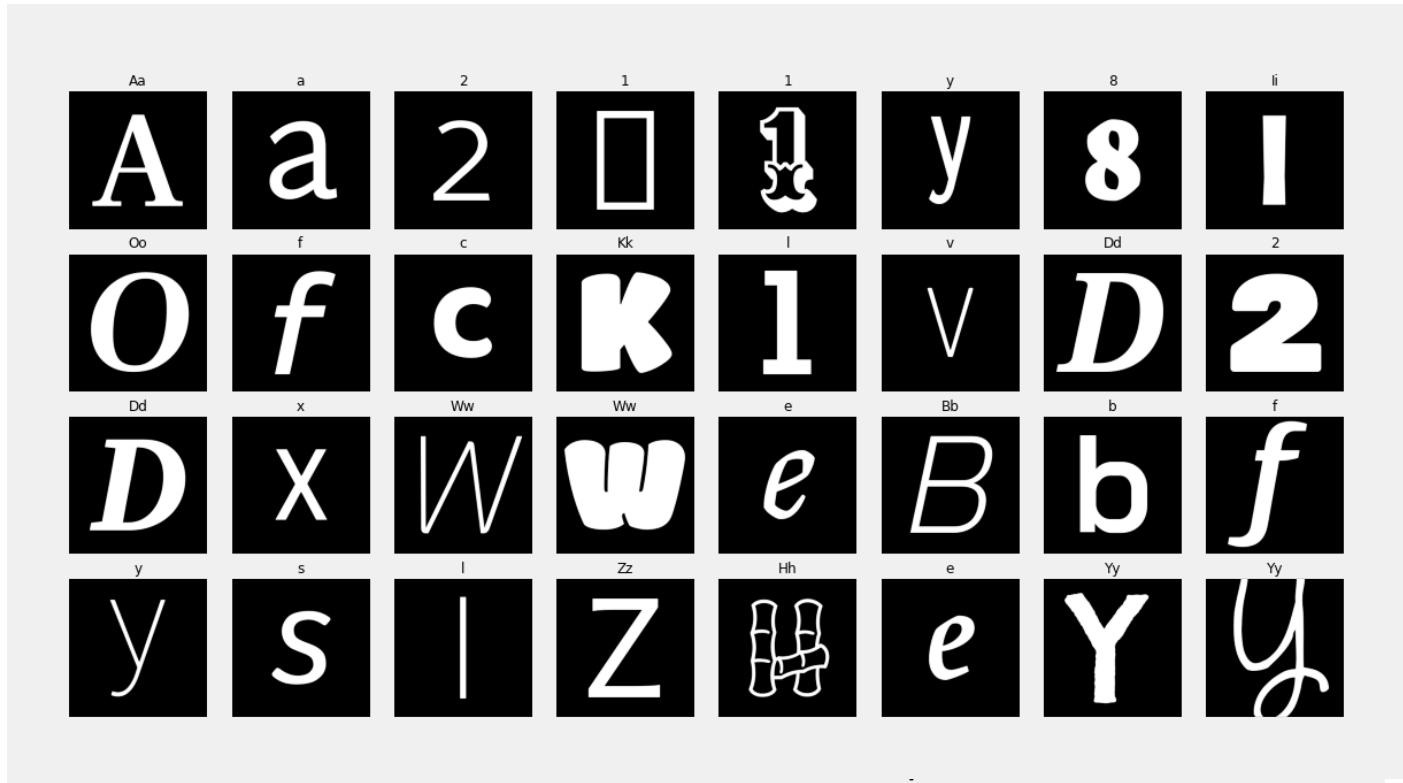


I trained two Generative Adversarial Network (GAN) architectures including a Deep Convolutional GAN (DCGAN) and a Conditional GAN in order to generate new and realistic typeface characters for a specific class.

APPROACH

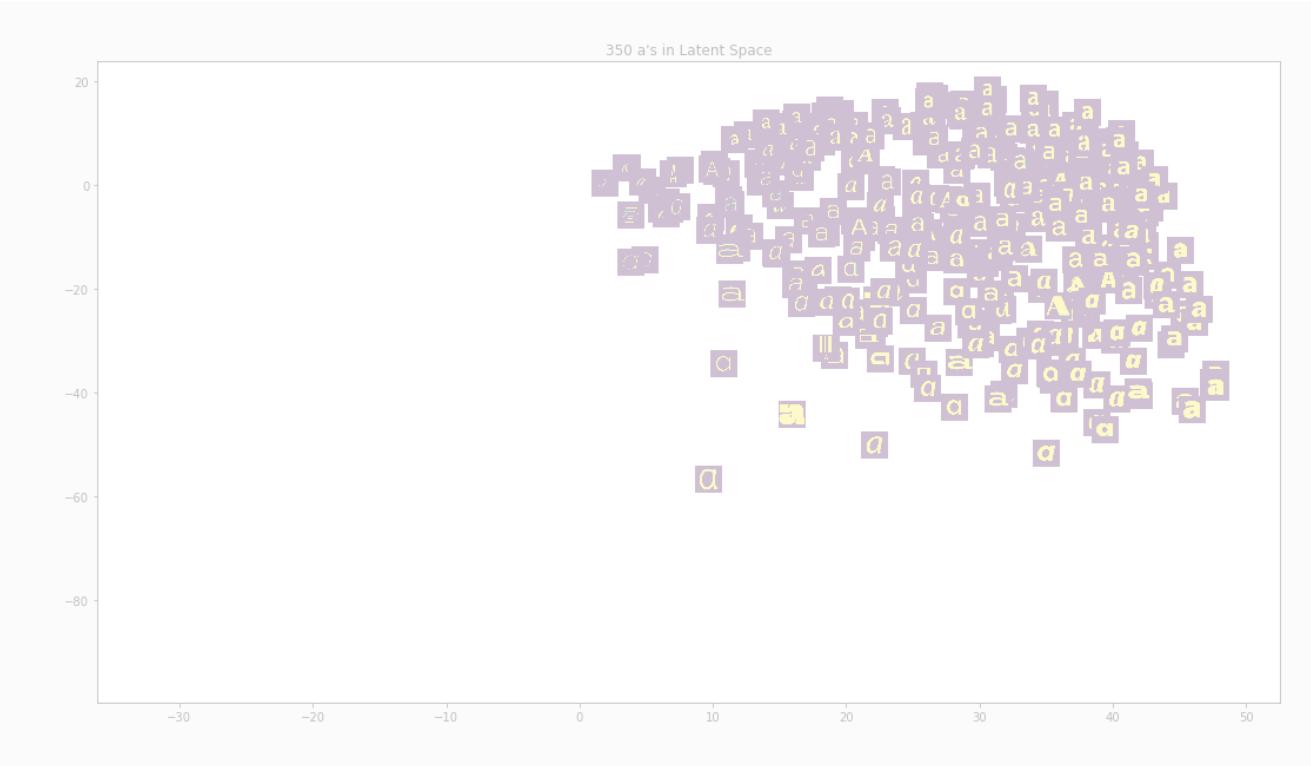
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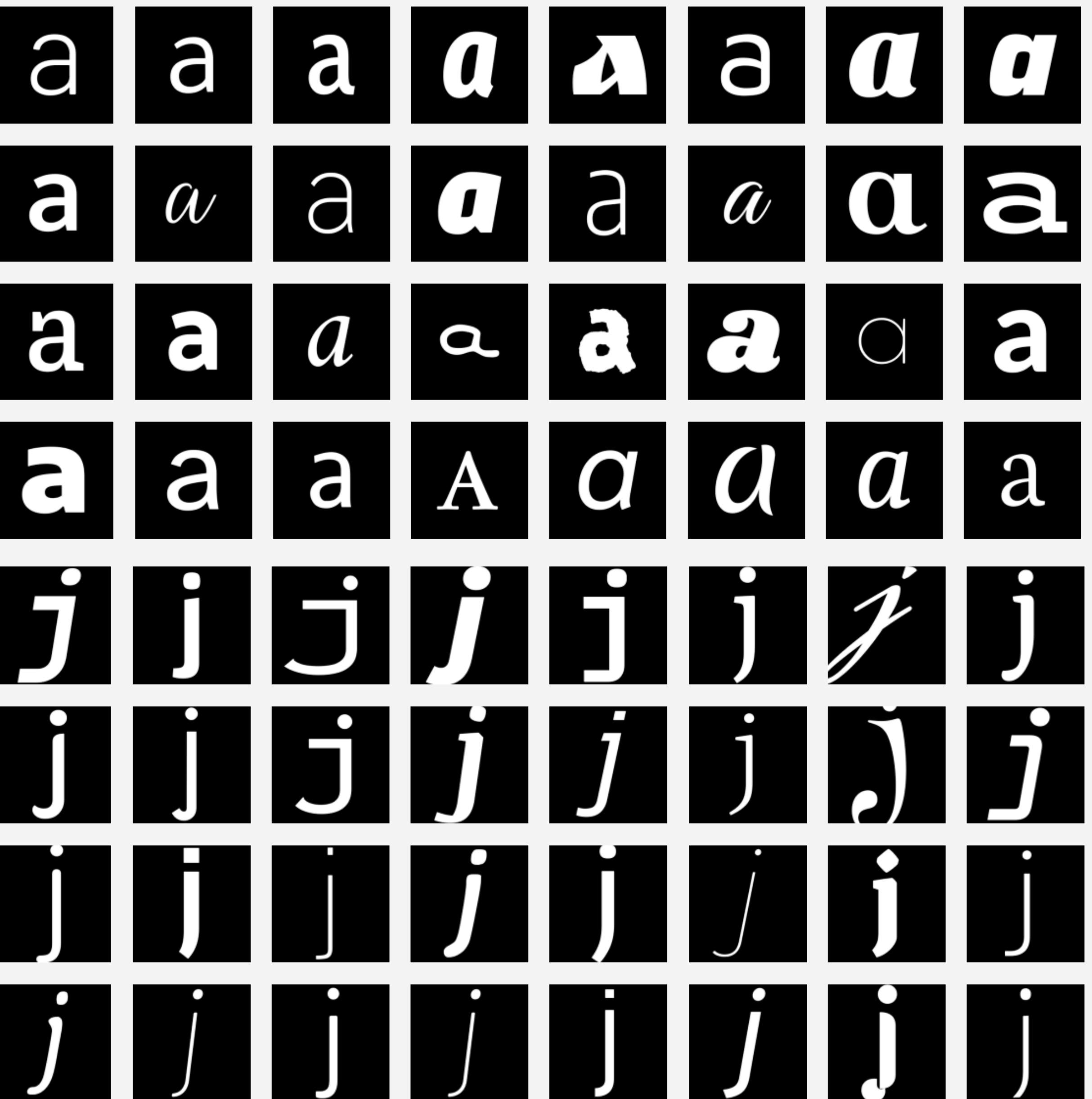


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A new image dataset

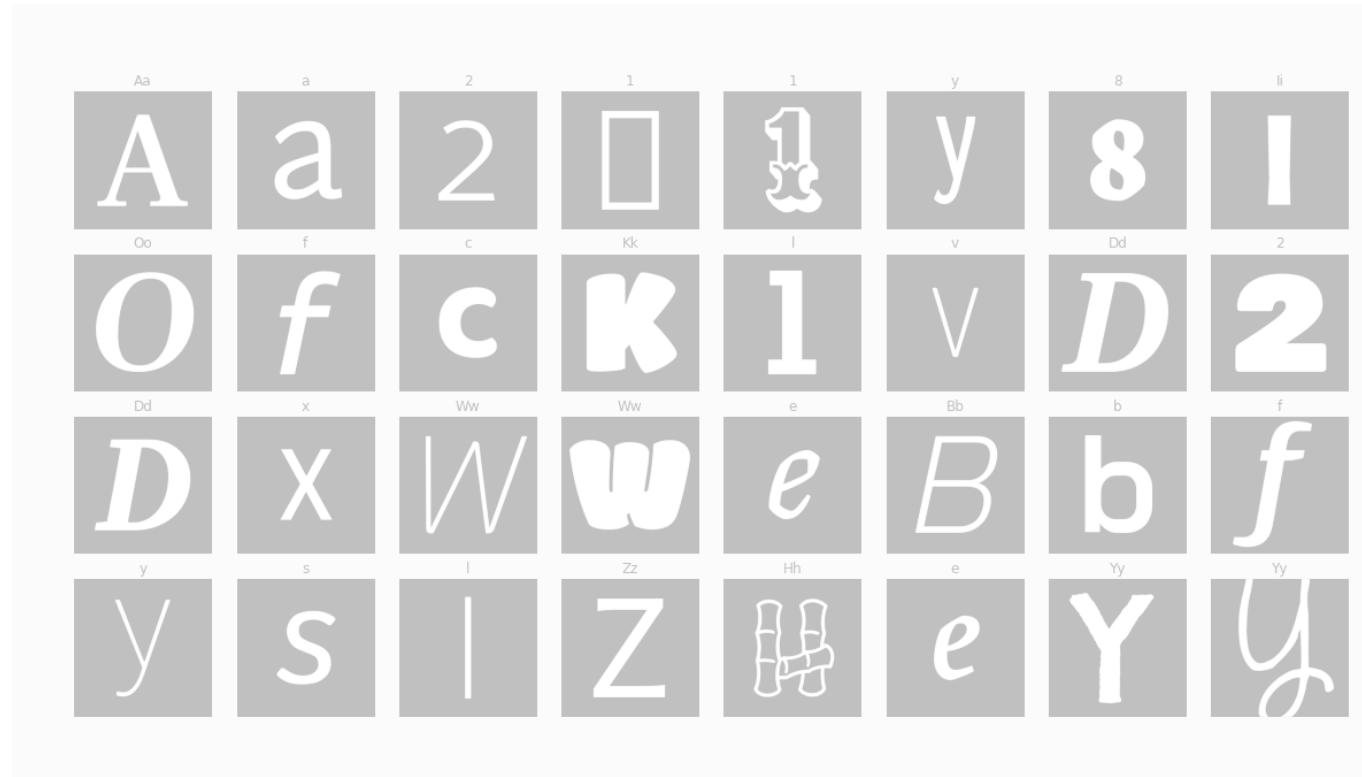
Using the computer's filesystem a custom image dataset was successfully constructed. Each image in the dataset represents a single typeface character and was constructed using 62 character representations from 3865 fonts (.ttf files). The resulting dataset contains:

- 239,630 224px x 224px grayscale images (.png files) belonging to 62 classes
- A balanced set with 3865 images per class
- Each class represents a single character limited to uppercase and lowercase Latin characters (52) as well as digits (10)



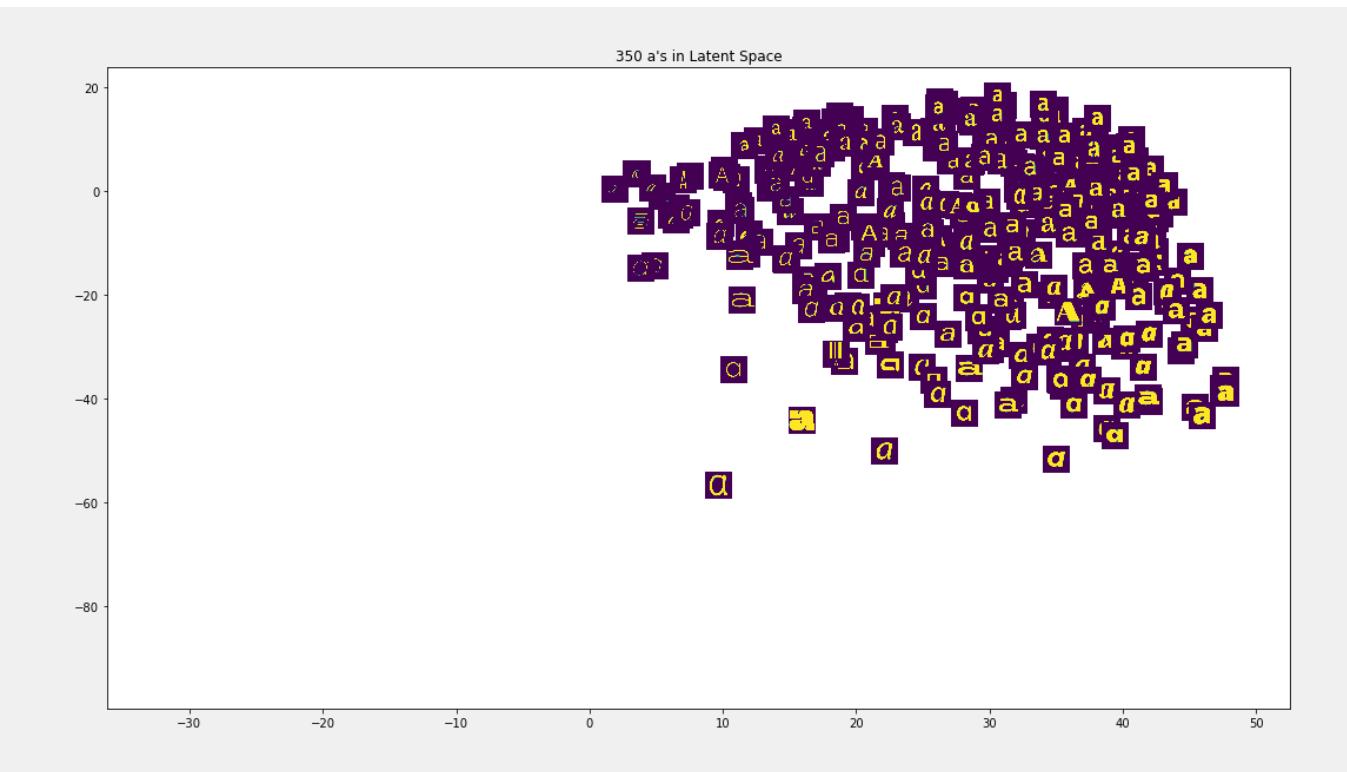
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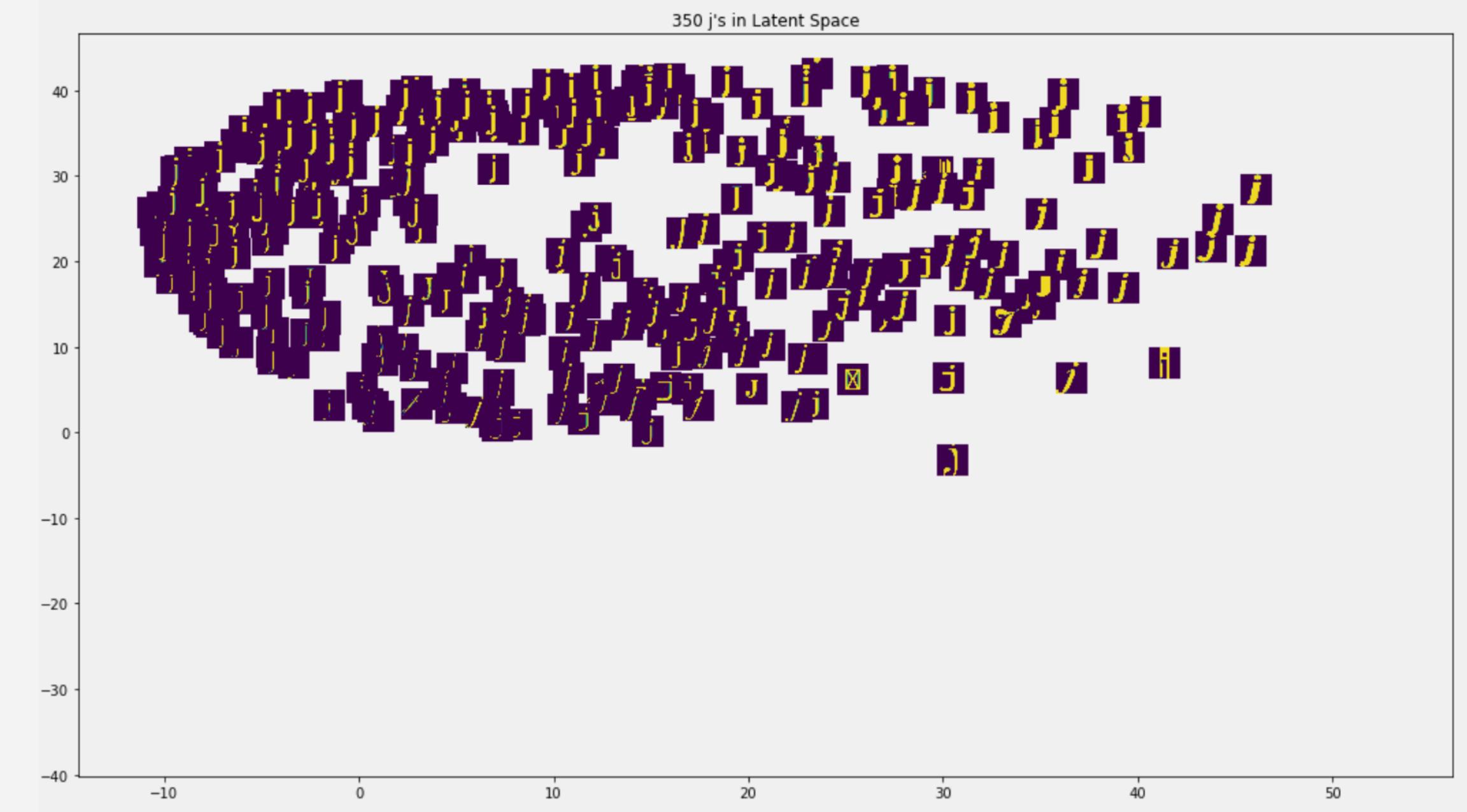


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PROJECT

The latent space of characters

Observations from the latent space visualizations showed that the thin 'j's were clustered on the left side of the plot, the thicker/bolder 'j's on the right, and the italic 'j's clustered toward the bottom of the distribution. The 'a' characters showed a similar distribution. The thinner 'a's appear on the left while the thicker 'a's appear on the lower right.

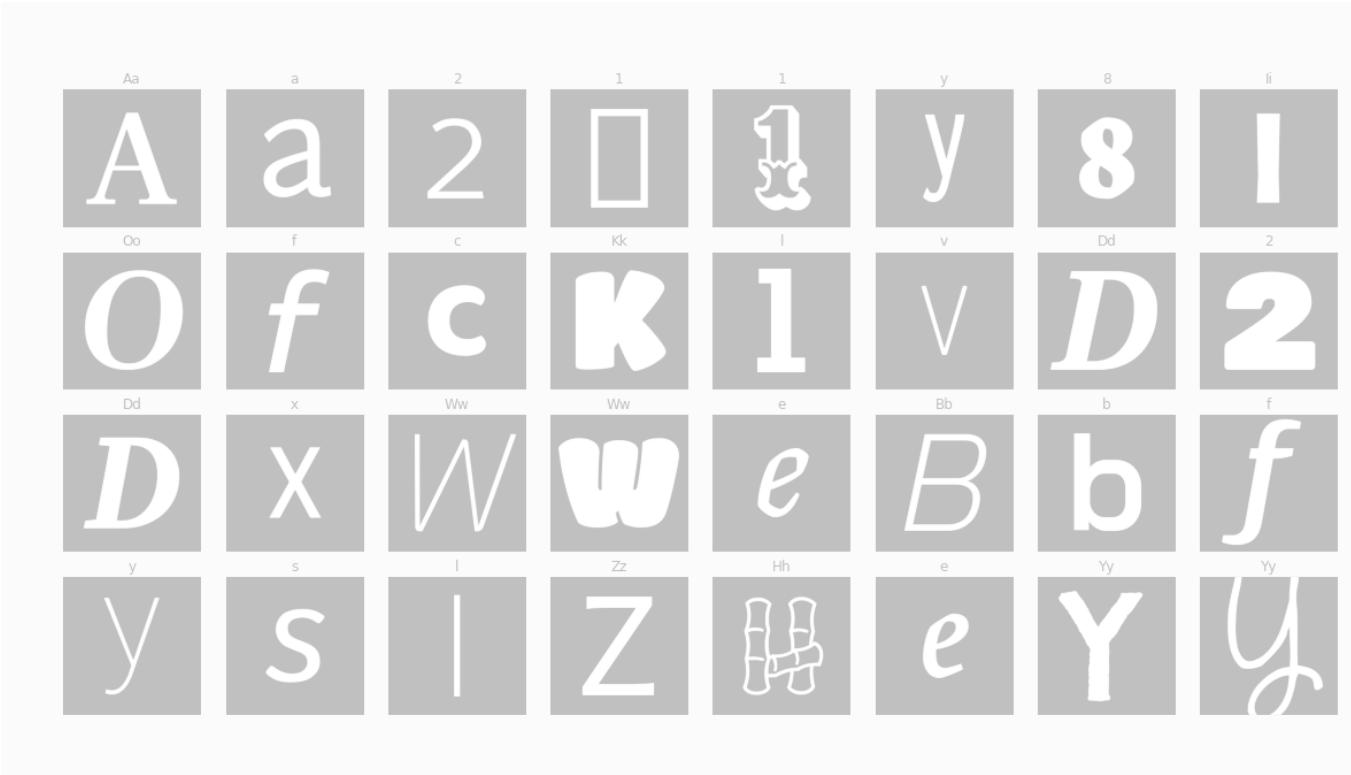


Latent vectors of 'a' & 'j' characters

APPROACH

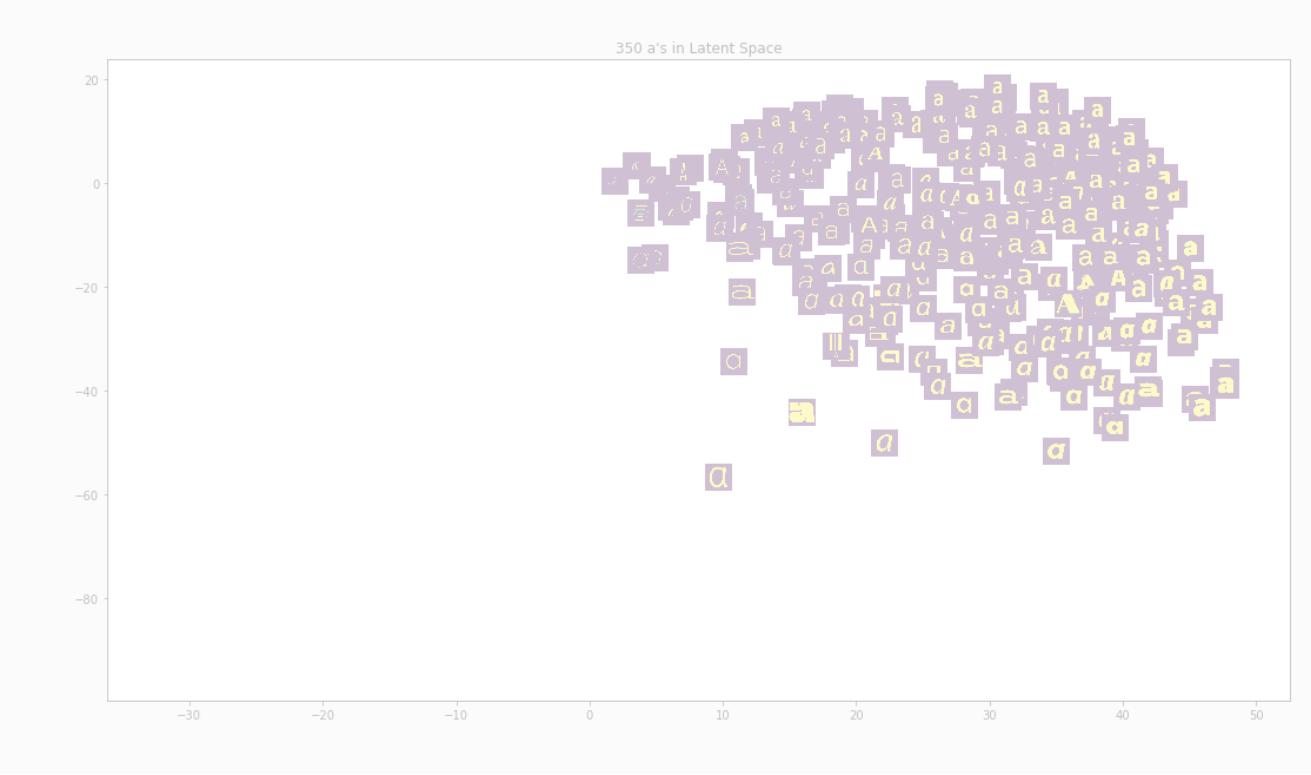
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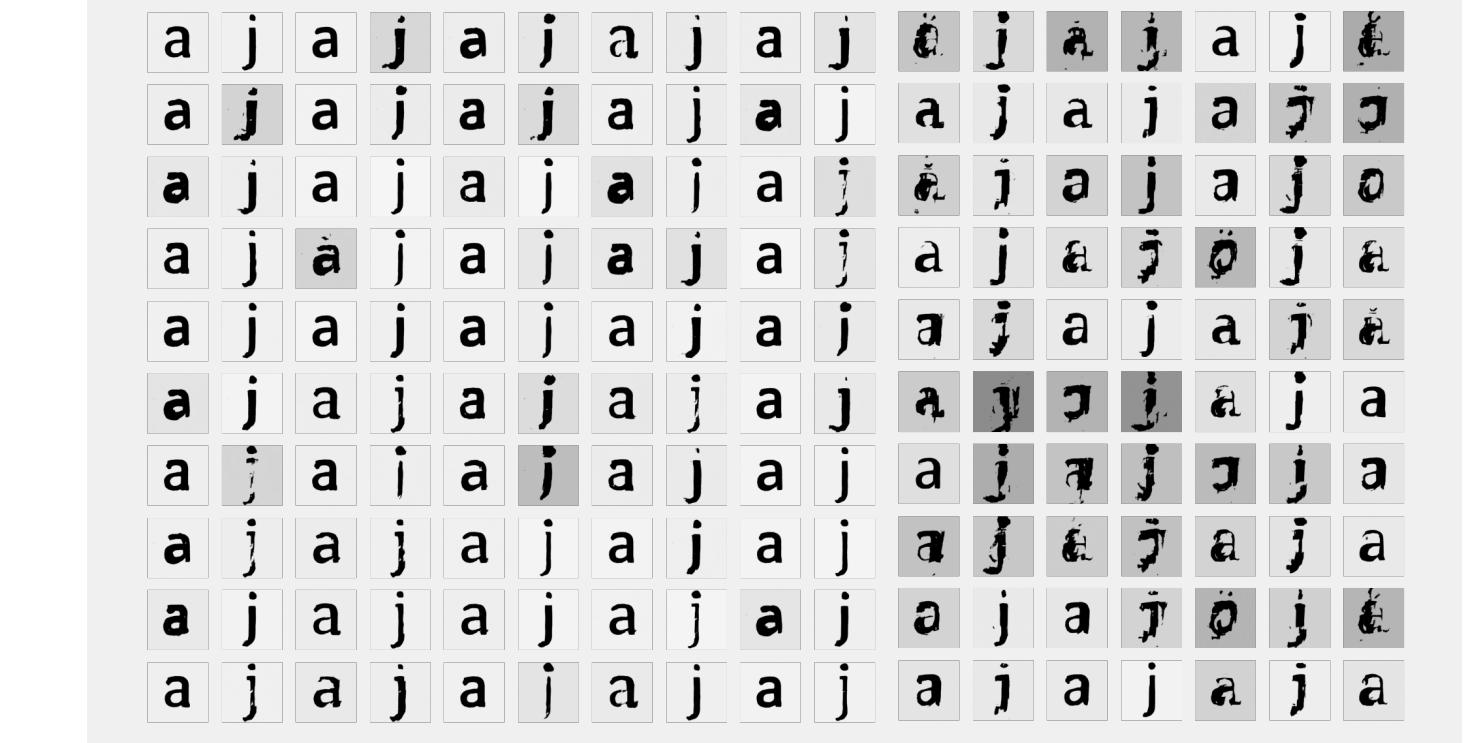
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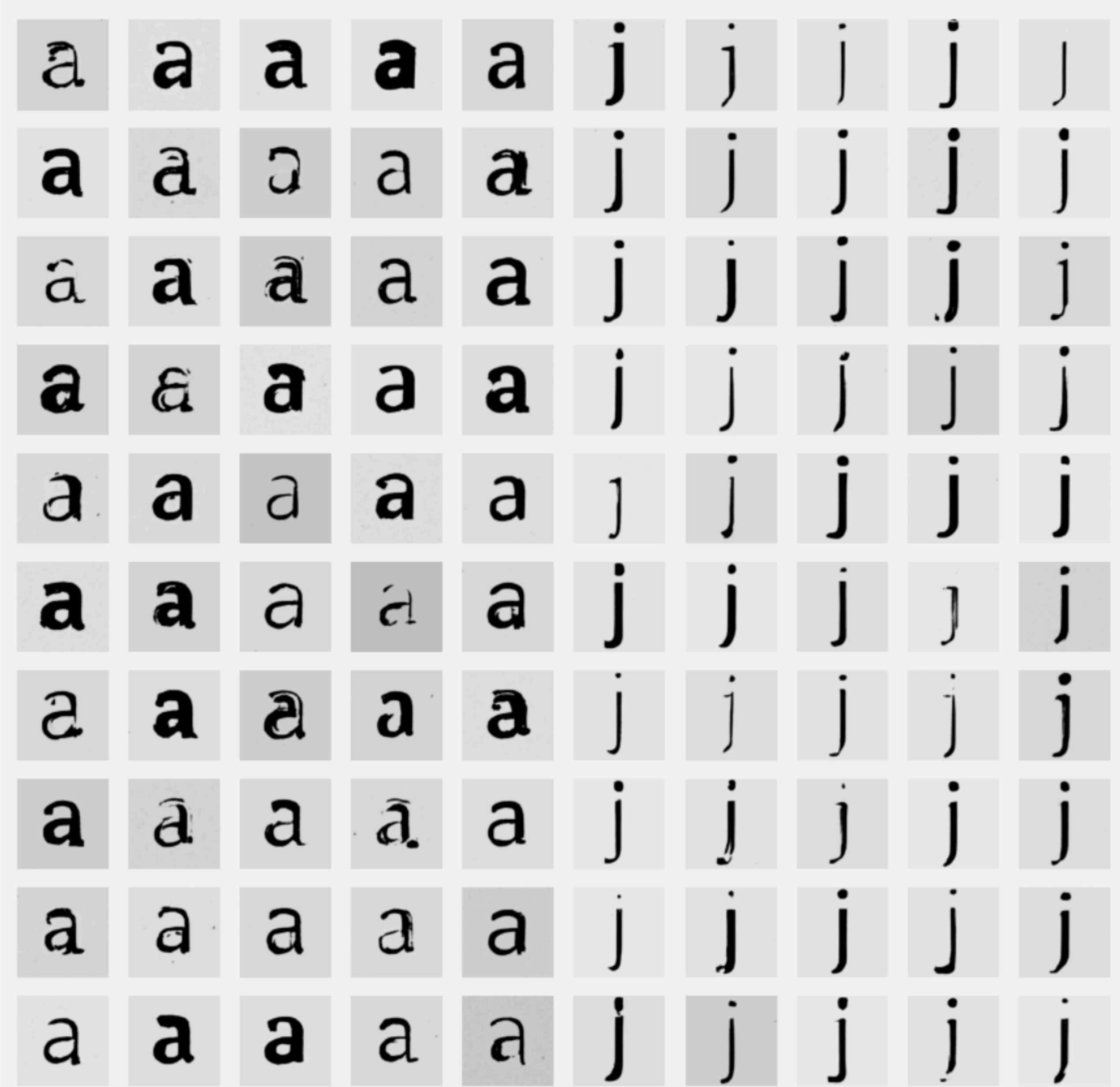


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GENERATE

New ‘a’s and ‘j’s

Multiple generative models in an attempt to recreate convincing ‘a’ and ‘j’ characters that appear as though they could be from the dataset. I trained two Generative Adversarial Network (GAN) architectures including a Deep Convolutional GAN (DCGAN) and a Conditional GAN in order to generate new and realistic typeface characters for a specific class.



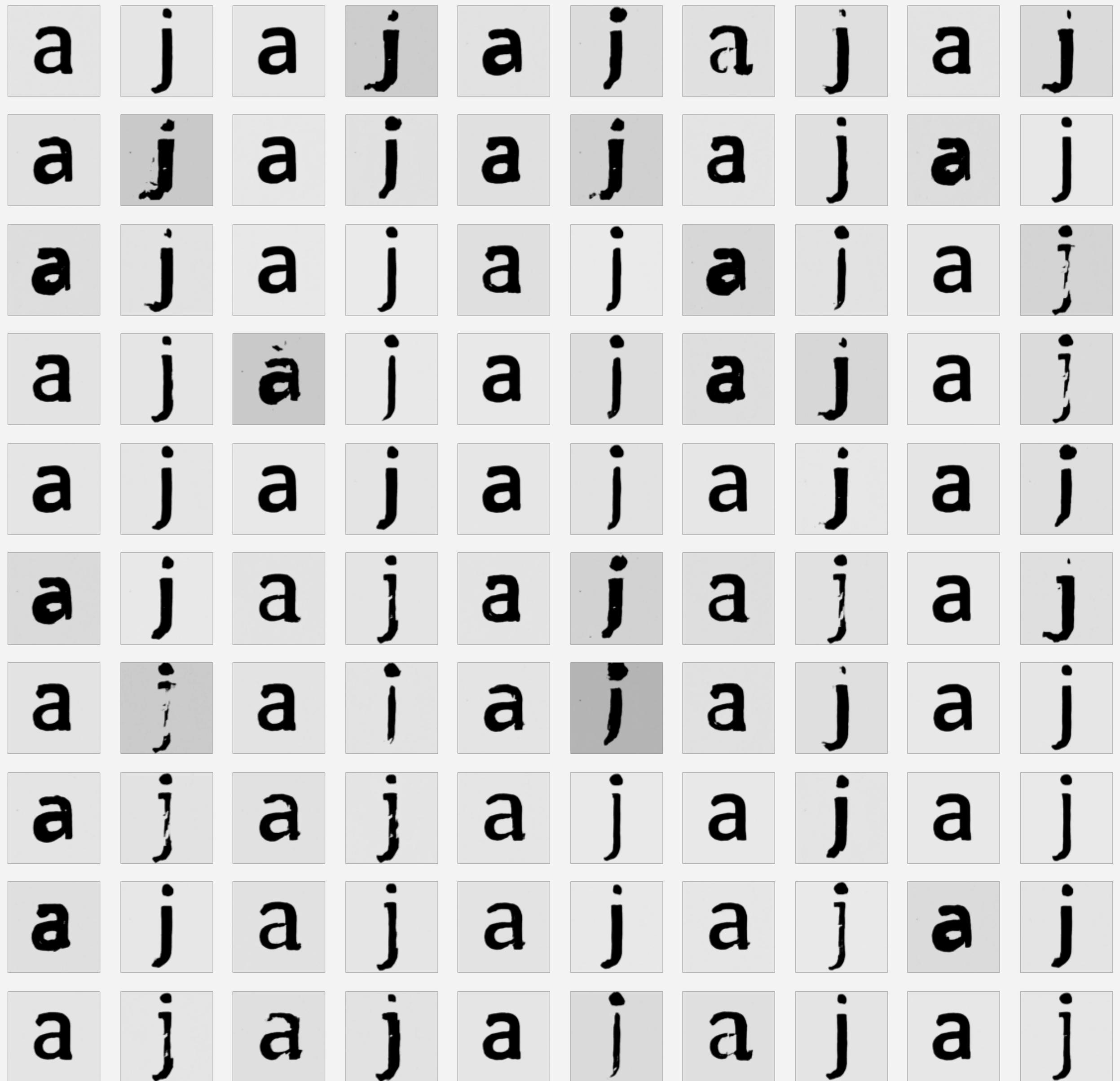
Output from baseline DCGAN model. ‘a’ 100 epochs and ‘j’ 300 epochs

GENERATE

A class conditional GAN model

After 50 epochs of training, the paired character output appeared realistic and convincing to the human eye. Though the model could benefit from more training, the fidelity was acceptable and could easily be mistaken for printed word—with a bit printer smear.

After further inspection, neither the ‘a’s nor the ‘j’s from either DCGAN represent the full diversity of the class (as observed in the EDA phase). The output shows a lack of representation for the class features including italic characters and alternative letter forms.



Output from conditional DCGAN model. 50 epochs

WHAT'S NEXT

The full set needs more work

The existing implementation is transferable to all 62 character classes. Though the size of the dataset holds some computing constraints (2 epochs in 24 hours on an Google Colab GPU), the initial 62 class output suggests it would improve at the same rate as the 2-class ‘a’ and ‘j’ output.

In addition, I’d like to extend the latent space understanding to help designers control the output of their work. Instead of selecting fonts by name, a tool that allows them to generate the font or typeface they’re looking for: something between two named fonts for example, or between a bold and an italic, would save designers a large amount of time during projects.



Output from 62 class, conditional DCGAN model. 2 epochs

Thanks.