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May Levin
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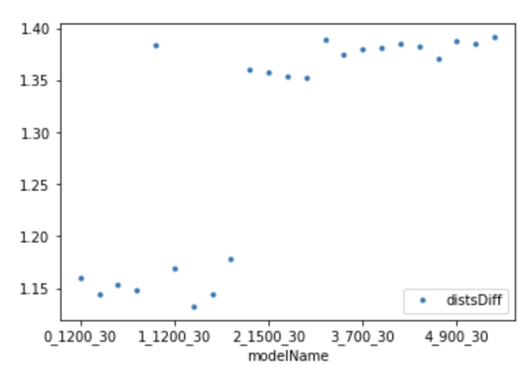
Optimizing transformations on GAN face reconstruction based on fMRI data

Proposal:
In the past few years, there has been an interest in reconstructing stimuli from exposed brain data using AI and other statistical processes. One example of this has been using fMRI data to reconstruct visual input revealed to the human eye, which can later be applied for use cases in VR and any other Brain-Machine-Interfaces. For this project, I attempt to implement more complicated transformations from a recent 2022 paper that used fMRI data to reconstruct GAN generated faces that were shown to subjects.

The Original Paper:
The original paper "Hyperrealistic neural decoding for reconstructing faces from fMRI activations via the GAN latent space" has a github, medium post, and google drive containing data and code, making an edited implementation very accessible. The paper itself uses a simple linear transform on the fMRI data to generate the latent vectors of the faces.

Method:
Attached is a Jupyter notebook that is based on the original jupyter notebook of the paper. What it does differently is contain a bunch of models defined as classes that have varying neural networks that include both linear and nonlinear transformations.
The notebook proceeds to loop through each model, run different epochs for each model, and then locally store data points from each iteration including: the generated predicted latent vector, assumed difference, and a picture comparison file of the ground truth GANs vs. the generated GANS. The generated GANs are based on the predicted latent vectors from the fMRI data.
In order to improve the manner that the generated GANs are compared to the Ground Truth GANS, the notebook now includes an implementation of a face recognition model called Facenet that can map a face image into Euclidean space. As such, face similarity is attributed to the euclidean distance between the processed GAN ground truth image and the generated GAN image after being run through the Facenet module.

Results:
Below is a graph with the success of the face similarity of the different models based on the average euclidean distance between each face pair. Surprisingly enough the simple linear transformation proved to be the most successful model by far, with a significant increase in non-similarity between the simple linear regression models (Model 0 and 1) versus the other models. Model 0 was the original model



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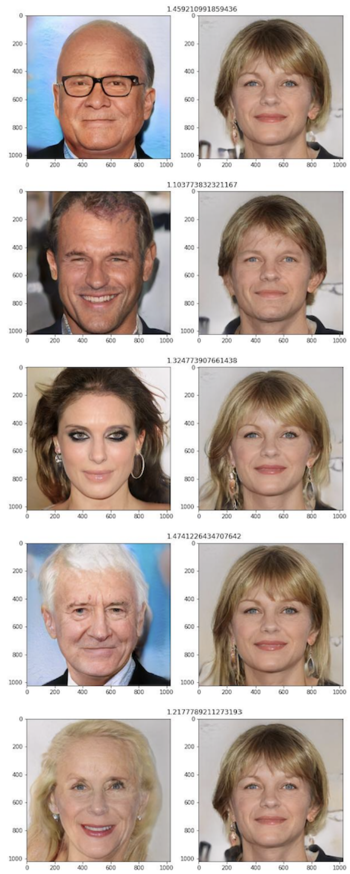
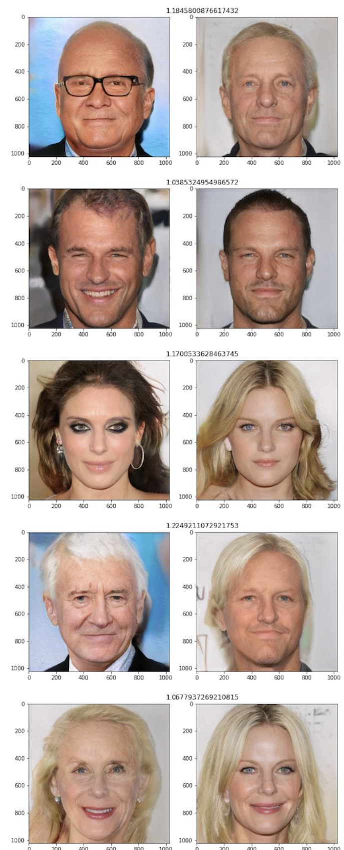
used in the paper, while Model 1 is identical but with bias removed. Oddly enough the more complex models seemed to remove too much information from the fMRI data, having the predicted latent vectors clustered around one place and thus creating images that look incredibly similar. Other transformations just created abnormal faces.





	modelName	distsDiff
0	1_1500_30	1.132379
4	0_1500_30	1.143644
21	1_700_30	1.143913
17	0_900_30	1.148636
13	0_700_30	1.153088
10	0_1200_30	1.159802
12	1_1200_30	1.169655
5	1_900_30	1.177605
16	2_900_30	1.352438
7	2_700_30	1.354133
8	2_1500_30	1.35779

Onwards:

Being able to implement more optimizations such as lasso regression, or other network structures seems promising in order to improve the model then the current attempts. Specifically processes that would not remove as much data and cause the latent vectors to cluster seem necessary. This would require a better understanding of mxnet, and further editing the current model processing that exists. On a separate note, getting more fMRI data through exposing subjects to additional GAN images would also improve the model.

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References:

Dado, T., Güçlütürk, Y., Ambrogioni, L. *et al.* Hyperrealistic neural decoding for reconstructing faces from fMRI activations via the GAN latent space. *Sci Rep* 12, 141 (2022). https://doi.org/10.1038/s41598-021-03938-w

F. Schroff, D. Kalenichenko and J. Philbin, "FaceNet: A unified embedding for face recognition and clustering," *2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2015, pp. 815-823, doi: 10.1109/CVPR.2015.7298682.