## Chris Chen Github:

https://github.com/compscichris/CSCI611 Summer25 Chris Chen/tree/main/Assignment%203

Part 1: I was able to follow the skeleton code that guided me in using the VGG-19 CNN to apply the Image Style Transfer, detailed in the paper by Leon A. Gatys, Alexander S. Ecker, and Matthias Bethge. I was able to understand how to use the pytorch libraries to flatten the input and transpose to calculate the Gram-matrices used for texture feature extraction. My end result looks a little stranger than I anticipated, and I included the first result so far.

The **first run** seemed a little fishy, so I verified my code. I fed the image into the gram matrix, which led to unexpected results. The color was wrong. I changed that, and fed the individual features into image, and it gave me just the original image. That was because the gram matrix was the improper shape, I flattened it to batch, feature\*spacials, instead of feature, spacials. After changing it, I got the results of the **second run**.

## \*second run had total loss of

24.14239501953125

12.477807998657227

8.492374420166016

6.720818519592285

5.793830871582031





Part 2
My first modification was changing the steps.
The base was 2000, and I tested 3000, 4000, and 1000.

stepEdit1 was 3000 step, and yielded a total loss of 24.140098571777344, 12.473718643188477,

```
8.490579605102539,
```

- 6.719324111938477,
- 5.794463157653809,
- 5.246639251708984,
- 4.88814640045166

```
# display content and final, target image
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(20, 10))
ax1.imshow(im_convert(content))
ax2.imshow(im_convert(target))
plt.show()
```





stepEdit2 had a mistake, but I tested 4000 without refreshing.

- 3.621861696243286,
- 3.6169984340667725,
- 3.613125801086426,
- 3.6072707176208496,
- 3.6004316806793213,
- 3.5945520401000977,
- 3.5872647762298584,
- 3.5828256607055664,
- 3.5791311264038086,
- 3.5735409259796143 were the loss values, but it seems the more you steps passed through, the more intermediate images are generated as the model learns and reduce the total loss.

## stepEdit3 was 1000 step, and yielded a total loss of

24.142976760864258,

12.477656364440918





What I noticed was that more steps led to less total loss, and much more intermediate images.

My second modification was changing the alpha and beta values.

## 1e6 base total loss =

24.14239501953125

12.477807998657227

8.492374420166016

6.720818519592285

5.793830871582031

The base was 1e6 for beta, and I tested 1e5 and 1e7.

betaEdit1 total loss 1e5

24.140886306762695,

12.47514533996582,

8.493656158447266,

6.720850944519043,

5.795681476593018

betaEdit2 total loss 1e7

24.139070510864258

12.482877731323242

8.491659164428711

6.7243804931640625

5.800724983215332

$$\mathcal{L}_{\text{total}}(\vec{p}, \vec{a}, \vec{x}) = \alpha \mathcal{L}_{\text{content}}(\vec{p}, \vec{x}) + \beta \mathcal{L}_{\text{style}}(\vec{a}, \vec{x})$$

By changing the value of beta, I expect that the total loss would increase with a higher coefficient, and decrease with a lower one. But the results appeared inconsistent, so I cannot really draw a conclusion from the results, on what

the exact impact of changing beta and alpha are. It may be affected by the weights.