Assignment 2

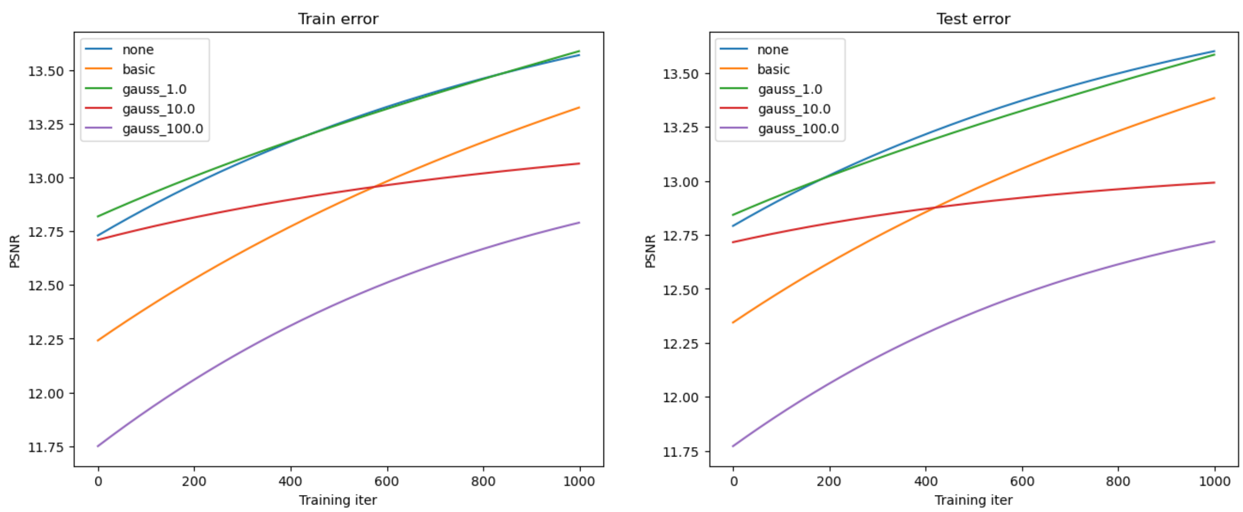
Name(s): Ziheng Chen, Yutong Zhang
NetID(s): zihengc2, yutongz7

In each the following parts, you should insert the following:

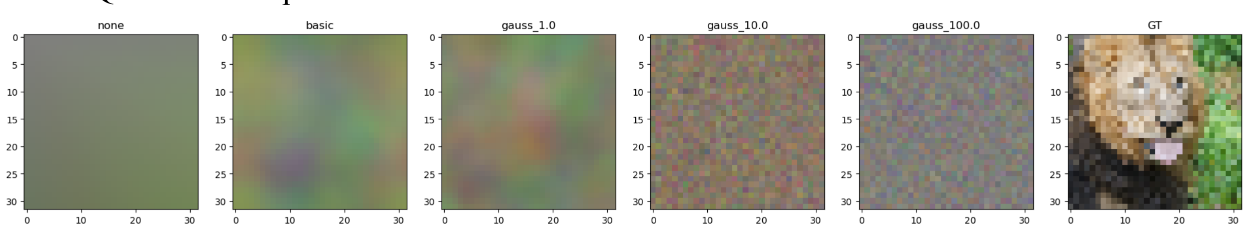
- Train/test loss plots
- Qualitative outputs for GT, No encoding, Basic Positional Encoding, and Fourier Feature Encoding at three different scales

Part 1: Low resolution example - SGD

- Train/test loss plots

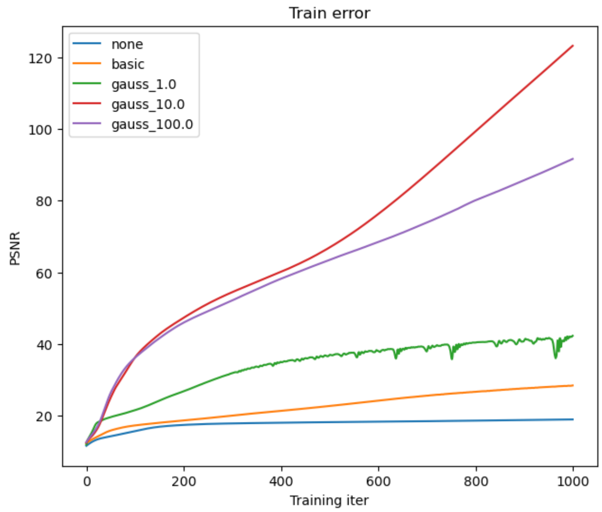


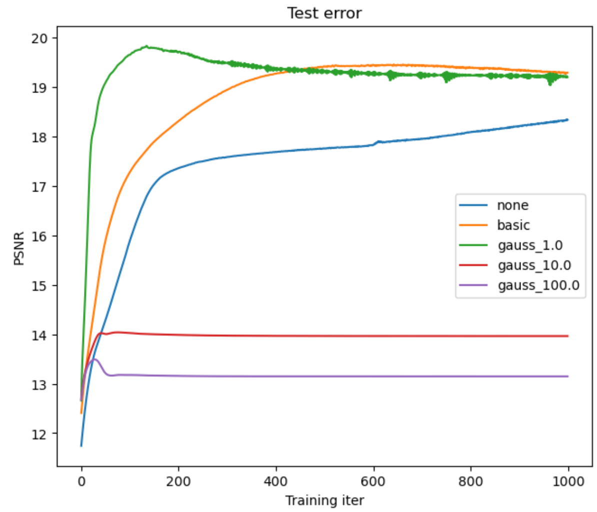
- Qualitative outputs



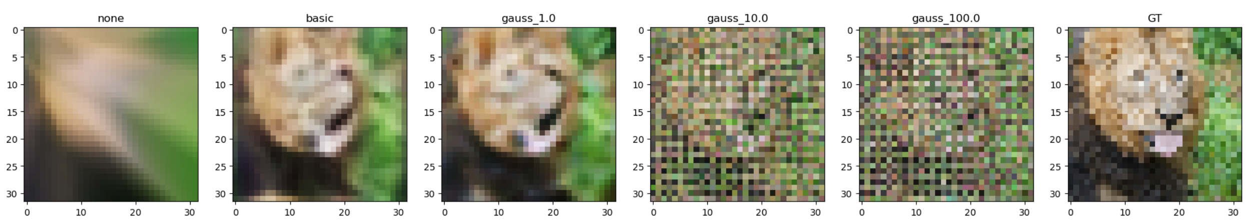
Part 2: Low resolution example - Adam

- Train/test loss plots



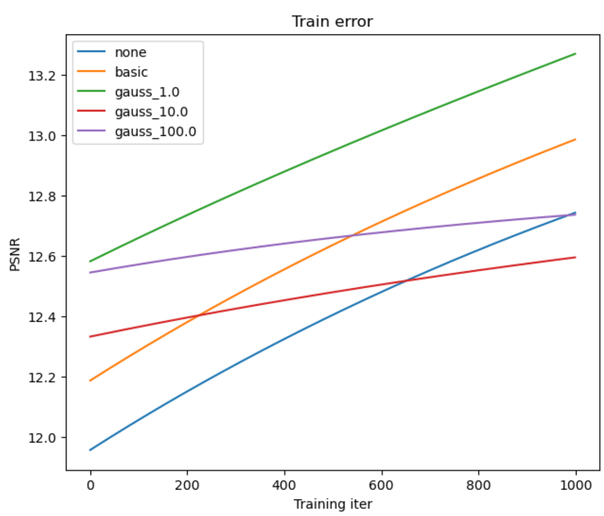


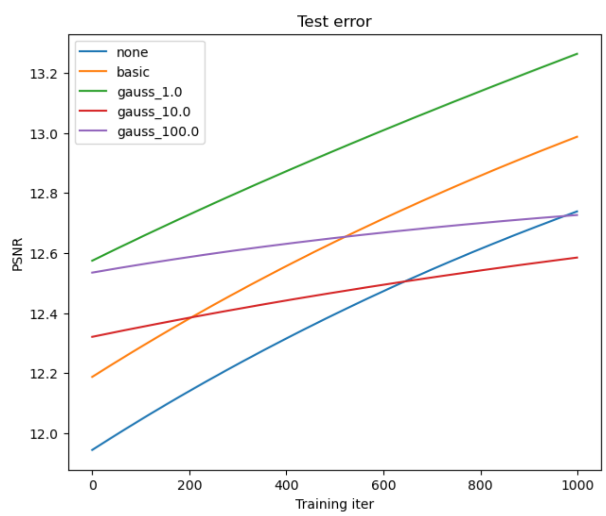
- Qualitative outputs



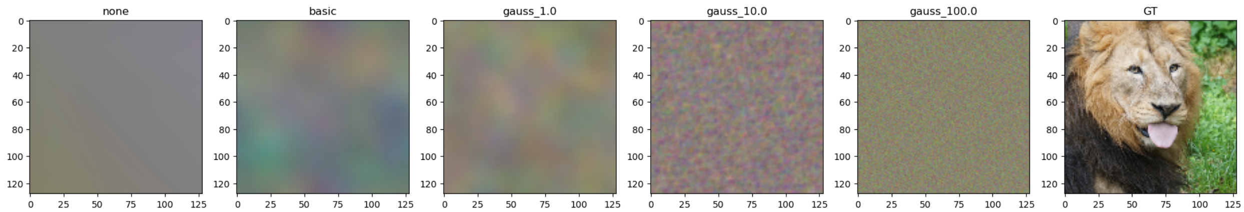
Part 3: High resolution example

- Train/test loss plots using SGD

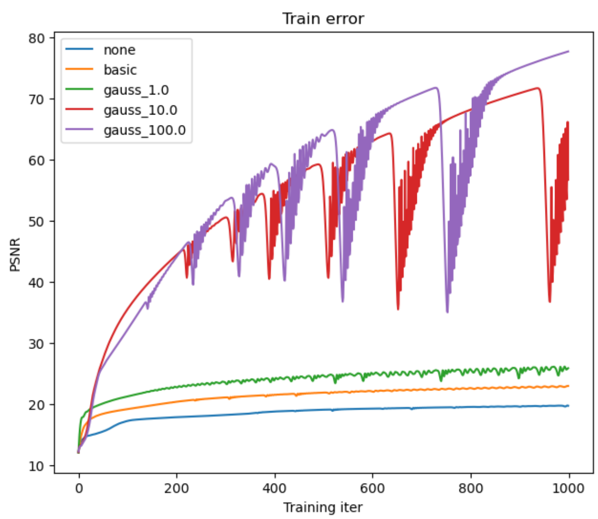


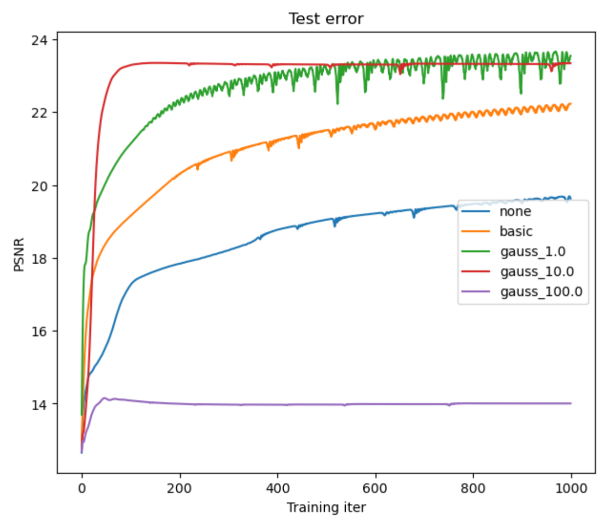


- Qualitative outputs using SGD

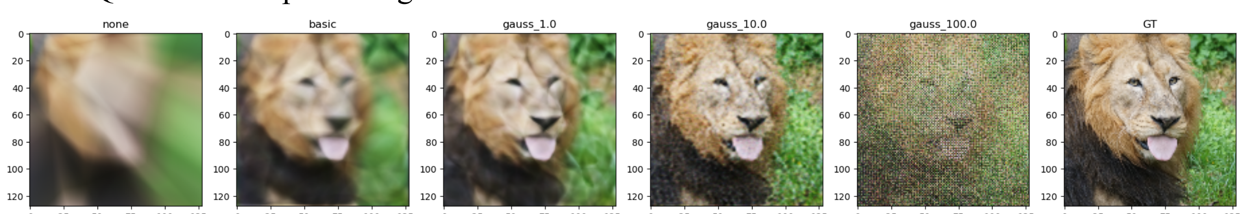


- Train/test loss plots using Adam





- Qualitative outputs using Adam

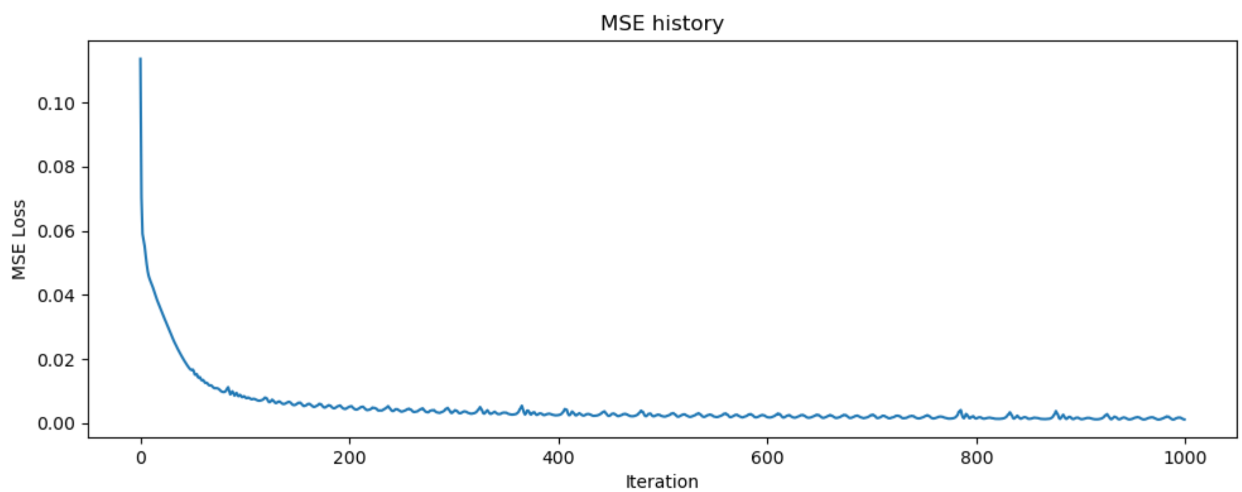


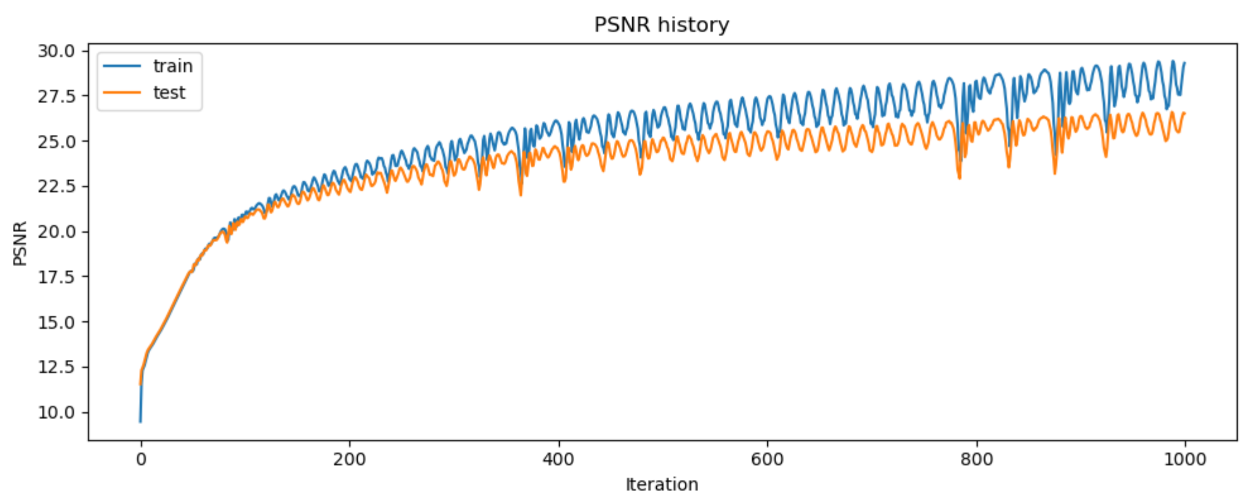
Part 4: High resolution (image of your choice)

(For this part, you can select an image of your choosing and show the performance of your model with the best hyperparameter settings and mapping functions from Part 3. You do not need to show results for all of the mapping functions.)

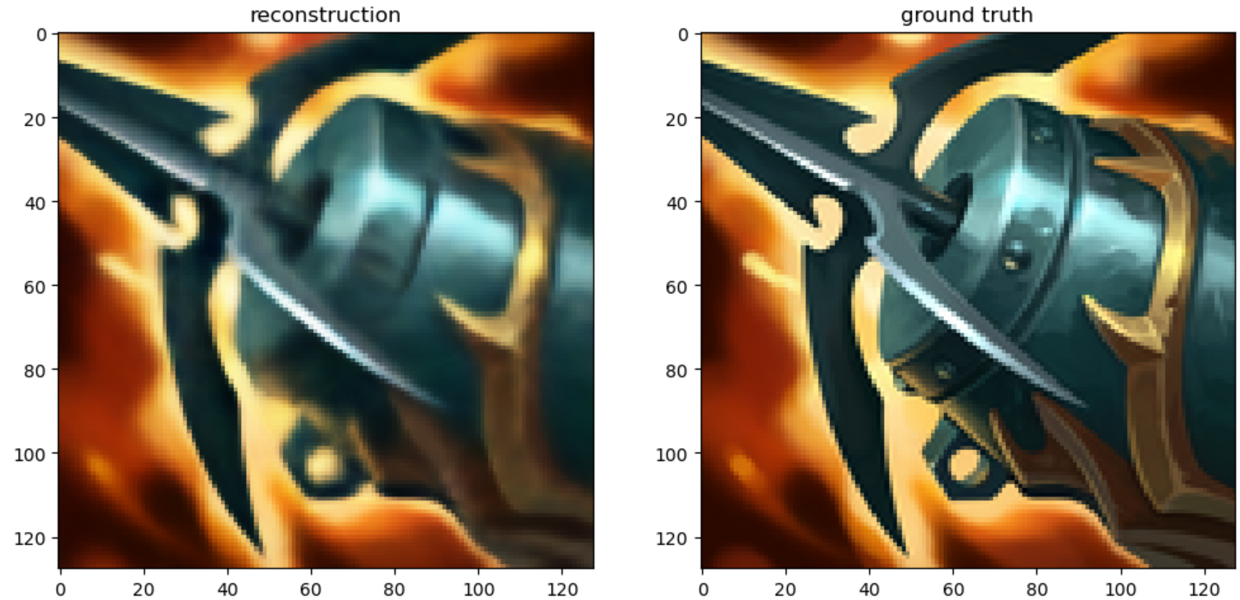
- Best parameter settings
  - Mapping: gauss_1.0
  - input_size=512
  - num_layers=4, hidden_size=3
  - hidden_sizes = [256] * 3
  - output_size=3
  - epochs=1000
  - learning_rate=1e-4
  - opt="Adam"

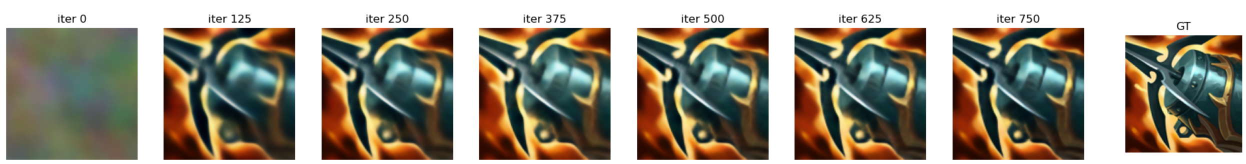
- Train/test loss plots





- Qualitative outputs





Part 5: Discussion

Briefly describes the hyperparameter settings you tried and any interesting implementation choices you made.

We tried different strategies to tune the hyperparameters. We start from the hidden size of 256, as the suggested hyperparameters mentioned in the instruction. Then we tried to increase the hidden size to 1024, and from the result, we found out that although the larger hidden size produced better losses, qualitative outputs only improved incrementally. And since using 256 as the hidden size costs less time, we use it in the final result. We also try SGD and Adam with the same setting, and Adam has better performance of losses and qualitative outputs.

How did the performance of SGD and Adam compare? How did the different choices for coordinate mappings functions compare?

Having more complicated mappings brings more differentiability in more fine-tuned predictions. When using SGD, it simply means that the prediction can have more colors broken down into smaller regions, which shows that the prediction tries to stay closer to the ground truth.
However, due to the inferior nature of SGD compared to Adam, the accuracy is the severely upper bound. When using Adam, having more complex mapping allows clearer boundaries in the predictions, and we can see the outline much more accurately. However, it is important to note that as the scale goes up to 100, the prediction can be extremely fine-grained so that the prediction overshoots and produces incomprehensible results.

What insights did you gain from your own image example (Part 4)?
The algorithm is not only good at photos of nature but paintings too.
The algorithm can handle similar colors (red and orange) as well as colors of contrast (objects and the vibrant background).
The algorithm is not very good at reflection, small detail, or sharp edges.