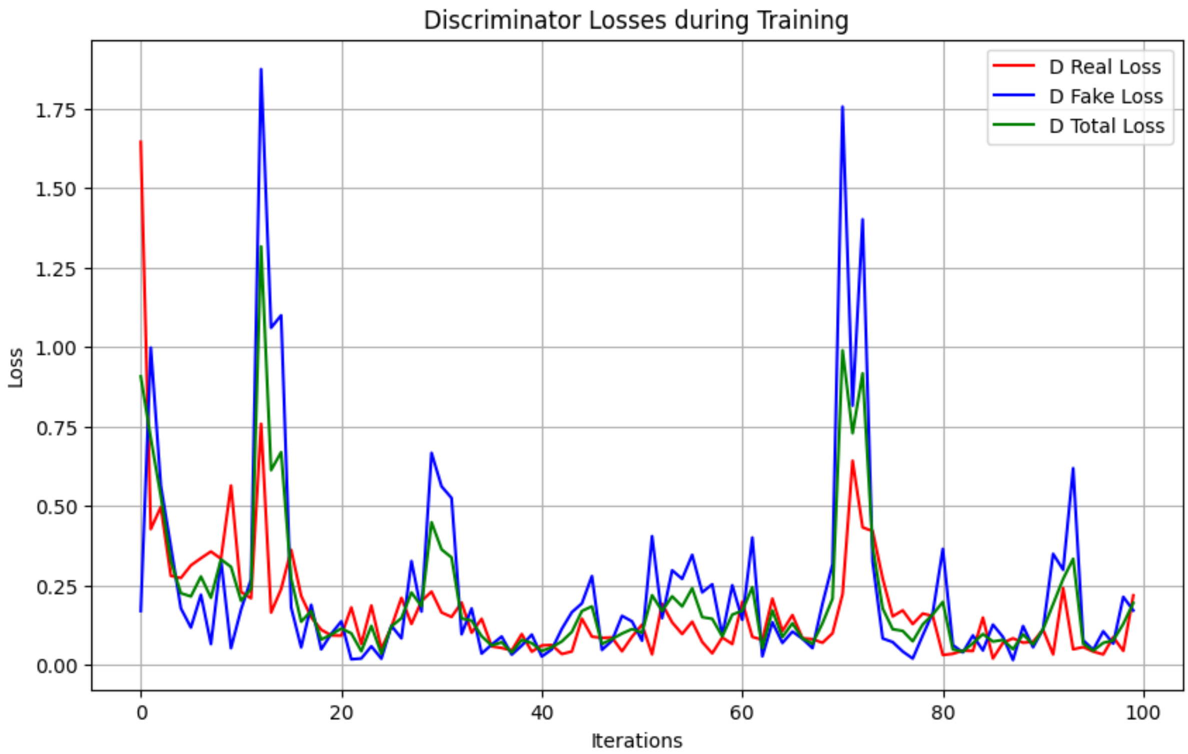
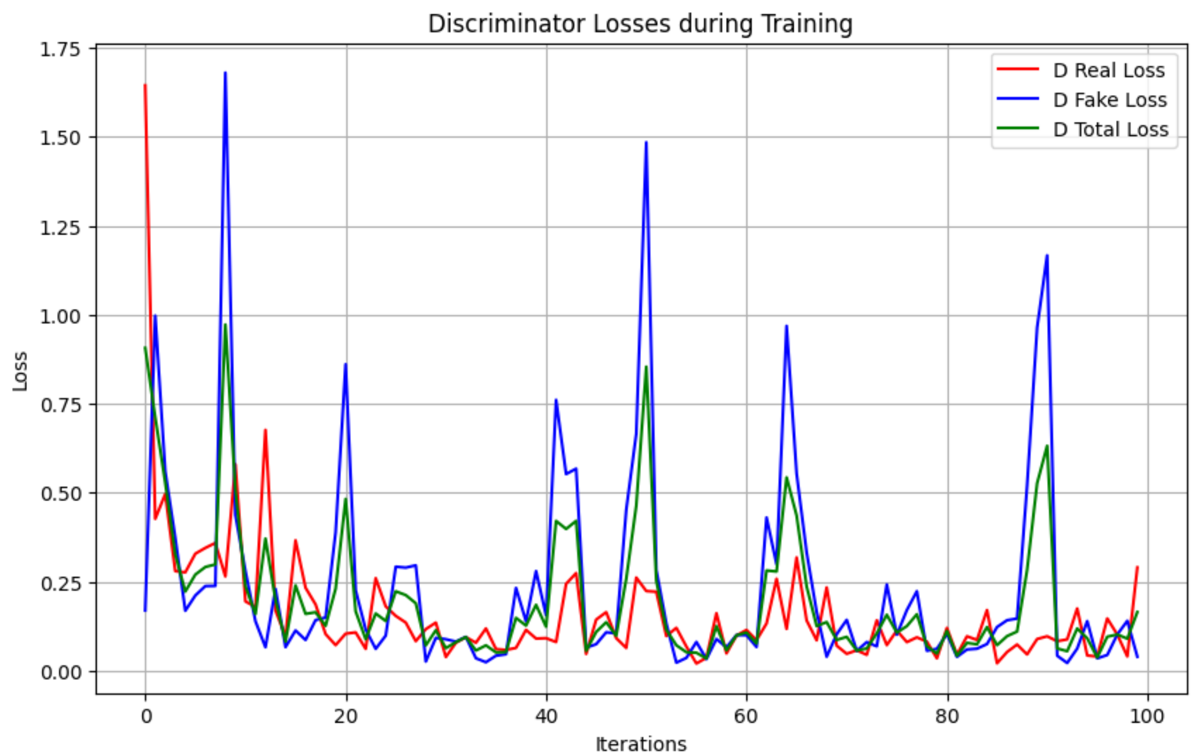
Part1

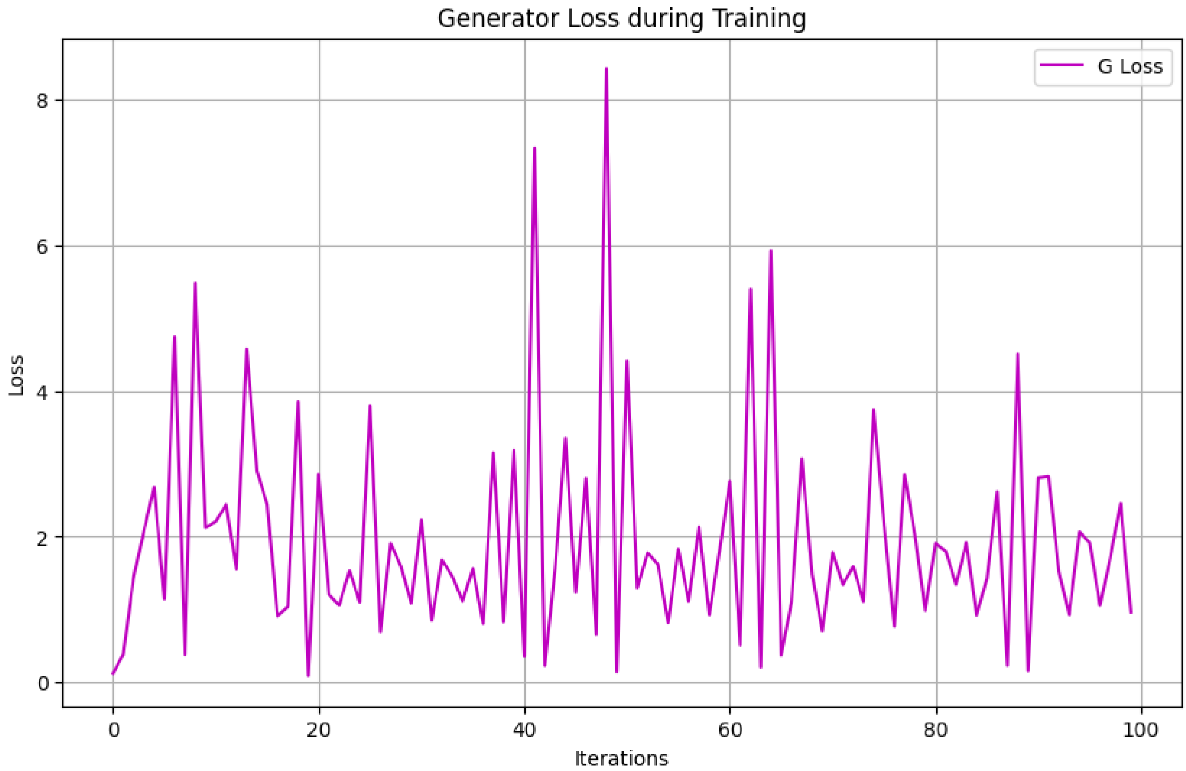
1.1

grumpifyAprocessed_basic

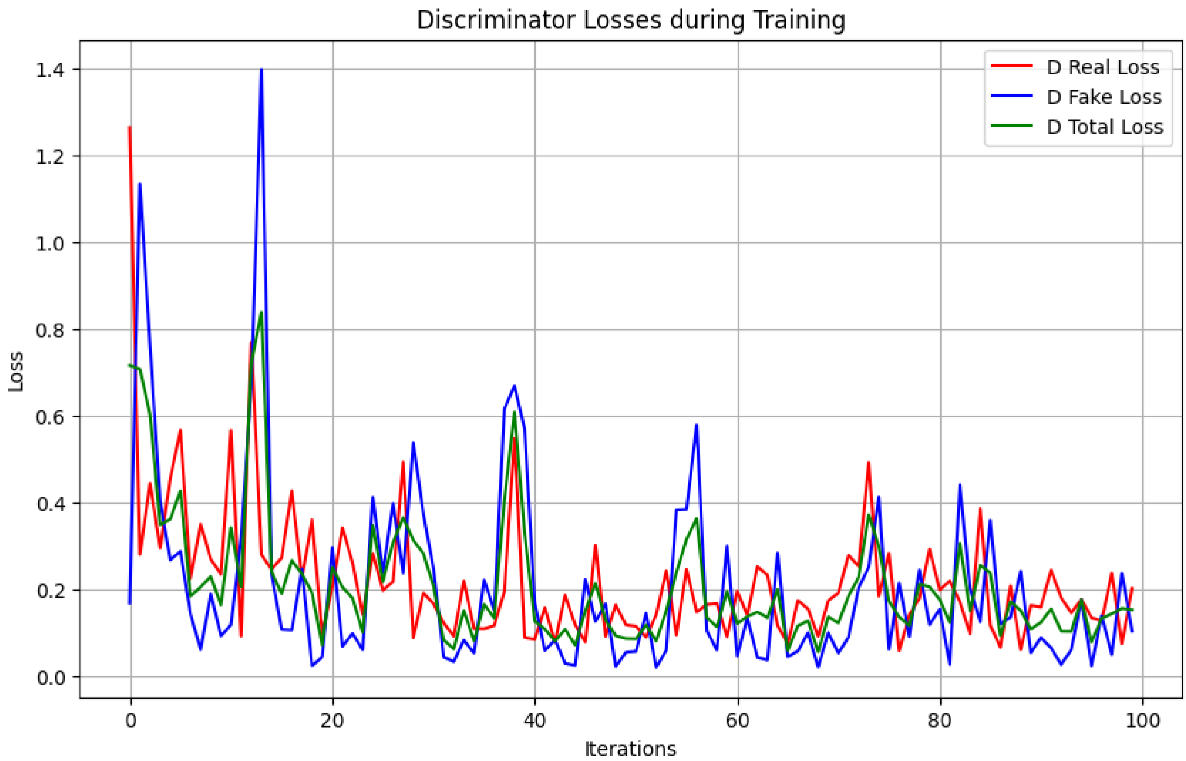


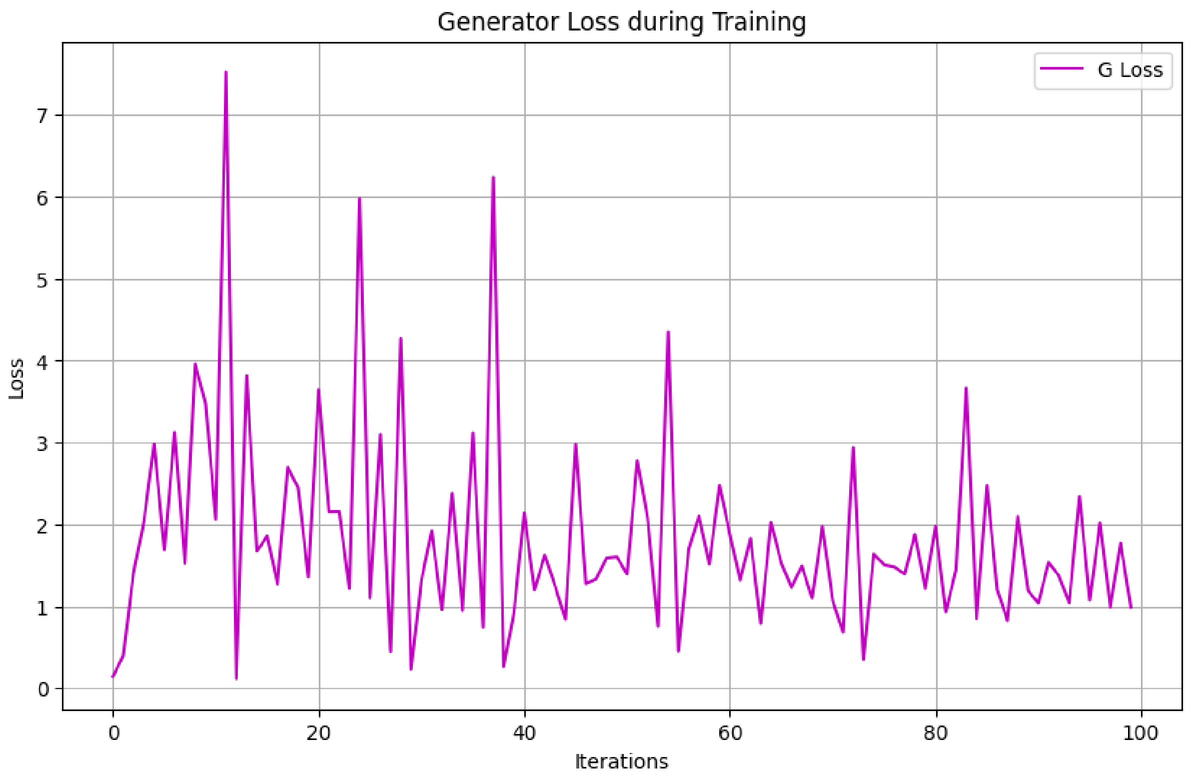
grumpifyAprocessed_basic_diffaug



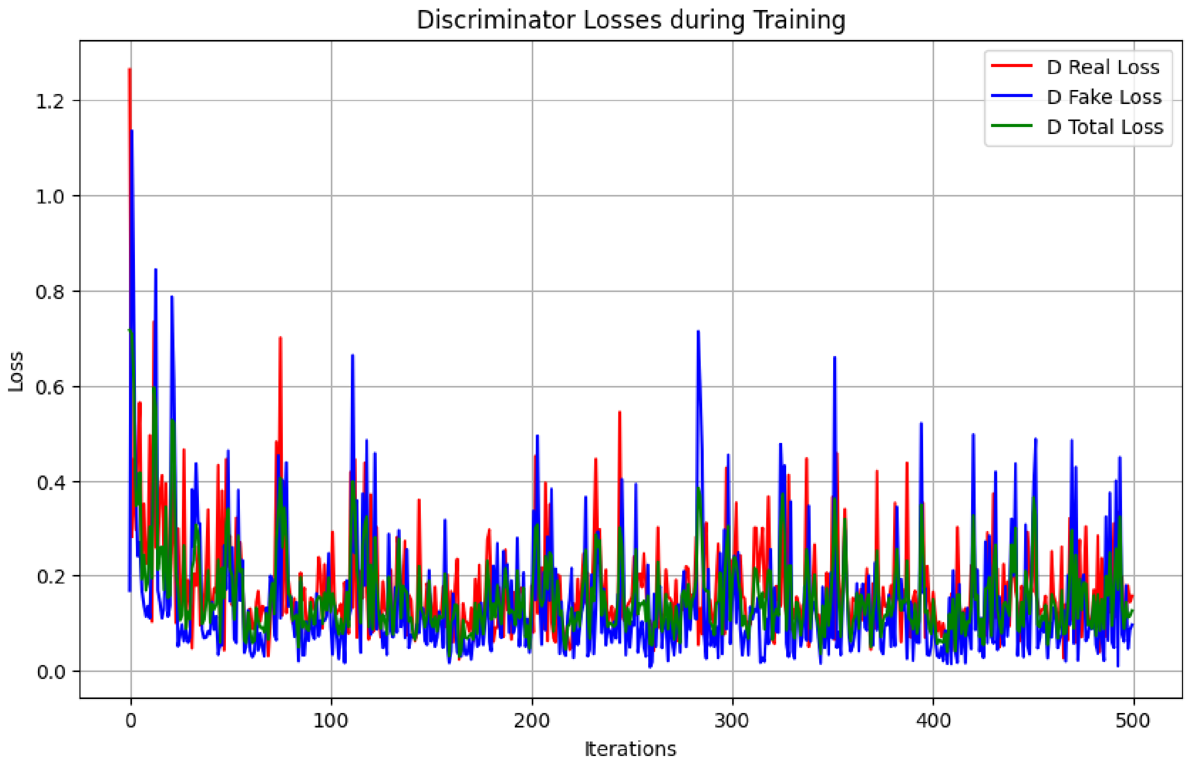

Generator Loss during Training
G Loss
Loss
Iterations
0
2
4
6
8
0
20
40
60
80
100

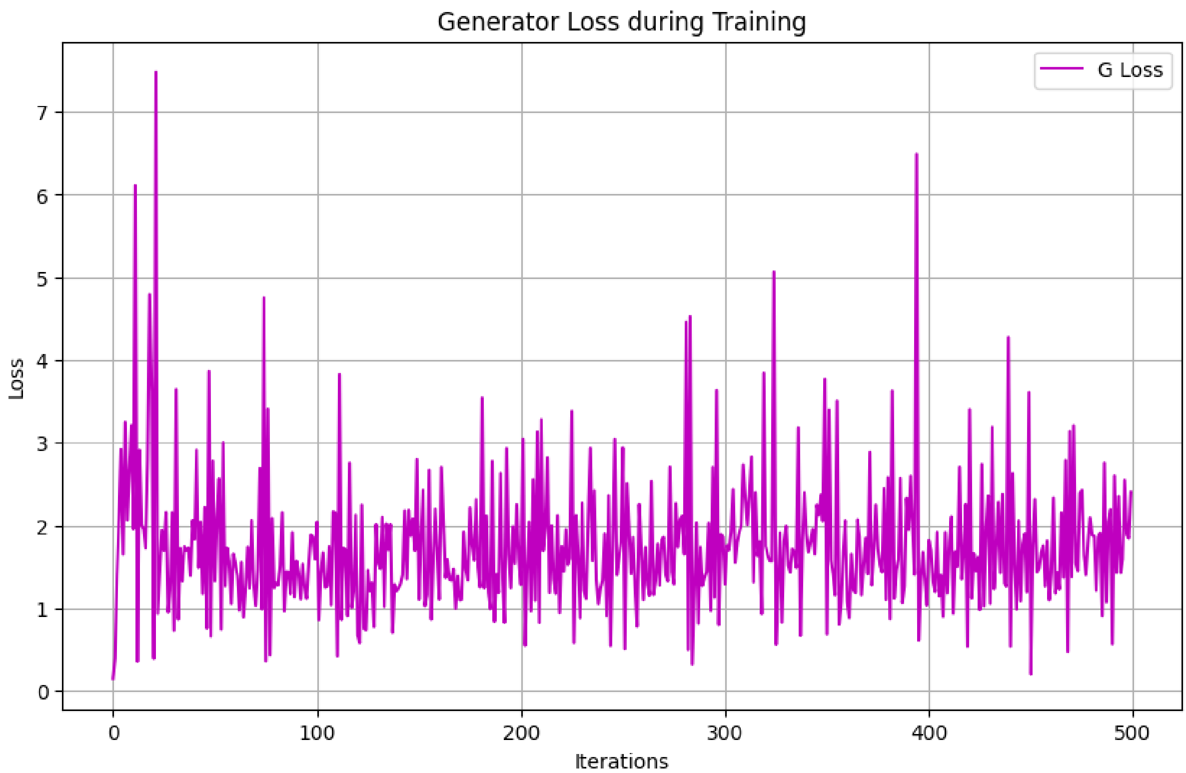
grumpifyAprocessed_deluxe





grumpifyAprocessed_deluxe_diffaug





从训练结果来看，加上 DiffAugment 的模型训练更稳定，生成图像更清晰，尤其是在数据量较小的场景下。

不使用 DiffAugment 时，判别器 loss 很快下降，生成器 loss 上升后振荡，说明判别器太强，训练不稳定。

使用 DiffAugment 后，判别器 loss 稳定维持在 0.3~0.5，生成器 loss 稳定下降，生成质量也有明显提升。

说明 DiffAugment 有助于抑制判别器过拟合，提高生成器学习的空间。

1.2

200：

400：

As you can see from the image above, the generated diagram of step 200 is rough, but some of the contours and symmetrical structures are still relatively clear. By step 400, however, the image becomes blurry, and detail is lost. This may be due to training instability in the GAN model, such as mode collapse or the discriminator being too strong for the generator to converge.

Part2：

2.1

1000:

XY: 

XYuse_cycle_consistency_loss：

YX: 

YXuse_cycle_consistency_loss:

NO cycle-consistency loss：

Although the style of the image of the XY direction conversion has changed, it tends to be "out of shape", and the structural information is seriously lost.

Have cycle-consistency loss：

Whether it is XY or YX direction, the content structure of the image is well preserved, and the basic shape of the input map can be restored more accurately after conversion. The style shifts while maintaining the main contours and object positions.

With the addition of cycle-consistency loss, the model learns not just "style transfer", but "constrained transfer", which greatly improves the interpretability and stability of the generated image.

2.2

10000:

XY: 

YX: 

Both XY and YX have sharper images and more natural color saturation. Edges and details are richer than at 1000 steps, and textures are more realistic.

After the training time was extended to 10,000 steps, the generation capacity of the model was significantly improved, and the images were not only more beautiful, but also consistent. The generated graph in the XY direction is already ideal (it can be seen that it is a cat).

2.3

After adding cycle-consistency loss, the shape of the cat's face is closer to the original image, not only the style has changed, but the structure has been preserved, and it looks more like "the same cat has cross-dressed".

If you don't add it, it's easy to "lose shape", and some of the colors of the picture are changed, but the facial features are crooked, and the cat's face can't be seen clearly, as if it was casually pasted.

So this loss is the key, it is equivalent to setting a rule for the model: change and change, do not scribble, but become back and forth, so that what you learn is reliable.

2.4

CycleGAN with the DCDiscriminator：

XY:

YX: 

After using the Patch Discriminator, whether it is the cat's face or the background, the details are clearer, and the whole picture is more like a real cat than a messy block of color. In contrast, when using the DC discriminator, the generated image is particularly easy to paste, and the cat's face is often distorted, looking like a mosaic.

Therefore, the patch discriminator pays more attention to "local truth and falsehood", and can force the generator to learn to draw small details such as clear eyes, and the effect is naturally much better.