SmallSEOTools

PLAGIARISM SCAN REPORT

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8.2 RESULTS AND DISCUSSIONS
In the following section, we briefly compare and summarize the results of the implemented architectures and evaluate their performance. The evaluation is done qualitatively as well as quantitatively. We compare the performance of each model using L1 and L2 norm distance between the predictions and targets. Though unreliable, this method provides us with a somewhat decent ground to perform a comparative study and evaluate the reliability of such metrics on GAN evaluation compared to qualitative, visual evaluation.
To evaluate the model performance by virtue of convergence of the objective function, we plot the generator loss throughout the training on two different networks. Figure 8.1a and 8.1b shows that the generator converges quite nicely. The discriminator on the other hand oscillates because of the convergence that the generator shows. GAN losses are pretty non-intuitive but we can draw some observations from the loss curves. It seems that the pattern of oscillation and convergence repeats when networks are trained in an adversarial fashion.
Figure 8.2a and 8.2b show the same trend repeating even when trained using pre-trained weights with state of the art networks that show excellent results. It is observed that the ResNet U-net with a pre-trained ResNet-18 for its backbone converges decently in the beginning but later shows spikes when nearing the end of training loop. The ResNet50 used as a discriminator shows identical behavior as the custom discriminator above refer fig.8.1b.
We draw some conclusions based on our understanding of the plots. It seems that the loss convergence doesn’t signify whether the model is predicting expected results. The loss function just converges to the minimum value that the cost function descends to, permitted by the learning rate. It would normally signify that the GAN has found some optimum point in the vector space that is at the lowest potential and cant decrease any further. It essentially means that the GAN has leaned enough. Due to the large number of dimensions, owing to the high amount of trainable variables, such combinations, where the function converges, can be huge in volume. Thus, these numbers don’t provide any better understanding of the bias or variance the model is facing. Also, we discover that if the loss hasn’t converged well, it doesn’t necessarily mean that the model hasn’t learned anything. On visual inspection, the generated results show similar results to the ground truth, even with high generator losses. This might be due to presence of a content loss parameter in the loss function where we try to minimize the function by minimizing the L1 norm between the generator predictions and target.
The discriminator shows an increase in the objective loss function in the initial epochs and then settles down in the later phase around an oscillation point. This shows that the discriminator is converging to some permanent number or rather,

oscillating around it. We assume this point to be a point of stability between the two networks as the networks are in a constant adversarial battle, meaning if one performs better, the other is bound to perform worse.

8.2.1 Image Colorization

We present a comparative study of the following models: Basic U-net generator with a custom, residual VGG16 discriminator, hereafter referred to as Basic U-net. A modified U-net with pre-trained ResNet18 as its backbone. We evaluate this model by training it in RGB color space to predict 3 numbers for every pixel and in L*a*b color space where the model predicts the a and b channel alone. We then further train this model to fine-tune it to the task of colorizing astronomical images. From figure 8.3 we observe that on this particular example, the Basic U-net performs better at predicting results that closely map to the ground truth but the finetuned ResNet-18 shows promising results over a larger set of inputs. It can also be observed that the Basic U-net architecture does a decent job of faking the sharpness in the original image and that makes the image appear more realistic as compared to rather blurry outputs from the other networks.

We also observe that the model trained in the RGB color space performs poorly at predicting values of the three color channels and that results in dominance of one channel (blue in this case) over others. This causes the output, even thoughreconstructed quite accurately, to have a varied color pattern with high emphasis on one color channel. This might be because of presence of deep layers which cause gradients of certain colors to diminish over time, causing the model to be strongly biased towards the blue color in this case. An increase in the volume of training data and some random pixel shuffling in forward propagation might solve this problem.

The pre-trained ResNet18 U-net performs decently with the weights gathered by training it over the COCO dataset. The model still lacks the specific coloring intuition in astronomical images and plainly colors specific parts of the images in light colors, leaving majority of the image unaltered. This causes the images to have a slight gray tinge.

Figure 8.6 shows how the other models perform in different color spaces. We can observe that the Basic U-net model performs good at predicting the outputs but doesn't predict the brightness level of pixels quite accurately. The model seems to be overfitting on the dataset and suffers a high variance on output because there are a lot of testing samples which demonstrate the poor performance of the Basic U-net model as can be seen in figure 8.4.Figure 8.5a shows the ground truth images and figure 8.5b shows the predictions of the ResNet18 full trained model in the L*a*b color space. This model seems to perform best, visually.

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