SmallSEOTools

PLAGIARISM SCAN REPORT

Words	613	Date	June 21,2021
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To quantitatively estimate the model performance, we measure the L1 and L2 distance between the predictions and the ground truth images in both RGB as well as L*a*b colorspace.Table 8.3 shows that the RGB color space performs poorly on the task of colorization. In terms of the L1 distance, the best performance is achieved on the ResNet18 U-net with pre-trained weights. This goes to prove the unreliability of distance metrics in model performance evaluation. The model, although quantitatively, performs better than the fine-tuned model but in reality, fails to produce images that might be visually appealing. The L2 distance metric shows how the fine-tuned model might, in reality, be fitting slightly better over the data to predict correct color combination as its output. We still consider the results from the fine tuned model to be better than the other performing models and further investigate the per-channel predictions by the model.
Table 8.2 shows the RGB channel averages of the outputs produced by the fine tuned model. It can be observed that the feature embeddings produced by the model in *a, *b color spaces maps to the green channel with the least error. This might be indicative that the model is performing poorly on images that have a high content of red-blue colors.
To further evaluate the actual outputs produced in the L*a*b color space, we compare the *a, *b channels of the ResNet18 architectures.
In table 8.3, L1 distance, we can see the performance of fine-tuned model to be better in channel *a but poor in *b compared to the pre-trained model. The L2 distance metric rules out the possibility of the fine-tuned model performing better than the pre-trained model. In reality, the fine-tuned model is orders of magnitude better at predicting output abstractions with the L channel as its input, thus contradicting the quantitative results.
8.2.2 Image Super Resolution
We implement the basic SR-GAN proposed by Ledig and train it to improve super-resolution task. We compare the trained model with pre-trained SRGAN model, EDSR-GAN proposed by Lim et al. (2017) and WDSR-GAN proposed by Yu et al. (2018).Figure 8.7 shows how the networks perform on the task of predicting pixels while upscaling of the image. All the networks perform really well and its difficult to distinguish the outputs visually. It may be observed that the fine-tuned network produces images that look slightly better than the other counter-parts. The best performing network seems to be the WDSR-GAN with a very little error in predicting the output.
It is evident that the model produces acceptable results on visual inspection.
The main reason behind this might, again, be the random pixel shuffling between every upscaling pass.
As opposed to colorization, super-resolution needs a quantitative estimation

to determine which model performs best among the give models.
Table 8.4 shows the L1 and L2 distances of predicted results by each model with the ground truth image. It is observed that Ledig's SRGAN, after a bit of finetuning performs really well in comparison to the the pre-trained version. To further improve this, Lim et al. (2017) proposed an optimized version of SRGAN by removing the unnecessary modules in the conventional resnets and showed that Enhanced Deep Residual Networks performed better at upscaling task. When trained in an adversarial manner, the ED-SRGAN performs better than the traditional SRGAN. Yu et al. (2018) further improved the idea by increasing the widening factor (2 and 4) to (6 and 9). This Wide Activation Deep Super Resolution network further improved the performance for single image super-resolution. When we implement this in an adversarial manner, we achieve excellent results. It is evident from the results that the best performing network is the WDSR.

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