Implementation of Neural Style Transfer

GNR 652: MACHINE LEARNING FOR REMOTE SENSING COURSE PROJECT

Code available [here]

OBJECTIVE

- To extract content and texture information from the images using a Deep Neural Network Model.
- To create a new image by using different proportions of the two features from two different images.

MOTIVATION

- To understand the natural phenomena of art sense and visual perception in humans
- To understand how the natural neurons interpret the texture of a visual observation and distinguish it from the content component of the visual source
- Texture relates to spacial similarity between pixels of an image, this project attempts to understand the behaviour similarity between natural neurons

IMPLEMENTATION

- VGG16 Convolutional Network is used is used for initializing the weights of the convolution layers
- The content and style losses are calculated at each layer and the total loss is taken as the weighted sum of two.
- The relative is decided as per requirement of extent of mixing.

$$\mathcal{L}_{content}(\vec{p}, \vec{x}, l) = \frac{1}{2}\sum_{i,j}\left(F^l_{ij} - P^l_{ij}\right)^2 .$$

$$E_l = \frac{1}{4N_l^2 M_l^2}\sum_{i,j}\left(G^l_{ij} - A^l_{ij}\right)^2$$

$$\mathcal{L}_{style}(\vec{a}, \vec{x}) = \sum_{l=0}^{L} w_l E_l$$

- A random image is initialized, say target image
- Input content Image and target image are passed through the content network
- The squared error is calculated for each layer and the weighted sum is denoted as the total content loss
- Similarly, for the input texture image with style network, total style error is the weighted sum.
- Total error is weighted sum of two errors, the weights are the user defined hyper-parameters

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

- Total error is minimized with variable values being the target image pixel values
- The minimization done by calculating the loss gradient wrt the pixels of target image using error back propagation

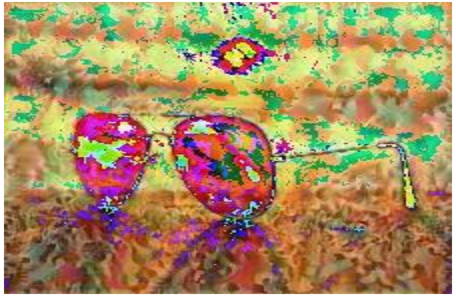
$$\frac{\partial \mathcal{L}_{content}}{\partial F^l_{ij}} = \begin{cases} \left(F^l - P^l\right)_{ij} & \text{if } F^l_{ij} > 0 \\ 0 & \text{if } F^l_{ij} < 0\,. \end{cases}$$

$$\frac{\partial E_l}{\partial F^l_{ij}} = \begin{cases} \frac{1}{N_l^2 M_l^2} \left(\left(F^l\right)^{\mathrm{T}} \left(G^l - A^l\right)\right)_{ji} & \text{if } F^l_{ij} > 0 \\ 0 & \text{if } F^l_{ij} < 0\,. \end{cases}$$

OBSERVATIONS

- Observation made for alpha = 0.000008 and beta = 0.00003 with 200 epocs





- Another made with same set of images, alpha = 0.00001 and beta = 0.00002 with 100 epocs

- The following set is made to understand the effect of increasing the number of epocs with alpha = 0.000001 and beta = 0.00005
- For number of epocs = 300



- For number of epocs = 1000

- For number of epocs = 2000

CONCLUSION

- The target image gets more similarity to the image input which has more weight to reduce the loss
- As the number of epocs increase, the target image gets more and more closer to the higher weighted input image
- Texture and content of the images cannot be totally isolated, therefore, the target image do show the features of both images

References

- https://www.robots.ox.ac.uk/~vgg/rg/papers/1508.06576v2.pdf
- https://www.tensorflow.org/api_docs/python/tf