Multiple Style-Transfer in Real-Time

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Abstract

Style transfer aims to combine the content of one image with the artistic style of another. It was discovered that lower levels of convolutional networks captured style information, while higher levels captured content information. The original style transfer formulation used a weighted combination of VGG-16 layer activations to achieve this goal. Later, this was accomplished in real-time using a feed-forward network to learn the optimal combination of style and content features from the respective images. The first aim of our project was to introduce a framework for capturing the style from several images at once. We propose a method that extends the original real-time style transfer formulation by combining the features of several style images. This method successfully captures color information from the separate style images. The other aim of our project was to improve the temporal style continuity from frame to frame. Accordingly, we have experimented with the temporal stability of the output images and discussed the various available techniques that could be employed as alternatives.

1. Introduction

1.1. Style Transfer Background

Style transfer was introduced by Gatys et al [1] as a generative method to combine the loss from different layers of a convolutional neural network trained on image recognition. The authors noticed that the filters contained in the lower layers of the VGG-16 network captured information that closely represented the style of an image. Similarly, the filters contained in higher layers captured more abstract information that could be interpreted as image content. Their original idea was to create a new image that minimized the combination of style and content loss that they obtained from the VGG-16 network.

The process in [1] was iterative and so could not be accomplished in real-time. Johnson et al [2] accomplished real-time style transfer by introducing a feed forward convolutional neural network that learned the optimal combination of style and content. Once training was complete, the feed-forward network could be used to directly stylize a new image. This method was improved by Ulyanov et al [3], who noticed that replacing the transformer network’s batch normalization layers with instance normalization layers improved the visual quality of the style transfer. The intuition of why instance normalization improved upon batch normalization was explained well in Huang et al [4]. They determined that, “Each single sample [content image], however, may still have different styles.” Each content image within the training batch has its own inherent style, and batch normalization of several content images would create some incoherent mixture of these during training.

1.2. Multiple Style Transfer Motivation

The real-time style transfer implementation introduced in Johnson et al [2] can only be trained for one style at a time. This was our motivation behind trying to combine the information from multiple style images. Concretely, the first aim of this paper was to simultaneously minimize the loss function of the content image and several style images.

1.3. Style Continuity Background

The effect of running the transformer-net as a standalone feed forward network(with no grad-computation) after training provided fast computation results [2]. However this process produced temporal inconsistencies. This was a similar problem in the case of image segmentation which required the output to be penalized based on the incorrect pixel labelling with respect to its neighbours. [5] was one of the first papers to incorporate the concept of a conditional-random field (CRF) that could be trained end-to-end in the form of an recurrent neural network (RNN). It yielded better results than even post possessing the image labels through a CRF using the predictions made by the neural network as a prior. This was seen as a possible solution to reduce the temporal inconsistencies in the images. Yet another method that could be used to reduce computational
complexity is the reduction of trainable parameters by either compressing the bulky network into a much portable form that is more suitable for deployment [6], or designing networks that perform convolution with lesser parameters or less tunable weights [7, 8]. These networks perform similar to the original less-compact version network however the computing cost is highly reduced and as a result the training time can be substantially reduced in-turn we speculate a faster evaluation module.

1.4. Style Continuity Motivation

Like in every other CNN algorithm the strive in the community always remain to make the process computationally inexpensive or in real time. This sometimes takes its toll on the network’s accuracy or visual quality. We wanted to make sure that the computation of the results is fast enough and additionally, it should be stable with less jittery outputs. This called for including a form of constraint between the styling of two separate images in the sequence.

1.5. Related Work

1.5.1 Arbitrary Style Transfer

The most significant limitation of the real-time style transfer implementation in Johnson et al [2] was a new transformer network had to be trained for each style. There have been several real-time style transfer methods that aim to create a high-dimensional, learned representation of style, which would allow them to incorporate this information into a transformer network to output a content image in any desired (“arbitrary”) style [9, 4, 10]. Dumoulin et al [9] discovered that styles share many artistic qualities, and that this similarity can be represented in a high dimensional embedding space. They successfully created a high-dimensional embedding space learned from 32 distinct artistic styles and demonstrated the possibility of combining artistic styles by combining their embedding features in an intelligent way. Huang et al discovered that they were able to render and image in an arbitrary style by aligning the mean and variance of the content and style images using what they called Adaptive Instance Normalization, or AdaIn, layers. Lastly, Ghiasi et al [10] trained a network to create an embedding space for describing style images using approximately 80,000 paintings. They were able to show that their embedding space grouped together similar styles and allow them to render content images in unique styles that were not used during training.

1.5.2 Style Continuity

One of the notable methods that has been used to preserve the consistency of the images after their transformation is the use of CRFs. Conditional random fields, apply a layer of pairwise loss in addition to the per-pixel loss. The main objective function that CRFs try to minimize is written in the form of a Gibbs per pixel energy of the assignment as,

$$E(x) = \sum_i \psi_u(x_i) + \sum_{i<j} \psi_p(x_i,x_j)$$

which is comprised of the unary component $\psi_u(x_i)$, that accounts for the cost/loss of assigning a style (in our case) $x_i$ to the pixel $i$, while the pair wise energy is computed by the second term. [5] took this process one step further and was able to model the CRF into an RNN allowing the parameters to be learning while training. This was employed by using the mean field iteration technique which is essentially a way to employ the KL divergence in a more tractable manner. Another inspiring model was that of the Unet [11]. This is again another example of how techniques that are applied in the image segmentation domain can be cross over to our application. The image is downsampling to break it down to its essential representative features and then is upsampling/reconstructed back up again. This is a pretty similar approach that we take in the transformer network albeit with a number of modifications. An interesting feature of the UNet is the “crop -and-copy” functionality as shown in Fig. 1, where the output from previous layers are concatenated with the outputs from subsequent layers. This was thought of as a striking feature that could probably allow us to extend the concept of temporal pixel relationship a bit further. Another such method that has been popular in the context of accounting for temporal changes is Long-Short-Term Memory(LSTM)[12]. This technique was invented to be useful in handling time series data specially for the case of vanishing gradient or exploding gradient which was a common issue while training RNNs. Finally, reduction of computation could be trace to the reduction in the number of parameters requiring to be trained. Iandola et al [7] proposed the SqueezeNet where they have made use of...
a FireModule to reduce the number of weights requiring to be trained. Here the authors achieve a network as efficient as the famous AlexNet however using 500 times lesser parameters. These FireModules replace the 3x3 convolutions with 1x1 convolutions. In our work we have tried to take some features from FireModule and the UNet architecture to reduce the computation time of training of our network.

2. Methods

2.1. Combining Style and Content

The original formulation of style transfer proposed by Gatys et al [1] described the loss function as a weighted combination of content loss and style loss. That is,

\[ L_{total} = \delta_{content} \cdot L_{content} + \delta_{style} \cdot L_{style} \]  (1)

The VGG-16 network that was used to define the perceptual losses is composed of five convolutional blocks separated by maxpool layers. The activations used to define the content and style losses were taken from the ReLU layer immediately preceding the maxpool layers because they represented the activation at each spatial scale in the VGG network. The content loss is given by the following,

\[ L_c = ||\phi_l(\hat{y}) - \phi_l(y_c)||^2 \]  (2)

where \( \phi_l() \) is the activation of the ReLU layer from the \( l^{th} \) convolutional block of the VGG-16 network (used to define perceptual losses), \( \hat{y} \) is the output image of our transformer network, and \( y_c \) is the content image. This loss is unchanged in our implementation. We used the output of the second convolutional block (i.e. \( l = 2 \)) to define our content loss as done in [2].

The style loss is given by the following,

\[ L_s = ||\sum_l (G_l(\hat{y}) - G_l(y_s))||^2_f \]  (3)

where \( G_l() \) is the gram matrix in [1, 2] and \( y_s \) is the style image. The gram matrix is the inner product of the filters for a particular style layer.

\[ G_{l,(i,j)} = F_{l,i} \cdot F_{l,j} \]  (4)

The \((i,j)\) position of the gram matrix for layer \( l \) is given by the dot product between the \( i^{th} \) filter, \( F_{l,i} \), and \( j^{th} \) filter, \( F_{l,j} \). If there are several style layers, the overall style loss is the summation of each style layer loss. We used the activations from convolutional blocks one through four, \( l = \{1, 2, 3, 4\} \), to minimize the style loss across several spatial scales as done in [2].

2.2. Combining Multiple Styles

In order to combine several styles, the natural extension of the original method was to incorporate the weighted sum of losses from multiple style images. This is given by the following,

\[ L_s = \frac{1}{n}(L_{s_1} + L_{s_2} + \ldots + L_{s_n}) \]  (5)

where \( L_{s_i} \) is the loss described above in Eq. 3 for style image one. This was the new objective function that we used to combine the features from several style images. Further, it is possible to include a weighted sum of each style image. For example, if there were two style images,

\[ L_s = \frac{1}{n}((\alpha \cdot L_{s_1}) + ((1 - \alpha) \cdot L_{s_2})) \]  (6)

This would allow us to vary the contribution of each style image to the overall transfer; effectively interpolating between styles.

The hyperparameters used for training are summarized in Table 1. Unless otherwise stated, these are the parameters that we used for training.

| Parameter          | Value   |
|--------------------|---------|
| Content Weight     | 1e5     |
| Style Weight       | 1e10    |
| Content Layers     | 2       |
| Style Layers       | 1-4     |
| Epochs             | 1       |
| batch size         | 4       |
| Learning Rate      | 1e-3    |
| Optimizer          | Adam    |

Table 1: Summary of Hyperparameters

2.3. Dataset

Our network was trained using the Common Objects in COText, or COCO \(^1\), dataset. More specifically we used the 2014 training images. This dataset contains 83,000 images of everyday objects such as food, people, household furniture. While this dataset contains segmentation information, it is not useful for this application. We needed a large corpus of images so that our transformer network can successfully apply the style in a variety of circumstances.

2.4. Transformer-Net

The transformer net is one the main features of [2]. The main objective of the network is to act as the feed-forward network that can quickly compute the optimization for the style transfer. [3] showed that style transfer performed even better when the batch normalization is replaced by instance normalization. The detailed network is shown in Fig. 3. It is a typical encoder decoder network as show in the representative network in the left bottom. First there are a number of

\(^1\)http://cocodataset.org/#home
downsamplling steps which is followed by a bottleneck and futher by the umsampling process. Most of the convolutions are standard 3x3 or 9x9 kernels with strides of either 1 or 2 as is the case for upsampling or downsampling. ReLU is used as the activation function. We have used reflection padding in our network to minimize artifacts near the edge caused by zero-padding. We now focus on a few important parts in the network, namely the instance norm and the ResNet.

2.4.1 Instance Norm

The main objective of normalization is to reduce the so called covariance shift that resets the data to a zero mean and unit covariance every time it is fed to a new layer. This allows for the layer to learn more independently and also allows for faster convergence. Batch normalization is computed over the whole batch of the image while the instance norm is the one that is computed only over a specific instance in the input. This can be represented as,

\[ y_{tijk} = \frac{x_{tijk} - \mu_{ti}}{\sqrt{\sigma^2_{ti} + \epsilon}}, \quad \mu_{ti} = \frac{1}{HW} \sum_{i=1}^{H} \sum_{m=1}^{W} x_{tilm} \]

\[ \sigma^2_{ti} = \frac{1}{HW} \sum_{i=1}^{W} \sum_{m=1}^{H} (x_{tijk} - \mu_{ti})^2 \]

where the t,i,j,k is are the tensor, channel, abscissa and ordinate indices respectively. The \( \sigma^2 \) is the instance variance while \( \mu \) is the instance mean respectively, while \( y \) is the output. This choice of normalization prevents the instance specific mean and co-variance shift over simplifying the learning procedure. Instance-norm is used both during the training as well as during the testing.
2.4.2 ResNet

ResNets [13] were discovered as one of the processes to reduce the problem of vanishing gradient allowing us to train much deeper networks. ResNets essentially allow us to easily learn the identity function and make sure that the losses are not saturated over the length of the network. Our network uses 5 ResNet blocks inside the bottleneck region. This allows us to effectively train the 20-layer network. [13]

2.5. Correlation of the features

2.6. Style Consistency

![Figure 4: The modified Transform net used in our pipeline.](image)

Fig. 4 is the modified version of the transformer net that we have experimented our style consistency approaches on. This method tries to combine the novelties of both the UNet[11] as well as that of the FireModule[7]. We will just resize and copy the frame that is given as the input (which will act as the stylized image at time $t$) to the transformer network and merge it with the output of the transformer network. This achieved by the 1x1 convolutions that has been so effective in the case of Firemodules. The process is relatively fast since it does not have to many parameters and it just has to learn an identity function just like the ResNet which additionally helps us even in the case of vanishing gradients.

3. Results and Discussion

3.1. Combining Multiple Styles

![Figure 5: Training losses for one style (Picasso) and both styles (Picasso and Monet). The style loss dominated the total loss for combining both styles. This change can be attributed to the failure to rectify the high-level features for both styles.](image)

The first experiment we performed was to combine the style from two paintings that were visually very different. The thought process behind this experiment was that the output should show very different styles and the outcome would be obvious. These two paintings were Weeping Woman by Picasso (Style 1) and Woman With a Parasol by Monet (Style 2). The stylized images are shown in Fig. 2. The resultant stylization was barely able to capture the color information of the two styles. The style loss dominated the total loss during training for combining both styles (Fig. 5), which was indicative of the inability to combine the high-level perceptual features from the VGG network. For example, the style for training one style was around the same magnitude as the content loss (Fig. 5).

Next, we experimented with the style weighting to see if we could resolve the high style loss issue. We thought that if we increased the style weighting, that the network would learn how to better resolve the discrepancies between the style features of both paintings. The stylizations with several different style weightings are shown Fig. 7 (default style weight = 1e10). We were not able to achieve a stylization of the content image that successfully combined the color and texture from both styles. In fact, when the style weight was increased, triangular-shaped artifacts started to appear within the frame (style weight = 1e11). Therefore, we decided to test our method on two paintings that were visually more similar.

The original experiment was reran with two new paintings. The two paintings were the Scream by Munch (Style 1) and Starry Night by Van Gogh (Style 2). The stylization of these images is shown in Fig. 8. The resulting stylizations successfully combined the colors of the two paintings as before, but also included small textures such as the “sun-like” objects from Starry Night. This improvement was reflected in the lower style loss for “both styles” in Fig. 6 as compared to Fig. 5.

We also tested the ability of our network to interpolate between styles using Eq. 6. Our results for style inter-
Figure 6: Convergence of total, style, and content losses during training for similar styles (Scream and Starry Night). For the default style weight (1e10), the style loss was much less than for two perceptually very different paintings Fig. 5. This indicated that the network was able to better combine high-level features from both paintings.

α = 0.7 incorporates more color from style 1 while α = 0.3 incorporates more color from style 2. Further, on the door frame of α = 0.7, there are waves reminiscent of the textures from style 1. Similarly, for α = 0.3, there are more "sun-like" features that are reminiscent of style 2.

While our method for combining multiple styles was successful in capturing details from two perceptually similar paintings, it failed to rectify differences between two dissimilar paintings. This was likely due to the inability of the high-level features used in VGG network to describe the "style" in these two paintings in a meaningful way. This provides motivation to use methods described in the related works section where they created a network to semantically describe paintings in a higher dimensional space [10]. Further, they papers were able to train their network on many styles, rather than just two in our case. Any of these methods may serve as an inspiration to improve upon our method.

3.2. Style Consistency

In order to check our network for style consistencies we fed the network a stream of the same images after training. Any change in the style element in the output would be considered a not a consistent result. Fig 10 shows the result of how our architecture holds up. Fig 10a shows the output of the original image used as the base line Fig 10b shows the output without any from of correlation performed while Fig 10c shows the result of the correlated network. Each of the images show a zoomed in portion of their top left area in order to display and compare the artifacts properly. It can be seen that Fig 10a and Fig 10c shows pretty similar results while Fig 10b artifacts deviate a lot. By this we say that the output of the first and the third images are consistent and they do not vary with time. We can loosely claim that the style of our network completely depend on the "local-content" that it is focused on. If the local-content remains unchanged so do the style. This can further be used a shallow example of time independency of our network.

However, it must be declared that the network is really inconsistent. Some of the outputs that we received were not even images, they were just random number. Sometimes it was just a white color and no content. This was one of the very few correct outputs that we had received. The

4. Future Work

Another method we thought of that may be able to combine style and content information is based upon the work of [6]. This "distillation" method was intended to combine the information learned from one large network or an ensemble of networks ("learned network") into one, possible smaller, network ("new" network). Within this paradigm, the "learned" networks would be the transformer networks trained on fixed individual styles and the "new" network would be the transformer network to combine several styles. For the style consistencies, a lot of research has to be done to figure out why the outputs are not uniform. Additionally, implementation of the LSTM maybe considered as a long term goal or a CRF-RNN network to better preserve consistencies.

4.1. Original Contributions

Our first contribution was the idea to combine multiple styles in one training. Secondly, we developed a method to interpolate between styles. Concretely, we coded from scratch the transformer network and function to return the VGG network activations. The transformer network structure we used was the same as Johnson et al [2]. Their supplementary material was a useful resource to determine the exact structure of their transformer network. The training script used to train our transformer network was a heavily modified version of the script from the Pytorch examples for real-time style transfer. In particular, we altered the script to mesh with our implementation of the VGG loss.
Figure 7: This illustrates stylizations similar to Fig. 2, but with different style loss weightings. There is a clear trend that as the style weight increases, the content image is rendered more abstractly. Further, for style loss weighting $1 \times 10^{11}$, triangular-shaped artifacts start appearing.

Figure 8: This depicts a style image rendered for styles 1 and 2. The last column shows the content image rendered using our method for combining multiple styles. This combination rendering captures color information from both styles as well as some textures. For example, there are "sun-like" patterns that mimic Style 2.
Figure 9: This demonstrates the ability to interpolate between styles based upon different weighted contributions to the total style loss as described in Eq. 6. There is a clear transition from more orange on the left to more blue on the right; mimicking the style transition from Scream (style 1) to Starry Night (style 2).

Figure 10: Image Consistency results.

and transformer network. We also altered the script to allow for our multiple styles method and style interpolation method. Additionally, we altered it to save training loss,
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