**SRM: A Style-based Recalibration Module for Convolutional Neural Networks**

1. **Abstract**

In our project paper, we aim to improve the representational ability of a CNN, by considering the style of the image. SRM stands for a Style-based Recalibration Module. This module is directly fed into existing CNN architectures. (resnet?) SRM ﬁrst extracts the style information from each channel of the feature maps by style pooling, then estimates per-channel recalibration weight via channel-independent style integration. By incorporating the relative importance of individual styles into feature maps, SRM learns to suppress the contribution of nuisance styles, and by doing that, the network can concentrate more on meaningful features, which boost its representational power. Finally, we performed experiments on a few general vision tasks and show the improvement of results when using SRM over other approaches such as Squeeze-and-Excitation (SE). Throughout the experiments, SRM outperforms recent approaches though it requires orders of magnitude less additional parameters.

, while boosting meaningful features while suppressing weak ones.

1. **Intro**

CNNs are capable of handling not only the content (i.e. shape) but also the style (i.e. texture) of an image. We aim to enhance the utilization of styles in a CNN to boost its representational power. We will start by mentioning some relative work, first of all Gatys et al discovered that the feature statistics of a CNN effectively encode the style information of an image, which laid the foundation of neural style transfer. Then,

1. **Methods**

Other types of style features such as the correlations between different channels can be also included in the style vector. In the paper, the writers focused on the channel-wise statistics for efﬁciency and conceptual clarity. We try to add the information about different channels statistics and see if we can benefit from it.

By including the feature correlations of multiple layers, we obtain a stationary, multi-scale representation of the input image, which captures its texture information but not the global arrangement.

We used convolution layer with kernel size equals the number of style features. In this case the CNN essentially becomes fully connected channel-independent layer.

Moreover, we try to apply the recalibration module in different stages of the CNN representation. Our assumption is that this kind of recalibration module would be more efficient when applying it into a low-level features representation.

We present a style pooling approach which is superior to the standard global average or max pooling in our setting, as well as a channel-independent style integration method which is substantially more lightweight than fully connected counterparts yet more effective in various scenarios.

1. **Implementation and experiments**

In order to verify the effectiveness of SRM, we conduct several experiments using different general object classiﬁcation problems and datasets.

First we evaluate the performance of SRM on the CIFAR-10 dataset, in comparison with the state-of-the-art method Squeeze-and Excitation (SE).

Later on, we also evaluate the performance of SRM on the ImageNet-1K.

We implemented all competitors to compare under consistent settings for fair comparison.

1. **Results**

Throughout the experiment, SRM outperforms recent approaches though it requires orders of magnitude less additional parameters.

<https://arxiv.org/pdf/1808.08127.pdf>

* ‘Squeeze & Excitation’ Blocks
* <https://ieeexplore.ieee.org/document/8789527> -

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# <https://towardsdatascience.com/visualising-filters-and-feature-maps-for-deep-learning-d814e13bd671>

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<https://zpascal.net/cvpr2016/Gatys_Image_Style_Transfer_CVPR_2016_paper.pdf> -

Image Style Transfer Using Convolutional Neural Networks -