Le Project Quotidien

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Abstract

Self-supervised pretraining for feature extraction has recently gathered a lot of attention in the computer vision community. We implement and experiment with the Split Brain Auto-Encoder [1] model from Zhang et al. (2017). The method splits the input channels into two and feeds them into disjoint sub-networks trained to reconstruct each other's data channels. We use the pretrained features to fine-tune a 1000-class image classifier using only a few labelled examples per class.

1 Introduction

Deep learning algorithms have been shown to achieve human-level performance on computer vision tasks when given large collections of labelled data. However, for many practical tasks, the availability of data is limited. Self-supervised pretraining is the method of training a network to predict a part of its input using an another unseen part, which acts as the label. The objective is to learn useful representations of the data in order to fine-tune on supervised downstream tasks such as image classification.

We explore a recent method based on image colorisation, the Split-brain autoencoder [1]. This method finds useful global features for classification by solving complementary prediction tasks and therefore utilizing all the data in the input. The network is divided into two fully convolutional subnetworks and each is trained to predict one subset of channels of input from the other. For fine-tuning, a classifier is added as the last layer. Using a given dataset with image sizes 96x96 composed of 512k unlabeled images, 64k labelled training images, and 64k labelled validation images, we perform image classification.

2 Motivation and Related Work

Autoencoders [2] are one of the de-facto architectures for self-supervised pretraining. They reduce the dimensionality of the input data to create an information bottleneck and use a latent space representation to reconstruct the input. Extensions to this method include adding a denoising task [3] to prevent learning the identity function, stacking autoencoders to get a deeper network [4], and making the architecture convolutional [5] to learn hierarchical feature representations and exploit the spatial locality of the input. Unfortunately, all these approaches suffer from a domain gap between the pretraining and the finetuning task. In fact, there's evidence to suggest that the features required for image reconstruction and classification are generally uncorrelated. [6]

Successful pretraining implies learning more global context. Research has tried to achieve this by solving puzzles [7], teaching class independent features [8], using image redundancy [9], using different non-linearities [10], exploiting the max and argmax data contained by pooling layers [11], adding adversarial noise generators [12], or relating denoising and inpainting [13]. Inpainting consists of generating large image regions missing from the input, an approach which caught our attention. Along this direction, we found context encoders [14], a convolutional version used for semantic inpainting, and cutout [15], which performs significantly better than [11] on the STL-10 dataset for image classification. Despite this, [15] and other inpainting-based methods suffer from an input handicap: they remove a lot of useful information from the input.

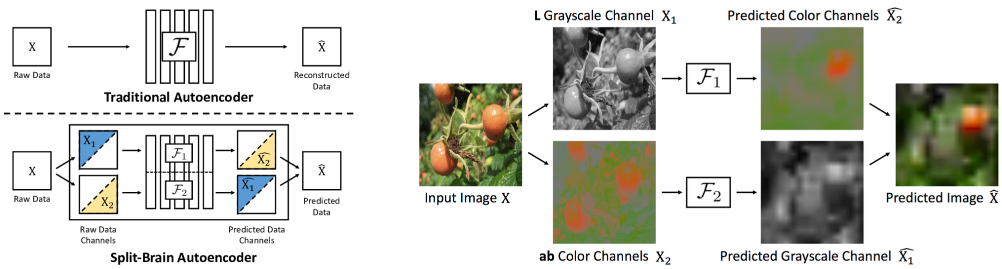

Figure 1: Split Brain Architecture and CIE-LAB Space Visualization

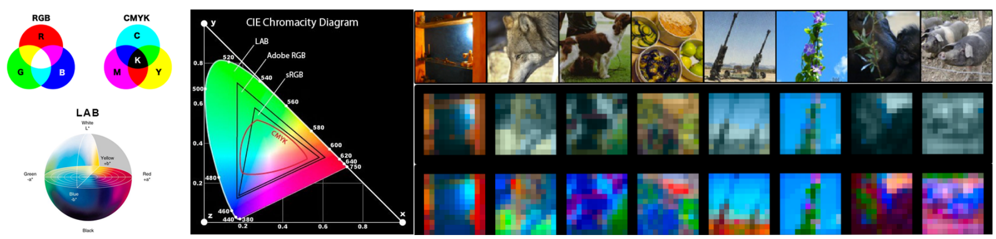

Figure 2: Left to Right: Topology of CIE-Lab, Gamut of CIE-Lab, Examples of Downsampled 12x12 images and their re-scaled LAB counterparts

Instead of removing spatial data, one can just hide spatial data and train the network with maximal information. Colorization[16][17] is the task of predicting color channels from gray-scale and [18] showed its use for self-supervised feature learning. Therefore, we arrived at Split-Brain Autoencoders, which exceed the performance of the other methods listed and overcomes both domain gaps and input handicaps.

3 Method

The Split-Brain method is depicted in Figure 1 above. The approach consists of splitting the image into two subsets of input channels (2 to 1 for a 3-channel space), preferably using a color space that separates color and luminosity. It then passes each subset through a fully convolutional architecture [19] with the objective of predicting the other subset. To make this prediction, it takes the Cross Entropy loss between the network output and a downsampled, quantized version of the original image (acting as labels). To clarify this with our numbers, the input image has 96x96 input features and each subnetwork has 12x12 output features, each of which corresponds to a pixel in a 12x12 downsampled ground truth of the input image. The number of output channels in each sub-network corresponds to the number of classes for each pixel, which is exactly the number of colors into which each channel was quantized into. Fine-tuning consists of adding a classifier on top of the concatenated output of the two subnetworks.

The original paper uses the CIE-Lab color space, which reduces feature extraction to colorization ($L \rightarrow ab$) and gray-scale prediction ($ab \rightarrow L$). Whereas the use of LAB is effective, it has one drawback. Naturally occurring colors in RGB map to a narrow sub-domain in LAB, meaning that the mapping between color spaces is non-linear. Therefore, quantizing the transformed images into a reduced number of bins is a very lossy process, as most colors fall into the same bins. To address this, we normalized the range of the bin values over each image. Doing so results in a distorted image, but provides more information to the network and significantly better classification performance.

4 Experiments

We train three fully convolutional architectures in three color spaces, and use denoising autoencoders with various noising strategies as our baselines. Our color spaces include RGB (split R and BG), LAB (split L and ab), and the re-scaled LAB space, where the image is quantized according to the min and max values of the image. We trained three fully convolutional [19] models: AlexNet (140M params) [20] as in [1], ResNet18 (7M params) [21] which performs well on colourization tasks, and SimpleNet (700k params), a shallower 5-layer convnet inspired by [22]. Each model represents a different scale in the number of parameters. Cross Entropy loss is used for pretraining because regression-based losses tend to learn blurry representations inclined towards mean values.[1].

For hyperparameter tuning, we were conditioned by our compute power. After trying downsized images of size 12x12, 16x16, and 25x25, we stuck with the former. Similarly, we chose a quantization size of 100 for the single channel, and 10 for the dual channel (100 bins over the entire subset) due to computational restrictions. Nonetheless, the final chosen values are the same as those used on [1]. After a hyperparameter grid search, we determined an optimal batch size of 64, a initial learning rate of 1e-4, and a learning rate decay of 0.1 every epoch of pretraining and finetuning.

We report top-1 and top-5 validation accuracy metrics for all three models and all three color spaces described, using the optimal hyperparameters. Further, we report the same metrics for our best model when finetuning on different numbers of samples per class. Our baseline is a 6-layer denoising autoencoder trained with salt-and-pepper noise. We experimentally found that this was the strongest of all the models we trained (including masking, gaussian, and salt-and-pepper noise at different noise levels).

5 Results

The original paper achieves up to 35% top-1 accuracy on ImageNet Classification, which is similar to our classification task in that the number of classes are the same. However, we trained on less than half the number of unlabeled samples and each image was smaller, a difference of about 72% less pixels per image. Our experiments also trained for much shorter (48 hours). The number of pretraining epochs varied widely: AlexNet pretrained for 7 epochs, ResNet18 for 11 epochs and SimpleNet for 7 epochs. Training time on gpu was limited by the time taken to convert images to lab, which is currently performed in cpu due to the availability of libraries. Despite these complications, we were able to achieve almost half of the original Split-Brain's top-1 accuracy at 14.04%. We set a limit of 12h for finetuning and FC AlexNet could only complete 2

Architecture	Image Space	FT Epochs	Top 1 Acc.	Top 5 Acc.
FCAlexNet	RGB	2	0.0943	0.2343
FCAlexNet	LAB	2	0.0301	0.0988
FCAlexNet	Re-scaled LAB	2	0.0958	0.2479
ResNet 18	RGB	5	0.1227	0.2711
ResNet 18	LAB	5	0.1351	0.2945
ResNet 18	Re-scaled LAB	5	0.1404	0.3015
SimpleNet 18	RGB	5	0.1081	0.2476
SimpleNet 18	LAB	5	0.1093	0.2558
SimpleNet 18	Re-scaled LAB	5	0.1266	0.2799
DAE S&P 5% Noise	RGB	5	0.6530	0.1815

Table 1: Summary of Experiments

Samples per class	1	2	4	8	16	32	64
Top-1 Acc.							
Top-5 Acc.							

Table 2: Summary of Experiments

6 Conclusion

We showed how Split-Brain overcomes many of the problems faced by self-supervised image pretraining methods. We further ran experiments on our own implementation and showed that ResNet18 was able to provide good results, much faster than the large FC AlexNet from the original paper. Our best top-1 accuracy is 14.04% and our best top-5 accuracy is 30.15%. We show that the method continues to do well even when reducing the number of labelled examples to zzzzzzz.

For this project, we coded the entire method from scratch and made our code publicly available on **Github**.

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