COL775 Assignment 1.1*

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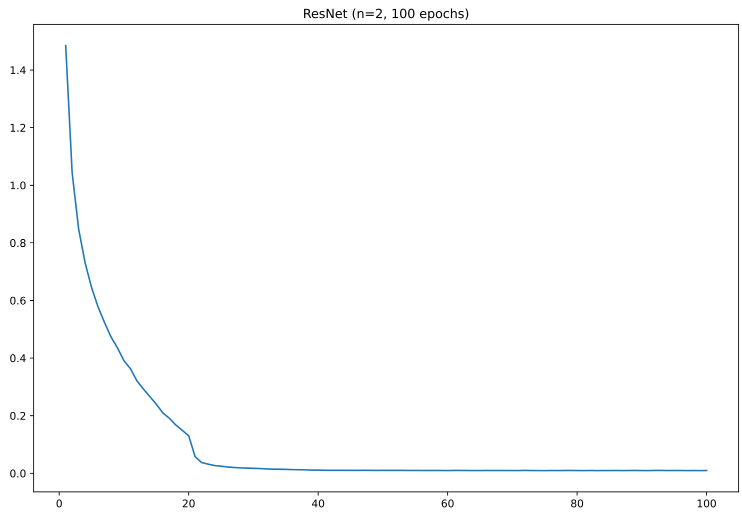
1 Image Classification using ResNets

The ResNet network was implemented in Pytorch and trained using SGD, with a learning rate of 0.1. For 100 epochs, we used a stepped learning rate schedule, which multiplies the learning rate by 0.1 every 20 epochs.

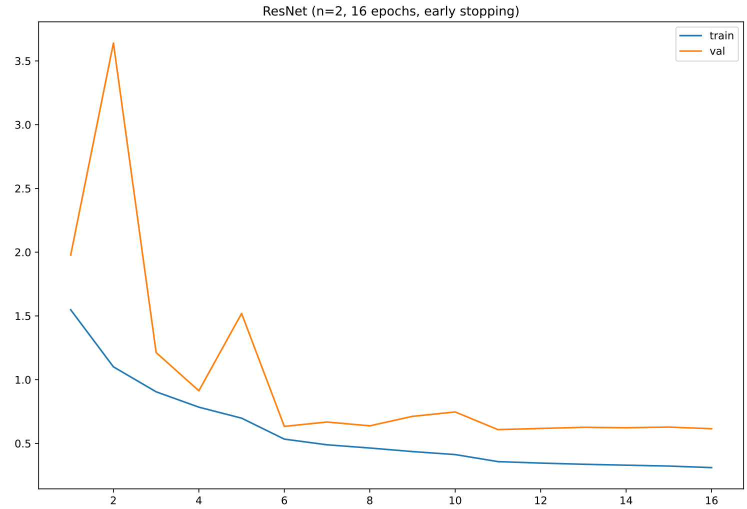


With validation and early stopping, we used a more aggressive learning rate schedule, as we noticed the validation loss being very unstable with a high learning rate, which impacted the patience and led it to prematurely early stop. We reduced the step size to 5 and increased the multiplier to 0.2.

The final statistics are as follows:

	Accuracy	F1 micro	F1 macro
train	0.916	0.916	0.916
val	0.797	0.797	0.796
test	0.791	0.791	0.790

*Models for this assignment can be found here



2 Impact of Normalization

2.1 Implementation Details

Normalization was implemented by taking inspiration from the PyTorch implementation, which uses a base Normalization class, and subclasses which use it's buffers. The weight buffers are used by all the implementations, and BatchNorm and InstanceNorm would use the mean/stdev buffers if needed. Layer normalization does not make use of any buffers, and neither does group normalization.

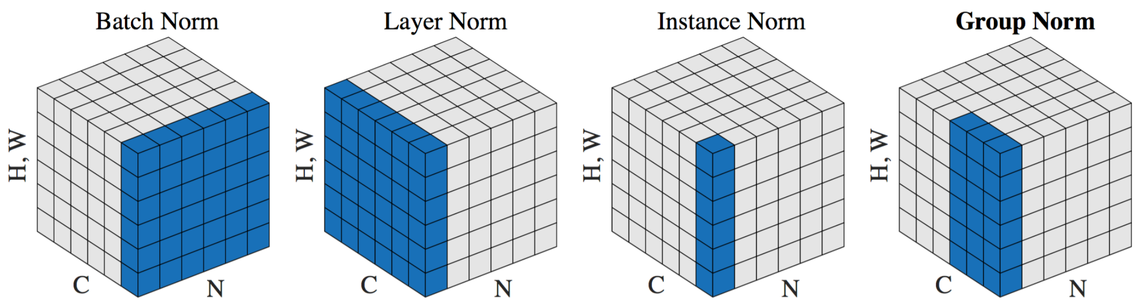


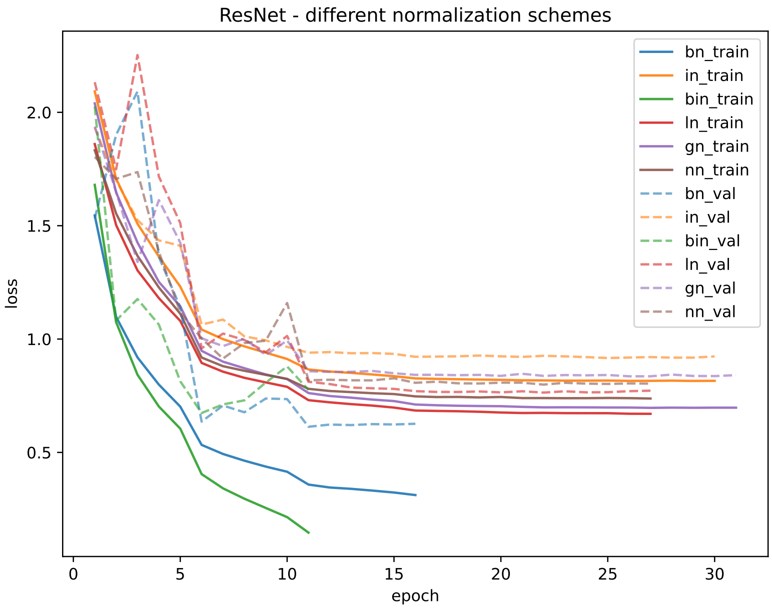
Figure 1: Normalization schemes (Taken from He et al)

A minor implementation detail was clipping the rho parameter in BatchInstanceNorm: the original implementation did this while training, and we do the same. We use 16 groups in the Group Normalizer implementation (down from the original 32 suggested in the original paper) because of the fewer number of layers in our ResNet implementation. Another constraint of our GroupNorm implementation is that the number of groups always has to be a multiple of the number of channels.

2.2 Results

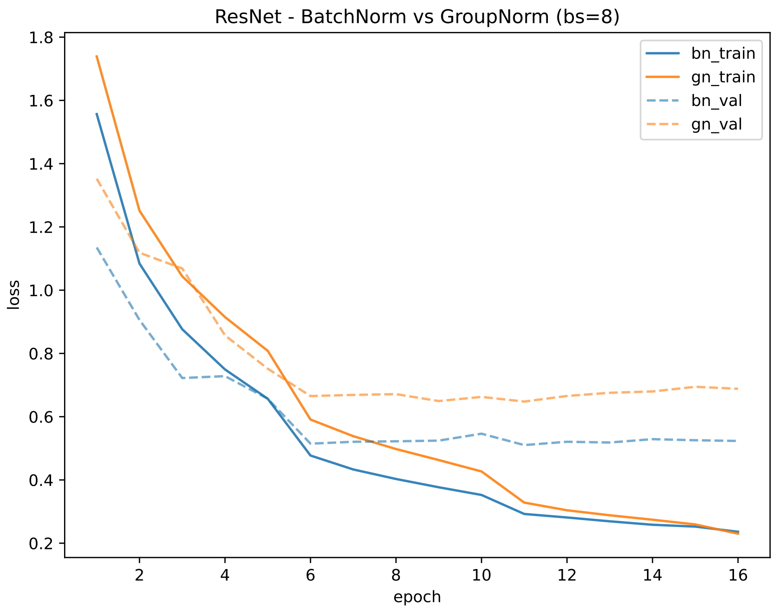
The training results and loss curves of the various normalization schemes are shown on the next page. All schemes were trained using early stopping with the same learning rate/scheduler as before, to be comparable to the default PyTorch implementation. BatchNorm constantly outperforms the other normalization schemes, and BatchInstanceNorm would probably be setting all it's gates to 1, to use the BatchNorm layers more.

Norm	set	Accuracy	F1 micro	F1 macro
BN (torch)	train	0.913	0.913	0.913
	val	**0.791**	**0.791**	**0.790**
	test	0.783	0.783	0.783
BN	train	0.913	0.913	0.913
	val	0.782	0.782	0.781
	test	**0.785**	**0.785**	**0.785**
IN	train	0.725	0.725	0.724
	val	0.684	0.684	0.682
	test	0.669	0.669	0.667
BIN	train	**0.933**	**0.933**	**0.932**
	val	0.788	0.788	0.787
	test	0.780	0.780	0.780
LN	train	0.766	0.766	0.765
	val	0.725	0.725	0.723
	test	0.727	0.727	0.725
GN	train	0.757	0.757	0.756
	val	0.706	0.706	0.705
	test	0.699	0.699	0.697
NN	train	0.737	0.737	0.736
	val	0.714	0.714	0.712
	test	0.706	0.706	0.705



2.3 BatchNorm vs GroupNorm

We find results contrary to those mentioned by Wu and He: BatchNorm outperforms GroupNorm in our setting. Both reach the same training accuracy, but GroupNorm falls short on the validation accuracy compared to BatchNorm. This may also be attributed to the fact that our model simply has fewer filters (64 at max), while the original ResNet had a minimum of 64 and a maximum of 512 filters, and was much deeper, hence the benefits of GroupNorm are not apparent.



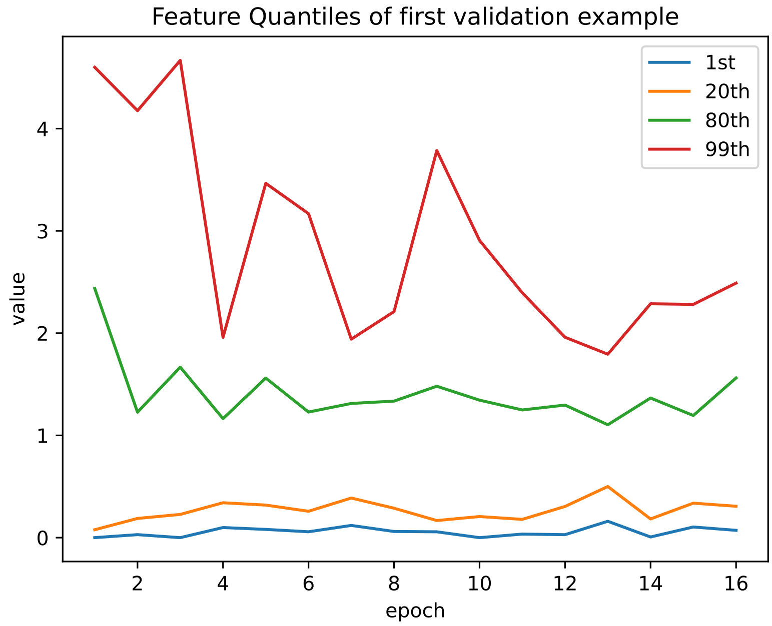
The comparision with batches of size 128 is as follows:

Norm	set	Accuracy	F1 micro	F1 macro
BN-128	train	0.913	0.913	0.913
	val	0.791	0.791	0.790
	test	0.783	0.783	0.783
GN-128	train	0.757	0.757	0.756
	val	0.706	0.706	0.705
	test	0.699	0.699	0.697
BN-8	train	**0.956**	**0.956**	**0.956**
	val	**0.828**	**0.828**	**0.828**
	test	**0.818**	**0.818**	**0.818**
GN-8	train	0.939	0.939	0.939
	val	0.789	0.789	0.788
	test	0.784	0.784	0.783

Noticeably, the models with smaller batch sizes perform better than the ones with larger batch sizes. According to Goodfellow, this is because smaller batch sizes have a regularizing effect: the path the optimizer takes through the loss landscape is noisier, and as a result it has more chance of falling into a local minima (as there are several equally good local minima, and more saddle points than local minima in a high-dimensional space).

2.4 Quantile Plot

The quantile plot of the first validation example is plotted below: the features are expressed as a 64-dimensional vector. We sort this vector and plot the first, twentieth, eightieth and ninety-ninth quantile of features.



Although it is noisy, we see that the upper quantiles decrease, while the lower quantiles marginally increase for the best-trained model (which is around epochs 10-13). This shows that the features converge to the mean as the model trains.