MLNS - 1 Report

1 Model

- 1. A Resnet50/Resnet101 model for all classes 0-36 (all possible sums)
- $2.\ \ A$ ResNet model trained to predict each digit separately trained on synthetic data.

2 Extra additions

• Synthetic data - Since our data is not enough (only 10k examples) we can generate synthetic dataset to improve performance and since we can generate data ourselves we have also information of what individual digit is.

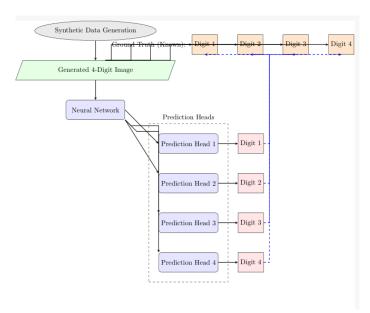


Figure 1: Synthetic data usage

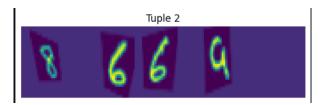


Figure 2: Synthetic data example

• EMA (Exponential moving average) - We can observe that training procedure is not stable. So we introduce EMA to enable more stable training.

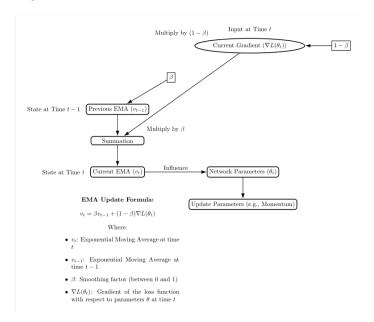


Figure 3: Effect of EMA on training stability

3 Results

- Baseline = $\sim 10\%$
- Resnet50 trained from scratch = $\sim 30\%$
- Resnet50 with EMA = $\sim 90\%$
- Resnet50/101 trained exclusively on synthetic data = $\sim 50\%$

4 Observations

- Small model vs big model: We know that big models overfit on the data, and since this dataset is MNIST like (almost trivial) I thought 4 layer Conv network is enough.
 - However experiments show that big (50 layer network) is able to represent complicated distribution (addition is non-trivial) much better than simple models. Even 101 layer network has no fast overfitting.
 - Experiments with Resnet18 show that network is not able to learn at all, which means it is a matter of scale not just architecture

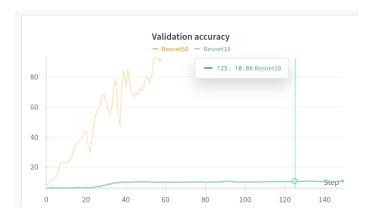


Figure 4: Comparison of different model sizes

Very unstable training even al small learning rates: Training is heavily unstable, adding EMA has improved it

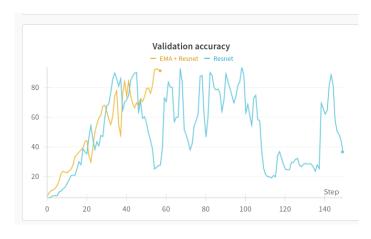


Figure 5: Unstable training behavior

- Regular data vs synthetic data: Since data is scarse we can generate a bigger synthetic dataset. The big issue is synthetic dataset should be follow distribution of test set. My pipeline can get $\sim 50\%$ accuracy of test set, without ever seeing any example once.
- Predicting sum vs predicting each digit separately: The task of predicting final sum can be simplified into predicting 4 digits. Once we have synthetic data, the constraints put on tasks make it easier to approach.
- Pretrained vs training from scratch: ResNet initialized from scratch severally underperformed the version trained on ImageNet. Intrestingly the model which gives better performance on ImageNet (and thus overfits on it) is worse on this dataset.
- Big models do not overfit: Below image shows model continuing to improve test accuracy on a very different dataset when trained on synthetic dataset even when 100% accuracy and 1e-5 loss is reached.

```
| 1805| | 1806| | 18/150| | Train Loss: 0.0006899169306146571, Validation Loss: 0.04410249509567841, Test loss: 2.4175922813417 | 1806| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150| | 18/150|
```

Figure 6: No overfitting observed in large models

5 Hyperparameters

- Lr = 0.001
- Weight decay in regularization helps in reducing overfitting
- EMA beta coefficient: 0.99

6 Future approach

• Try combining synthetic data loss, with real dataset.