Homework 7 Report
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Github Repository: https://github.com/vipravlipare/ECGR-5105-Intro-to-Machine-Learning

Problem 1A

For Problem 1A, a convolutional neural network (CNN) was built to classify all 10 classes in the CIFAR-10 dataset. The network consisted of two convolutional layers, each followed by a Tanh activation and MaxPool2d, and a fully connected classifier with one hidden layer of 64 units. The model was trained for 300 epochs using SGD with a learning rate of 0.001. Training and validation were performed using the normalized CIFAR-10 dataset. After training, the final training time, training loss, and evaluation accuracy were recorded. The model produced the following results: a training time of 1710.6581 seconds, a final training loss of 0.5593, and an evaluation accuracy of 0.7074.

These results show that the CNN learned the dataset more effectively than the fully connected network from Homework 6, which previously achieved lower accuracy. The homework 6 results showed a training time of 627 seconds, a training loss of 0.497, and an evaluation accuracy of 0.4871. This means that the training took longer for the CNN, but the training loss was slightly higher, but the evaluation accuracy was significantly higher. The CNN model is not just memorizing the data, but actually learning from the data, and it shows with higher evaluation accuracy as compared to homework 6. The CNN performs better because convolution layers capture spatial features that fully connected layers cannot. As with previous work, preprocessing was performed outside the training loop, and the model was run on the GPU to keep training efficient. Overall, this CNN provides a clear improvement in accuracy compared to the earlier fully connected model.

Problem 1B

For Problem 1B, the convolutional neural network (CNN) from Problem 1A was extended by adding a third convolutional layer, followed by a Tanh activation and a MaxPool2d operation. The rest of the training setup remained the same, as well as most of the preprocessing code. The model was trained for 300 epochs using SGD with a learning rate of 0.001. Training and validation were performed using the normalized CIFAR-10 dataset. After training, the final training time, training loss, and evaluation accuracy were recorded. The model produced the following results: a training time of 1944.0797 seconds, a final training loss of 0.5673, and an evaluation accuracy of 0.7333.

These results show that the deeper CNN performed slightly better than the baseline CNN from Problem 1A. The accuracy improved from 0.7074 to 0.7333, suggesting that the additional convolution layer helped the model extract richer spatial features. Compared to Homework 6-3B's fully connected network, which had a training time of 1167.7 seconds, a training loss of 0.0151, and an evaluation accuracy of 0.4552, the extended CNN achieves far better accuracy, even though its training time is longer. The higher loss value paired with higher accuracy also indicates that the model is generalizing well rather than overfitting. As before, preprocessing

was performed outside the training loop, and the model was run on the GPU to maintain efficient training. Overall, the extended CNN increased model capacity and provided further improvement in accuracy over both the fully connected network and the 2-layer CNN baseline.

Problem 2A

For Problem 2A, a ResNet-based convolutional neural network (ResNet-10) with skip connections was implemented to classify CIFAR-10 images. The model used three convolutional layers with a residual connection, followed by two fully connected layers. The CIFAR-10 dataset was normalized as before, and the network was trained for 300 epochs using SGD with a learning rate of 0.001 on the GPU. After training, the model achieved a training time of 2188.1524 seconds, a final training loss of 0.6781, and an evaluation accuracy of 0.6853. Compared to Problem 1B's deeper CNN, the ResNet-10 model performed worse in accuracy (0.6853 vs. 0.7333) while also taking longer to train. Overall, while ResNet-10 added complexity, it did not outperform the extended CNN from Problem 1B.

Problem 2B

For Problem 2B, three variations of the ResNet-10 model were trained to evaluate the effects of different regularization methods: weight decay (lambda = 0.001), dropout (p = 0.3), and batch normalization. Each model was trained for 300 epochs using SGD with a learning rate of 0.001 on the normalized CIFAR-10 dataset. After training, the final training time, training loss, and evaluation accuracy were recorded for each model.

The ResNet-10 with weight decay achieved a training time of 2230.95 seconds, a final training loss of 0.7093, and an evaluation accuracy of 0.7079. The dropout model performed the worst, with a higher final loss of 1.0689 and a lower accuracy of 0.6555, likely due to aggressive regularization reducing model capacity. Batch normalization produced the best loss (0.5698) but a moderate accuracy of 0.6912, while also taking significantly longer to train at 3162.85 seconds.

Compared to Problem 1A's baseline CNN, all models trained longer due to the more complex ResNet architecture. In terms of accuracy, only the weight-decay variant surpassed the baseline CNN's performance, while dropout reduced accuracy noticeably. Overall, the results show that weight decay provided the most consistent improvement for ResNet-10, while dropout was overly restrictive and batch normalization increased stability but not accuracy. However, the batch normalization accuracy is very close to both the problem 1A CNN model as well as the weight decay model.