CS512: Advanced Machine Learning.

Assignment 3: Adversarial Training on Sequence Classification

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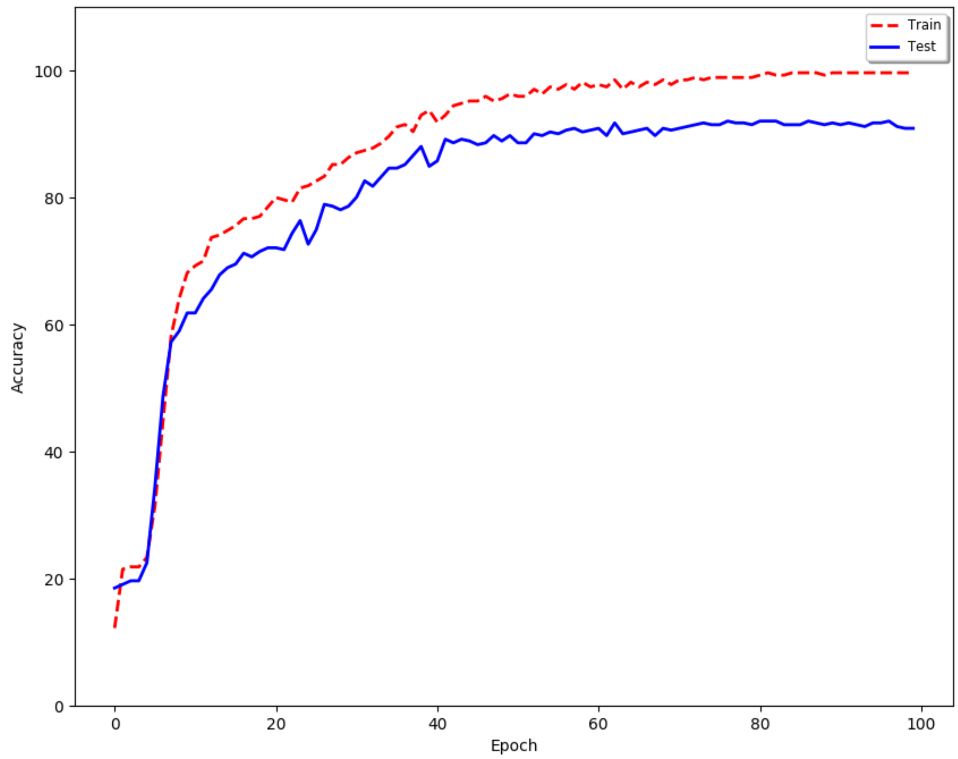
1 Introduction

2 (15 points) Training the Basic Model

Hyperparameters values:

`batch_size = 27`, `hidden_size = 10`, `basic_epoch = 100`, `out_channels = 64`, `kernel_size = 10`, `stride = 3`, `lr = 1e-3` (learning rate), `weight_decay = 1e-3`.



3 (10 points) Save and Load Pretrained Model

See code in `training.py` under the comment `Part 3, Save and Load model`.

4 (25 points) Adversarial Training as Regularization

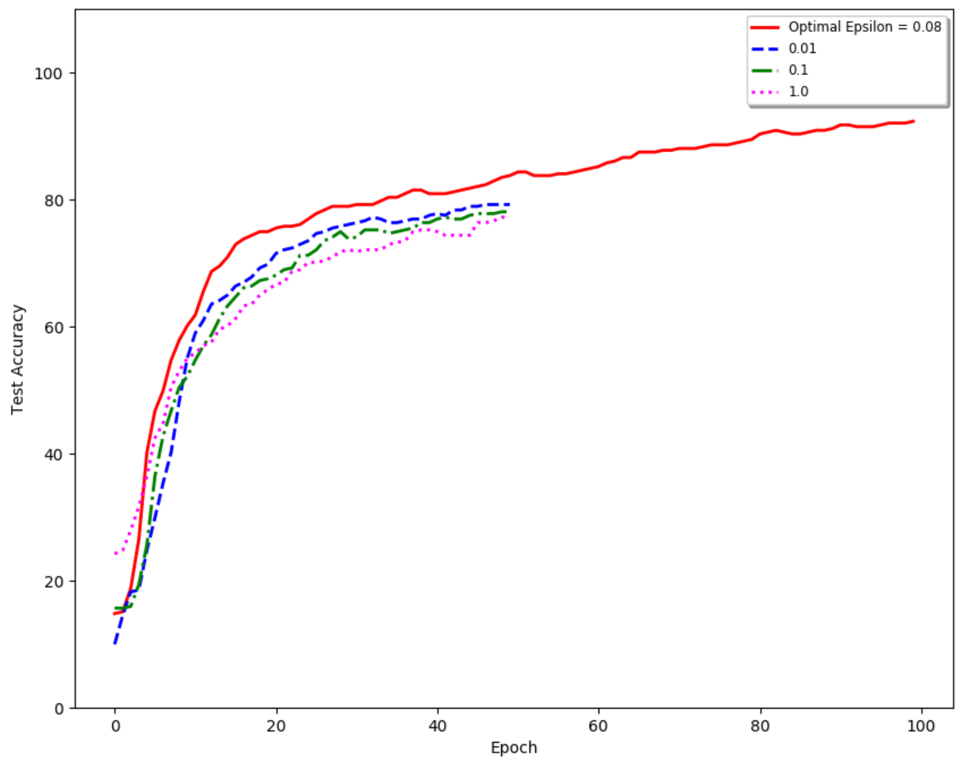
a **(10 points)** See the `compute_perturbation` function in `training.py`.

b **(5 points)** See the branch `mode` = 'AdvLSTM' in `LSTMClassifier` in `Classifier.py`.

c **(10 points)**

Among the ϵ's we have tried ($\epsilon = [0, 2, 4, 6, 8, 10, 0.001, 0.01, 0.08, 0.1, 1, 10, 100, 1000]$), $\epsilon = 0.08$ gives the optimal performance at the end of 100 epochs. The other hyperparameters were set the same as those in the basic model. The adversial training improved the test accuracy although this improvement is not significant. The basic model test accuracy is about 92.02%, while with adversarial training, the test accuracy reached 92.3%. The output of basic model test accuracy and test accuracy with adversarial training were stored in `BasicModel_test.txt`, and first 100 rows of `AdvModel_acc.txt` in folder `Figures`.

As shown in the figure, the performance of the model changes slightly with the change of ϵ between $[0.01, 0.1, 1]$, meaning our model is pretty robust to disturbance. At the end of epoch 50, $\epsilon = 0.01$ seems to give the best test accuracy among $\epsilon = [0.01, 0.1, 1]$.



5 (40 points) Adversarial Training as Proximal Mapping

a **(30 points)** We have implemented the ProxLSTMCell in `ProxLSTM.py`. We have implemented `forward` pass, but we are having issues with `backward` pass.

b **(10 points)** We have written a branch in `LSTMClassifier` that can handle `mode = 'ProxLSTM'`. Because we haven't made `backward` pass work, we cannot perform the experiment with different $\epsilon = \lambda^{-1}\sigma^2 = [0.1, 1.0, 5.0]$. But we can imagine that by using the similar code in `plot.py`, we can generate curves similar to that in the previous section. We can also imagine that by adding adversarial training as proximal mapping would further increase the test accuracy, especially when compared with basic model.

6 (10 points) Dropout and Batch Normalization

a **(5 points)** We have initiated a dropout layer in `Classifier.py` and we use it with a flag `apply_dropout`. When the flag is set to `True`, we apply the dropout before the convolution layer. We hypothesize this is an optimal position for the dropout layer as the dropped out connections can help regularize the convolution parameters.

b **(5 points)** We have implemented a batch normalization layer in `Classifier.py` and like dropout, we have a flag `apply_batch_norm`, which when set to `True`, is applied before the ProxLSTM layer. We believe it could help the optimization by normalizing the batch of inputs to the ProxLSTM layer.