University of Waterloo
CS 480
r2knowle: 2023-11-28

Exercise # 3

Q3a) For this question, we will be using our VG11 NN trained for the last assignment. The test accuracy is 98.99% and the model summary is:

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Model: "sequential"
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 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 32, 32, 64)        640
 batch_normalization         (None, 32, 32, 64)        256
 (BatchNormalization)
 max_pooling2d               (None, 16, 16, 64)        0
 (MaxPooling2D)
 conv2d_1 (Conv2D)           (None, 16, 16, 128)       73856
 batch_normalization_1       (None, 16, 16, 128)       512
 (BatchNormalization)
 max_pooling2d_1             (None, 8, 8, 128)         0
 (MaxPooling2D)
 conv2d_2 (Conv2D)           (None, 8, 8, 256)         295168
 batch_normalization_2       (None, 8, 8, 256)         1024
 (BatchNormalization)
 conv2d_3 (Conv2D)           (None, 8, 8, 256)         590080
 batch_normalization_3       (None, 8, 8, 256)         1024
 (BatchNormalization)
 max_pooling2d_2             (None, 4, 4, 256)         0
 (MaxPooling2D)
 conv2d_4 (Conv2D)           (None, 4, 4, 512)         1180160
 batch_normalization_4       (None, 4, 4, 512)         2048
 (BatchNormalization)
 conv2d_5 (Conv2D)           (None, 4, 4, 512)         2359808
 batch_normalization_5       (None, 4, 4, 512)         2048
 (BatchNormalization)
 max_pooling2d_3             (None, 2, 2, 512)         0
 (MaxPooling2D)
 conv2d_6 (Conv2D)           (None, 2, 2, 512)         2359808
 batch_normalization_6       (None, 2, 2, 512)         2048
 (BatchNormalization)
 conv2d_7 (Conv2D)           (None, 2, 2, 512)         2359808
 batch_normalization_7       (None, 2, 2, 512)         2048
 (BatchNormalization)
 max_pooling2d_4             (None, 1, 1, 512)         0
 (MaxPooling2D)
 flatten (Flatten)           (None, 512)               0
 dense (Dense)               (None, 4096)              2101248
 dropout (Dropout)           (None, 4096)              0
 dense_1 (Dense)             (None, 4096)              16781312
 dropout_1 (Dropout)         (None, 4096)              0
 dense_2 (Dense)             (None, 10)                40970

=================================================================
Total params: 28153866 (107.40 MB)
Trainable params: 28148362 (107.38 MB)
Non-trainable params: 5504 (21.50 KB)
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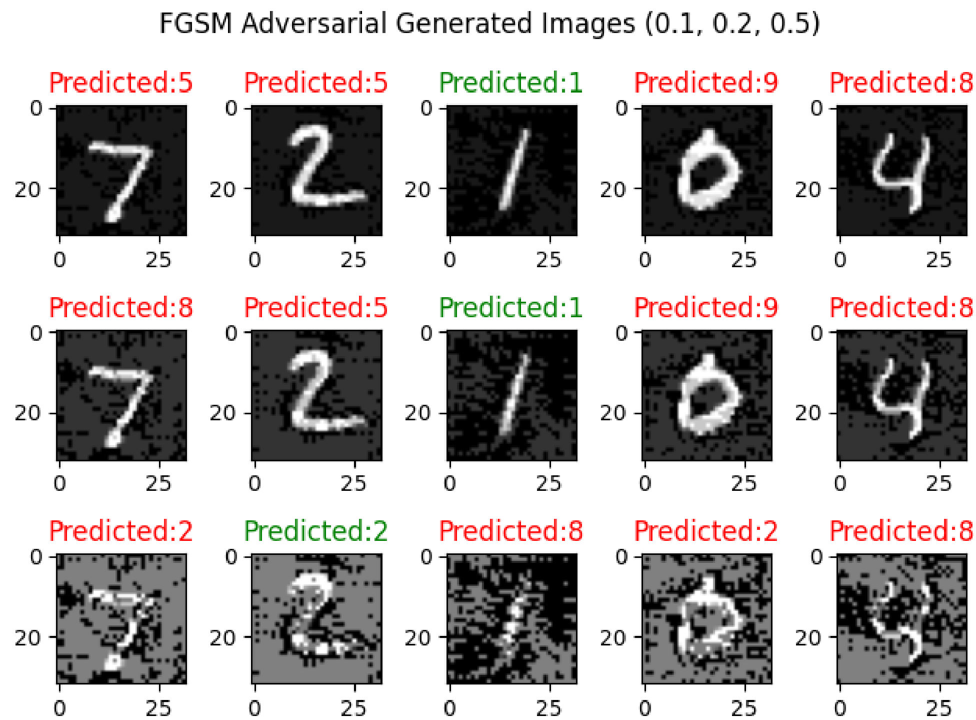
Q3b) Below are 15 samples of test images for the 3 degrees of epsilon in FGSM adversary training. The first row denotes $\epsilon = 0.1$, the middle row denotes $\epsilon = 0.2$ and finally the last row denotes $\epsilon = 0.5$:



We can observe that as epsilon increases the amount of noise in the images increases. The background intensity will always increase, and the pixels of the actual digit tend to decrease. At epsilon 0.5 it means the perturbed parts of the digit are indistinguishable from the perturbed parts of the background.

With our base model we receive the following test accuracies for the perturbed test set:

Test Accuracy on $\epsilon = 0.1$	Test Accuracy on $\epsilon = 0.2$	Test Accuracy on $\epsilon = 0.5$
59.95%	31.63%	15.58%

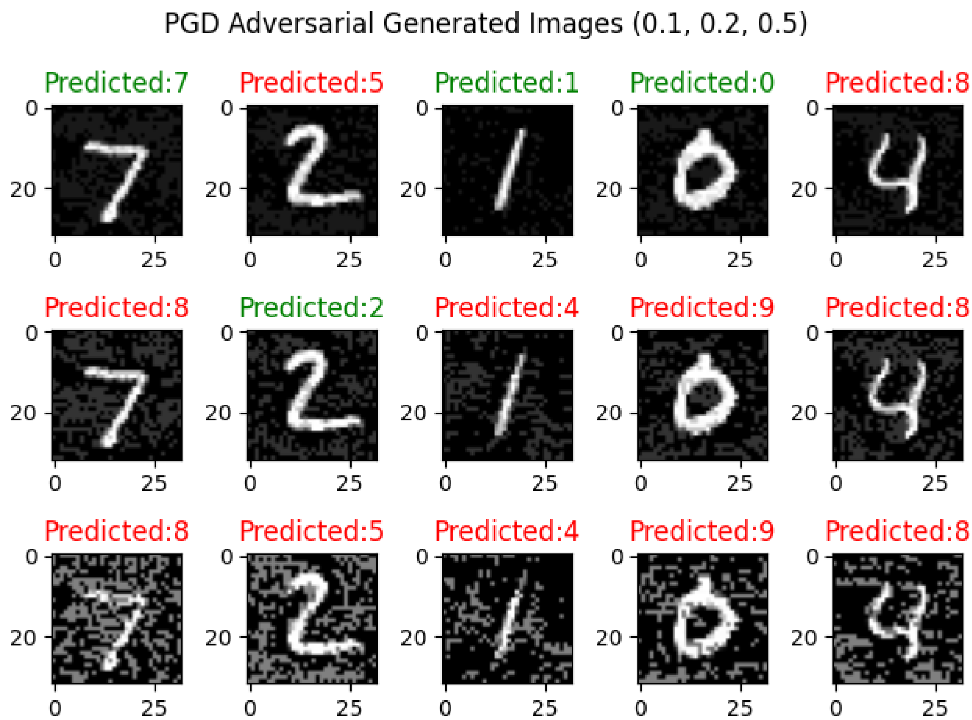
As should be expected we see that as epsilon increase the training accuracy decreases.

Q3c) After doing adversarial training (one generated image per training image) we get the following test accuracies:

Test Accuracy on $\epsilon = 0.1$	Test Accuracy on $\epsilon = 0.2$	Test Accuracy on $\epsilon = 0.5$
97.04%	91.18%	80.32%

After doing adversarial training we can see that our model accuracies increase by a very large extent. We also notice that expect of epsilon 0.2, that as epsilon increase our model accuracy decreases proportionately.

Q3d) Below are 15 samples of test images for the 3 degrees of epsilon in PGD adversary training. The first row denotes $\epsilon = 0.1$, the middle row denotes $\epsilon = 0.2$ and finally the last row denotes $\epsilon = 0.5$:



Below are the three tables comparing the 3 different trained models versus the three different test sets:

Model Type	Unperturbed Test Set	FGSM Test Set	PGD Test set
Untrained	98.37%	59.94%	77.81%
FGSM	74.12%	97.04%	86.07%
PGD	73.10%	99.07%	98.07%

Table 1: Test Accuracies for $\epsilon = 0.1$

Model Type	Unperturbed Test Set	FGSM Test Set	PGD Test set
Untrained	98.37%	31.63%	33.65%
FGSM	74.12%	99.18%	89.23%
PGD	73.10%	97.54%	96.68%

Table 2: Test Accuracies for $\epsilon = 0.2$

Model Type	Unperturbed Test Set	FGSM Test Set	PGD Test set
Untrained	98.37%	15.58%	9.36%
FGSM	74.12%	80.32%	61.23%
PGD	73.10%	62.23%	87.38%

Table 3: Test Accuracies for $\epsilon = 0.5$

Note that both FGSM and PGD were trained with an $epsilon = 0.2$. From this we can identify some trends. The first is that as epsilon increases, each model tends to do worse on tests that they were note trained on. The untrained model's accuracy falls off far faster on adversary tests and then adversarial trained models do on normal data. We also notice that the model trained on PGD data tends to be more robust and has higher accuracy on FGSM data then the FGSM model has on PGD data. Lastly we notice that each model has around 98% accuracy on the data it was trained on.