Harnessing adversarial examples

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1 Introduction

For this project a model for a multi-label problem is trained, using the MNIST dataset. Once the model is obtained, adversarial examples can be generated. An adversarial example is an example that is only slightly different from the original and correctly classified example that a model misclassify with a high confidence.

The objective of this projects is to harness adversarial examples to make train more robust model, by lower the classification error and the confidence associated with those misclassification.

2 Dataset

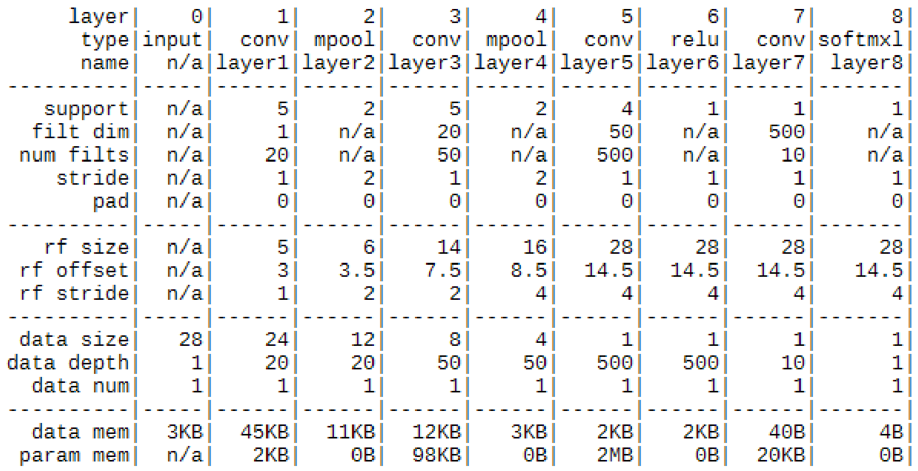
The MNIST dataset is a large dataset of handwritten digits, thus including ten mutually exclusive classes. It was creates from the samples of the NIST dataset; the originally black and white images were normalized to fit 28x28 pixels images and anti-alisiasing were used, which introduced grayscale levels, so that the pixel values are in the range [0, 255].

The MNIST dataset contains 60,000 training images (divided in two sets, train and validation, with 55,000 and 5,000 images resprectively) and 10,000 testing images.

For this project, from each sample the mean image of the dataset were subtracted.

3 CNN

The net is based on LeNet and consists of eight layers, as shown in the following image.



```
     layer|    0|     1|     2|     3|     4|     5|     6|     7|      8|
      type|input|  conv| mpool|  conv| mpool|  conv|  relu|  conv|softmxl|
      name|  n/a|layer1|layer2|layer3|layer4|layer5|layer6|layer7| layer8|
----------|-----|------|------|------|------|------|------|------|-------|
   support|  n/a|     5|     2|     5|     2|     4|     1|     1|      1|
  filt dim|  n/a|     1|   n/a|    20|   n/a|    50|   n/a|   500|    n/a|
 num filts|  n/a|    20|   n/a|    50|   n/a|   500|   n/a|    10|    n/a|
    stride|  n/a|     1|     2|     1|     2|     1|     1|     1|      1|
       pad|  n/a|     0|     0|     0|     0|     0|     0|     0|      0|
----------|-----|------|------|------|------|------|------|------|-------|
   rf size|  n/a|     5|     6|    14|    16|    28|    28|    28|     28|
 rf offset|  n/a|     3|   3.5|   7.5|   8.5|  14.5|  14.5|  14.5|   14.5|
 rf stride|  n/a|     1|     2|     2|     4|     4|     4|     4|      4|
----------|-----|------|------|------|------|------|------|------|-------|
 data size|   28|    24|    12|     8|     4|     1|     1|     1|      1|
data depth|    1|    20|    20|    50|    50|   500|   500|    10|      1|
  data num|    1|     1|     1|     1|     1|     1|     1|     1|      1|
----------|-----|------|------|------|------|------|------|------|-------|
  data mem|  3KB|  45KB|  11KB|  12KB|   3KB|   2KB|   2KB|   40B|     4B|
 param mem|  n/a|   2KB|    0B|  98KB|    0B|   2MB|    0B|  20KB|     0B|
```

4 Generation of adversarial examples

Let θ be the parameters of a model, x the input to the model, y the targets associated with x (for machine learning tasks that have targets) and $J(\theta, x, y)$ be the cost used to train the neural network. We can linearize the cost function around the current value of θ, obtaining an optimal max-norm constrained pertubation of ,

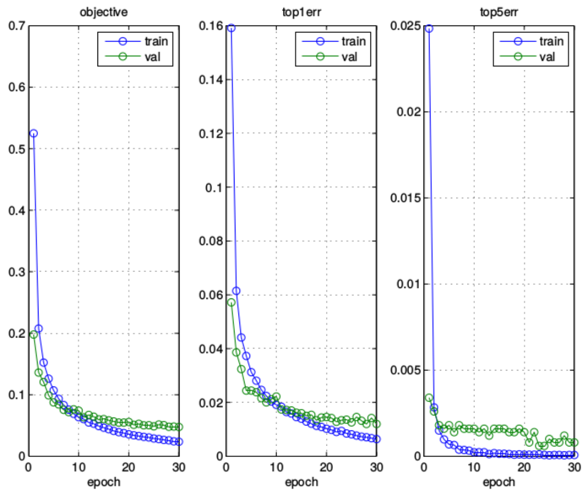
$$\eta = \epsilon * sign(\nabla_x J(\theta, x, y))$$

The adversarial examples can thus be obtained as follow,

$$x = x + \eta$$

5 Standard Training

The net was trained in a standard way, using the 60,000 images of the train and validation sets. The training went on for 30 epochs.



The tests carried out on the trained model were of two kind. The first test was made using the 10,000 clean samples from the testing set; the second test was made using the adversarial examples, that is the same samples as the first test but with an added perturbation computed as shown in Section 0.4.

	Clean	Adversarial
Correctly Predicted	98.47	3.36
Error	1.53	96.64
Confidence	98.59	93.82
Confidence Correctly Predicted	99.04	91.67
Confidence Error	69.95	93.89

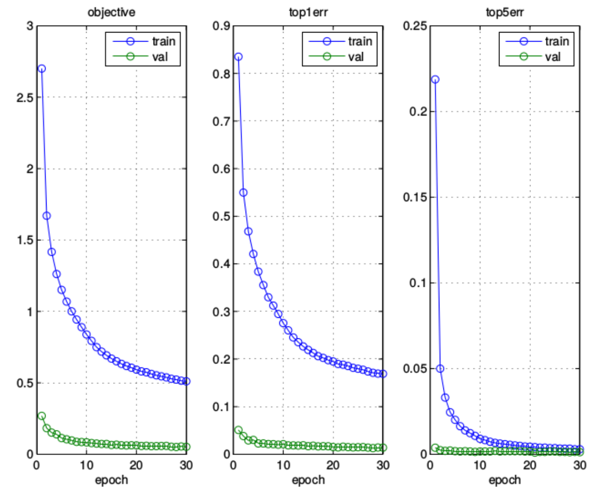
Table 1: Test results for standard training model.

As we can see from the results shown in Table 1, the classification using the clean samples as test images worked great, with high prediction rate and confidence. The results for the adversarial test, however, behaved as expected, with a large percentage of misclassification with a high confidence.

6 Mixed Training

For this case, adversarial examples were included in the training phase. At each epoch, the adversarial example of each images were computed, given the model at that particular epoch. Both images, clean and adversarial, were used in the training process, similar to data augmentation. This way, both the clean example and the adversarial example participate in the optimization of the parameters of the model in order to decrease the loss.

Adversarial examples are thus generated dynamically at each epoch, so that the model is trained considering its blind-spots. The training went on for 30 epochs using 120,000 samples, half clean and half adversarial.



The tests were carried out as for the standard training.

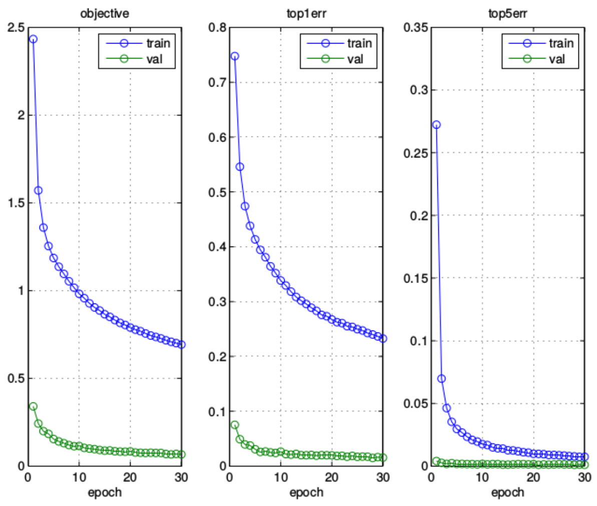
	Clean	Adversarial
Correctly Predicted	98.21	85.28
Error	1.79	14.72
Confidence	97.89	86.30
Confidence Correctly Predicted	97.85	89.07
Confidence Error	66.91	70.22

Table 2: Test results for standard training model.

The results in Table 2 shows that for the clean samples the prediction behaved as for the standard training. For the adversarial examples, however, the results are much better than the previous case. The error rate dropped from 97% to 15% and the confidence for the misclassification also dropped significantly, from 94% to 70%, which is in a similar range as the clean samples for both cases.

7 Adversarial Training

The method of training used for this case follows the one proposed in the paper "I. J. Goodfellow, J. Shlens and C. Szegedy, "Explaining and harnessing adversarial examples", arXiv preprint arXiv:1412.6572, 2014".



The objective function is modified to include adversarial examples in the training phase:

$$\tilde{J}(\theta, x, y) = \alpha J(\theta, x, y) + (1 - \alpha) J(\theta, x + \epsilon sign(\nabla_x J(\theta, x, y)), y)$$

The tests were carried out as for the standard and mixed training.

	Clean	Adversarial
Correctly Predicted	97.97	77.80
Error	2.03	22.20
Confidence	96.03	79.05
Confidence Correctly Predicted	96.69	82.55
Confidence Error	64.23	66.79

Table 3: Test results for standard training model.

As for the mixed training, the results in Table 3 shows significant improvement toward the classification of adversarial examples. Compared to the standard training, the error rate dropped from 97% to 22% and the confidence for the errors also dropped significantly, from 94% to 67%. Compared to the mixed training, the adversarial training has a lower confidence for both error and corrected prediction; it also has a higher percentage of misclassification. However, the adversarial training is faster than the mixed training.