# HARNESSING ADVERSARIAL EXAMPLES

## Project

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.

## 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.

## 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 |

## 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(θ, 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,

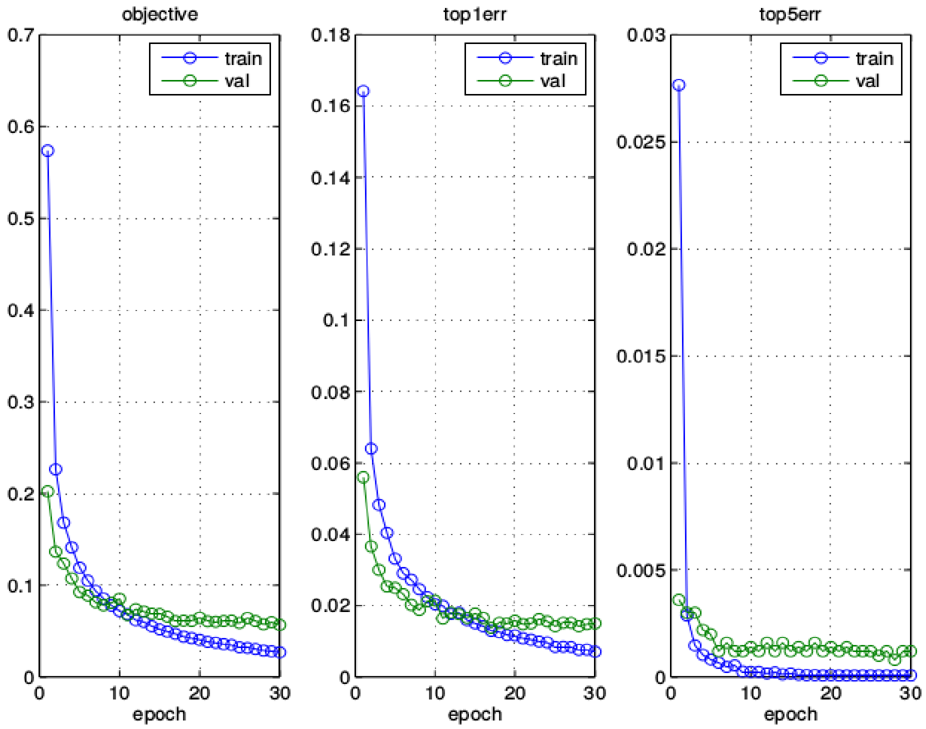
$$\eta = \epsilon * sign(\nabla_x J(\theta, x, y)) \tag{1}$$

The adversarial examples can thus be obtained as follow,

$$x = x + \eta \tag{2}$$

**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.



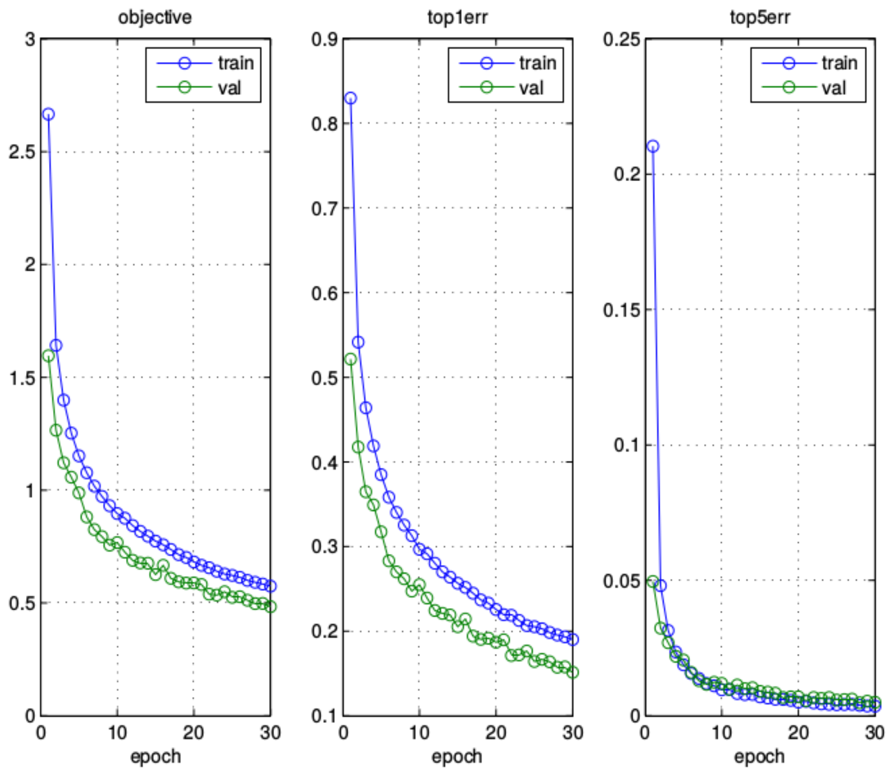

The tests carried out on the trained model were of two kind. The first test was made using the 10,000 clean samples from the testing set; the second test was made using the adversarial examples, that is the same samples as the first test but with an added perturbation computed as shown in (2).

| | Clean | Adversarial |
|---|---|---|
| Correctly Predicted | 0,9858 | 0,0496 |
| Error | 0,0142 | 0,9504 |
| Confidence | 0,9858 | 0,9305 |
| Confidence Correctly Predicted | 0,9899 | 0,8869 |
| Confidence Error | 0,7029 | 0,9328 |

As we can see from the results shown in the table, 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.

**Adversarial training**

For the 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 dinamically at each epoch, so that the model is trained considering its blindspots.
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 | 0,9840 | 0,8328 |
| Error | 0,0160 | 0,1672 |
| Confidence | 0,9721 | 0,8458 |
| Confidence Correctly Predicted | 0,9761 | 0,8761 |
| Confidence Error | 0,6734 | 0,6947 |

The results shows that for the clean samples the prediction behaved as for the standard trainig. For the adversarial examples, however, the results are much better than the previous case. The error rate dropped from ~95% to ~17% and the confidence for the misclassification also dropped significantly, from ~93% to ~69%, which is in a similar range as the clean samples for both cases.