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SUMMARIZATION BY KUNAL DARGAN:

**‘Deep Big Simple Neural Nets Excel on Handwritten Digit Recognition’**

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Introduction and Aim of the Paper:

Aim of the paper is to establish the fact that Deep Artificial Neural Networks works in complete harmony with on-line Backpropagation to yield a very low error rate on the famous MNIST handwritten digits Benchmark and can be of great commercial use and have varied implementation into fields ranging from banking, postal services etc. where better sorting and identification of human handwriting is a tedious task and labor can be reduced significantly. Although paper doesn’t goes into depth and didn’t explains nits and bits of On-line Back propagation which acts as the basis for all the exercise it has been analyzed in the paper by (Garcia).

In this given paper implementation has been boosted by making the use of GPU to greatly speedup the process of training and validation and deformations has been applied over the MNIST data to make this Deep NN resistant to the variations.

Literature review: Prominently by the advent other techniques which have been applied with neural networks such svms and other forms of NN such as CNN and graph and tree based architectures ‘*Combinations of NNs and SVMs (Lauer et al., 2007) etc. Convolutional neural networks (CNNs) achieved a record-breaking 0.40% error rate (Simard et al., 2003), using novel elastic training image deformations’* have been observed already and writer is interested in implementation of good old on-line Back propagation technique.

Techniques used:

As MNIST data consists of huge set of 60K images in al different form writer points out that training such a huge network as each image is built up pixels whose intensities are provided as inputs, *“Pixel intensities of the original gray scale images range from 0 (background) to 255 (max foreground intensity). 28×28 = 784 pixels per image get mapped to real values pixel intensity 127.5 −1.0 in [−1.0, 1.0], and are fed into the NN input layer”,* would not be feasible nor possible in today’s technology even with the use highly efficient parallel computing ,even it can take long time if the case had been standard computers with standard back propagation .

To implement this project GPU accelerated NN or (GANN) has been used which makes use ‘2 core CPU and 3GB of RAM, and a GTX280 graphics card’. Because the size of input as already stated is huge writer has proposed to input only 50000 images (training) and 10000 (testing) images for this particular project to train and test the network.

Architecture: 5 Deep NN or MLPS have been implemented with 2 to 9 hidden layers and varying number of hidden units. Standard on-line Back propagation with variable learning rate is used which iteratively updates the weights assigned to hidden units or individual perceptron as a new input is provided for training from the train-set and works in a Heuristic fashion i.e. Stepwise on the first step improves weights on training data and separately adjusts learning rate on testing set only hence after each epoch learning rate decreases. This results in deep NN has almost 12 million free parameters.

Input data in the form of images has been deformed intentionally thus it increases inputs and makes networks insensitive to in-class variations. Affine Rotations, Scalling and shearing along with elastic deformation were obtained.

Result: Of this 10000 images which were input only 35 were not recognized or mere 0.35 % error was obtained which is significantly greater than 0.40% previously obtained from using CNN and Svms. Even in the best case on .32% error was found which even better any previous similar project is. On- line BP is the improved form of Back propagation algorithm which get optimized quickly .As computing power has grown significantly so even 1.12 million nodes in Deep Neural net of which they have created 5 samples get solved quickly by making use of GPU accelerated online- BP which adjusts learning rate after every transition. As already data was 60K images still to make the pool of training and testing can be infinitely increased by creating variation in images by implementing various factors to transform images it makes Model more stable.

**Conclusion:**

As computing power has grown significantly ,results have shown that better hardware in future can solve even deeper NN in constant time or in significantly less time for given algorithms and Already GPUs which are way advanced from the previous times along with On-line Back propagation helps in solving problems in a heuristic fashion and in limited time and precision obtained on the *“the very competitive MNIST handwriting benchmark, single precision floating-point GPU-based neural nets surpass all previously reported results, including those obtained by much more complex methods involving specialized architectures, unsupervised pretraining, combinations of machine learning classifiers etc.” ,* 0.32% error rate is significant reduction from previous best models and hence it proves that Deep neural nets doesn’t only hold high prominence in solving Handwriting detection rather other advanced problems also.

# Bibliography

Similar Paper with basis for explanation about On- Line Learning Back Propagation Algorithm:

Garcia, S. D. (n.d.). An Online Backpropagation Algorithm with Validation Error-Based Adaptive Learning Rate. *Orange Labs, 4, Rue du Clos Courtel, 35512 Cesson-S´evign´e, France*.

http://liris.cnrs.fr/Documents/Liris-6097.pdf

***Feedback Appreciated***

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