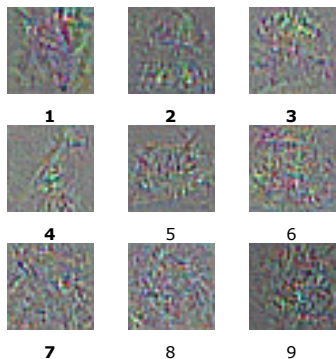


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**Figure 2.** Residual gradient after each epoch

# Towards the creation of Deep Learning-Aware Ensembles

## Research Aims

The principal goal of the research is to create faster methods and techniques for training **Deep Learning** models on GPUs, to facilitate the use of **Ensemble Methods** in Deep Learning. The secondary goal of the research is to use this increased speed to enable the research of sophisticated Ensemble Methods that make use of the information available about the structure of the base classifier, such as Deep Learning-aware Ensemble Methods.

## Better Training Methods for Deep Learning

Even using GPUs, which enable a large amount of computation to be done in parallel, it is often necessary to train a single model for days or even weeks at a time. Such long training times hinder the ability to conduct research on aggregate models, and as such it is first necessary to develop and improve existing training algorithms to drastically reduce the amount of computation required to reach good (or better) generalization.

## Deep Learning-Aware Ensembles

The following step is to generate Ensemble Methods which make use of concepts from Deep Learning and adjacent fields, such as **Transfer of Learning**, or knowledge about the underlying specific Deep Learning model being used to improve generalisation and accelerate the training.

## Research Methodology

We developed a framework for experimenting with Deep Learning Ensembles on GPUs, based on existing technology (**CUDA**, **Theano**), that supports most of the state-of-the-art techniques, and facilitates the creation of new algorithms.

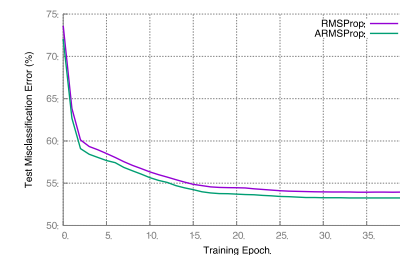
We use an array of GPUs to verify our new theoretical formulations on benchmark datasets commonly used in the literature, such as **MNIST**, **CIFAR**, **ImageNet** and **SVHN**.

## Research Outputs

- A new method for training Deep Neural Networks that include Dropout regularization with RPROP has been developed, which

reduces training time and enables the use of Ensembles in full-batch learning mode [1].

- A new training algorithm called ARMSProp that proposes the use of weight-wise adaptive learning rates in mini-batch learning has been developed. **Figure 1** shows an example of ARMSProp on CIFAR-100, compared to a best-in-class method (RMSProp).



**Figure 1.** Improved training on CIFAR-100

- A new method for updating the input vector during training, to increase speed of convergence on images. **Figure 2.** shows the residual gradient that is passed on to the training input vector on CIFAR-10 during the first few epochs.
- A new Ensemble method that uses knowledge of the underlying classifier to apply Transfer of Learning between Boosting rounds, called Deep Incremental Boosting. **Table 1.** shows preliminary results on CIFAR-10 and MNIST.

(MISCLASSIFICATION)	SINGLE NET	ADABOOST	D.I.B
<b>CIFAR-10</b>	27%	23%	<b>18%</b>
<b>MNIST</b>	0.72%	0.63%	<b>0.49%</b>

**Table 1.** Preliminary results on Deep Incremental Boosting

## Publications

A. Mosca, G. D. Magoulas: "Adapting Resilient Propagation for Deep Learning", UK conference on Computational Intelligence, 2015