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| **Title:** EFFICIENT PARALLEL LEARNING ALGORITHMS FOR NEURAL NETWORKS  **Main author:** Alan H. Kramer and A. Sangiovanni-Vincentelli  **Year:**  **Link:** |
| **Journal:**  **IF:**  **Pages:** 9 |
| **Structure of the paper**  Abstract   1. Introduction 2. Neural Network 3. Learning. 4. Optimization Techniques 5. Convergence Criterion 6. Back propagation 7. Conclusion |
| **Detail of figures and plots**  **Regarding Encoder Results:**  Here given a table where we consider how many average Epoch are required to evaluate tune able parameters**.** |
| **Experimental setup and experimentation**   * **Experiment-1:**  Compared the performance   + **Compared with:** Polak-Ribiere (P-R), Steepest Descent (S-D), and Batch Back-propagation (B-B) algorithms.   + **Outputs:** Polak-Ribiere algorithm to be significantly more efficient than the others**.**   + **Output structure:** Table with given tunable parameters are evaluated |
| **A brief summary of the proposed work [one paragraph]**  In this paper, we describe the network learning problem in a numerical framework and investigate parallel algorithms for its solution. In a learning problem for neural network node function and architecture kept same while the weights tuned and they are free parameters. In learning problem refers to the **Network Function** which should be match some **Target Function** only on “trained set”. If the minimum value is “0” in instance error formula then the network function approximates the target function exactly. In **optimization Technique**, network learning is a problem of function approximation, where the approximating function is a finite parameter-based system. The goal is to find a set of parameter values which minimizes a cost function, between the target function and the approximating function. |
| **Critical review** |
| **Any idea to upgrade the concept** |
| **Name five papers from references, you’d like to read next**   1. R.M. Bell and Y. Koren. Lessons from the netflix prize challenge. ACM SIGKDD Explorations Newsletter, 9(2):75–79, 2007. 2. A. Berg, J. Deng, and L. Fei-Fei. Large scale visual recognition challenge 2010. www.imagenet.org/challenges. 2010. 3. D. Cire¸san, U. Meier, and J. Schmidhuber. Multi-column deep neural networks for image classification. Arxiv preprint arXiv:1202.2745, 2012 4. V. Nair and G. E. Hinton. Rectified linear units improve restricted boltzmann machines. In Proc. 27th International Conference on Machine Learning, 2010 5. P.Y. Simard, D. Steinkraus, and J.C. Platt. Best practices for convolutional neural networks applied to visual document analysis. In Proceedings of the Seventh International Conference on Document Analysis and Recognition, volume 2, pages 958–962, 2003. 6. S.C. Turaga, J.F. Murray, V. Jain, F. Roth, M. Helmstaedter, K. Briggman, W. Denk, and H.S. Seung. Convolutional networks can learn to generate affinity graphs for image segmentation. Neural Computation, 22(2):511–538, 2010. |
| **Name five papers from citations, you’d like to read next** |