Short communication

Open Access CrossMark

FPGA firmware helps unify the supervised and un-supervised deep learning for BDA

Abstract

Gap: Traditional approach requires epidemiologists labor intensively sort the big databases analysis (BDA) into two different batches: one batch for Machine Supervised learning, e.g. for malignant tumors.

Innovation: We estimated the exemplars cases with a factor Alpha α and then focused on a simultaneous implementation of both supervised and unsupervised deep earning in the following simple logic deduction:

$$unsupervised\ BDA = (1-\alpha)(supervised + unsupervised)\,BDA + \alpha\ supervised\ BDA$$

Approach: Our methodology implemented in terms of the *electric power changes* that may be labeled as Artificial General Intelligence to combine both the supervised deep learning and unsupervised deep learning.[1,2]

Results: All sort big databases analysis (BDA) problems in biomedical wellness (BMW) in cancers prevention, or defense surveillance challenge e.g. the most-wanted face analysis gathered using in-situ legacy, day EO night IR,RF,MF sensor suites, after individual pre-processing feature extraction.

Keywords: methodology, deep learning, sensor, multi layers, arbitrary

Volume 3 Issue 4 - 2019

Harold Szu
Department of Biomedical Engineering, The Catholic University, USA

Correspondence: : Harold Szu, Department of Biomedical Engineering, The Catholic University, Wash DC, USA, Tel 2404 8268 89, Email szuharoldh@gmail.com

Received: July 10, 2019 | **Published:** July 16, 2019

Abbreviations:

BDA, big databases analysis; BMW, biomedical wellness; AGI, artificial general intelligence; FPGA, field programmer gate array

Introduction

Artificial general intelligence (AGI) has been advocated by both MIT Prof. *Lex Friedman,* and Stanford CS Prof. *Andrew Ng*. The deep learning is a recursive multi-layers learning emulating human visual system (V1-V4) which have been campaigned by Prof. *Geoffrey Hinton* (now at Google) and his protégée Prof. *Yann Le* Cun (no at NYU Facebook), Prof. *Yoshua Bengio* (remains at Univ. Toronto)).[1] Together they have been demonstrated in recent Nature publication "(Supervised) Deep Learning" circa 2015.

In this proposal, we have extended supervised learning to unsupervised learning[2] and implement both supervised and unsupervised learning rules together in a Firmware, "*Power Law Learning*" under one roof and realized in the Power Circuitry Firmware, defined the following field programmer gate array (FPGA) (Figure 1).[3,4]

In this communication notes we illustrate the math formula for applying both current I/O and Voltage I/O to execute the multiple layer (by recursive) deep learning in the power change defined as follows:

Figure 1 Exemplar FPGA board (e.g. Intel Cyclone10 at the cost $13.2).

Given the basic physics, we have the Power, P, definition as the product between the Ohms Voltage, V, and the Ampere Current, I,

$$\boldsymbol{P} = \boldsymbol{VI} \tag{1}$$

Then the perturbation of power law $\Delta \boldsymbol{P}$ in MKS units as Watts as joule per sec:

$$\Delta \boldsymbol{P} \equiv \boldsymbol{P} - \Delta \boldsymbol{P} = \mathbf{VI} - \boldsymbol{I}\Delta\mathbf{V} - \mathbf{V}\Delta\mathbf{I} + \boldsymbol{Order}(\Delta V \Delta \boldsymbol{I}) = (V - \Delta V)(\boldsymbol{I} - \Delta \boldsymbol{I}) + \mathbf{Order}\ (\Delta V \Delta \boldsymbol{I}) \tag{2}$$

Approaches:

Assume an unknown Alpha α factor to all supervised e.g. Epidemiologist supervised learning among BDA those potential malign cancer cases out of BDA.

Then, we can apply to all BDA with the following perturbation formula of equivalent circuitry:

$$\Delta P = (Unsupervised\ benign)\, I \Delta V + (Supervised\ malign)\, V \Delta I$$

The medical equivalent circuitry ΔV could be the X-ray imaging applied voltage, the total current I as the total patients. We have called physician involvement the current changes ΔI as the supervised learning for the sick patients. Thus we have divided the total patients I as the sick supervised patients ΔI and not-sick patients as unsupervised patients who may have gone home. We further introduce an arbitrary factor α as the percentage of sick patients, the $(1-\alpha)$ non-sick patients.

$$\Delta P=(1-\alpha)Unsupervised\,(I\Delta V)+\alpha\, Supervised\,(V\Delta I)$$

We denote P= VI to to be total patients = (1-α) unsupervised BDA + α Supervised BDA.

This concludes our result. In words, we apply Epidemiologists result multiplied the unknown proportional factor α of BDA. We then derived the final result BDA in terms of Power P and subtract α Supervised Learning of positive cases of selected malign cases $V\Delta I$.

Consequently, we shall integrate a loop in the power firmware design. We can minimize in the pre-launch the current $I_{actural}$ with supervised learning $I_{desired}$ measured by known exemplars in the least mean square sense

$$\|I_{actural}-I_{desired}\|^2\leq\varepsilon_I\,,$$

Likewise, the unsupervised learning at the reservoir temperature T so-called the minimum helmholtz free voltage energy

$$min.\left[Total\ Energy-V_{temperature}\,Entropy(unusable\,energy)\right]\leq\varepsilon_V$$

Anticipated results

i. Speed up time is estimated to be at least a factor of O(10) plus immeasurable human labor intensive sorting and errors. .

ii. The results will be relevant and useful to BDA (Big Database Analysis).

iii. The know Exemplars will be used for the supervised current learning; the unknown Exemplars will be used for unsupervised voltage learning.

iv. The double loop deep learning will be done recursively with dimension patch as Andrew Ng demonstrated in his "Course Ra" Internet Course.

v. Gap (nails)**:**

vi. In some data basis apps, human accountants involve in sorting them into the batch mode traditional and novelty modes. We need the speed "time is the money" thus the goal is to increase the throughput rate (time band-width product). It's desirable to execute both the supervised (with known exemplars) and the unsupervised learning (without exemplars). The question is how we can efficiently integrate both, without labor intensive sorting.

vii. Innovation (Program Manager's built already his or her Hammer @$13.2).

Acknowledgments

None.

Conflict of interest

The authors declare that there are no conflicts of interest.

References

1. Yann LeCun, Yoshua Bengio, Geoffrey Hinton. Deep learning. *Nature*. 2015;521:436–444.
2. H Szu, Lidan Miao, Hseung Qi. Unsupervised learning. *Proceeding of SPIE circa*. 1990.
3. H Szu, Pat Ho, Y Sun. Unified learning rules based on different cost functions. *MOJ App Bio Biomech*. 2019;3(3):45–47.
4. Power Learning on FPGA. 2017.

DOI: 10.15406/mojabb.2019.03.00108