FPGA firmware helps unify the supervised and unsupervised 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 examplers cases with a factor Alpha and then focused on a simultaneous implementation of both supervised and unsupervised deep earning in the following simple logic deduction:

unsupervised BDA = (1 – α)(supervised + unsupervised) BDA + α 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

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 learning2 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:

$$\Delta P = P - \Delta P = V I - \Delta V \Delta I = \text{Order} (\Delta V \Delta I) = (V - \Delta V)(I - \Delta I) + \text{Order} (\Delta V \Delta I)$$

Approaches:

Assume an unknown Alpha 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:

$$\Delta P = \text{(Unsupervised benign)} I \Delta V + \text{(Supervised malign)} V \Delta I$$

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

\[
\Delta P = (1 - \alpha) \text{Unsupervised} (I \Delta V) + \alpha \text{Supervised} (V \Delta I)
\]

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

This concludes our result. In words, we apply Epidemiologists result multiplied the unknown proportional factor \( \alpha \) of BDA. We then derived the final result BDA in terms of Power \( P \) and subtract \( \alpha \) 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 \( I_{\text{actual}} \) with supervised learning \( I_{\text{desired}} \) measured by known exemplars in the least mean square sense

\[
\| I_{\text{actual}} - I_{\text{desired}} \|^2 \leq \varepsilon_I.
\]

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

\[
\min \left[ \text{Total Energy} - V \text{ temperature Entropy (unusable energy)} \right] \leq \varepsilon_V
\]

**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**