

# Cutting-edge AI apply un-supervised learning to BDA

## Preface

In order to take advantage of modern computing power, we shall apply AI to Big Data Analysis (BDA) partially from the so-called Art, Culture, Science, and Technology (ACST) --- "experience of Homosapien", recorded at the 20 Smithsonian Museums and at the National Library of Medicine affiliated with dozens National Institutes of Medicine as well as non-profit Max-Planck ResearchGate.net. We furthermore define unsupervised learning capability that is innate to the Homosapien based on (1) ionic current responsible for Rational IQ and (2) chemical signals supporting Emotional IQ. Thus, we assume that AI computing tools must incorporate thermal temperature to the computer machine, but not operate at low temperature Electromagnetic physics. We begin by reviewing Homosapien intrinsic characteristics: (1) warm blooded brains that provide steady kinetic transport for efficient cellular operations, and (2) the 'power of paired sensors' (pops) which gather vector time series order set data  $X_p(t)$  for self-referenced unsupervised learning. Likewise, Homosapien have pair time series sensors (ears, eyes, nostrils, olfactory bulbs, taste buds, limbs extremities) which communicate with each other through the nervous system. The nervous system of human brain must be kept in reference at thermodynamics equilibrium, known in biology as homosapiens=37°C. These are necessary but not sufficient conditions for intelligent beings. A higher temperature does not necessarily imply smarter or quicker learning. For example, the chicken's brain is in equilibrium at 40°C but they lack hands, tools and past experience keeping through evolution to be our growth human beings.

Volume 8 Issue 1 - 2024

Harold H Szu

Res. Ord. Professor, Bio-Med. Engineering, Visiting Scholar at CUA, Catholic University of America, USA

**Correspondence:** Harold H. Szu, Research Ordinary Professor, BME, CUA, Wash DC, Fellows of IEEE, INNS, OCA, SPIE Life Fellow of IEEE, Foreign Academician of RAS, Wash D.C, USA, Email suzharoldh@gmail.com

**Received:** May 13, 2024 | **Published:** May 27, 2024

## Introduction

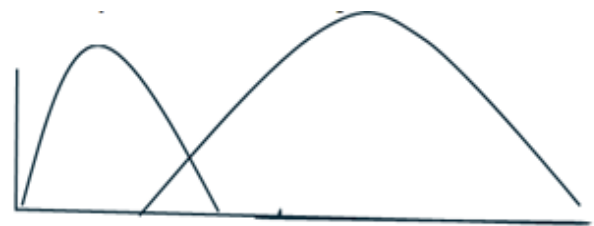
The short history **Big Data Analyses (BDA)** we introduce Cande, Rambo and Tao, Tao, Donoho, Szu and his associates Hsu Lidan, Qi, Cha, Willey, Jenkins, et al. that has led to decade applications of AI. Cutting-Edge of Artificial Intelligence indicates further the future frontier direction of AI. We discuss both the quantity (law of large numbers) and quality (law of small exceptions) two reasons directions with unsupervised learning as follows without slow down by supervision, (2) if we can further minimize false negative rate for the quality reasons, given the advantage of fast speed of massive parallel computational power, including recently **Mr. Elon Musk** and industries have advocated quantum computing (QC) with Multi-Billion Dollars using both momentum and coordinate amplitude and phase to computing, as well as without dense VLSI heat loss using the room temperature superconductor ( $CuO_{25}P_6Pb_9$ , **Lee-Kim 1999** of Korean University) remained to be verified in 2024 (cf. Wikipedia LK-99) [compared with early attempt of ceramic material **Yttrium barium copper oxide YBCO 123** Paul C.W. Chu et. al. under at liquid Nitrogen temperature 77°k & high pressure]. Meanwhile, CEO of Nvidia, **Mr. Jensen Huang** from Taiwan, Thailand to EE of Stanford Univ., provided few hundred Billion dollars assets to the this Massively Parallel Accelerated computing for Matrix Multiplication as follows.

**Big data analysis:** AI has Intelligent IQ and Emotion EQ; both are difficult to define or to quantify. One is 'homoserinely driven ion current' modulated synaptic gap resistance, the other is measured by source and collector through large chemical molecule signal through diffusion.

Given every data points we artificially assign a small Gaussian envelope over each data set,

1. *Given data set*  $G(\mu, g) \rightarrow x_i$  (1)
2. *Assign Gaussian Group to each data*  $\{x_i | \approx (\mu_i, g_i)$  (2)

3. *Two Major Groups*  $\{G(\min. False Neg. Rate.); G(Positive Rate)\}$  (3)



**Improved by mans of unsupervised learning; The major groups are done by unsupervised learning reviewed based on Boltzmann as follows.**

A well-known short history of unsupervised learning as follows based on Ludwig Boltzmann Concept of Uniformity Called the Entropy as follows

$$S = K_B \text{Log } W; W = \exp\left(\frac{S}{K_B}\right) \quad (4)$$

Learning is a hallmark of Natural Intelligence (NI), among which the understanding of unsupervised learning help increase the speed without checking for Labels, which is a key breakthrough. 2nd Law info energy said: "as energy diffuses, the entropy increases" helping reach the equilibrium- Hubel-Wiesel edges map.

**2nd Law info energy said: "as energy diffuses, the entropy"**

(MHF) that has an internal energy  $E$ , and entropy  $S$ , which operates at the equilibrium temperature  $T_o$ .

$$\min. H \equiv E - T_o S \quad (5)$$

**Thermodynamic learning rule**

**Lemma:** Due to unsupervised learning, the energy cost function is unknown for image processing at remote sensing. The first order

Taylor series becomes 2<sup>nd</sup> order in the smallness, requiring the second order Taylor series expansion, curvature  $C_k$ , to determine the Lagrange error slope vector together with the estimation error which converge self-consistently

$$S = S_{in} + S_{out}; \quad (6)$$

Let us define what do we mean by Big Data Analysis (BDA). There are much more order of magnitude of data set than algebra operation in matrix sensed such as Clinical trial by Kubick WR; Nada Elgendy & Abarek Eliagal Glen Univ in Cairo Egypt.

$$\Delta H_{object} \equiv \Delta E_{object} - T_0 \Delta S_{object} \leq \quad (7)$$

**Proof:**

Let  $S_{Total}$  denote the total entropy of a closed system. Then  $S_{Total}$  is the sum of entropy of reservoir and object,

$$S_{Total} = S_{Reservoir} + S_{object}$$

If the object takes  $\Delta E_{object}$  energy from its surroundings, the entropy change of  $S_{Reservoir}$  will be  $\Delta S_{Reservoir} = -\Delta E / T_0$ , and the total entropy change is

$$\Delta S_{Total} = \Delta S_{Reservoir} + \Delta S_{object} = -\frac{\Delta E_{object}}{T_0} + \Delta S_{object} = -\frac{\Delta E_{object} - T_0 \Delta S_{object}}{T_0} = -\frac{\Delta H_{object}}{T_0} \quad (8)$$

where  $\Delta H_{object} \equiv \Delta E_{object} - T_0 \Delta S_{object}$  is the change of the object's Helmholtz free energy which is an analytic state function defined by  $H = E - T_0 S$ . Note that  $\Delta S_{Total} > 0$  since the total entropy of a closed system is always increasing, and  $\Delta H_{object} \leq 0$  given a positive  $T_0$  Q.E.D.

**Remarks: In this brief review we shall consider** 1) Hebb Product Rule; 2) Helmholtz Free Energy; 3) Boltzmann Entropy

### Hebb learning product rule

Donald Hebb discovered that the neuro-biological synaptic junction learning rule is similar to a pipeline flow, that is proportional to how much goes in and how much comes out the. The Hebb product learning rule between input  $X_i$  and output  $Y_j$

$$W_{i,j} = X_i Y_j$$

What is the unsupervised thermodynamic learning is based on the equilibrium at maximum entropy, or equivalently at the minimum free energy.

It's a systematic way to guess the most probable inverse source solution by directly computing the maximum probability.

Note that by systematic trial and errors, we can de-mix the local mixtures by the MFE principle. There is a finite number of ways that the positive sum of a photon counts can be. Among them, we choose the lowest energy cases: e.g. giving **Ludwig Beethoven** first 3 notes: "5, 5, 1....": We split the sum  $5 = (0+5; 1+4; 2+3; 3+2; 4+1; 5+0)$  in the unit of energy at temperature  $K_B T = 1/40 eV$  for  $T=300^\circ$ ; and find hidden sources tones  $2=3$  and  $3+2$  occurring twice that have the highest canonical probability  $2 \exp(-2/K_B T) \exp(-3/K_B T)$ . In MFE, we might wish to rule out the rare *high energy* cases:  $0+5$  and  $1+4$ , in favor with lower energy but *higher chances* in equilibrium: twice  $2+3$ ; unless other summations involve also these specific pixels.

### Helmholtz MFE

Helmholtz assumed such an open dynamic sub-system within the heat reservoir closed system where Boltzmann heat death at maximum entropy was assumed.

$$\Delta H_{object} \equiv \Delta E_{object} - T_0 \Delta S_{object} \leq \quad \min. H \equiv E - T_0 S$$

**Proof:**

Let  $S_{Total}$  denote the total entropy of a closed system. Then  $S_{Total}$  is the sum of entropy of reservoir and object,

$$S_{Total} = S_{Reservoir} + S_{object}$$

If the object takes  $\Delta E_{object}$  energy from its surroundings, the entropy change of  $S_{Reservoir}$  will be

$$\Delta S_{Reservoir} = -\Delta E / T_0, \text{ and the total entropy change is}$$

$$\Delta S_{Total} = \Delta S_{Reservoir} + \Delta S_{object} = -\frac{\Delta E_{object}}{T_0} + \Delta S_{object} = -\frac{\Delta E_{object} - T_0 \Delta S_{object}}{T_0} = -\frac{\Delta H_{object}}{T_0} \quad (9)$$

where  $\Delta H_{object} \equiv \Delta E_{object} - T_0 \Delta S_{object}$  is the change of the object's Helmholtz free energy which is an analytic state function defined by  $H = E - T_0 S$ . Note that  $\Delta S_{Total} > 0$  since the total entropy of a closed system is always increasing, and  $\Delta H_{object} \leq 0$  given a positive  $T_0$  Q.E.D.

### Conclusion

This thermodynamics learning rule has a long history proposed Candes Romberg and Tao,<sup>1</sup> and Tao<sup>2</sup> Domoho,<sup>3</sup> Miao, Qai, Hsu Jenkins, Cha Landa as well as Szu et al,<sup>4-6</sup> may be a paradigm shift for dealing with spectral image processing with thermodynamics. Various applications have been developed and reported in different journals. It might allow us to consider virtually crossing the full electromagnetic spectrum. Compressive modeling and simulation based on NL LCNN will be published in Optical Engineering (Krapels, Cha, Espinola, Szu). IR triplets for seeing through hot fire and cold dust will be published in IEEE Tran IT (Cha, Abbott, Szu). Thermodynamics physics laws and modern applications will be published in Journal of Modern Physics (Szu, Willey, Cha, Espinola, Krapels). Lots more can happen with your participation in Appendix A BSS by Engineering Filter Approach pixel parallelism. MATLAB pseudo source code is given in Appendix B BSS by Physics Source Approach pixel sequentially, a benchmarked result showed there.<sup>7-13</sup>

### Acknowledgments

Cutting AI applications must minimize the detrimental False Negative Rate (FNR) by means of unsupervised learning Artificial Neural Networks operated at the minimum of Helmholtz free energy, introduced early by INNS scientists Szu et. al.

### Funding

None.

### Conflicts of interest

Author declares that there are no conflicts of interest.

### References

1. Candes EJ, Romberg J, Tao T. Robust uncertainty principle: exact signal reconstruction from highly incomplete frequency information. *IEEE Trans IT*. 2006;52(2):489–509.
2. Candes EJ, Tao T. Near-optimal signal recovery from random projections: universal encoding strategies. *IEEE Trans IT*. 2006;52(12):5406–5425.
3. Donoho D. Compressive sensing. *IEEE Trans IT*. 2006;52(4):1289–1306.
4. Szu H, Hsu C, Moon G, et al. Smartphone household wireless electroencephalogram hat. *Appl Comp Intel Soft Comp*. 2012;2013:1–8.

5. Szu H, Miao L, Qi H. *Unsupervised learning with minimum free energy*. *SPIE Proc* 6576. IN: Independent component analysis, wavelets, unsupervised Nano-biomimetic sensors, and neural networks V (edited by Harold H. Szu, Jack Agee). 2007:657605.
6. Szu H, Hsu C. Landsat spectral unmixing a la super resolution of blind matrix inversion by constraint maxent neural nets. *SPIE Proc*. 1997;3078:147–160.
7. USPTO Patent. Szu H. 7355182 *Infrared multispectral camera and process of using infrared multispectral camera*. 2008; US PTO 7366564. Szu HH, et al. *Nonlinear blind demixing of single pixel underlying radiation sources and digital spectrum local thermometer*. 2008.
8. Szu H, Hsu C, Jenkins J, et al. Capture significant events with neural networks. *Neural Netw*. 2012;29–30:1–7.
9. Appleby R, Coward P, Sanders-Reed JN. Evaluation of a passive millimeter wave imaging for wide detection in degraded visual condition. *SPIE Proc* 7309. 2009. Coward P, Appleby R. Comparison of passive millimeter-wave and IR imagery in a nautical environment. *SPIE Proc* 7309. PMMW Img Tech. 2009:1–8.
10. Cha JH, Abbott AL, Szu HH. Passive ranging redundancy reduction in diurnal weather conditions. *SPIE Proc* 8750. “ICA, Compressive Sampling, Wavelets etc.” (ed. Szu & Dai ) (Baltimore). 2013:1–3.
11. Hsu C, Hsu MK, Cha J, et al. Adaptive compressive sensing camera. *SPIE Proc* 8750. “ICA, Compressive Sampling, Wavelets etc.” (ed. Szu & Dai ) (Baltimore). 2013:1–3.
12. Kubick WR. BDA Lecture Series. *Clinical trial information*. 2012:26–28.
13. Elgendy N, Elragal A. *Big data analytics: A literature review paper*. 2014:214–227.