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Fintech Model: The Random Neural Network with Genetic Algorithm

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Abstract

This paper proposes the Random Neural Network with a new learning algorithm based on the genome model. Following genetics, where information is transmitted in the combination of genes rather than the genes themselves, the proposed genetic model transmits information to future generations in the network weights rather than the neurons. The innovative genetic algorithm is implanted in a complex Deep Learning structure that emulates the human brain: Reinforcement Learning takes fast local current decisions, Deep Learning Clusters provide identity and memory, Deep Learning Management Clusters take final strategic decisions and finally Genetic Learning transmits the information learned to future generations. The presented algorithm and Deep Learning structure has been applied and validated in a Fintech Model; a Smart Investment application where an Intelligent Bankers are specialised in Buy and Sell decisions on several Assets, Markets and Risks. The obtained results are promising; the proposed model combines human brain and genetics with Deep Learning structure based on the Random Neural Network model where biology; similar as Artificial Intelligence is learning gradually and continuously while adapting to the environment.

Keywords: "Genetic Learning; Deep Learning Clusters; Reinforcement Learning; Random Neural Network; Smart Investment; Fintech"

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1. Introduction

Biology learns continuously and gradually while it adapts to the environment using genetic alterations to produce innovative complex structures in organisms [1], the current arrangement of the organisms outlines the type and level of future genetic variation that will deliver a better adaption to the environment or increased reward to a goal function. Random genetic changes have an increased probability to be successful in organisms that change in a systematic and modular routine where the new structures acquire the same set of sub goals in different combinations; therefore they not only remember their reward evolution but also generalize goal functions to successfully adapt future environments [2]. The adaptations learned from the living organisms affect and guide evolution even though the characteristics acquired are not transmitted to the genome [3], however, its gene functions are altered and transmitted to the new generation; this enables learning organisms to evolve much faster.

This paper proposes a new genetic learning algorithm on Section 3 based on the genome and evolution; where the information transmitted to new generations is learned when interacting and adapting to the environment using reinforcement and deep learning respectively. Information in the proposed genetic algorithm is transmitted in the network weights through the different combinations of four different nodes (C,G,A,T) rather than the value of nodes themselves where the output layer of nodes replicates the input layer as the genome. This innovative genetic algorithm is inserted in a complex deep learning structure that emulates the human brain on Section 4: Reinforcement Learning takes fast local current decisions, Deep Learning clusters provide identity and memory, Deep Learning Management Clusters takes final strategic decisions and finally Genetic Learning transmits the information learned to future generations. This innovative model has been applied and validated in Fintech, a Smart Investment Model on Section 5; an Intelligent Banker that performs Buy and Sell decisions on several assets with an associated market and risk. The results shown on Section 6 are promising; the Intelligent Banker takes the right decisions, learns the variable asset price, makes profits on specific markets at minimum risk and finally it transmits the information learned to future generations.

2. Related Work

Genetic Algorithms have been proposed as method to increase learning. Arifovic, J. [4] analyses genetic algorithms in inflationary economies. Kim, K. et al [5] uses a genetic Algorithm to feature discretization in artificial neural networks for the prediction of stock market index. Ticona, W. et al [6] applies a hybrid model based on Genetic algorithm and Neural Networks to forecast Tax Collection. Hossain, D. et al [7] present a Genetic Algorithm based Deep Learning Method. Sremath, S. [8] and David, O. et al [9] review of the latest deep learning structures and evolutionary algorithms that can be used to train them.

Artificial Neural Networks have been applied to make financial predictions. Leshno, M. et al [10] evaluate the bankruptcy prediction capability of several neural network models based on the firm's financial reports. Chen, W. et al [11] uses Artificial Neural Networks for a financial distress prediction model. Kara, Y. et al [12] apply an Artificial Neural Network to predict the direction of Stock Market index movement. Guresen, E. [13] evaluates the effectiveness of neural network models in stock market predictions. Zhang, G. et al [14] analyse Artificial Neural Networks in bankruptcy prediction. Kohara, K. et al [15] investigate different ways to use prior knowledge and neural networks to improve multivariate prediction ability. Sheta, A. et al [16] compares Regression, Artificial Neural Networks and Support Vector Machines for predicting the S&P 500 Stock Market Price Index. Tung, T. et al [17] includes Artificial Neural Networks and Fuzzy Logic for market predictions. Pakdaman, M. et al [18] use a feedforward multilayer perceptron and an Elman recurrent Network to predict a company's stock value. Iuhasz, G. et al [19] create a hybrid system based on a multi Agent Architecture to analyse Stock Market behaviour to improve the profitability in a short or medium time period investment. Nicholas, A. et al [20] examine the use of neural networks in stock performance modelling.

3. The Random Neural Network Genetic Deep Learning Model

3.1. The Random Neural Network

The Random Neural Network [21-22] represents more closely how signals are transmitted in many biological neural networks where they travel as spikes or impulses, rather than as analogue signal levels. The RNN is a spiking recurrent stochastic model for neural networks. Its main analytical properties are the "product form" and the existence of the unique network steady state solution. The Random Neural network has been Genetics [23-24].

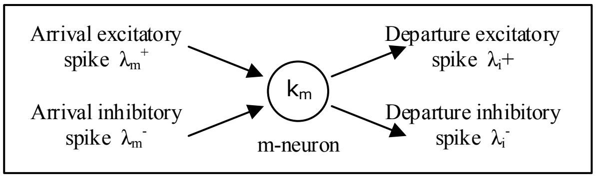

Fig. 1. The Random Neural Network

3.2. The Random Neural Network with Deep Learning clusters

Deep Learning with Random Neural Networks is described by Gelenbe, E. and Yin, Y. [25]. This model is based on the generalized queuing networks with triggered customer movement (G-networks) where customers are either "positive" or "negative" and customers can be moved from queues or leave the network. G-Networks are introduced by Gelenbe, E. [26, 27]; an extension to this model is developed by Gelenbe, E. et al [28] where synchronised interactions of two queues could add a customer in a third queue.

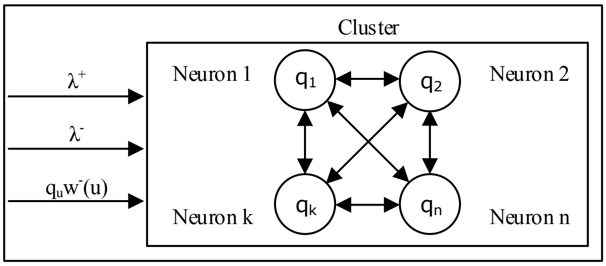

Fig. 2. Cluster of Neurons

3.3. Deep Learning management cluster

The Deep Learning management cluster was proposed by Serrano, W et al [29]. It takes management decisions based on the inputs from different Deep Learning clusters.

3.4. Genetic Learning Algorithm model

The proposed Genetic learning algorithm is based on the auto encoder presented by Gelenbe, E. and Yin, Y. [25] based on two instances of the Network shown on Figure 3, the auto encoder models the genome as it codes the replica of the organism that contains it. Network 1 is formed of U input neurons and C clusters and Network 2 has C input neurons and U clusters.

The organism is represented as a set of data X which is a U vector X Є $[0,1]^U$. The proposed Genetic learning algorithm fixes C to 4 neurons that represent the four different nucleoids G, C, A and T and it also fixes W_1 to generate 4 different types of neurons rather than random values.

Network 1 encodes the organism, it is defined as:

- a U-dimensional vector $q_1 \in [0,1]^U$ that represents the input state q_u for neuron u:

$$q_1=(q^1{}_1, q^1{}_2, \dots, q^1{}_u) \tag{1}$$

- the U x C matrix of weights $w_1^-(u,c)$ from the U input neurons to the neurons in each of the C clusters:

$$W_1 \tag{2}$$

- a C-dimensional vector $Q^1 \in [0,1]^C$ that represents state q_c for the cluster c where $Q^1=\zeta(W_1X)$.

$$Q^1=(Q^1{}_1, Q^1{}_2, \dots, Q^1{}_c) \tag{3}$$

Network 2 decodes the genome, as the pseudo inverse of Network 1, it is defined as:

- a C-dimensional vector $q_2 \in [0,1]^C$ that represents the input state q_c for neuron c with the same value as $Q^1=(Q^1{}_1, Q^1{}_2, \dots, Q^1{}_c)$:

$$q_2=(q^2{}_1, q^2{}_2, \dots, q^2{}_c) \tag{4}$$

- the C x U matrix of weights $w_2^-(c,u)$ from the C input neurons to the neurons in each of the U cells:

$$W_2 \tag{5}$$

- a U-dimensional vector $Q^2 \in [0,1]^U$ that represents the state q_u for the cell u where $Q^2=\zeta(W_2Q^1)$ or $Q^2=\zeta(W_2\,\zeta(XW_1))$

$$Q^2=(q^2{}_1, q^2{}_2, \dots, q^2{}_u) \tag{6}$$

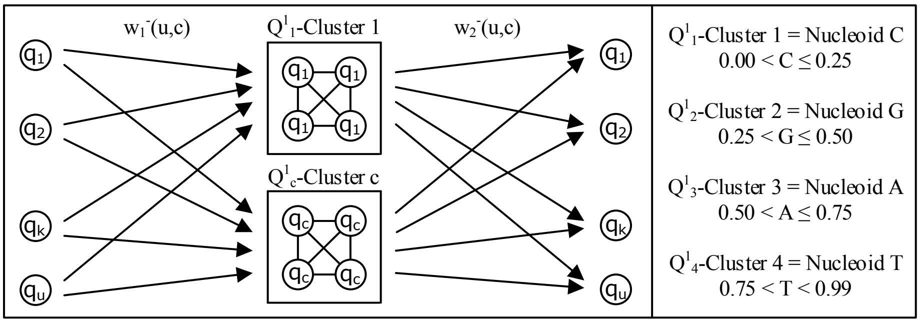

Fig. 3. Genetic Learning Algorithm.

The learning algorithm is the adjustment of W_1 to code the organism X into the four different neurons or nucleoids and then calculate W_2 so that resulting decoded organism Q_2 is the same as the encoded organism X:

$$\min\left\| X-\zeta\left(W_2\zeta(XW_1)\right)\right\| \text{ s.t. } W_1 \ge 0 \tag{7}$$

Following the Extreme Learning Machine on [30]; W_2 is calculated as:

$$W_2=\mathrm{pinv}\left(\zeta(XW_1)\right)X \tag{8}$$

Where pinv is the Moore-Penrose pseudoinverse:

$$\mathrm{pinv}(x) = (x^T x) x^T \tag{9}$$

3.5. Reinforcement Learning

The Reinforcement Learning algorithm is used to take fast binary decisions such as investment “Buy or Sell”, it is based on Cognitive Packet Network presented by Gelenbe, E. [11-15]. The Intelligent Banker is formed of two interconnected neurons “q_0 or Buy” and “q_1 or Sell” where the investment decision is taken according to the neuron that has the maximum potential. The state q_0 and q_1 is the probability that it is excited [11-15], these quantities satisfy the following system of non linear equations:

$$q_0 = \frac{\lambda^+(0)}{r(0)+\lambda(0)} \quad q_1 = \frac{\lambda^+(1)}{r(1)+\lambda(1)} \tag{10}$$

where:

$$\begin{aligned} \lambda^+(0) &= q_1 w^+_{10} + \Lambda_0 & \lambda^+(1) &= q_0 w^+_{01} + \Lambda_1 \\ \lambda^-(0) &= q_1 w^-_{10} + \lambda_0 & \lambda^-(1) &= q_0 w^-_{01} + \lambda_1 \\ r(0) &= w^+_{01} + w^-_{01} & r(1) &= w^+_{10} + w^-_{10} \end{aligned} \tag{11}$$

On the above equations, w^+_{ij} is the rate at which neuron i transmits excitation spikes to neuron j and w^-_{ij} is the rate at which neuron i transmits inhibitory spikes to neuron j in both situations when neuron i is excited. Λ_i and λ_i are the rates of external excitatory and inhibitory signals respectively.

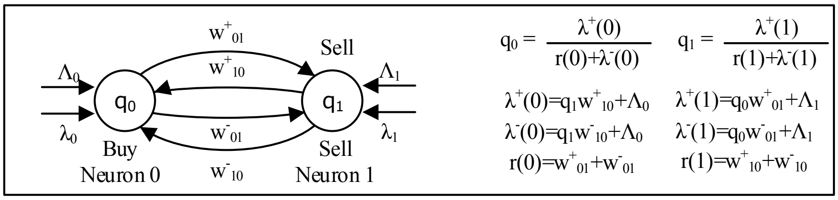

Fig. 5. Reinforcement Learning

The Reward R is based on the economic profit that the Asset Bankers achieve with the decisions they make, successive measured values of the R are denoted by R_l, l=1,2… these are used to compute the Predicted Reward:

$$PR_l = \alpha PR_{l-1} + (1-\alpha)R_l \tag{12}$$

where α represents the investment reward memory.

If the observed measured Reward is greater than the associated Predicted Reward; Reinforcement Learning rewards the decision taken by increasing the network weight that point to it, otherwise; it penalises it.

4. Smart Investment Model

The Smart Investment model, called “GoldAI Sachs”, combines there different learnings: Reinforcement Learning, Deep Learning and Genetic Learning.

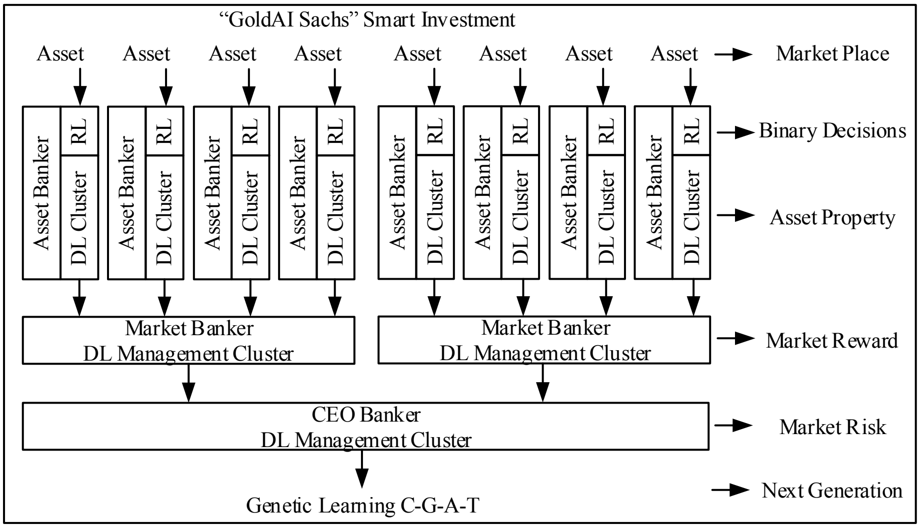

Fig. 6."GoldAI Sachs" Smart Investment Model assets

4.1. Asset Banker Reinforcement Learning

"GoldAI Sachs" is formed of clusters of Intelligent Bankers that take local fast local binary decisions "Buy or Sell" on a specific assets through the interactions and adaptations with the environment where the Reward is the profit made.

4.2. Asset Banker Deep Learning Management Cluster

Each Asset Banker has an associated Deep Learning cluster that memorizes asset identity such as Asset Reward or Profit Prediction, the Asset price and the Asset Price Prediction. Deep Learning is used to memorize key investment values that generate asset identity.

4.3. Market Banker Deep Learning Management Cluster

Asset bankers are dynamically clustered to different properties such as investment reward, risk or market type and managed by a Market Banker Deep Learning Management Cluster that selects the best performing Asset Bankers. The Market Banker Deep Learning Management cluster analyses the predicted reward from its respective Asset Banker Deep Learning Clusters, prioritizes their values based on local market knowledge and finally reports to the CEO Banker Deep Learning Management Cluster the total predicted Profit that its Market can make.

4.4. CEO Banker Deep Learning Management Cluster

Finally, a CEO Banker, "AI Morgan", Deep Learning Management Cluster manages the different Bankers and takes the final investment decisions based on the Market Reward and associated Risk prioritizing markets that generate more reward at a lower Risk as every banker would do. This approach enables decisions based on shared information where Intelligent Bankers work collaborative to achieve a bigger reward.

4.5. CEO Banker Genetic Learning

Genetic Learning transmits the knowledge acquired from the CEO Banker to future Banker generations when "AI Morgan" final career decision is to cash the pension and take early retirement. Genetic Learning is purely based on the Genome as the biological method to transmit information. Reinforcement Learning is applied in decisions, Deep Learning in identity and Genetic Learning in immortality.

5. Experimental Results

"GoldAI Sachs" is evaluated with eight different assets to assess the adaptability and performance of our proposed Smart Investment solution for eleven days. The assets are split into the Bond Market with low risk and slow reward and the Derivative Market with high risk and fast reward. Experiments are carried with very reduced memory α =0.1 where the Reinforcement Learning is first initialized with a Buy Decision.

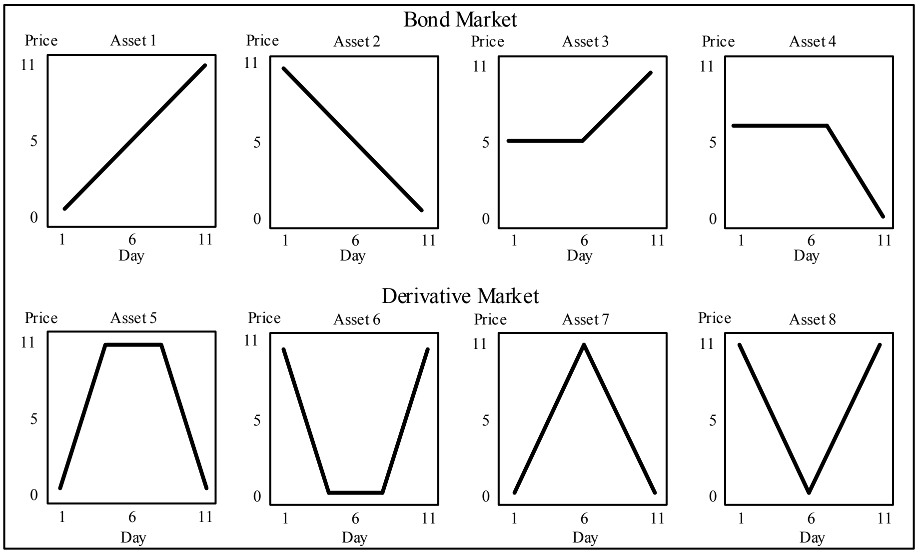

Fig. 7."GoldAI Sachs" Smart Investment Model assets

5.1. Reinforcement Learning Validation

Table 1 represents the average Buy/Sell Potential and the Profit that each Asset Banker makes when buying or selling 100 Assets for 11 days with the Maximum Profit.

Table 1. Asset Banker Reinforcement Learning Validation

Asset	1	2	3	4	5	6	7	8
Buy / Sell Potential	0.53/0.41	0.33/0.45	0.46/0.39	0.36/0.39	0.40/0.41	0.32/0.33	0.45/0.43	0.32/0.36
Profit	1000	800	600	300	2000	1200	1600	800
Maximum Profit	1000	1000	600	500	2000	2000	2000	2000

The Profit made in assets that start downwards such as Asset 2, Asset 4, Asset 6 and Asset 8 is worse than the upwards ones because the Asset Bankers are initialized with a buy decision. The Reinforcement Learning Algorithm adapts very quickly to variable asset prices.

5.2. Deep Learning Cluster Validation

The Asset Banker Deep Learning cluster validation for the eight different Assets during the 11 different days is shown in Table 2. The learning algorithm error Threshold is set at 1.0*10E-25. The first value is the final iteration number for learning algorithm number and the second is the normalized error at 1.0*10E-26.

Table 2. Asset Banker Deep Learning Cluster Validation

Day	Asset 1	Asset 2	Asset 3	Asset 4	Asset 5	Asset 6	Asset 7	Asset 8
2	It: 1725 E: 9.87	It: 983 E: 9.70	It: 663 E: 9.48	It: 519 E: 9.38	It: 389 E: 9.51	It: 416 E: 9.79	It: 302 E: 6.59	It: 337 E: 9.92
3	It: 1720 E: 9.73	It: 889 E: 9.74	It: 663 E: 9.48	It: 519 E: 9.38	It: 367 E: 9.86	It: 324 E: 8.10	It: 300 E: 7.90	It: 277 E: 8.81
4	It: 1720 E: 9.77	It: 886 E: 9.47	It: 663 E: 9.48	It: 519 E: 9.38	It: 366 E: 9.95	It: 321 E: 9.00	It: 299 E: 9.81	It: 273 E: 9.70
5	It: 1718 E: 9.93	It: 884 E: 9.69	It: 663 E: 9.48	It: 519 E: 9.38	It: 386 E: 7.83	It: 352 E: 9.80	It: 300 E: 7.57	It: 273 E: 9.53
6	It: 1718 E: 9.97	It: 884 E: 9.68	It: 628 E: 9.90	It: 519 E: 9.38	It: 429 E: 9.00	It: 373 E: 8.38	It: 300 E: 7.48	It: 287 E: 7.51
7	It: 1720 E: 9.83	It: 884 E: 9.16	It: 627 E: 9.10	It: 547 E: 9.26	It: 431 E: 9.81	It: 374 E: 8.78	It: 370 E: 9.33	It: 336 E: 9.77
8	It: 1720 E: 9.42	It: 884 E: 9.49	It: 627 E: 9.46	It: 494 E: 8.82	It: 388 E: 9.89	It: 409 E: 9.50	It: 303 E: 9.11	It: 335 E: 8.75
9	It: 1720 E: 9.41	It: 884 E: 9.57	It: 627 E: 9.17	It: 491 E: 8.95	It: 367 E: 9.77	It: 324 E: 8.55	It: 300 E: 8.38	It: 277 E: 9.54
10	It: 1719 E: 9.89	It: 886 E: 9.11	It: 627 E: 9.12	It: 491 E: 8.29	It: 369 E: 9.94	It: 319 E: 8.34	It: 299 E: 9.87	It: 274 E: 7.56
11	It: 1720 E: 9.74	It: 896 E: 8.21	It: 626 E: 9.55	It: 495 E: 9.99	It: 407 E: 8.76	It: 335 E: 7.38	It: 315 E: 8.07	It: 273 E: 9.83

5.3. Genetic Algorithm Validation

The Genetic Algorithm validation for the four different Nucleoids (C,G,A,T) during the 11 different days is shown in Table 6 with the Genetic Algorithm Error.

Table 3. Genetic Algorithm Validation

Day	Error	Nucleoid-C	Nucleoid-G	Nucleoid-A	Nucleoid-T
2	3.05*10E-31	0.2048	0.3893	0.6295	0.9268
3	5.85*10E-31	0.2026	0.3861	0.6263	0.9259
4	6.78*10E-32	0.2025	0.3859	0.6262	0.9259
5	1.17*10E-31	0.2029	0.3865	0.6267	0.9260
6	4.44*10E-31	0.2033	0.3870	0.6272	0.9262
7	1.29*10E-31	0.2049	0.3894	0.6296	0.9269
8	3.61*10E-31	0.2031	0.3868	0.6271	0.9261
9	2.96*10E-31	0.2021	0.3852	0.6255	0.9257
10	6.90*10E-31	0.2020	0.3851	0.6254	0.9256
11	1.36*10E-31	0.2023	0.3856	0.6259	0.9258

6. Conclusions

This paper has presented a new learning Genetic Algorithm based on the Genome where the information is transmitted in the network weights rather than the neurons. The algorithm has been incremented in an Fintech Application; Smart Investment model that simulates the human brain with reinforcement learning for fast decisions, deep learning to memorize properties to create asset identity, deep learning management clusters to make global decisions and genetic to transmit learning into future generations.

In the Smart Investor Model, "GoldAI Sachs" Asset Banker Reinforcement Learning Algorithm takes the right investment decisions with great adaptability to asset price changes; the profits made by the algorithm makes are close to the maximum achievable figure. The Asset Banker Deep Learning provides asset properties and identity at reduced error with low number of learning iterations. Finally Genetic learning algorithm has a minimum error and it exactly codes and encodes the CEO Banker, "AI Morgan".

Future work will validate our model in a Fintech cryptocurrency environment with real market values. In addition the relevance of memory in investment with its optimum value will be analyzed.

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Appendix: Smart Investment model - Neural Schematic