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Survey on Real Time Financial Signal Representation and Trading Using Recurrent Neural Network

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Abstract
The DRL (deep reinforcement learning) techniques are a combination of DL (deep learning) and RL (reinforcement learning). This field is capable of solve wide range complex decision-making problems that were previously inaccessible to the machine. Thus, now DRL is used in many numbers of new applications in areas such as healthcare, robotics, finance, smart grids, and many more. Here, we study the RDNN (Recurrent Deep Neural Network) structure for the recurrent decision making and environment sensing for the online financial trading management. The proposed techniques are composed of the two parts such as DNN (deep neural network) for learning features and RNN (recurrent neural network) for the RL. For improvement the robustness of market summarization and reducing the uncertainty of the data we are using fuzzy learning technique. In previous study DL has been shown the accurate result in the signal processing problems as recognition of speech and image, DL is designing to real trading applications for the financial signal representation.

***Keywords:** Deep Neural Network, RNN, Reinforcement Learning, Fuzzy Learning, and Financial Signal.*

I. INTRODUCTION

Many of the methods of machine learning or artificial In a recent year, many methods of AI (Artificial Intelligence) or ML (Machine Learning) can be traced back to 1950s. Evolving from the study of computational learning and pattern recognition theory, investigate by the researchers and studied design algorithms that can predict data. In the predictions, the researchers come up with the many ideas of learning techniques that solve problems, which adapts its behavior to maximize the signal from that environment. It is the creation of "a hedonistic" learning of system [1]. The idea behind this training system can be considered adaptive optimal control, currently its call as enhanced learning [2]. To achieve the level of performance and generality as a human, for that it needed to build up and learns knowledge directly from the raw data such as vision, without the manual engineering functions; it can be achieved by an in-depth study of NN (Neural Networks) toils. By combines them, by the use of deep reinforcement training that can create an artificial agent that it calls as "Artificial Intelligence".

In this, we only focus on the recurrent reinforcement and direct reinforcement or to the referring algorithms that don't need to learn the value function for getting the policy. In previous researches, they have proposed the policy gradient algorithms within the Markov's decision-making processed a direct reinforcement to usually refer to any reinforcement learning techniques it does not

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require any study of a value function. Here, we focus on periodic training methods like dynamic programming [3], Q-Learning [4], or TD Learning [5] have been the focused on the most current research these method attempts to learn the value function. The actor-critical methods [6], which are an intermediate link between the methods of direct reinforcement and the value function, consist in the fact that the "critic" studies the function of value; it is used to the updating of parameters of “actor”.

The value function approach described to the cost function has dominated this field for the last thirty years. This technique worked well in the many applications, such as alpha go, training the helicopter. However, the value function technique has a number of limitations. The Q-learning technique is the context of the action discrete state and spaces. In the many situations from this suffers the “curse dimensions”, when Q-learning extends to function approximates, the researchers showed that it does not converge a simple Markov decision-making process. Fragility, which means a small change in the value function, can lead to large policy changes. In the world of trading signals, data can be in the presence of the larger amount of the noise and unsteadiness in data sets, which can cause serious problems for the value functions.

The RRL (recurrent reinforcement learning) technique it providing the immediate feedback for the optimizing strategy, the ability of the producing real value actions or weighted naturally without any resorting for the discretization needed for cost function approach. There are many other approaches available such as portfolio optimization approach, evolution strategies and linear matrix inequalities that rely on covariance matrix forecasting and optimization. For all optimization tasks or in reinforcement training, it needed a goal, and such a goal can be formulated in terms of risk or reward. Moody et al. it is showing that as it is possible to formulate differential forms of the Sharpe ratio and the deflection coefficient downwards to provide effective online training with recurrent training with reinforcement, Lu showed using a linear matrix Inequalities can beat risk-free bet, and Dan et al. shows that the max return value is used as a target in recurrent reinforcement learning and it used when deep learning transformations initialize functions.

II. LITERATURE REVIEW

In here we present the review of literature financial signal representation and trading in details:
Ahmet Murat Ozbayoglu, Omer BeratSezer [1],the author proposes algorithm-trading model CNN-BI(convolutional neural network with 2-D convolutional neural network)they use 2D image-30-day movement window histogram of the Dow 30 shares, and this algorithm-trading model deep penetration of the neural network.Zekun Shi, JoonSern Lee, Pengqian Yu, IlyaKulyatin, and SakyasinghaDasgupta [2],the author propose a deep reinforcement learning (RL) architecture using an autonomous trading agent so that investment decision and action can be autonomously carried out based on Global Goals.HuangChien Yi [3], in this paper, we propose a model of Markov decision-making process (MDP), suitable for solving the problem of financial trading, and it is solved using a modern algorithm of deep recurrent Q-network (DRQN). They offer several modifications of the existing learning algorithm to make it more suitable in financial trading, namely.Shiyue, Dong

W. Zhang, Y. Wang, S. Li,and Q. Zhou [4], in this article, authors suggest using a deep Q-learning to build end-to-end Deep Q-trade system, which will automatically determine which position to hold every moment of trading.Timothy P. Lillicrap and Jonathan J. Hunt [5] they propose a technique for automatic control of high-speed trains for this they used a combining approach of tracking/braking dynamics and longitudinal aerodynamics on the basis of velocity and reliable position of tracking in face tracking/breaking failures. In this, they combine actor-critic with the Deep-Q-Networks. Y.

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Zhu and D. Zhao [6] they PAC (probably approximately correct) algorithm is used to the continuous deterministic system. They also introduce some new techniques such as NUQF, NUQI Operators, and Escape Event. For the operator mapping used NUQI (Near Upper Q Iteration). In this, they use the PAC algorithm with the MEC (Multisamples in Each Cell) and the function of this MEC algorithm is to collect online observed samples.

V. Mnih [7] they used training deep neural networks for developing novel artificial agents it is deep Q-networks it learns from the high dimensional sensor input for this they used 'end-to-end' reinforcement learning mechanism. Reinforcement learning called as unstable or even to diverge. They also divide the work between high dimension sensory input and action and result are shows that the learning to the excel in the diverse array is a challenging task. In this [8] they present a new RL (Reinforcement Learning) techniques for the algorithm problems in trading and they also define classical RL problem framework. Aim of this approach to optimizing agent performance within an unknown environment. Y. D. Song and Q. Song [9] they used a deep Q-learning for the addressing braking/traction failures in braking and traction phases in high-speed trains. An actor-critical and model learning algorithm based on a deterministic policy gradient operating on continuous action spaces is presented. Deng Y. and Dai Qionghai [10] they propose an LHR (Long Sum Heuristic Recovery) for learning low ranked structures from the corrupted data. For this, they used l1 norm for the measuring sparseness. A. Graves and A. R. Mohamed [11] in this they combine deep bidirectional long short term memory with RNNs for the speech reorganization. RNN gives a good result for the speech reorganization. Deng, Y., and Wang Y. [12] they showed the DNN-Hidden Markov (deep neural network hidden Markov) technique is the main component of this model it trained DNN to generate the distribution on senones (Tied Triphone State) as its output, and it described method of how to apply CD-DNN-HMM with the LVSR, and analyzed modeling effect of the various models on the performance. In this, they also verify the effectiveness of this framework with the LPC algorithm.

G. E. Dahl and D. Yu [13] they present RNNs (recurrent neural networks) powerful models of the sequential data. The end-to-end training model like the connectionist temporal classification, it is the combination of the long short-term memory with the RNN architecture and these methods that train RNN to find sequence label problems in the alignment of input and output is unknown, provide cutting edge results in handwritten recognition and prove especially real. Liang Jiuzhen, Song Wei, and Wang Mei, [14] in this they present a technique for the prediction of the stock price for this they used procedural neural network model (PNN). This PNN approach is compared with the traditional approach such as HMM (Hidden Markov Model), SVM (Support Vector Machine) and Back- propagation Neural Networks. Yang Jianchao, Gong Yihong, and Huang Thomas, [15] they present a new technique which is an extended version of the SPM method for representation of spatial pyramid images based on the SIFT feature. In this, they used three class of SPM such as LSPM, KSPM, and ScSPM.LeeHonglak, Grosse Roger, and Ng Andrew [16] they propose the technology in translation invariant to support efficient bottom-up and top-down probabilistic reasoning. This technique is based on probabilistic max-pooling; it is used to reduce the representation in higher-layers stochastically in a healthy way. Experiment with algorithms to learn useful levels of built-in visuals and other object parts, UN-labeled images of objects in the natural landscape. BengioYoshua, [17], they present the learning algorithm of deep architecture and the limited volume used to build deeper models, especially deep belief networks.

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Dempster and V. Leemans [18] they develop ARL (adaptive reinforcement learning) technique for automated trading. This technique is developed for the trading the FX market and selects the machine learning technique RRL as an algorithm which becomes the basis of ARL which consists of risk management overlay, machine learning technique, and dynamic utility optimization layer. Kal K. Ang and QuekChal [19] propose the RSPOP (Rough set based pseudo outer product) for the trading decision making and it is based on technical analysis. This experiment is conducted on the real-time market dataset such as DBS and NOL stock prices and this dataset contains 4000 data-points in the training phase.

III. COMPARATIVE ANANLYSIS

Table1. ComparativeAnalysis Table

Sr. No	Author Name	Study	Conclusion
1.	O. BeratSezer, A. M.Ozbayoglu [1]	Here they use a 2D convolutional neural network to create an algorithmic trading model CNN-BI(Convolutional Neural Network with Bar Images) using a 2-D CNN.	The results show that the model was able to outperform the buy-and-hold strategy, especially in trendless or bearish markets.
2.	Pengqian Y, J. S. Lee, I. Kulyatin, Z. Shi, and S. Dasgupta [2]	This paper proposes a deep reinforcement learning (RL) architecture using an autonomous trading agent.	Using historical data on actual capital markets, they simulate transactions with practical constraints and demonstrate that the proposed model is robust, cost-effective and risk-sensitive, relative to core trading strategies and RL agents without a prior work model.
3.	H.Chien Yi [3]	Here to offer a few modifications to the existing learning algorithm to make it more suitable under the financial trading environment	They have a substantially smaller replay memory (although in size) compared to what is used in modern deep reinforcement learning algorithms (often millions in size). They provide agents access to mitigate the need for random discovery by providing extra feedback signals for every action.
4.	Y. Wang, D. Wang, S. Zhang, Y.Feng, S. Li and Q. Zhou [4]	In this paper, we propose to adopt deep-Q learning in order to construct an end-to-end Deep-Q trading system which can automatically determine which position should be held in each trade.	The experimental results showed that the Deep Q trading system was more effective than q-learning, as well as the strategies learned by the Recurrent reinforcement learning (RRL).
5.	T. P. Lillicrap and J.J. Hunt [5]	Here we study they propose a technique for automatic control of high-speed trains for this they used a combining approach of tracking/braking dynamics and longitudinal aerodynamics on the basis of velocity and reliable position of tracking in face tracking/breaking failures.	For this experiment, they use high-dimensional rendering data and low-dimension state descriptors such as positions and joint angles. This technique has many benefits in data efficiency and this technique is applicable for real-world manipulation of robotic.

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6.	Y. Zhu and D. Zhao [6]	The PAC (probably approximately correct) technique using for the continuous deterministic system. In this, they introduce some new techniques such as NUQF, NUQI Operators, and Escape Event.	In this, they compared the proposed algorithm with the conventional online RL algorithm and this algorithm required less time as compared to the conventional RL algorithm. This algorithm repeats the process until the satisfaction and it stops automatically.
7.	V. Mnih [7]	They developed artificial agents used in the Deep Neural Network (DNN) 9-11, directly using the end-to-end reinforcement training, high-dimensional so they tested this agent in the complex domain of the classic Atari2600games12.	They also divide the work between high dimension sensory input and action and result show that the learning to excel at diverse array is a challenging task.
8.	C. James [8]	They present a new RL (Reinforcement Learning) technique for the algorithm problems in trading and they also define classical RL problem framework.	They used a State-of-Art method which is based on the Least-Square Temporal difference learning. They find out the success of this approach in the foreign exchange market and they also identified limitations.
9.	Y. Song and Song Q. [9]	They used a deep Q-learning for the addressing braking/traction failures in braking and traction phases in high-speed trains.	The evaluation result of this technique shows that the proposed technique is applicable to the real application.
10.	Deng Y. and Dai Qionghai [10]	They propose an LHR (Long Sum Heuristic Recovery) for learning low ranked structures from the corrupted data.	The LHR is used for computing stock clustering and low-rank matrix for the motion segmentation. System result shows that this model performance is better than previous l1 based method.
11.	A. Graves, and A. R. Mohamed [11]	In this, they present the functionality of RNNS and provide some of the expressions that have been proving that this technique is very effective for the deep networks and it flexible to use of long-range contexts.	Analysis of the results shows the combination of the end-to-end training and deep bi-directional long-term short-term memory RNNs with body weight noise is the degree of large speech recognition dictionaries, the next obvious step now in the recognition of phonemes in the TIMIT database.
12.	Deng, Y., and Wang Y. [12]	They showed the DNNHM technique is the main component of this model it trained DNN to generate the distribution on senones (tied triphone state) as its output and it described the method of how to apply CD-DNN-HMM to the LVSR and analyzed the modeling effect of various models on the performance.	The absolute sentence accuracy improvements are achieved by using these CD-GMM-HMM techniques, for this they used MPE (Minimum Telephone Error Rate) and it gives maximum error rate 5.8% and 9. 2 % or 16. 0 % respectively.

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13.	Dahl G. E., and D. Yu [13]	This context-sensitive (CD) model is used for speech recognition with a large vocabulary (LVSR), which uses the latest advances in the use of deep persuasion networksto recognize the phone.	The Context-dependent model of the DNN-HMM for LVSR, which provides significantly better results as compared to strong, trained baseline CD-GMM-HMM on the complex dataset business search.
14.	Liang Jiuzhen, Song Wei, and Wang Mei [14]	This they present a technique for the prediction of the stock price for this they used procedural neural network model (PNN).	This model handles a series of time spaces in large scale data and this model is flexible with the problems in time series.
15.	Yang Jianchao, Gong Yihong, and Huang Thomas [15]	In this, they present a new technique which is an extended version of the SPM method for representation of spatial pyramid images based on the SIFT feature	In this, they three methods of SPM implemented and evaluated performance on four datasets Caltech 256, Scenes 15, Caltech 10, and 2008 TRECVID surveillance video and this approach significantly reduce the training and testing complexity by the use of linear SVM.
16.	Lee Honglak, Grosse Roger, and Ng An-drew [16]	They propose the technology in translation invariant to support efficient bottom-up and top-down probabilistic reasoning.	Experiment with algorithms to learn useful levels of built-in visuals and other object parts, UN-labeled images of objects in the natural landscape. They show excellent performance for some visual tasks recognition.
17.	BengioYosh-ua, [17]	They present the learning algorithm of deep architecture and the limited volume used to build deeper models, especially deep belief networks	For building a Deep Multi-Layer Neural Network they used auto associates and this is used to the training phase.
18.	M. Dempster and V. Lee-mans[18]	They develop ARL (adaptive reinforcement learning) for the automated trading technique. This technique is developed for trading the FX market and selects the machine learning technique RRL as an algorithm.	The main advantage of this technique is that dynamically optimization of layer and eliminates the tuning parameters. This technique allows the trade-offs of risk returns made by users in the system. It gives much better performance on high-frequency FX dataset.
19.	Kal K. Ang and QuekChal[19]	Propose RSPOP for the trading decision making and it is based on technical analysis.	This experiment is conducted on the real-time market dataset such as DBS and NOL stock prices and this dataset contains 4000 data-points in the training phase.

IV. System Description

In this, we present the novel technique such as RDNN (Recurrent Deep Neural Network), for this used recurrent decision making and environment sensing for the online financial assert trading. In which RDNN is composed of two sections such as DNN using to feature learning and second is the RNN using to the RL. Improve the robustness of market summarization for that fuzzy learning concept is employing and it reduces the uncertainty from input data.

The main function of DDR technology to analyses the actual financial market data of future contract acquisitions.Here, the real market data collected is directly used to test performance. The effectiveness of this proposed deep RL technique will be compared with other existing trading techniques in a distracting test.Figure 1 shows the proposed system architecture.

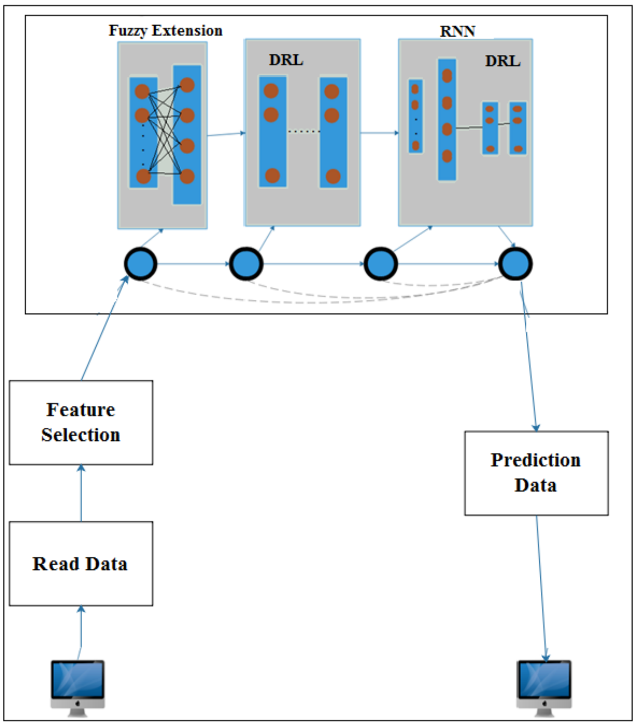

Fig. 1.System Architecture

V. CONCLUSION

Over the past few years, RL has become increasingly popular due to its success in solving complex problems of consistent decision-making. This combination RL with a deep neural network is useful in solving problems in high dimensional state-space. The DRL has been successful in challenging tasks with a lower level of prior knowledge due to its ability to learn different levels of abstractions from data. The entire learning model results are very complex Neural Network (NN) that includes both recurrent and deep structures. To process the recurrent structure, the BPTT (Back-Propagation Trough Time) method is used to deploy RNN as series of the time-dependent stacks without feedback. Form our study we conclude that this strategy increases the effectiveness of learning in finical trading.

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