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Survey on Financial Signal Representation and Trading using Deep Neural Network

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***Abstract*: Financial signal management is the process of constant redistribution of a fund into different financial products. In this paper, we try to address this challenge by introducing a recurrent deep neural network (NN) for real-time financial signal representation and trading. This proposed model is inspired by two biological-related learning concepts of deep learning (DL) and reinforcement learning (RL). In the technique, the DL part automatically senses the dynamic market condition for informative feature learning. Then, the RL module interacts with deep representations and makes trading decisions to accumulate the ultimate rewards in an unknown environment. The learning system is implemented in a complex NN that exhibits both the deep and recurrent structures. We propose a task-aware back propagation through time method to cope with the gradient vanishing issue in deep training. The robustness of the neural system is verified on both the stock and the commodity future markets under broad testing conditions.**

***Index Terms*: Reinforcement Learning, Recurrent Deep Neural Network, Deep learning, High Frequency Trading, Financial Market.**

I. INTRODUCTION

Portfolio management is the decision making process of continuously reallocating an amount of fund into a number of different financial investment products, aiming to maximize the return while restraining the risk. Traditional portfolio management methods can be classified into four categories, “Follow-the-Winner”, “Follow-the-Loser”, “Pattern-Matching” and “Meta-Learning”[1]. The first two categories are based on prior-constructed financial models, while they may also be assisted by some machine learning techniques for parameter determinations. The performance of these methods is dependent on the validity of the models on different markets. “Pattern-Matching” algorithms predict the next market distribution based on a sample of historical data and explicitly optimizes the portfolio based on the sampled distribution. The last class, “Meta-Learning” method combine multiple strategies of other categories to attain more consistent performance [2].

There are existing deep machine-learning approaches to financial market trading. However, many of them try to predict price movements or trends [3]. With history prices of all assets as its input, a neural network can output a predicted vector of asset prices for the next period. Then the trading agent can act upon this prediction. This idea is straightforward to implement, because it is a supervised learning, or more specifically a regression problem. The performance of these price-prediction-based algorithms, however, highly depends on the degree of prediction accuracy, but it turns out that future market prices are difficult to predict. Furthermore, price predictions are not market actions, converting them into actions requires additional layer of logic. If this layer is a hand-coded, then the whole approach is not fully machine learning, and thus is not very extensible or adaptable. For example, it is difficult for a prediction-based network to consider transaction cost as a risk factor.

Previous successful attempts of model-free and fully machine-learning schemes to the algorithmic trading problem, without predicting future prices, are treating the problem as a Reinforcement Learning (RL) one. These include Moody and Saffel , Dempster and Leemans, Cumming , and the recent deep RL utilization by Deng et al. (2017). These RL algorithms output discrete trading signals on an asset. Being limited to single-asset trading, they are not applicable to general portfolio management problems, where trading agents manage multiple assets. Deep RL is lately drawing much attention due to its remarkable achievements in playing video games and board games. These are RL problems with discrete action spaces, and cannot be directly applied to portfolio selection problems, where actions are continuous. Although market actions can be discretized, discretization is considered a major drawback, because discrete actions come with unknown risks. For instance, one extreme discrete action may be defined as investing all the capital into one asset, without spreading the risk to the rest of the market. In addition, discretization scales badly.

II. LITERATURE REVIEW

Here we discussed the literature review of existing techniques:

In this paper [1] Probably Approximately Correct (PAC) algorithm are using for the continuous deterministic system. In this they combining the state aggregation techniques and efficient exploration principle it is make a high utilization of online observed samples. In this they are using a grid to the partitioning continuous state space into the different types of cells for saving samples. Near-Upper Q operator is defining in this for Near-Upper Q function use of sampling in the cell. A simulation study shows that it is better performance than the other similar PAC algorithms.

In paper [2] they using training deep neural networks for developing novel artificial agent it is deep O-networks it can be learn from the high dimensional sensory input for this they using End-To-End reinforcement learning. Reinforcement learning is also called as unstable or even to diverge. In this they divide the work between high dimension sensory input and action and result are shows that the learning to excel at diverse array is challenging task.

James Cumming [3] reducing trading latency by purchasing highly demanded property as near to stock exchanges as possible to continuously honing technical methods over many years, both market participants and academic researchers are constantly seeking novel and successful methods to help them achieve greater success. In this they propose a reinforcement learning approach for algorithm trading problem in which they defining classical reinforcement learning problem framework. Aim of this techniques to optimizing agent performance within the unknown environment. In this they use a State-of-Art method which is based on the Least-Square Temporal difference learning. They evaluate the success of this approach in foreign exchange market identified the limitations of this.

In this paper [4] they using a deep Q-learning are using. Present actor-critic and model learning algorithm which is based on deterministic policy gradient which are operating on the continuous action spaces. Also they using machine learning algorithm hyper-parameter and network architecture which is solves problems such as dexterous manipulation, cart pole swing-up, car driving, and legged locomotion.
In the train controlling advanced control is key technology for the safe and reliable operation of high speed trains. In this paper [5] they presenting a technique for automatic control of high speed trains using a combine approach of tracking/braking dynamics and longitudinal aerodynamics with basis of reliable position and velocity of tracking in face breaking/tracking failures. Controller used a so called Virtual Parameter based Brake stepping adaptive control method which has some features namely inherent coupling effects are take in to the accounts as a result of combining both longitudinal and traction/braking dynamics; 2) fully parameter independent rather than partially parameter independent control algorithms are derived; and 3) closed-loop tracking stability of the overall system is ensured under unnoticeable time-varying traction/braking failures..

In this paper [6] signal processing and machine learning recovering of intrinsic data structure from corrupted is an important. In this they propose a Long sum Heuristic Recovery (LHR) for learning essential low ranked structure from the corrupted data. In this they use l1 norm for the measuring sparseness. For this they use Robust Principal Component Analysis (RPCA) and Low-Rank R representation (LRR) and also compare performance LHR to the benchmark principal component pursuit (PCP) simulation and practical performance. LHR are used to compute the low rank representation matrix for motion segmentation and stock clustering. System result shows that the Log-Sum model performance better than the l1 based method.

In this paper [7] they introduce framework to fuse noisy point clouds from multi-view images of the same object. Solving classical vision problem they use signal processing technique known as Matrix Completion. In this they construct initial incomplete matrix from observed point clouds by all cameras, with invisible points by any camera denoted as unknown entries. The observed points corresponding to the same object point are put into the same row. When properly completed, the recovered matrix should have rank one, since all the columns describe the same object. Therefore, an intuitive approach to complete the matrix is by minimizing its rank subject to consistency with observed entries. In order to improve the fusion accuracy they propose general noisy matrix completion method called Log-Sum Penalty Completion (LPC), which is particularly effective in removing outliers. Based on the Majorization–Minimization (MM) algorithm, the non-convex LPC problem is effectively solved by a sequence of convex optimizations.

III. Comparative Analysis

Sr. No.	Paper Name	Author	Method Proposed	Limitations
1.	MEC-A Near-Optimal Online Reinforcement Learning Algorithm for Continuous Deterministic Systems	Y. Zhu and D. Zhao	Probably approximately correct (PAC) algorithm for continuous deterministic systems without relying on any system dynamics is proposed	They cannot give a rigorous theoretical analysis of the length they need for the running
2.	Human level control through deep reinforcement learning	V. Mnih and Koray Kavukcuoglu	A deep Q-network (DQN), which is able to combine reinforcement learning with a class of artificial neural network16 known as deep neural networks.	Experimental result shows that the performance of this technique is not good.

3.	An Investigation into the Use of Reinforcement Learning Techniques within the Algorithmic Trading Domain	James Cumming, and Dr. Dalal Alrajeh	Reinforcement learning approach to the algorithmic trading problem Which dene in terms of the classic reinforcement learning problem framework.	If there is a failure of the systems then the algorithm may not be able to recover its opening positions and this could lead to large losses.
4.	Continuous Control with Deep Reinforcement Learning	] Timothy P. Lillicrap and Jonathan J. Hunt	Actor-critic, model-free algorithm based on the deterministic policy gradient that can operate over continuous action spaces.	Limitation of this technique is that the DDPG requires a large number of training episodes to find solutions.
5.	Fault-Tolerant Adaptive Control of High-Speed Trains Under Traction/Braking Failures: A Virtual Parameter Based Approach	Y. D. Song and Q. Song	Automated train control scheme for high-speed trains with combined longitudinal aerodynamics and tracking/braking dynamics, with special emphasis on reliable position and velocity tracking in the face of traction/braking failures	Limitation of this is that the initialization data will not be used for out-of-sample tests.
6.	Low-Rank Structure Learning via Non-Convex Heuristic Recovery	Y. Deng and Q. Dai	Nonconvex framework to learn the essential low-rank structure from corrupted data. Different from traditional approaches, which directly utilizes convex norms to measure the sparseness	Each inner programming requires many loops to get to the optimum.
7.	Noisy Depth Maps Fusion for Multi view Stereo via Matrix Completion	Y. Deng, Q. Dai, and Z. Zhang, and Y. Wang	Formulation for matrix completion, called LPC, which achieves remarkable improvements in removing noises especially outliers in the rough point clouds	In this one critical problem that may hinder the application of the proposed method for practical applications is how to deal with extremely large point clouds.

Table.1 Survey Table

IV. CONCLUSION

In this paper we introduce complementary deep learning into typical DRL framework for financial signal processing and online treading. In this we are going to use two techniques known as technical indictor free treading system function this is selecting feature from the large amount of candidate. In this automatic feature learning mechanism of deep learning are using. For the financial signals finding using a fuzzy learning into the deep learning model it reduces the uncertainty in original time series.

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