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An Efficient method for optimizing the stock market prediction through the machine learning technique

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Abstract:

Stock market movements are becoming ambiguous for the investors due to its nature of influential factors. The risk can be reducing through the process of machine learning and deep learning algorithms. The RTP process is given input to reinforcement learning (RL) agent that provides the promising results for optimization process. Hyper parameter optimization is considered as more accurate forecasting model for evaluating Technical indicators and fundamentals. The stability of model has been demonstrated in terms of changes in feature importance.

Keywords: Machine Learning, CNN, Rainbow, Reinforcement algorithm.

1 Introduction

Deep learning has be converted into a capable way to model the convolution of stock movements. It allow us to capture non-linear data movements, to relate large data in order to reduce noise data. At the same time, it is difficult to select hyper parameters to which are used at resulting models, in order to obtain optimal model there should be model to select hyper parameters based on small change. To solve the above problem hyper parameters optimization in machine learning can be used for better configuration like SMAC,TPE and sprearmint [1]. Because of HPO systematic manner and automatic processing it has been consider as enormously powerful approach[2][3]. By considering large data set HPO avoid over fitting stock related data is the time-ordered. A key element for this increasing interest is connected to the inspiring successes of deep learning (DL) techniques which are based on deep neural networks (DNN) - mathematical models directly inspire by the human brain structure. These precise techniques are these days the situation of the art in many function such as speech recognition, image classification or natural language processing. In parallel to DL, one more field of research in recent times adds much more interest from the research society: deep reinforcement learning (DRL). This family of techniques is apprehensive with the learning development of an intelligent agent using DL techniques to simplify the information achieve from the interaction with the environment. The many current successes of DRL techniques highlight their potential to solve difficult in order to decision making problems, Nowadays, an rising industry which is increasing enormously fast is the financial technology industry, commonly referred by the contraction of financial technology. The objective of financial technology: to extensively take advantage of technology in order to innovate and extend activities in finance. In the upcoming years, the stock market industry is probable to improvement in the system lots of decision-making problems connected to the financial sector are deal with, comprise the problems convey to trading, investment, risk management, portfolio management, fraud detection and financial advising, to quote a few. Such complex decision making difficulty are mainly to explain as they normally have a sequential environment and are highly Stochastic, with an condition moderately evident and potentially adversarial. Traders utilize the technical analysis for entry and exit points. Fundamental analysis is considering for exploratory the stock real or correct market value. Machine learning algorithms make utilize for make routine processing of given data by using the variety of factors like determinate the price at the end-of day which supply related news. The recent technique called Convolution neural networks (CNN)[11] is used for extraction of features. We aspire to current the CNN-based structure all along with in particular dedicatedly propose CNNs. One of the rapid increasing industry is financial technology to search innovate in finance by using decision making. This paper includes the technical literature with algorithms solution with AI support solution with convolution neural network and merges with reinforcement learning method. This paper gives the new prediction scheme to progress the prediction method for stock markets. The outcome of STPM is given to reinforcement learning an (RL) agent which is an artificial intelligence strategy provides the promising result. In using reinforcement learning the most advancement algorithm such as Rainbow is applied for optimization process.

Literature Review: In general usage of individual bivariate regressions having one variable at a given time is defined in Goyal and Welch (GW) predictor variables [6]. Multivariate regression which has full set of GW predictors for the purpose of defining bivariate regression [7][8][9]. Sidra Mehtab [6] discussed regarding "efficient market hypothesis" for stock price prediction with hybid process for the period of four years. The parameters that are used in this model is "close price" with validation of loss stabilizes. This study has executed the higher capabilities for fetching and training the features with proper training data set. The author thibut [7] has proposed systematic approach for trending stock market they solved through DRL trading process which explained with numerical enhancement for rainbow algorithm. Genetic algorithm optimization [9] is a method of executing the learned and inspired biological brains. Author tries to implement this study in his work for stock data for multi-channel CNN. By means of neural network model the target problem can be resolve quickly [10]. In this paper the CNN output data is optimized by using Random algorithm with controlling.

Optimization Procedure:

The main findings are as follow:

The given input of fundamentals is processed for prediction model are supposed to be over fit the input feature. In an out-of-sample a dropout is more efficient for a positive predictability then batch normalization.

1. Technical analysis is one of the method for price prediction using historical prices and volume Technical analysis widely used by participants [4][5][8].

Time series momentum indicator MOM(m) , it generate the buy signal when price higher than historical price approximately for given year,

$$\mathrm{MOM(m)}=\left\{\begin{matrix} 1\, Buy\,(signal) if\; w_t \geq w_t - m \\ -1\, sell\,(signal) \quad otherwise \end{matrix}\right\}$$

w_t is the index value of time t, and m is the look back period.

Moving average indicator MA(s,l) , contain a signal for download or an upward trend move. Buy signal is emerged when short-term moving average else sell signal is generated.

2.Fundamental indicators: it is generated by [11] for stock market, the variables are as follows, dividend-payout ratio, stock variable, Boot-to-market ratio, net equity expansion(NTS), Treasury Bill rate, Long – term yield, Long term rate of return, Term spread(TMS), Default yield spread , DFY, Default return spread DFR, Inflation (INFL). Data at stock market is obtained from yahoo finance i.e the opening prices, high prices, low prices, adjusted closing price and end of day volume. After gathering complete data, Convert it into arrays with a specific size values like matrix form having input size of 7 as it contains 7 input features. Add first convolution layer with kernels, filters, strides , use_bias, activation, kernel initializer. After initialization of average pooling layer. Replace the input with dense layers and produce the data.

RTP observations:

1. Bring up to date of the existing market information it.
2. Implementation of the policy π(at|it) to acquire action at.
3. Appliance of the allocate deal action at at
4. Next time step t → t + 1, loop back to step 1.

Hyper parameters

Improve our profound learning models. One of the most significant approaches to improve the models is through the hyper boundaries (recorded in Section 5). Once having discovered a specific arrangement of hyper parameters we have to choose when to transform them and when to utilize the definitely known set (investigation versus abuse). Additionally, securities exchange speaks to a nonstop space that relies upon millions boundaries. On the off chance that the RL concludes it will refresh the hyper parameters it will call Bayesian improvement (examined beneath) library that will give the following best expected arrangement of the hyper params.

The hyper parameters that we will track and optimize are:

batch_size : batch size of the LSTM and CNN
cnn_lr: the learning rate of the CNN
strides: the number of strides in the CNN
lrelu_alpha: the alpha for the LeakyReLU in the GAN
batchnorm_momentum: momentum for the batch normalisation in the CNN
padding: the padding in the CNN
kernel_size':1: kernel size in the CNN
dropout: dropout in the LSTM
filters: the initial number of filters

Q-learning — in Q-learning we gain proficiency with the estimation of making a move from a given state. Q-esteem is the normal return subsequent to making the move. We will utilize Rainbow which is a mix of seven Q learning calculations.
Strategy Optimization — in strategy improvement we take in the move to make from a given state. (on the off chance that we use techniques like Actor/Critic) we additionally become familiar with the estimation of being in a given state. We will utilize Proximal Policy Optimization. One vital part of building a RL calculation is precisely setting the prize. It needs to catch all parts of the earth and the specialist's communication with nature. We characterize the prize, R, as:

Reward=2∗lossG+lossD+accuracyG,

Where lossG, accuracyG, and lossD are the Generator's misfortune and precision, and Discriminator's misfortune, individually. The earth is the GAN and the aftereffects of the LSTM preparing. The activity the various operators can take is the manner by which to change the hyper parameters of the GAN's D and G nets. Rainbow (interface) is a Q learning based off-approach profound support learning calculation joining seven calculations together: DQN. DQN is an augmentation of Q learning calculation that utilizes a neural organization to speak to the Q esteem. Like directed (profound) learning, in DQN we train a neural organization and attempt to limit a misfortune work. We train the organization by haphazardly testing advances (state, activity, reward). The layers can be completely associated ones, yet additionally convolution, for instance. Two fold Q Learning. Twofold QL handles a major issue in Q learning, specifically the overestimation inclination. Organized replay. In the vanilla DQN, all advances are put away in a replay support and it consistently tests this cushion. Be that as it may, not all changes are similarly helpful during the learning stage (which additionally makes learning wasteful as more scenes are required). Organized experience replay doesn't test consistently, rather it utilizes a circulation that gives higher likelihood to tests that have had higher Q misfortune in past cycles. Dueling networks. Dueling networks change the Q learning design a little by utilizing two separate streams (for example having two unique scaled down neural organizations). One stream is for the worth and one for the preferred position. The two offer a convolution encoder. The precarious part is the converging of the streams — it utilizes an uncommon aggregator (Wang et al. 2016). (Bit of leeway, equation is A(s,a)=Q(s,a)−V(s), as a rule is a correlation of how great an activity is contrasted with the normal activity for a particular state. Favorable circumstances are at times utilized when an 'off-base' activity can't be punished with negative prize. So preferred position will attempt to additionally remunerate great activities from the normal activities.) Multi-step learning. The huge contrast behind Multi-step learning is that it computes the Q-values utilizing N-step returns (not just the get back from the subsequent stage), which normally ought to be more exact. Distributional RL. Q learning utilizes normal assessed Q-esteem as target esteem. Be that as it may, as a rule the Q-qualities probably won't be the equivalent in various circumstances. Distributional RL can straightforwardly learn (or rough) the dispersion of Q-values instead of averaging them. Once more, the math is substantially more muddled than that, yet for us the advantage is more precise testing of the Q-values. Loud Nets. Essential DQN actualizes a basic ε-ravenous instrument to do investigation. This way to deal with investigation wasteful on occasion. The manner in which Noisy Nets approach this issue is by including a boisterous straight layer. After some time, the organization will figure out how to overlook the commotion (included as a boisterous stream). In any case, this learning comes at various rates in various pieces of the space, taking into account state investigation.

Conclusion:

In this paper, data has been gathered from yahoo finance to predict the stock market price with accuracy and evaluated with different hyper parameters which are given input to the CNN. The reinforcement algorithm is used for efficiency to get optimal solution. Rainbow algorithm has been used for validation by considering fundamental and technical indicators. This model has designed as a first step for better integration with hyper parameters by imposing the prediction accuracy with combination of fundamental and technical indicators.

References:

[1]: Matthias Feurer, Jost Tobias Springenberg, and Frank Hutter. Using meta-learning to initialize bayesian optimization of hyperparameters. In Proceedings of the 2014 International Conference on Meta-learning and Algorithm Selection-Volume 1201, pages.

[2] James Bergstra, Daniel Yamins, and David Daniel Cox. Making a science of model search: Hyperparameter optimization in hundreds of dimensions for vision architecture 2013.

[3] hitectures. 2013. [5] D Sculley, Jasper Snoek, Alex Wiltschko, and Ali Rahimi. Winner's curse? on pace, progress, and empirical rigor,2018.

[4]Seymour Smidt. Amateur Speulators: A Survey of Trading Styles, Information Sources and Patterns of Entry Into and Exit from Commodity-futures Markets by Nonprofessional Speculators. Graduate School of Business and Public Administration, Cornell University, 1965.

[5] Randall S Billingsley and Don M Chance. Benefits and limitations of diversification among commodity trading advisors. Journal of Portfolio Management, 23(1):65, 1996.

[6]. Matteo Hessel. "Rainbow: Combining Improvements in Deep Reinforcement Learning".

[7]. "An Application of Deep Reinforcement Learning to Algorithmic Trading" ,Thibaut Th´eatea, Damien , ErnstaMontefiore Institute, University of Li`ege (All´ee de la d´ecouverte 10, 4000 Li`ege, Belgium).

[8]. William Fung and David A Hsieh. The information content of performance track records: investment style and survivorship bias in the historical returns of commodity trading advisors. Journal of Portfolio Management, 24(1):30–41, 1997.

[9]. "Genetic algorithm-optimized multi-channel convolutional neural network for stock market prediction", Hyejung Chung, Kyung-shik Shin R Springer-Verlag London Ltd., part of SpringerNature 2019.

[10]. Goodfellow I, Bengio Y, Courville A (2016) Deep learning. MIT press, Cambridge.

[11]. Ivo Welch and Amit Goyal. A comprehensive look at the empirical performance of equity premium prediction. The Review of Financial Studies, 21(4):1455–1508, 2007.

[12]. "1D Convolutional Neural Networks and Applications – A Survey", Serkan Kiranyaz1, Onur Avci, Osama Abdeljaber, Turker Ince, Moncef Ga bbouj, Daniel J. Inman.