CS230

Deep Reinforcement Learning Framework for Factor Investing

Pierre. Nowicki[*] npierre9@stanford.edu

Abstract

Deep Learning for finance has always been applied through a wealth of techniques and network architectures to try to predict the evolution of financial instruments and specifically stock markets. A diversity of new sources such as tweets have also being used to gain superior predictive power. We suggest in this document to apply feature knowledge used factor investing to evaluate if a Q-learning network can better identify investments opportunities in the equity markets.

1 Introduction

The investment community has always been interested in integrating new quantitative methods of forecasting markets returns and risks to better navigate the so called "random walk" of price evolution. Several methods such has for example the Kalman filter have been used at identifying and correcting forecasts as the market reveals more information as time updates. Factor investing pioneered by (1) has set the base of Quantitative Investment with the 3 factors: size of firms, book-to-market values and excess return on the market. (2) introduced the concept of the selection of factors with the Information Ratio (IR) that consists of a measure of the value added per unit of risk of each independent factors (Information Coefficient (IC)) times how often that factor can be put in use in a trading setting (Breadth). Thus, historically, factor investing has focused on identifying factors returns and their respective correlations to generate superior returns. Methods have ranged from ordering factor Z-scoring, moving-average z-score as presented in (3).

2 Related work

With the availability of ever more data to financial market, Deep Learning methods present an interesting route to leverage information beyond typical financial information by using new information like sentiment in tweeter feeds. Deep Learning in Finance as presented in (4) and (5) try to identify complex data interactions that could not fit in an econometric model. Deep learning can detect and exploit interactions that could lead to superior factor identification.

Most recently, Deep Reinforcement learning as added an extra layer in which the outpout could be the learning the optimal actions that could achieve superior returns. Thus, this project proposes to analyse a set of Information Coefficient time-series and investigates the benefit of DRL to infer Q-Learning features in managing an investment portfolio.

[*]permanent email: p.nowicki09@alumni.imperial.ac.uk—*Github:https://github.com/PierreNowi/cs230-project*

CS230: Deep Learning, Winter 2019, Stanford University, CA. (LateX template borrowed from NIPS 2017.)

3 Dataset and Features

To build the Deep Learning module, the following time series data has been downloaded from Reuters Datastream:

- Stocks prices (Open/Close/High/Low) of S&P500 stocks constituents and some of their fundamental values (collected as a time series along the prices): Dividends, Earnings, Book-to-Market, Free Cash-flow, EBITDA/EV.
- information for the Q-Learning to base prediction on.
  - S&P500 index and VIX index time-series
  - SP500 and SP500 constituents Stock options times-series, i.e. implied volatility,
  - Interest Rate, 2y-30y curve time-series (this will also be used to discount the reward function),
  - Commodities, mainly gold and WTI crude oil,
  - Credit Derivatives like Itraxx to account for lending environment.

  It is important to extract information that contains market view of the future such as the implied volatility to build effective Q-Learning functions and ensure that the system has access to information rich data. Additionally, for computational reason, we will at the beginning assess 5 stocks representing key industries in the S&P500.
- “Data pre-processing" will simply consist of joining the data along the time axis.

- “Feature extraction" consist in generating the Information Coefficient (IC) time-series (see (2)). It will be a set of constructed for a set of signals z (like price-momentum, forecasted earnings, forward-volatility curve shape) called Jensen α defined as:

  $$\alpha = IC_{i,z} \times \sigma_j \times z \tag{1}$$

  where
  - σ_j is the volatility of the stock j,
  - $IC_{i,z}$ is the information coefficient, i.e. the correlation of the returns of stock j and the values of signals z.
  - z current value of the signals normalised.

  (6) in p282 presents the different methodology and details of integrating the factors into the prediction of the returns through the Information Coefficient with:

  $$IC_{i,z} = IC_{(t,t_+k]} = corr(z_t, r_{(t,t+k]}) \tag{2}$$

  where:
  - z_t represents the factor under consideration at time t,
  - $r_{(t,t+k]}$ represents the returns over $t, t+k$

  The IC is a linear statistic that measures the cross-sectional correlation between a factor and its subsequent realized return. A positive IC indicates a positive relation between the factor and return. A negative IC indicates a negative relation between the factor and return. An alternate specification of this measure is to make z_t the rank of a cross-sectional factor. This calculation is similar to the Spearman rank coefficient. By using the rank of the factor, we focus on the ordering of the factor instead of its value. Ranking the factor value reduces the unduly influence of outliers and reduces the influence of variables with unequal variances. For the same reasons we may also choose to rank the returns instead of using their numerical value. (7) and (8) list an overview of the different methodologies of scoring, scaling and ranking into a quantitative trading model. (9) and (3) quote the results of IC over a time horizon of the different sets of factors for quantitative equity investing ranging from: Value factors, momentum factors. We will here integrate the following classical factors based on the time-series that we have downloaded:
  - Stock Price momentum, (Stock specific)
  - Value factor: Dividend yield. (Stock specific)

- Value factor: EBITDA/EV: Earning Before Interest Debt and Amortization divided by Enterprise Value (Stock specific)
- Options volatility curve (At-the-Money vs Out-the-Money), (Market specific)
- Index Price momentum (Market specific)

The data will be daily mainly with fundamental data weekly. Additionally, a mix of slow frequency IC such as based on earnings will be used alongside higher frequency one like volatility shape curves. Data ranges from 2004 to 2014 to have information prior to 2008-crisis. It is important to have information of different investment regime as information since 2010 will mainly emphasize rise taking into the parameters of the model.

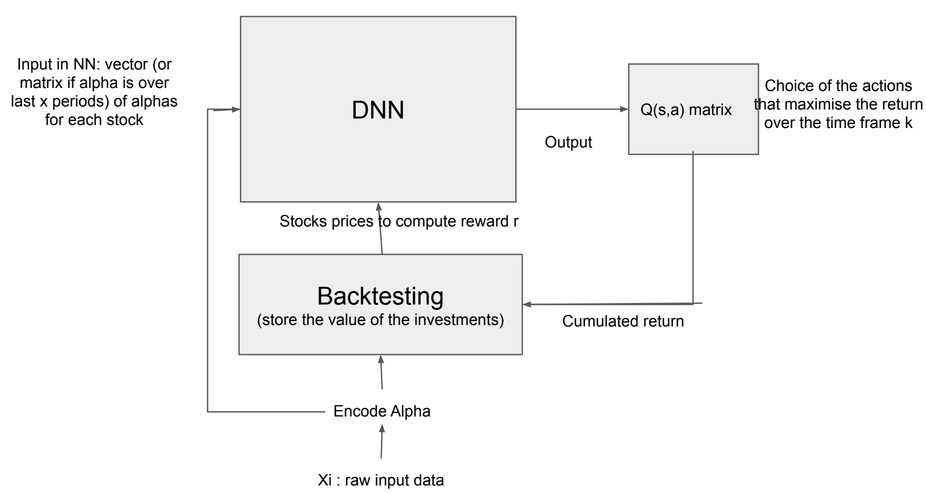
Snapshot of the data and constructed factors on Github repository.

4 Methods

To investigate the methods of Deep Learning in a context of identifying factors and their Information Coefficient to implement factor investing, (10) and (11) point in interesting directions in using Deep Reinforcement Learning. (10) compares different type of Neural Networks (LSTM, CNN, RNN) to build optimal Portfolio through policy functions. (11) is more interesting in focusing in factor investment by building a genetic algorithm to select the factors that will build the portfolio. (10) notably mention the fact that the genetic algorithm is superior in that it will not be subject of several local minimum compared to gradient descent methods.

Thus, I plan to investigate/build the model below that identifies IC factors though a policy function by forecasting rewards with simulation of expected returns.

proposal-4.pdf



- Dimensionality of the features for the input matrix in the DNN: It should be a matrix (or flattened vector when put into network) of dimension:

$$W_{n_m,n_z} \tag{3}$$

with

- n_m: the number of stocks from the S&P500 selected (n_m =10 to start)
- n_z: the number of α-factors under consideration. (could start with the Fama-French 3 factors first, and forward looking data like volatilities after.)

- State: represent the vector of the positions in stock,
- Agent: the agent is simply be the change of positions in the n_m stocks that maximises the returns r_k over the horizon k. That would be based on a Q-table using states of each of the stocks and the actions for each stock (-100,0,100: for reducing, no-change, augmenting positions.)
- Reward function of learning reinforcement. The reward of the model after an action (ie. modification of weights of the positions) can be.

$$r_k = \frac{r^{\pi}_{t+k}}{r^{b}_{t+k}} - 1 \tag{4}$$

  with

  - k: time horizon from prediction,
  - r^{π}_{t+k}: return of the selected portfolio over k periods,
  - r^{b}_{t+k} : return of the benchmark over k periods. In case, we have n_m =10 stocks the benchmark (baseline index) would be a buy-and-hold for those 10 stocks, and in case of the n_m is all the S&P500 constituents than we can use the S&P500 index.

- Model can be evaluated over several metrics since the rewards are cumulated over the time-horizon of the simulation defining the total return. We can thus include the also the running return of the constructed funds and it's max drawdown like

$$r_{projected} = \sum_{i=0}^{T/k} r_i - \beta \times \textit{drawdown} \tag{5}$$

  where we can set several severity parameter β to account for risk preference. Finally a comparison to the return generated from a Buy-and-hold strategy will also indicate if the model can learn and benefit from "market timing".

- transaction costs in the reward: if the period k is several days, 10 days typically before rotation, the market impact of trading in-and-out of positions should be a average-fees percentage applied at each transactions.

5 Experiments/Results/Discussion

The current model is not stabilised yet and does not present satisfaction and needs to be improved. The passive Buy-and-hold strategy delivers better returns and less volatile (Sharpe Ratio).

PS: The Github repository results will be corrected along with some of the stock factors.

6 Conclusion/Future Work

The collection of the financial featured data and the factor choices and computation represent a sizable aspect of the success or failure of this model and thus is close to the approach of classical investment.

The current approach could gain by using Reinforcement Learning architecture such as the Double Q-Network by decoupling the action choice from the target Q-value generation. This could ensure that we put forward looking risk like volatility of options into the Q-value computation. In a same fashion, Asynchronous Actor-Critic Agents could gain from the critic observations of the errors of the agents such as over-trading or risk taking.

References

[1] E. F. Fama, K. R. French, Common risk factors in the returns on stocks and bonds, Journal of Financial Economics 33 (1993) 3–56.

[2] Active portfolio management : A quantitative approach for producing superior returns and selecting superior money managers, McGraw-Hill Education (1999, author =) –.

[3] E. E. Qian, R. H. Hua, E. H. Sorensen, Quantitative equity portfolio management: Modern techniques and applications, Chapman and Hall/CRC Financial Mathematics Series.

[4] J. B. Heatonm, N. G. Polson, J. H. Witte, Deep learning in finance, Booth School of Business, University of Chicago, Department of Mathematics, University College London, (Jan 2018) –doi:arXiv:1602.06561v3.

[5] G. Feng, J. He, N. G. Polson, Deep learning for predicting asset returns, Booth School of Business, University of Chicago, City University of Hong Kong (Apr 2018) –doi:arXiv:1804.09314v2.

[6] F. J. Fabozzi, S. M. Focardi, P. N. Kolm, Quantitative equity investing - techniques and strategies, The Frank J Fabozzi Series.

[7] P. Hervé, Allocation d'actifs - théories et pratiques, Economica vol 2 (2007) 163–167.

[8] T. Roncalli, A. Dubois, La gestion d'actifs quantitative, Economica vol 1 (2010) 450–$_4$60.

[9] L. Chincarini, D. Kim, Quantitative equity portfolio management - an active approach. to portfolio construction and management, McGraw-Hill.

[10] Z. Jiang, D. Xu, J. Liang, A deep reinforcement learning framework for the financial portfolio management problem, Xi'an Jiaotong-Liverpool University (Jul 2017) –doi:arXiv:1706.10059v2.

[11] Z. Wang, N. Leung, Factor selection with deep reinforcement learning for financial forecasting, University of Chicago, McKinley Capital Management (Oct 2018) –doi:https://ssrn.com/abstract=3128678.