Deep Actor-based Reinforcement Learning for Portfolio Management

Aurora Jiekun Feng (jf646)
Joint Work with Yuan Cheng (yc956), Zhengdi Shen (zs267), Pu Yang (py75)

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In our paper, we seek to solve the portfolio management problem through the application of deep reinforcement learning. Specifically, our reinforcement learning, or RL in short, architecture solves for the weights of a preselected collection of assets over multiple periods of time, given a carefully devised set of features as input. We emphasize two points here. First, we are particularly interested in the case where all or some of the assets exhibit high comovement, that is, significantly positive correlation between returns. This is motivated from the intuition that in this case, the resulting asset weights should be very different from those implied by considering each asset individually, which is not able to capture the additional degree of risk incurred by holding correlated assets together. By comparing these results, we can understand the advantage for an agent of considering a portfolio over considering its constituent assets individually. Second, we use an actor-based RL approach, which differs from both the price prediction approach and from the value function-based RL approach, in that it learns the policy, that is, asset weights, directly from features. Our decision to adopt this approach is motivated from two observations, including (1) predicting future price is notoriously hard, and (2) value function incorporates future price by definition.

There is a line of recent works on applying actor-based RL frameworks to algorithmic trading problems, of which two papers are particularly relevant. The first paper [1] analyzes the single-asset trading problem for which the authors introduce a deep learning architecture into the RL framework in [2]. While inspired by the general framework, we notice that the paper considers only a single asset, and that the feature set does not include the policy performance history, which can be valuable information. The second paper [3] addresses both these issues. In addition, the authors use convolutional neural networks to convolve time series input temporally, and use policy gradient algorithms [4] instead of the conventional error backpropagation. Our paper builds upon [3] in two ways, that is, we explicitly account for the effect of asset comovement on the optimal policy, and we allow the assets to be traded at a much higher frequency, for example, 1 minute, compared to 1 day in [3].

In terms of methodology, our initial thought is to apply the frameworks in [1] and [3] to portfolios which may (or may not) consist of assets with high comovement. We are going to extend the frameworks there by refining the feature engineering, for example, one of the features we are going to add is the correlations between asset returns. In terms of data, we are able to download asset price time series from Bloomberg and Thomson One, which provide daily-basis and minute-basis data respectively.

To evaluate the performance of our approach, we are going to compare the profit generated through our framework to that through various other frameworks, including those from [1], [2], [3], and price prediction-based neural networks [5].

References

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