Machine Learning for Quantitative Trading

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Abstract

In contrast to great success of machine learning in many fields like computer vision, natural language processing and robot controlling, little has been achieved in dealing with quantitative investing problem, where the data is both highly noisy and unstable. Despite the difficulties induced by the data, traits of quantitative investment may be utilized to make the problem tractable. We provide two potential paths to better solve quantative investing problem with the aid of machine learning.

Introduction

Financial market involves numerous traders of different backgrounds, making it a noisy and unstable system mixed with various information from different places. Despite the noise in the data, the trading rules are quite simple in the market where price of an asset plays a central role. This is in contrast with fields that deep learning has shown great power where the relationship among the components is complex or *deep* and signal-noise ratio is high. We are interested in what the roles can machine learning play in such a *noisy* and *shallow* system.

Quantitative investment problem is one of the core problems in the field of finance where steady profit is maximized. Previously, this problem is studied from perspectives of operation or statistics[1, 2], whereas we expect to view this problem from a machine learning or control theory perspective[3, 4]. Trait in this problem that different from other machine learning problems is that when agent is not sure about the market, it can do nothing without suffering any loss, whereas in for instance image labeling task an agent has to label every image to minimized the loss.

Therefore, reduce noise and utilize agent's confidence are the two biggest challenges in the field of quantitative investment.

Proposed Paths

We proposed to potential paths that may solve real quantative investment problem. The first follows *observation-prediction-strategy* path. Instead of using currently available machine learning tools to do a simple prediction, we belief an additional prediction indicating confidence may be of great help. The challenge in this path is that a confidence (variance) learning mechanism must be designed instead of traditional mean learning methods.

The second follows directly *observation-transaction* path with the aim of reinforcement learning which is a powerful end-to-end learning tool. Despite criticism on financial application of reinforcement learning such as different reward structure and nonrepeatable nature of market, reinforcment learning is fair potential in its ability of direct strategy learning and potential to incorporate noise reducing components.

Besides the above two possible approaches, traditional machine learning method also yeilds fair result on real market. Figure 1 is the out-sample live result we obtained from real A-share market in China. Transactions and operation schemes are set the same with real environment.

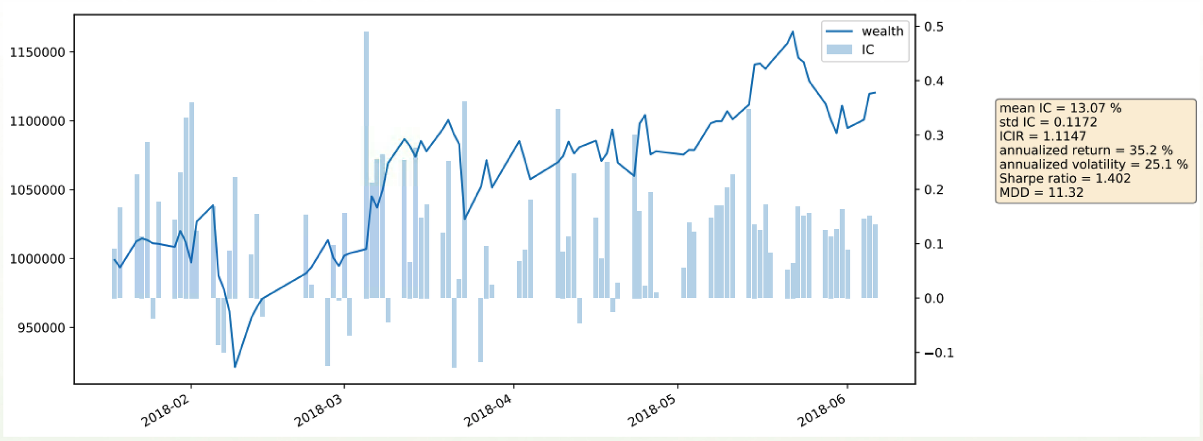

Figure: Out-sample live result on A-share market

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