Course Project Proposal

MF803

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Summary & Application

In this project, we will have a deep research in radial basis function (RBF) system with adaptive input and composite trend representation (AICTR), whose input is adaptive according to the market conditions. We choose SMA, EMA and PP as three main trend representations (trend-following and trend-reversing) and Gaussian basis function as our RBF. For each day, we generate three price prediction series, namely SMA, EMA and PP series, and find the best performing trend as the center of RBF. The center gains more influence in the portfolio updating weight. While the other two trend representations, the influence of each trend in the portfolio update depends on its similarity to the best performing trend, which is quantified by the RBF. As time t goes on, the whole system, with the center of RBF switching among different trend portfolios and keeps to the newest financial environment, returns its updating weight. We continue this process until the end of investment period. Finally, we will check whether our optimized portfolio weight work compared to separate trending representations as well as the benchmark.

Forecasting the future is a permanent topic in quantitative finance field. Trend representation, as one of those forecasting techniques, never fails to fascinate investors in financial market. The goal of our project is to research on a system can effectively which can combine different representations. Combining constructed composite representation and optimization system, we can further construct an updating-weight portfolio, which may be a good strategy for investment.

Data source

The data that we will use is all the composites from S&P 500 from 20090101 to 20181231. The composites are updated every month, and the data comes from
https://gist.github.com/kafkasl/078f2c65c4299d367b57c9835b34c333/

Besides, we acquire the price data from yahoo! finance.

The data from 20090101 to 20161231 will be used to train the PS systems while the rest data from 20161231 to 20181231 will be proposed as a new data challenging for the trained PS systems.

Moreover, the data of S&P 500 from 20090101 to 20181231 itself serves as a benchmark to which the performance of the PS systems will be compared.

Reference

[1] Z.-R. Lai, D.-Q. Dai, C.-X. Ren, and K.-K. Huang, “Radial Basis Functions With Adaptive Input and Composite Trend Representation for Portfolio Selection,” *IEEE Trans. Neural Netw. Learn. Syst.*, to be published. [Online]. Available: https://ieeexplore.ieee.org/document/8356708/, doi:10.1109/TNNLS.2018.2827952.

[2] Z.-R. Lai, D.-Q. Dai, C.-X. Ren, and K.-K. Huang, “A peak price tracking-based learning system for portfolio selection,” *IEEE Trans. Neural Netw. Learn. Syst.*, to be published. [Online]. Available: https://ieeexplore.ieee.org/document/7942104/, doi:10.1109/TNNLS.2017.2705658.

[3] J. Duchi, S. Shalev-Shwartz, Y. Singer, and T. Chandra, “Efficient projections onto the _1-ball for learning in high dimensions,” in *Proc. Int. Conf. Mach. Learn. (ICML)*, 2008, pp. 272–279.

Methodology

1 Propose a set of RBFs with multiple trend representations as their centers, which forms a composite trend representation.

We first find the smallest increasing factor in the time window for each trend portfolio and choose the one with the largest increasing factor among different trend portfolios. By this way, we obtain the best performing trend representation in the worst financial environment, which improves the robustness of the whole system.

1.1 Compute the corresponding trend portfolios $\{\tilde{\mathbf{X}}_{l,t-k},\}_{k=0}^{\omega-1}$ by

$$\tilde{\mathbf{X}}_{l,t+1} = \underset{\mathbf{X}\in\Delta_d}{\mathbf{argmin}} \parallel \mathbf{X} - \hat{\mathbf{X}}_{l,t+1} \parallel^2, \quad l = 1, \dots, L$$

1.2 Compute the recent increasing factors $\{R_{l,t-k},\}_{k=0}^{\omega-1}$ of different trend representations by

$$R_{l,t-k} = \tilde{\mathbf{X}}_{l,t-k}^{\mathrm{T}} \mathbf{X}_{t-k}, \; k = 0, \dots, \omega - 1$$

to evaluate their recent investing performance.

2 Propose a scheme to automatically select the trend representation with the best investing performance as an adaptive input for the RBFs.

2.1 Choose the common adaptive input $\tilde{\mathbf{X}}_{*,t+1}$ by

$$\tilde{\mathbf{X}}_{*,t+1}, * \triangleq \underset{1\le l\le L}{\mathbf{argmax}} \underset{0\le k\le \omega-1}{\mathbf{min}} R_{l,t-k}$$

3 Propose an optimization model to update the portfolio, and design a fast solving algorithm.

Given parameters ω, ϵ, $\{\sigma_l^2\}_{l=1}^L$, compute the trend representations and the actual price relatives in the recent time window $\{\hat{\mathrm{X}}_{l,t-k}, \mathrm{X}_{t-k}\}_{k=0}^{\omega-1}$, and the current portfolio $\hat{\mathbf{b}}_t$

3.1 Compute the radial basis functions $\{\phi_l\}_{l=1}^L$ by

$$\phi_l(\tilde{\mathbf{X}}_{*,t+1}) = e^{\frac{-\|\tilde{\mathbf{X}}_{*,t+1} - \hat{\mathbf{X}}_{l,t+1}\|^2}{2\sigma_l^2}}$$

3.2 If $\left(\mathbf{I} - \frac{1}{d}\mathbf{1}\mathbf{1}^{\mathrm{T}}\right)\hat{\mathbf{X}}_{t+1}\mathbf{\Phi}\mathbf{1}_{(L)} = \mathbf{0}$, then the increment

$$\mathbf{c}_{t+1} = \mathbf{b}_{t+1} - \hat{\mathbf{b}}_t = \mathbf{0}$$

Where the $\hat{\mathrm{X}}_{t+1} = [\hat{\mathrm{X}}_{1,t+1}, \dots, \hat{\mathrm{X}}_{L,t+1}] \in \mathbb{R}^{d\times L}$, $\Phi = [\phi_1, \phi_2, \dots, \phi_L]^{\mathrm{T}}$, $1_{(L)}$ is an L-dimensional vector with elements of 1.

3.3 If $\left(\mathbf{I} - \frac{1}{d}\mathbf{1}\mathbf{1}^{\mathrm{T}}\right)\hat{\mathbf{X}}_{t+1}\mathbf{\Phi}\mathbf{1}_{(L)} \neq \mathbf{0}$, then the increment

$$\mathbf{c}_{t+1} = \frac{\varepsilon\left(\mathbf{I} - \frac{1}{d}\mathbf{1}\mathbf{1}^{\mathrm{T}}\right)\hat{\mathbf{X}}_{t+1}\mathbf{\Phi}\mathbf{1}_{(L)}}{\parallel \left(\mathbf{I} - \frac{1}{d}\mathbf{1}\mathbf{1}^{\mathrm{T}}\right)\hat{\mathbf{X}}_{t+1}\mathbf{\Phi}\mathbf{1}_{(L)} \parallel}$$

3.4 Update and normalize to obtain the next portfolio $\hat{\mathbf{b}}_{t+1}$ by

$$\hat{\mathbf{b}}_{t+1} = \underset{\mathbf{X}\in\Delta_d}{\mathbf{argmin}} \parallel \mathbf{b} - \mathbf{b}_{t+1} \parallel^2$$

3.5 Output the next portfolio $\hat{\mathbf{b}}_{t+1}$.

4 Propose a new data set which is challenging for the existing PS systems and examine the performance of the PS systems by comparing to the performance of benchmark.