

**Topic 1: Improving Basket Trading Using Bayesian Optimization**

Bayesian Optimization (BO) is a global optimization framework used to efficiently sample from a noise-perturbed, black-box function in search of the global optimum. While the Johansen test can generate cointegrating weights corresponding to a low p-value for in-sample data, the out-of-sample performance is not guaranteed. Thus, an interesting question is, how would the solution (cointegrating weights) obtained look like when compared to the results from the Johansen test?

Evaluation: To be evaluated based on a rolling window approach where in-sample solution is assessed on out-of-sample data. Choose your evaluation metrics based on the class contents covered.

Optional extension:

- There are several hyperparameters used in basket trading strategy, including the upper and lower thresholds used to generate trading actions. Are these hyperparameters optimizable by BO as well?
- Often, there are more than one evaluation metric of interest to us. Use multi-objective BO to cater to this scenario and evaluate the solution.

Data source:

Forex data (can be provided upon request)

References:

Quantitative trading strategies with Python, Chapter 9

Bayesian Optimization Theory and Practice

[https://ink.library.smu.edu.sg/cgi/viewcontent.cgi?article=8471&context=lkcsb\\_research](https://ink.library.smu.edu.sg/cgi/viewcontent.cgi?article=8471&context=lkcsb_research)

**Topic 2: Robust Portfolio Optimization via Smart Predict-then-Optimize**

The process of portfolio optimization often requires forecasting future expected returns and covariance matrix, making it a two-stage procedure. The potential issue is that the prediction model, while being good at the predictive task, may perform poorly in the optimization task when making asset allocation decisions. The Smart Predict-then-Optimize (SPO) framework is proposed to bridge the gap by bringing prediction and optimization tasks under the same roof and optimizing the prediction model to minimize the decision error at the optimization stage. The framework is embedded in a neural network to enable automatic training.

Evaluation: Compare SPO with traditional two-stage procedures over both mean-variance and mean-CVaR portfolios, where the prediction module can use any machine learning algorithm.

Optional extension:

- Use a distributionally robust optimization model in the optimization layer
- Experiment with different weighting schemes for prediction and decision losses

Data source:

You can choose your own dataset.

References:

<https://optimization-online.org/wp-content/uploads/2018/12/6398.pdf>

<https://arxiv.org/abs/2206.05134>

**Topic 3: Derivative Hedging Using Reinforcement Learning**

This topic intends to use Reinforcement Learning (RL) to improve the performance of traditional derivative hedging techniques by learning dynamic, adaptive strategies. Traditional approaches, such as delta hedging, might not be optimal in a complex, stochastic environment. Reinforcement learning has the potential to dynamically adjust hedging strategies based on market conditions and future uncertainty.

The use of the RL framework requires defining proper ingredients, including action space, state space, reward function, and the choice of training algorithm. Use a rolling window approach, where RL agents are trained on past data and tested out-of-sample.

Evaluation: Compare with traditional delta and gamma hedging as benchmark strategies.

Optional extension:

- Consider incorporating distributionally robust reinforcement learning (DRRL), where the RL agent accounts for model uncertainty by hedging against a range of possible future scenarios.
- Experiment with alternative reward structures, such as directly penalizing large drawdowns or implementing cost constraints dynamically.

References:

A Review on Derivative Hedging using Reinforcement Learning

<https://github.com/YukiYasuda2718/rl-bsmodel-with-costs>

Other similarly challenging open problems:

**Topic 4: Designing Card Tricks using Bayesian Optimization**

The classic Fitch Cheney's Five Card Trick is a famous card magic trick where a magician can correctly identify a hidden card from a set of five randomly chosen cards. This trick relies on mathematical principles, specifically combinatorics, and the pigeonhole principle. The goal of this topic is to design new card tricks by formulating a proper optimization model and solving for the optimal design.