

Hyper-parameter optimization for strategy calibration

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1 Objectives

Let us denote by $G(X; h)$ the (random) profit obtained from running a trading strategy with (random) market data X and using the strategy hyperparameter h . We assume $G(X; h) \sim N(\mu(h), \sigma^2(h))$. Our objective is to choose h to maximize a risk-penalized gain, i.e.

$$\hat{h} = \operatorname{argmax}_h \frac{\mu(h)}{\sigma(h)^\beta}, \quad (1)$$

where $\beta \in [0, 1/2]$ is a coefficient controlling the amount of risk penalization. Note that the objective function is not directly observable for a given h . The function value must be estimated by sampling several realizations for X . This yields noisy observations.

Our objective is to discuss (a) how to select an optimum over a finite set of hyperparameter values, and (b) how to efficiently search the parameter space.

2 Optimization on finite parameter sample set

We estimate the objective function for a given hyperparameter value h as $\hat{\mu}_n(h)/\hat{\sigma}_n^\beta(h)$, where

$$\hat{\mu}_n(h) = \frac{1}{n} \sum_{i=1}^n G(X_i; h), \quad (2)$$

$$\hat{\sigma}_n^2(h) = \frac{1}{n-1} \sum_{i=1}^n (G(X_i; h) - \hat{\mu}_n(h))^2, \quad (3)$$

and X_1, \dots, X_n are drawn from the distribution of X .

3 An explanatory model

The model assumes a response function follows a binomial distribution, i.e. $f(X; h) \sim B(p(h))$. Say we observe n realizations of that random variable on a grid of hyperparameter values h_1, \dots, h_p . We can estimate $\hat{p}(h) = \sum_1^n f(X_i; h)$. We try to

$$\hat{h} = \operatorname{argmax}_h \mathbb{E}[f(X; h)] / \operatorname{Var}[f(X; h)]^{\beta/2} \quad (4)$$

4 A need for robust objective functions

Optimization problems relying on a data-dependent objective function might be prone to producing spurious results. Examples of possible issues include:

- Objective function values can be non robust against minor changes in the underlying dataset,
- The objective function might exhibit large discontinuities that are data dependent.

How can we guarantee robustness of the results?

Interesting links:

- Robust statistics