Algorithmic Trading (COMP0051)

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Performance Indicators

- Sharp Ratio

$$SR = \frac{\mu}{\sigma},$$

  where μ is the average return and σ volatility,
- Value-at-Risk (VaR) is the value such that, taking the cumulative distribution function of the strategy returns, $CDF(-VaR(\alpha)) = 1 - \alpha$. $VaR(\alpha)$ represents a potential relative loss of the strategy for a given confidence level α,
- Conditional Sharpe Ratio

$$CSR = \frac{\mu}{ES(\alpha)},$$

  where $ES(\alpha)$ is the expected shortfall, i.e. the average of the strategy returns that are lower than the $VaR(\alpha)$.

Performance Indicators

- Burke Ratio

$$BR = \frac{\mu}{\sqrt{\sum_i DD_i^2}},$$

where the i-th drawdown DD_i within the interval considered is given by $DD_i = \frac{ThroughValue_i - PeakValue_i}{PeakValue)}$ where the i-th through value of the price time series has to follow in time the i-th peak value,

- Maximum Drawdown

$$MDD = \frac{MinThroughValue - MaxPeakValue}{MaxPeakValue},$$

where the minimum through value of the price time series has to follow in time the maximum peak value,

- Calmar Ratio

$$CR = \frac{\mu}{MDD}.$$

Criteria for a solid scientific report:

- Clarity of presentation and explanations;
- Justification of the methodology;
- Validity of results;
- Consistency of language and mathematical notation;
- Critical interpretation of results;

Clarity of presentation and explanations:

- Solid and clear report structure
- Plain explanations
- Clear plots, appropriate scale, no cropping, labeled axes
- Clear tables, 2 or 3 digits well-defined and comparable quantities
- Summary of the report

Clarity of presentation and explanations, a simple structure:

- Introduction
- Methodology
- Results
- Discussion
- Bibliography

Make things as easy as possible for the reader

(Source: Makridakis, Spyros, Assimakopoulos, Vassilis, Spiliotis, Evangelos, 2018)
”Revised Guidelines for Authors and Reviewers: Forecasting journals should update their policies and guidelines in order not only to encourage the implementation of standards promoting reproducibility and replicability, currently depending on the goodwill of the authors, but to obtain in practice all the information and material required for doing so. For instance, PLOS ONE states that “refusal to share data and related metadata and methods in accordance with this policy will be grounds for rejection” and that “if restrictions on access to data come to light after publication, we reserve the right to post a correction, to contact the authors’ institutions and funders, or in extreme cases to retract the publication”.

2. Required Data: The dataset used for evaluating a proposed method should be publicly available. Alternatively, instructions should be provided about how the data can be obtained. If there is any kind of restrictions for sharing the data, such as confidentiality, the authors should mention them and, if possible, replicate the main findings of their study using reproducible simulations. Undoubtedly, achieving exact reproducibility through simulations can be challenging. However, a very good approximation should be attainable if a welldocumented data generation function and the random numbers used for initializing the whole process are to be provided. Increasing the sample size of the generated series could also mitigate randomness and lead to more comparable results.

3. Describe Methods: Any method implemented within the paper should be clearly defined. This includes describing the methods used, as well as the initialization and parameterization processes adopted. Perhaps, the authors should provide the original code used for generating the results (Koenker & Zeileis, 2009) and an informative flowchart of the proposed methodological approach. Simultaneously, forecasting journals should impose rules and offer special forms in their websites for uploading the code and the supplementary material. Complementarily, a public online hosting service such as GitHub, BitBucket or GitLab should be used by researchers to share the original method as well as later versions of it.

4. Software: The authors should specify what software was used for producing the published results, as well as its version. If specific packages or libraries were used, these should be also mentioned. For cases of complex projects, where lot of dependencies may be present, the authors should define their computational environment and system characteristics, or provide a virtual machine, e.g. VirtualBox or VMware, capturing the entire environment (Marwick, 2017). Open-source programming languages, such as R, should be preferred and forecasting journals should encourage their exploitation through their guidelines. For instance, providing code as an R package or using Rmarkdown to format a paper, significantly simplifies reproducibility (Marwick et al., 2018).

5. Measures: The authors should define the formulas used for evaluating their results, including all the measures, metrics and criteria exploited. Moreover, they should specify within the experimental design which data were specifically used for training, validating and testing the proposed method.

6. Discussion: Forecasting journals should offer the readers the ability to comment on the papers published, submitting thoughts, questions and requirements publicly visible. On the other hand, authors should be notified about those comments and respond if possible. This “post-publication” discussion will enable forecasters to become aware of potential issues identified by researchers when trying to replicate the results, bugs fixed on the submitted code, helpful clarifications made and corrections.

7. Invite Papers and Replications: Editors of forecasting journals should regularly call for replications of important studies and encourage reviewers to accept such submissions on the basis of the quality of the experiments conducted, the significance of the hypotheses tested and the new information provided.

8. Advocacy and Bias: Editors and reviewers should be objective, judging the work made by the authors based on its quality and potential impact and not just on the conclusions drawn. Advocacy, by seeking support for a favored hypothesis, should be tackled and editors should make sure this principle is not being violated, especially for papers that challenge the common belief and are likely to receive biased reviews (Armstrong & Green, 2017).

9. Benchmarks: As suggested by Keogh & Kasetty (2003), new methods should be tested on multiple large-sized datasets, unless the usefulness of the approach is only been claimed for particular types of data. Simulations should also be welcomed as long as the data generating process utilized is well defined and justified. In any case, the dataset used should be representative for the application considered and, ideally, widely used by other researchers so that relevant benchmarks are easily identified.”