Case study: Financial Science investment platform

This is one in a series of white papers intended to help investors educate themselves on funds and investment techniques in order to make the right decisions regarding their assets.

In this paper we present a case study of how a product based on machine learning, and data technologies could provide resilient returns for investors with transparency of fund performance and fee structures, with a strong fiduciary focus

1 Algorithmic fund for professional investors

The Financial Science research initiative is set up to investigate and optimise an algorithmic investment strategy focused on resilience and long term capital growth. Its key tenets are commitment to transparency, robust academic publication, continuously evolving machine learning and professional investment management. Its goal is constant improvement of returns through machine learning and data science techniques. In addition, we are innovating in fee structures and applying game and contract theory to provide long-term fiduciary value. Automation should achieve better performance than an index fund, at lower cost and with greater transparency than a traditional hedge fund. A target has therefore been set for outperformance over index returns, with greater downside protection for capital preservation (including in a declining market).

Using a combination of academic rigour and professional investment management experience, the fund aims to extend standards for governance, documentation, reporting and regulation. We strongly believe that machine learning processes should be demonstrable overtly to all stakeholders. We therefore apply openness and transparency to publish clear, accessible performance results, whether positive or negative. A comprehensive optimisation and reporting engine has been developed to support delivery of this data, regarding both successes and failures, to researchers and investors. This allows iteration with a long-term goal of leading machine learning enhancement for the benefit of investors.

1.1 Algorithmic trading model

The algorithmic trading model makes up the core of the Financial Science algorithmic trading platform through a data driven allocation methodology [Galas, 2014, Treleaven, 2013, Nuti, 2011].

The fund's operational procedures centre on an evolving research pipeline which feeds latest study findings and empirical results into the development process. In many funds the algorithmic approach is to generate signals which provide a model of properties of the future price trajectory such as growth or volatility. Literature has shown that even very sophisticated machine learning models can struggle to calculate these values with any great accuracy. Despite these inaccuracies, the portfolio allocation function will then use these values to infer the desirability of stocks as investment vehicles.

Financial Science takes the alternate approach of allocating scores to stocks which are designed to directly reflect the desirability of the stock as part of a portfolio. One advantage of this is that the score generation can take into account any number of different quantities that reflect a stock's appeal. A second advantage is that the allocation function can then directly optimise for the attractiveness of the stocks as investment vehicles, rather than having to infer this from other quantities.

The main operational process components for the fund are therefore:

- Pre-trade analysis examines the stock universe based on criteria including quality of the fundamentals of the relevant companies. The aim is to maximise the size of an available stock universe whilst controlling for risk. There are a number of research pipelines concerning the effectiveness of these screeners and whether the stock universe can be optimally separated.
- Feature ingestion and factor generation extract multiple features from the data including, but not limited to, stock prices, volatility and key microeconomic ratios and combine them to form factors which represent a relative score of a stock's performance against an evaluation criteria which matches the required risk-return profile. This process is under constant improvement from our research pipeline which analyses new features and factors.
- Generated features are combined into a single rating of overall desirability of each stock according to the relevant evaluation criteria. Our research pipeline investigates different weights assigned to individual factors and whether they can be optimised, especially under varying market conditions in different sectors across diverse markets.
- The score feeds directly into the allocation algorithm which optimises combined scores subject to constraints aspects such as cash ratio and diversification. Our research has evaluated several allocation techniques (Rutkowska et al, 2016; 2020) and these findings have fed directly into the operation of the fund.
- The asset allocation methodology is fully integrated with the risk profile of the fund, and diversification is incorporated into the process, rather than as an add-on. Asset allocation operates with a selected utility function, which is concave, representing risk aversion, and favouring consistent returns.
- In keeping with the fund's transparent philosophy, the investment process and performance are subject to a robust reporting regime. Research-based findings are published as academic papers, industry-orientated white papers with daily information provided directly to our investors and detailed reporting tearsheets.

The risk management module regulates algorithmic trading including calculation and tracking of profit and loss, volatility and diversification and provides information for risk identification and ongoing tracking.

1.2 Optimisation and simulation environment

The optimisation and simulation environment [Galas et al, 2012; 2014; 2015] enables us to run batches of back tests on the full stock universe under multiple configurations. The top-level results are presented in easy-to-read tearsheets and detailed logs provide in-depth insight into model performance.

This optimisation process is at the core of the fund's philosophy. This is not just for risk management but also for ongoing research and improvement. Machine learning enables it to evolve and the path of this progress, including missteps, is detailed in the fund's reports with back test tearsheets. Results will be published for better or worse as this allows constructive criticisms, feedback and development.

The backtest results provide inputs to parameter and hyper parameter optimisation processes. These comprise a detailed analysis of each stage in the algorithmic trading methodology and a consideration of how they combine to create an optimally allocated portfolio. The process also considers the effect of overfitting and the requirements for the allocation process to work consistently over all market regimes.

1.3 Portal

To serve professional investors, the fund provides a central website portal as the key point of contact. This provides customers with comprehensive information on their investments and management of their account, including transparent fees calculations.

To maximise transparency for investors, tearsheet capabilities present data on holdings, performance statistics and backtest research. This allows investors to evaluate the fund performance, including reviews of ongoing enhancements and their results.

Financial Science's core philosophy holds that the fiduciary interests of investors are best served through transparency in both performance and fee structures (particularly the compounding long term consequences). Aligned with our commitment to transparency and fairness, investors can access an online fee calculator and optimiser which is driven by game and contract theory and operates with long-term fiduciary management in mind.

1.4 Platform Architecture

To develop, simulate and test continuously improved versions of the core models, the Financial Science platform architecture has been designed to operate across six core modules, which are shown in Figure *1* and described in more detail below.

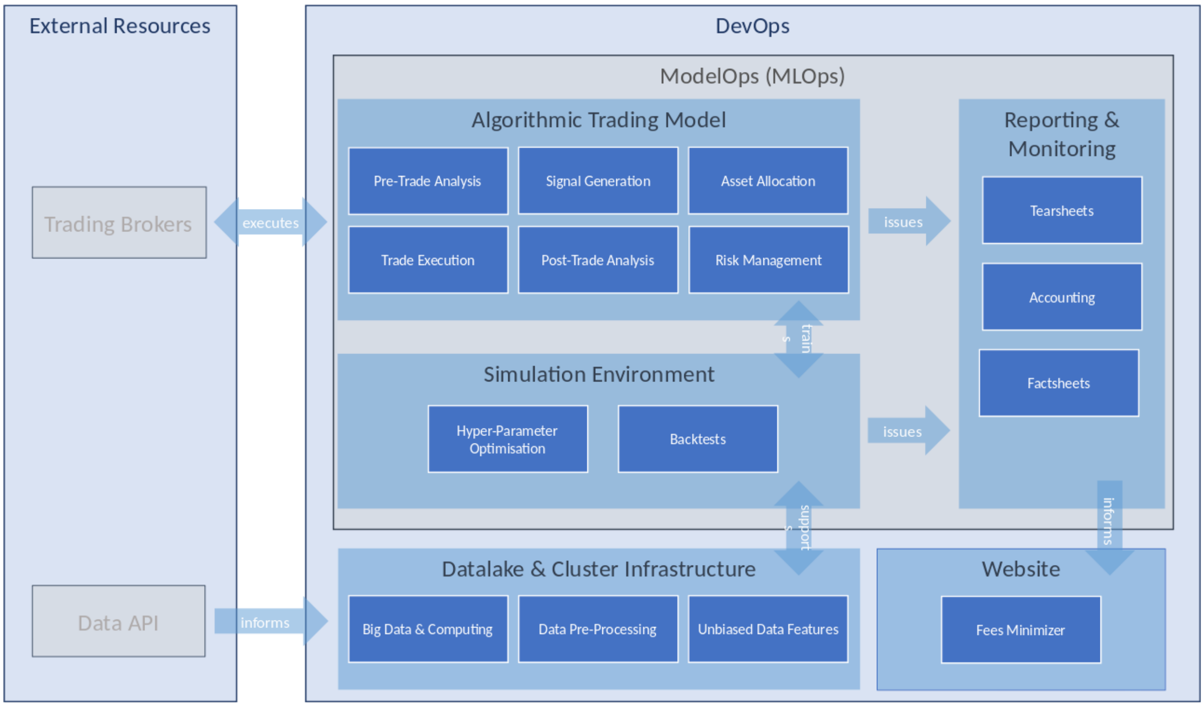

Figure 1 Financial science platform architecture overview

1.5 Data lake and cluster infrastructure

The data lake and related cluster infrastructure manages organisation and pre-processing of data from multiple sources. A secure Big Data environment provides the capacity to analyse large data sets including closing prices for the entire stock universe, and fundamental data. Functionality in this module includes identification and elimination of information bias. This part of the system includes automated test reports and other documentation produced with minimal human intervention.

1.6 Market Resources

Market resources interface with the market to trade in line with the portfolio strategy of the algorithmic trading models including pre-compliance checks, position reconciliation and post trade matching. The trade execution function controls aspects such as triggering a rebalancing event and manages the rebalancing strategy to take account of optimal order execution techniques. The system has API connectivity to the requisite data sources and the capabilities for data ingestion and data streaming.

2 Performance

Actual performance is presented in Table 2 and Figure 2 below

2.1 Operational returns

Table 2 presents the absolute and annualised returns with different versions of the algorithm. This is also presented as a graph in Figure 2 below.

	Algorithm version		
	2.4.0	**2.5.0**	**2.6.0**
Dates active	08-08-2019 to 04-05-2020	04-05-2020 to 03-09-2020	03-09-2020 to 13-09-2021
Fund	-13.3%	4.4%	25.6%
Fund Annualised return	-17.4%	12.8%	24.6%
S&P	-3.6%	21.5%	29.3 %
S&P Annualised return	-4.3%	63.6%	28.2%
Cash	0.7%	0.3%	0.6%
Cash Annualised return	1%	1%	1.6%

Table 2 Returns compared with S&P500 and cash vs. algorithm version.

Model	Added Features
2.4.0-RELEASE	- score normalisation per expert - score outliers filtering per expert rule - improved SIMPLEX allocation with multiple caps
2.5.0-RELEASE	- adaptation of new FactSet data scheme - preliminary research into enhanced Value rules
2.6.0-RELEASE	- enhanced rules for Value factor

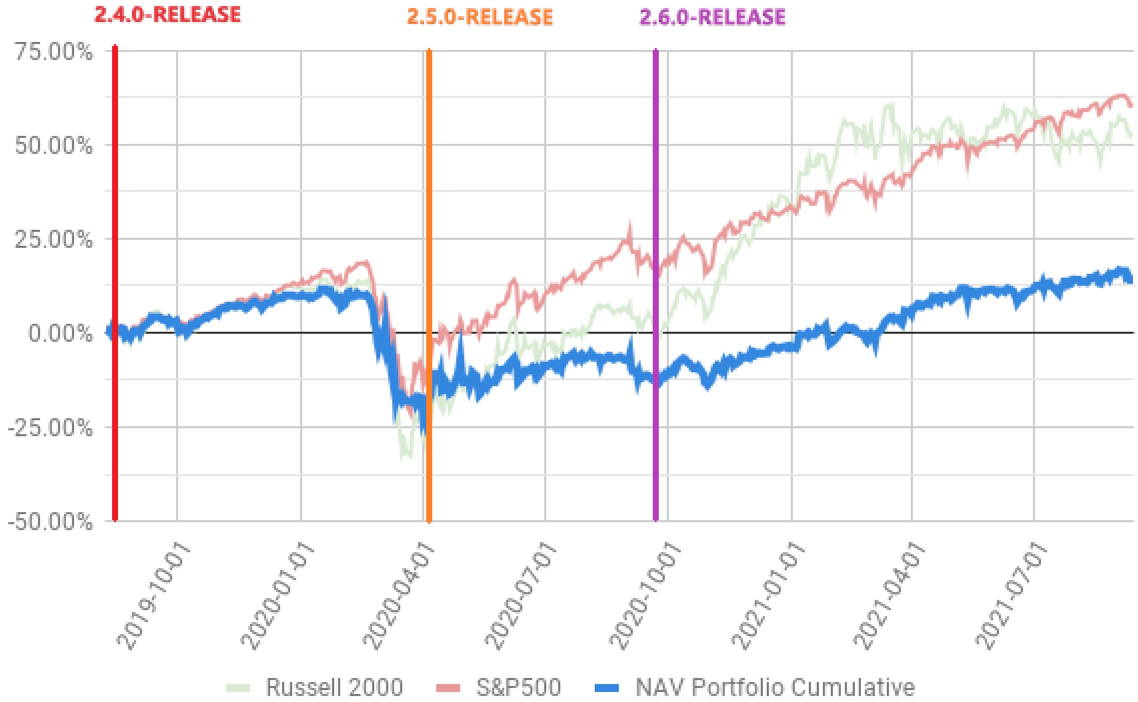

Figure 2 BSL returns vs. S&P500 and Russell 2000.

2.2 Equity backtest

Figure 3 below presents the results from a backtest performed using algorithm release v2.6.0.

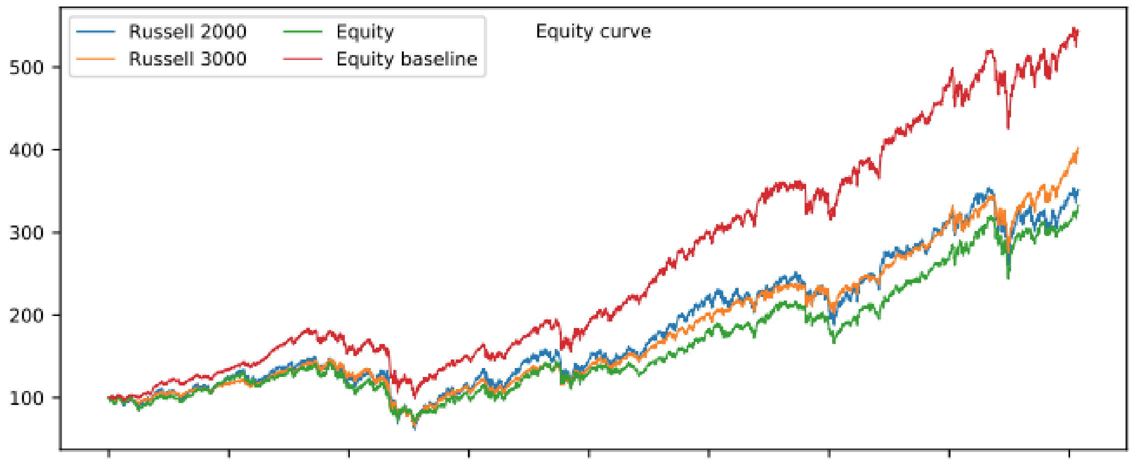

Figure 3 Backtest performance with 2.6.0.

2.3 Performance summary

Some points to note about the the Financial Science research platform operation to date

- It has performed in line with its financial targets (annual return > 7.5% net
- Annualised volatility < 15%
- Maximum drawdown < 45%)
- It has performed less well (albeit with lower volatility) than the S&P index during the overall period
- The performance is net of fees
- On an ongoing basis the algorithms are enhancing
- During 2021 its performance was 27.69% vs. S&P's 28.75%
- It is anticipated that, with iterative enhancements, the performance will keep improving relative to standardised benchmarks

3 References

[1] Galas, Michal. Experimental Computational Simulation Environments for Algorithmic Trading. Diss. UCL (University College London), 2014.
[2] Treleaven, Philip, Galas, Michal and Lalchand Vidhi "Algorithmic trading review." Communications of the ACM 56.11 (2013): 76-85.
[3] Giuseppe.Nuti,.Mahnoosh Mirghaemi, Philip.Treleaven, and Chaiyakorn Yingsaeree. Algorithmic trading. Computer, 44(11):61–69, 2011.
[4] Galas, Michal, Brown, Daniel and Treleaven, Philip "A computational social science environment for financial/economic experiments." Proceedings of the Computational Social Science Society of the Americas 1 (2012): 1-13.
[5] Galas, Michal. "Experimental Computational Simulation Environments for Big Data Analytic in Social Sciences." Handbook of Statistics. Vol. 33. Elsevier, 2015. 259-277.
[6] Rutkowska, Aleksandra. "Influence of membership function's shape on portfolio optimization results." *Journal of Artificial Intelligence and Soft Computing Research* 6.1 (2016): 45-54.
[7] Bartkowiak, Marcin, and Rutkowska, Aleksandra "Black-Litterman Model with Multiple Experts' Linguistic Views." *International Conference on Soft Methods in Probability and Statistics*. Springer, Cham, 2016.
[8] Bartkowiak, Marcin, and Rutkowska, Aleksandra "Vague expert information/recommendation in portfolio optimization-an empirical study." *Axioms* 9.2 (2020): 38.