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Editorial

Special Issue on Algorithms in Computational Finance

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Algorithms play an important part in finance. Financial markets have been transformed from human-driven to predominantly algorithm-driven. Algorithms have not only been used for traditional applications such as forecasting, trading, risk analysis and portfolio optimisation, they have also been used in new areas such as data sampling. This Special Issue collects eight papers. They provide readers with a glimpse of the state-of-the-art research in algorithms in computational finance.

Two papers in the Special Issue examine the role of machine learning in finance, especially in the field of forecasting. Li and Tam (2018) [1] compare a wide range of machine learning techniques in the prediction of momentum and reversal effect. The intention was to predict what happens in the next market period: Would we see momentum, reversal or neither of them? Such predictions are used to support momentum or contrarian trading.

With machine learning, Plaekandaras et al. (2019) [2] use the geopolitical risk (GPR) index proposed by the Federal Reserve to forecast oil prices, exchange rates, national stock indices and gold prices. Results suggest that the GPR index possesses significant forecasting ability for gold prices, but not for the other assets. The authors argue that such negative results are useful, as they warn against over-reacting in intervention policies.

With the aim of examining market efficiency hypothesis, Das et al. (2018) [3] use machine learning to predict future movement directions. The returns in individual stocks that make up the S&P 500 index are input into their deep learning (neural networks with multiple layers) algorithm. They conclude that, while the future direction of the S&P 500 index can be weakly predicted, there is not enough evidence to reject the market efficiency hypothesis.

Ma and Delahaye (2018) [4] take a new approach to study volatility clustering in the financial market. Instead of using autocorrelation on daily returns in the traditional way, they simply record whether a bigger-than-median return is followed by another bigger-than-median return. They find that volatility dependence computed this way cannot be totally captured by traditional GARCH models.

Wang et al. (2018) [5] bring a potentially useful variable into risk analysis. They study the effect of chronotype on risk: Would an individual being a morning type, an evening type or neither matter in assessing the likelihood of delinquent credit card payments? Would it be related to the individual's financial risk preference and stock market participation?

Portfolio optimization is a major problem in finance. When one deviates from the classical model (namely, the Markowitz model), finding near-optimal solutions become computationally challenging. Ren et al. (2018) [6] propose a nature-inspired portfolio optimization algorithm, gray wolf optimization (GWO). Preliminary results show that the GWO algorithm is both efficient and effective in portfolio optimization.

Traditionally, one samples transaction prices at fixed intervals (e.g., end of day prices) to form time series. Directional change (DC) is an algorithmic approach to determine sampling data points in the market. Under DC, one samples transaction prices when the market changes direction; in other words, sampling points are data-driven.

Two papers were built under the framework of DC. Bakhach et al. (2018) [7] propose a trading strategy based on DC events. The algorithm, Intelligent Dynamic Backlash Agent (IDBA), uses an order size management and risk management module. Tested in the forex market, results so far have been promising. Chen & Tsang (2018) [8] detect regime changes with DC-based indicators in different markets. With results from multiple markets (stocks, forex, and commodities) and different data frequencies (from second to second data to daily prices), they characterise "normal" and "abnormal regimes" in the DC-indicators space. Being able to characterise regimes paves the way to tracking market movements.

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