In addition to asset management, machine learning (ML) methods have been applied to a wide range of areas – speech and image recognition, self-driving cars, email spam filtering, medical diagnosis, to name just a few. ML offers various advantages that make it a useful tool in active portfolio management, including the ability to capture nonlinear patterns, generate accurate predictions, and extract information from textual data sources. Söhnke M. Bartram, Jürgen Branke, Giuliano De Rossi, and Mehrshad Motahari in “Machine Learning for Active Portfolio Management,” provide a survey of ML in active portfolio management. These applications include multi-factor signal generation (technical and fundamental), portfolio construction, and trade execution. Despite the promises offered by ML in active portfolio management, when the authors investigate the performance of a sample of active exchange-traded funds that use ML in their investment decision making, the results were mixed. They conclude that overall, although ML may offer great promise for active portfolio management, investors should be cautioned against their main potential pitfalls.

Markus Jaeger, Stephan Krügel, Dimitri Marinelli, Jochen Papenbrock, and Peter Schwendner in “Interpretable Machine Learning for Diversified Portfolio Construction” propose a procedure to benchmark rule-based investment strategies and to explain their differences in risk-adjusted performance using explainable artificial intelligence (XAI). They run a horse race of hierarchical risk parity (HRP) versus equal risk contribution (ERC) as examples of diversification strategies allocating to liquid multi-asset futures markets with dynamic leverage (volatility target). Applying model-agnostic Shapley values, the authors explain the relative risk-adjusted performances of those investment strategies with features of synthetic market data derived from an investment universe of 17 equity index, government bond, and commodity futures markets. They find that compared to ERC, HRP shows higher Calmar ratios while better matching the volatility target and explain this with better robustness of HRP to drawdowns.

Several studies in the past two years have demonstrated that improvements in language models using additional training with financial text can produce better prediction of sentiment of news headlines. In “Context, Language Modeling, and Multimodal Data in Finance,” Sanjiv Das, Connor Goggins, John He, George Karypis, Sandeep Krishnamurthy, Mitali Mahajan, Nagpurnand Prabhala, Dylan Slack, Rob van Dusen, Shenghua Yue, Sheng Zha, and Shuai Zheng assess whether language models improve on the simple use of text-based numerical features that have been identified in a recent study (e.g., sentiment, readability, positivity, negativity, riskiness, litigiousness). In much of the finance literature the practice is to create word-based features by applying finance-specific dictionaries with such word scoring then used as explanatory variables in regression analysis of regulatory filings, tweets, news, and so on. The authors show in their article that the recent developments in language modeling, such as bidirectional encoder representations from transformers (BERT), can extend the successes found for language models that have been reported in recent studies. They show that context-rich models perform better than context-free models; pretrained language models that mix common text and financial text are better than those pretrained on financial text alone.
In “Confronting Machine Learning with Financial Research,” Kristof Lommers, Ouns El Harzli, and Jack Kim compare machine learning (ML) to conventional quantitative research methodologies that have been used in finance. After explaining the idiosyncrasies of finance, they discuss the challenges in applying ML methodologies and the opportunities (and applications) that ML offers for financial research such as estimation, empirical discovery, testing, causal inference, and prediction. They dispute the popular view that ML is a black box that is only useful for prediction. Instead, they argue that it can be an intuitive tool for researchers in constructing hypotheses in the face of the complex realities and data structure of financial markets. As the authors note in discussing the challenges of applying ML, in addition to the difficulties that arise because of the idiosyncrasies of financial markets, there is also a fundamental tension between the underlying paradigm of ML and the research philosophy in financial economics.

Over the past 10 years, an increasing number of private equity firms have utilized artificial intelligence (AI) in making investment decisions. The application of AI by these firms and in the venture capital industry ranges in scope from simple standalone screening models to end-to-end decision support systems. For example, while prediction models in the form of credit scoring models have been employed by banks for more than 60 years, only recently have private equity and venture capital firms adopted AI-enhanced prediction models. A detailed account and a guide to the use of AI by private equity firms is described in “An Inside Peek at AI Use in Private Equity” by Thomas Åstebro. The good news is that increased use of AI by private equity and the venture capital industry will significantly increase operational efficiency by transforming the ways in which partners perform their work. The bad news from the perspective of the industry is that AI will lead to a technological arms race that will result in an eventual industry shakeout.

Compared to regression and classification methods, learning-to-rank algorithms potentially offer a superior method for portfolio construction. Conventional machine learning models primarily focus on constructing portfolios based on return forecasting and classification. A deep rank neural network, however, can robustly capture the statistical relationships between stock ranking and input features that can enhance the performance of an investment strategy. Yan Li and Zheng Tan in “Stock Portfolio Selection with Deep RankNet” show how the RankNet algorithm when applied to the Chinese stock market can partially extract several return-based anomalous patterns from the market, as revealed from the factor loadings in Fama–French regression analysis. They report significant outperformance using this algorithm compared to the corresponding regression and classification methods using neural networks. They also find that RankNet methods with deep neural net structures offer promising strategy profitability and comparable ranking precision in relative order predictions.

Deep reinforcement learning offers a framework for a feedback loop of state, action, and reward provided by the environment that can be used to approximate the best possible actions in a given state. One of the most popular uses of this algorithm in finance has been in the development of trading strategies. In “Deep Q-Learning for Trading Cryptocurrency,” Yu chien (Calvin) Ma, Zoe Wang, and Alexander Fleiss apply Deep Q-Learning, develop a model-free reinforcement learning algorithm to trade cryptocurrencies. They use deep neural networks to create a “Deep Q-Learning trading agent” that approximates the best actions to take based on rewards to maximize...
returns from trading the three cryptocurrencies with the largest market capitalization (Bitcoin, Ethereum, and Litecoin). The authors find that a Deep Q-Learning trading agent generates a return of almost 66% on average over the course of 2,000 episodes. However, given the highly volatile nature of the cryptocurrencies, returns exhibit a large standard deviation.

Because of the increased interest by investors in environmental, social, and governance (ESG) issues in making investment decisions, asset managers have seen growth in their assets under management for ESG portfolios. A theoretical framework for using an automated natural language processing (NLP) system for integrating the views of companies' ESG performance into portfolio optimization decisions is provided in “Weak Supervision and Black-Litterman for Automated ESG Portfolio Construction” by Alik Sokolov, Kyle Caverly, Jonathan Mostovoy, Talal Fahoum, and Luis Seco. Training a machine learning news data classifier to automatically identify several key ESG issues in news data, the authors aggregate these issues over time to generate a “views vector” under the Black–Litterman portfolio framework. Comparing the performance of an ESG-tilted portfolio against a standard Black–Litterman portfolio, they demonstrate how this can be achieved at scale, in a fully automated manner, and with consistency over large periods of time without sacrificing performance.

To assist the public to understand the price dynamics in the agricultural commodities market, the Commodity Futures Trading Commission (CFTC) publishes Commitments of Traders (COT) reports. The information provided in the COT reports provide a breakdown of the open interest for futures and options on futures markets in which there are 20 or more traders having positions equal to or exceeding the CFTC reporting levels. Typically, it is the Tuesday data that is included in the COT reports with the data released on Friday. There are four types of reports published: legacy, supplemental, disaggregated, and traders in financial futures. For the disaggregated report, the information includes reportable open interest positions into five classifications: producer/merchant/processor/user, swap dealer, managed money, other reportable, and nonreportable. Although several studies have examined the ability of large trader positions to predict returns in agricultural futures markets, Proskurin describes the limitations of these studies that have found predictive value in COT reports. Applying a nonlinear machine learning approach to the data in the disaggregated report, Oleksandr Proskurin in his article “Does the CFTC Report Have Predictive Power: Machine Learning Approach” investigates if these reports can be used to predict the price of agricultural commodities based on advanced features extracted from these reports. The author’s finding indicate that the CFTC report does not contain informative features because of the timing of the publication of information: it is published on Friday with information on Tuesday positions. However, the author finds that if instead the report is published on Tuesday, it would contain information to predict the price some commodities.

Francesco A. Fabozzi
Managing Editor