The lead article in this issue is by the co-editor of this journal, Marcos López de Prado, “Machine Learning for Econometricians: The Readme Manual.” As he notes, econometric tools are typically applied in investment research despite the fact that they are poorly suited for uncovering statistical patterns in financial data. This is because of the unstructured nature of financial datasets, as well as the complex relationships involved in financial markets. Researchers and analysts working for asset managers overlook these limitations as they take the view that econometric approaches are more appropriate than machine learning methods. One of their objections to using machine learning is that their tools are not transparent (i.e., it is a black box approach to problem solving). López de Prado demonstrates why it is not the case that machine learning is a black box. For each analytical step of the econometric process, he identifies a corresponding step in machine learning analysis. By clearly stating this correspondence, López de Prado has facilitated and reconciled the adoption of machine techniques among econometricians, offering a bridge from classical statistics to machine learning.

The process of meta-labeling, introduced by López de Prado, is used as the machine learning layer of an investment strategy that can determine the size of positions, filter out false-positive signals from backtests, and improve performance metrics. In “Meta-Labeling: Theory and Framework,” Jacques François Joubert provides an overview of meta-labeling’s theoretical framework (including its architecture and applications). Then the author describes the methodology for three controlled experiments designed to break meta-labeling down into three components: information advantage, modeling for false positives, and position sizing. The three experiments validated that meta-labeling not only improves classification metrics but also significantly improves the performance of various types of primary investment strategies. Because of this attribute of meta-labeling, this article provides a good case study of how machine learning can be applied in financial markets.

Studies have shown that security prices are driven by information beyond the financial information reported by companies in their filings with the Securities and Exchange Commission. This information includes news and investor-based sentiment. In “FinEAS: Financial Embedding Analysis of Sentiment,” a new language representation model for sentiment analysis of financial text called “financial embedding analysis of sentiment” (FinEAS) is introduced by Asier Gutiérrez-Fandino, Petter N. Kolm, Miquel Noguer i Alonso, and Jordi Armengol-Estapé. Their approach is based on transformer language models that are explicitly developed for sentence-level analysis which builds on Sentence-BERT, a sentence-level extension of vanilla BERT. The authors argue that the new approach generates sentence embeddings that are of higher quality that significantly improve sentence/document-level tasks such as financial sentiment analysis. Using a large-scale financial news dataset from RavenPack, the authors demonstrate that for financial sentiment analysis the new model outperforms several state-of-the-art models. The authors make the model code publicly available.

Deep reinforcement learning (DRL) has attracted substantial interest from practitioners. However, its application has been limited by the need for practitioners to
search through a large number of available methodologies that are seemingly alike. Some practitioners have elected to build their DRL algorithms from scratch based on classical theories. In “Deep Reinforcement Learning with Function Properties in Mean Reversion Strategies,” Sophia Gu investigates whether any of the recent commercially available deep reinforcement learning algorithms that were initially built for games can be applied to a class of optimal trading problems. The author demonstrates how to use a DRL library in a commonly used trading strategy—mean reversion. Gu also introduces a general framework of incorporating human insight, in particular economically motivated function properties when training DRL agents that can be used to solve common decision-making financial problems.

In 1952, the mean-variance model for determining the portfolios that are efficient in their allocation of funds among asset classes was introduced by Harry Markowitz. The problem with implementing the mean-variance model was that the allocations are heavily dependent on the estimated values for the model’s inputs—mean, variance, and co-variances. These inputs are drawn from historical returns. Almost 40 years later, Black and Litterman proposed an alternative asset allocation model, a view-based model. Ren-Raw Chen, Shih-Kuo Yeh and Xiaohu Zhang in “On the Black–Litterman Model: Learning to Do Better,” study the performance of the Black–Litterman model and compare it to the traditional mean–variance model. Beginning with standard Bayesian learning on which the Black-Litterman model is based, they perform a series of tests by applying machine learning tools and view specifications that are consistent with the literature. Their empirical evidence suggests that the Black-Litterman model is highly sensitive to the view specification.

Cross-sectional strategies are a popular trading style covering a broader slate of instruments and typically involve buying assets with the highest expected returns (winners) while simultaneously selling those with the lowest (losers). Several studies have documented technical variations of these strategies and their use across different asset classes. The classical cross-sectional momentum strategy, for example, was applied to equities and assumes the persistence of returns. Daniel Poh, Bryan Lim, Stefan Zohren, and Stephen Roberts in their article “Enhancing Cross-Sectional Currency Strategies by Context-Aware Learning to Rank with Self-Attention” apply the classical cross-sectional strategy to the foreign-exchange market. Prior to building a portfolio to implement the strategy, the instruments that are candidates for inclusion in the portfolio must be ranked. The accuracy of the ranking of the instruments is critically important for the performance of the strategy. Traditionally heuristics or sorting the outputs produced by a pointwise regression or classification techniques have been used for ranking. Recently, strategies using learning-to-rank algorithms have been found to be a competitive and viable alternative to the traditional ranking techniques. While ranking methods for this strategy are learned globally and on average improve ranking accuracy, they ignore the differences between the distributions of asset features over the times when the portfolio is rebalanced, making the rankings susceptible to producing suboptimal rankings. This may occur at important periods when accuracy is actually needed the most. The authors deal with this shortcoming by using a context-aware learning-to-rank model that is based on the transformer architecture to encode top/bottom-ranked assets, learn the context, and exploit this information to revise the initial results. Back testing for 31 currencies, they report
that their proposed ranking methodology improves the Sharpe ratio by around 30%, as well as enhancing other performance metrics.

Developing successful models for predicting economic cycles is challenging because of the highly dynamic nature of modern economies. Zihao Wang, Kun Li, Steve Q. Xia, and Hongfu Liu investigate the effectiveness of different machine learning methodologies in predicting economic cycles in their article “Economic Recession Prediction Using Deep Neural Network.” They report that the most accurate model to forecast the start and end of economic recessions in the United States is the deep learning methodology of bidirectional long short-term memory autoencoder with an attention layer. Adopting commonly available macroeconomic and market-condition features to compare the ability of different machine learning models to generate good predictions both in-sample and out-of-sample, they report that their proposed model is not only flexible, but it is dynamic when over time both predictive variables and model coefficients vary. They find good out-of-sample predictions of their proposed model for the past two recessions and an early warning about the COVID-19 recession.

In their article, “Machine Learning in Behavioral Finance: A Systematic Literature Review,” S. Navid Hojaji, Mahmood Yahyazadehfar, and Bahareh Abedin investigate the application of machine learning in behavioral economics and behavioral finance, systematically extracting 90 scientific studies published between 2000 and June 1, 2020. Applying text analysis techniques and related statistical methods, the abstracts of the 90 articles were reviewed and analyzed. The authors found that (1) attention to this field has developed in recent years with an accelerating trend, (2) specialized journals have bestowed more curiosity in these studies than in the past by publishing more relevant studies, and (3) machine learning has been applied in areas such as investor sentiment, decision making, consumer behavior, trading strategies, game theory, and other areas in the field of behavioral economics and behavioral finance.

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