Most portfolio optimization techniques require, in one way or another, forecasting the returns of the assets in the selection universe. In the lead article for this issue, “Deep Learning for Portfolio Optimization,” Zihao Zhang, Stefan Zohren, and Stephen Roberts adopt deep learning models to directly optimize a portfolio’s Sharpe ratio. Their framework circumvents the requirements for forecasting expected returns and allows the model to directly optimize portfolio weights through gradient ascent.

Instead of using individual assets, the authors focus on exchange-traded funds of market indices due to their robust correlations, as well as reducing the scope of possible assets from which to choose. In a testing period from 2011 to April 2020, the proposed method delivers the best performance in terms of Sharpe ratio. A detailed analysis of the results during the recent COVID-19 crisis shows the rationality and practicality of their model. The authors also include a sensitivity analysis to understand how input features contribute to performance.

Predicting business cycles and recessions is of great importance to asset managers, businesses, and macroeconomists alike, helping them foresee financial distress and to seek alternative investment strategies. Traditional modeling approaches proposed in the literature have estimated the probability of recessions by using probit models, which fail to account for non-linearity and interactions among predictors. More recently, machine learning classification algorithms have been applied to expand the number of predictors used to model the probability of recession, as well as incorporating interactions between the predictors. Although machine learning methods have been able to improve upon the forecasts of traditional linear models, the one crucial aspect that has been missing from the literature is the frequency at which recessions occur. Alireza Yazdani in “Machine Learning Prediction of Recessions: An Imbalanced Classification Approach,” argues that due to the low frequency of historical recessions, this problem is better dealt with by using an imbalanced classification approach. To compensate for the class imbalances, Yazdani uses down-sampling to create a roughly equal distribution of the non-recession and recession observations. Comparing the performance of the baseline probit model with various machine learning classification models, he finds that ensemble methods exhibit superior predictive power both in-sample and out-of-sample. He argues that nonlinear machine learning models help to both better identify various types of relationships in constantly changing financial data and enable the deployment of flexible data-driven predictive modeling strategies.

Most portfolio construction techniques rely on estimating sample covariance and correlations as the primary inputs. However, these
techniques are not forward looking and are inflexible with respect to incorporating additional information. In “Neural Embeddings of Financial Time Series Data,” Alik Sokolov, Jonathan Mostovoy, Brydon Parker, and Luis Seco propose a new approach utilizing learned representations of time-series data from deep learning networks to augment classical techniques. Their approach, which is capable of incorporating learned estimates of future performance, can be customized to create tailored representations best suited for meeting varying financial objectives. To improve upon common unsupervised algorithms for embedding multi-dimensional time series data such as principal component analysis, the authors draw upon concepts from Supervised Machine Learning and Natural Language and Image Processing. The authors illustrate their approach and compare it to classical approaches to portfolio construction.

Although deep reinforcement learning (DRL) has been used to create intelligent machines for many applications outside of finance, it is only recently that this machine learning technique has been applied to financial markets. In “Deep Reinforcement Learning for Option Replication and Hedging,” Jiayi Du, Muyang Jin, Petter Kolm, Gordon Ritter, Yixuan Wang, and Bofei Zhang propose models for the solution of option replication subject to discrete trading, round lotting, and nonlinear transaction costs using state-of-the-art DRL methods. Their methodology allows the user to train DRL models to hedge a whole range of strike prices with no additional training. The proposed models allow the user to “plug-in” any option pricing and simulation library without requiring any additional modifications. Through a series of simulations, the authors show that compared to the traditional delta hedging approach, the DRL models learn similar or better strategies. Of all the proposed models, the Proximal Policy Optimization DRL model performs the best in terms of profit and loss, training time, and the amount of data needed for training.

Recently, an increasing number of studies have looked into the information that can be extracted from option data. In “European Floating Strike Lookback Options: Alpha Prediction and Generation Using Unsupervised Learning,” Tristan Lim, Chin Sin Ong, and Aldy Gunawan use European floating-strike lookback call options, along with historical momentum and volatility variables, to recommend using K-means clustering equities for which call options should be purchased. Their backtests show that using European floating strike lookback call option data provides a clear choice of trading clusters, whereas this was not apparent using standard call option data. Their findings are useful not only for buyside investors searching for alpha-generation strategies and/or hedging underlying assets, but also for the manufacturers of sell-side products and developers of market trading platforms. Sell-side product manufacturers will find the approach useful in structuring European floating strike lookback call options, while market trading platforms will find the approach helpful in introducing new products and enhancing product liquidity.

There are many ways to overfit an investment strategy other than overfitting the predictive model itself. Systematic trading strategies require tuning a number of parameters such as trading frequency, sample sizes, entry and exit thresholds, stop losses, and more to improve the performance of the predictor. Such tuning inevitably leads to overfitting and can lead to implementing false investment strategies. A framework for estimating the level of overfit or performance gain arising from optimizing over trading parameters is introduced by Ilya Soloveychik in “Forecast Optimization via Parameter Tuning: Performance Gain and Overfit”. This framework allows researchers to make amendments to the performance metrics of different trading strategies in order to avoid investing in strategies with overfit backtests. Soloveychik illustrates this methodology using a simple exponential moving average strategy. It is shown that the improvement in the Sharpe ratio mainly depends on the signal autocorrelation and its alpha decay parameter. The results shed light on the overfitting phenomenon in the context of investment strategy construction and reveals the sources of performance improvement in forecast design.

Forecasting volatility is important in portfolio and risk management. Typically, GARCH-family models are employed for these tasks. Abdullah Karasan and Esma Gaygisiz extend the GARCH-based models to incorporate forecasts from a machine learning-based model in order to improve volatility forecasts generated by the traditional models. In their article, “Volatility Prediction
and Risk Management: An SVR-GARCH Approach,” the authors compare the prediction results of the SVR-GARCH model with other GARCH family models and show that their proposed model outperforms based on two performance metrics: mean absolute error and root mean squared error of the volatility forecasts. These forecasts are then used to calculate historical Value-at-Risk. The findings of Karasan and Gaygisiz suggest that the SVR-GARCH model boosts Value-at-Risk calculations and therefore offers a better financial risk management model.

Traditional portfolio theory relies on the assumption that returns are normally distributed. As a result, it does not take into account higher moments of the return distributions. Typically, the average return over some window is taken as the input for expected returns. By not accounting for higher level moments and tail dependencies, a mean-variance generated portfolio will not accurately reflect the true probabilities of expected outcomes. In “Portfolio Construction Using First Principles Preference Theory and Machine Learning,” Zava Aydemir builds on first principles preference theory to incorporate skewness and kurtosis of returns into the portfolio construction framework. Specifically, Aydemir uses clustering to identify portfolios with similar return profiles, taking advantage of the cumulative prospect theory which incorporates higher moments of the return distribution. The result of this framework is a cluster of portfolios for which the investor has the discretion to choose among. In a Monte Carlo study that incorporates co-skewness and tail-dependencies, this framework generates more realistic portfolios than mean-variance optimization, which is characterized by high asset concentrations.