Machine Learning for Active Portfolio Management

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KEY FINDINGS

- Machine learning (ML) methods have several advantages that can lead to successful applications in active portfolio management, including the ability to capture nonlinear patterns and a focus on prediction through ensemble learning.
- ML methods can be applied to different steps of the investment process, including signal generation, portfolio construction, and trade execution, with reinforcement learning expected to play a more significant role in the industry.
- Empirically, the investment performance of ML-based active exchange-traded funds is mixed.

ABSTRACT

Machine learning (ML) methods are attracting considerable attention among academics in the field of finance. However, it is commonly believed that ML has not transformed the asset management industry to the same extent as other sectors. This survey focuses on the ML methods and empirical results available in the literature that matter most for active portfolio management. ML has asset management applications for signal generation, portfolio construction, and trade execution, and promising findings have been reported. Reinforcement learning (RL), in particular, is expected to play a more significant role in the industry. Nevertheless, the performance of a sample of active exchange-traded funds (ETF) that use ML in their investments tends to be mixed. Overall, ML techniques show great promise for active portfolio management, but investors should be cautioned against their main potential pitfalls.

TOPICS

*Big data/machine learning, portfolio construction, exchange-traded funds and applications, performance measurement**

Machine learning (ML) is a branch of artificial intelligence (AI) concerned with the construction of computer algorithms that automatically improve as they gain experience (Mitchell 1997, p. xv). In financial contexts, Gu et al. (2020) narrow this down to a set of high-dimensional statistical models that incorporate optimization algorithms and regularization methods (to select the model specification and prevent overfitting). The promising ability of such models to make financial predictions and learn patterns from data has led to a surge in their application by asset managers in recent years (Bartram, Branke, and Motahari 2020). Their popularity is expected to

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grow because quantum computing, which is seen as a key innovation that will revolutionize the processing power of computers, facilitates the use of computationally intensive ML models (see Egger et al. 2020).

In this article, we focus on the use of ML methods in active portfolio management and the relevant empirical findings in the literature. Signals for portfolio construction often rely on one or more factors that predict future returns. Multifactor signals combine a range of indicators (e.g., technical and fundamental) with a history of return predictability in the cross section. However, the recent proliferation of style factors has led to serious concerns regarding the robustness of these predictors out of sample. ML approaches that have regularization and variable selection features (e.g., least absolute shrinkage and selection operator [LASSO] regressions, elastic nets, and artificial neural networks [ANNs]) are known to be useful in selecting the most relevant factors. This often leads to more robust signal estimates that are less likely to overfit and be based on spurious patterns in the data. Ensemble models that combine predictions from several types of ML models can further mitigate the overfitting issue.

ML approaches (e.g., ANNs, support vector machines [SVMs], and tree-based methods) are often able to capture nonlinear patterns, including interactions between input variables. This feature can enhance single-factor and multifactor signal construction by capturing higher-order relations and complex information contained in input variables. In addition, the natural language processing (NLP) branch of ML tools can allow creating factors that are based on textual information (e.g., corporate reports, news articles, social media posts, and conference call transcripts). The evidence suggests that NLP tools can successfully extract information that is relevant for the prediction of returns. This is usually carried out by either training the NLP model to make return forecasts directly or by using the model to capture sentiment and tone from the text.

Classic portfolio optimization approaches, such as the Markowitz (1952) approach, face various shortcomings that are rooted in their stringent structure and difficulty in estimating return and variance–covariance inputs. ML tools can mitigate these issues by producing more accurate estimates of expected returns and replacing the variance–covariance matrix with more robust structures. In addition, evolutionary algorithms can allow the portfolio optimization problem to incorporate additional constraints (e.g., holding thresholds) that prevent the model from having a closed-form solution. ML approaches such as deep learning and reinforcement learning (RL) can also be used to construct portfolios directly. These algorithms take historical market data as inputs and learn to track an index as closely as possible or to maximize portfolio Sharpe ratios.

Executing and rebalancing portfolios often involves modeling transaction costs, particularly market impact costs, and execution strategies that minimize such costs. An extensive literature has considered ML tools for the modeling and forecasting of market impact costs. Nonparametric ML tools (e.g., ANNs and random forests) can capture nonlinearities and complex dynamics in trades and quotes, and parametric ML tools (e.g., LASSO regressions) can shed light on market impact drivers. Unsupervised ML methods, such as cluster analysis, are useful for categorizing assets and using information from peer assets to provide liquidity and market impact estimates.

A recent, promising set of ML tools is based on RL, which is designed to make a sequence of decisions (e.g., trades over a period of time) that reach a specific goal (e.g., maximizing the Sharpe ratio). RL is not widely discussed in the literature, partly because it is often more computationally intensive than other ML approaches. However, this major hurdle is expected to be lifted soon with the advent of quantum computing. Currently, RL is primarily used to devise optimal execution strategies. However, it is shown to be able to automate all stages of portfolio management (i.e., signal generation, optimization, transaction cost analysis, and execution). The main advantage of RL is its ability to sequentially learn from and improve with experience, which is the closest an ML approach can get to the original objective set by Mitchell (1997, p. xv).

A number of active exchange-traded funds (ETFs) claim to use AI or ML in their investment strategies. Although these funds do not represent a significant share of the market, their assets under management (AuM) have grown rapidly over the past few years. Their active risk seems to be largely driven by factor exposures, which indicates that they tend to focus on style bets. At 0.75%, their average management fees are slightly above the level typically charged by active ETFs.[1] An equally weighted portfolio of all of these funds has a Sharpe ratio of 0.88 and has outperformed a broad market benchmark since inception. However, over the relatively short sample period, these funds do not exhibit a significant alpha after accounting for the portfolio's exposure to a set of standard style factors. Focusing on the US equity market (which accounts for a large proportion of the holdings), the aggregated portfolio loads positively on the market, momentum, and size factors but negatively on value, investment, and profitability.

SIGNAL GENERATION

One area of application of ML tools is the prediction of returns to financial assets. Such predictions are typically used as inputs, along with risk models, in portfolio construction.

Building Multifactor Signals

A number of recent papers have attempted to select and combine existing individual signals by using ML methods. This problem has a long history in financial economics, mostly in the fields of asset pricing and portfolio optimization. Over the years, the literature has witnessed a proliferation of trading strategies not explained by risk (often referred to as *anomalies*) as more and more stock characteristics are shown to have persistent predictive power for the cross section of stock returns. The set of available candidate signals is so large that a recent strand of literature has cast doubt on the robustness of the traditional tests used to identify useful predictors (see Harvey, Liu, and Zhu 2016).

Against this backdrop, the recent literature stresses the properties of ML methods that render them suitable for the task. These include the focus on prediction, the ability to detect potentially complex nonlinear relations, and the ability to deal with a large number of features. Regularized regression methods, particularly LASSO, have proven popular in this area of research. Feng, Giglio, and Xiu (2020) and Freyberger, Neuhierl, and Weber (2020) employ LASSO to create data-driven combinations of stock return predictors from large sets of signals. Similarly, Rapach et al. (2019) use LASSO to identify the most significant predictors and create optimal combinations among a large set of industry and market returns. Rapach et al. (2013) use adaptive elastic nets to explore the predictive ability of lagged US market returns on global indexes. Gu et al. (2020) provide an example of the application of elastic nets to the selection and combination of both fundamental and technical signals to predict stock returns. Messmer and Audrino (2017) conclude that adaptive LASSO outperforms both ordinary least squares and LASSO when used to select from a vast number of features. Kozak, Nagel, and Santosh (2020) adopt a shrinkage approach to build

[1] Using data from ETF Global, we find that the average management fee of active ETFs that are listed in the United States and belong to the equity asset class is 0.68% as of April 2021.

a stochastic discount factor summarizing the joint explanatory power of a large set of stock characteristics. As an alternative to these data-driven approaches, Bew et al. (2019) and Papaioannou and Giamouridis (2020) consider expert predictions as model inputs instead of stock characteristics.

Decision and regression trees are another popular class of ML methods employed in generating multifactor signals. In fact, Bryzgalova, Pelger, and Zhu (2019) point out that the standard factor models of Fama and French (1993, 2015) can be viewed as simple tree models with just two splitting points based on the quantiles of the distributions of company fundamentals, such as the book to price ratio or operating profitability. Coqueret and Guida (2018) produce tree-based forecasts of the returns of a large set of US equities between 2002 and 2016 using extreme gradient-boosted trees. Coqueret and Guida (2020) recommend training multifactor models in the tails of the distribution of the dependent variable to reduce training time without losing out-of-sample accuracy.

Gu et al. (2020) estimate a number of tree-based regression models using gradient-boosted regression trees. Most papers agree that shallow trees and models with a limited number of trees seem to outperform in applications to equities. Leung et al. (2020) use gradient-boosted trees to predict monthly stock returns using 20 stock characteristics. They conclude that, despite the statistical advantage of ML model predictions, the economic gains tend to be more limited and depend critically on the ability to take risk and implement trades efficiently.

In addition to decision and regression trees, SVMs and ANNs have promising applications in multifactor signal generation owing to their ability to capture nonlinear dynamics. SVMs are among the most recently developed ML tools and have not been studied as much as ANNs. Nevertheless, several studies have successfully employed SVMs in financial modeling and forecasting (e.g., Cao and Tay 2003; Kim 2003; Huang, Nakamori, and Wang 2005; Chen, Shih, and Wu 2006; Arrieta-Ibarra and Lobato 2015).

The most successful technique emerging from this line of work is arguably ANNs. The adoption of ANNs is not new in finance (see Trippi and Efraim 1992 for early examples). However, the recent advancements in the field and available computational power have rekindled enthusiasm among researchers. Vui et al. (2013) provide a short review of the literature. Gu et al. (2020) tackle the problem of building a multifactor strategy from more than 900 potential predictors of stock returns. They conclude that neural networks (NNs) outperform other ML approaches in this setting. In particular, they argue that shallow networks (with three layers) seem to do a better job than deep ones. Similarly, Abe and Nakayama (2018) use ANNs, among other techniques, to predict one-month-ahead returns for Japanese equities. Unlike Gu et al. (2020), they find that deep NNs yield the best results. Krauss, Do, and Huck (2017) conduct another example of this approach: They apply deep NNs to the prediction of daily stock returns and find that they are outperformed by both random forests and gradient-boosted trees.

A common challenge when dealing with ANNs is the interpretability of results. This issue is particularly relevant to the task of building a predictive model for active portfolio management. When running a day-to-day investment process, the ability to audit all past decisions is crucial. Therefore, portfolio managers appreciate models that allow for a clear attribution of risk and return to the individual building blocks of the model. An NN model with tens of thousands of parameters is sometimes perceived as a black box; that is, it is difficult to trace a certain decision back to the main drivers of the model. This issue has spurred a series of attempts (e.g., Gu et al. 2020) to use recent advances in the ML literature to interpret the importance of individual features. Dixon and Polson (2019) explore ways to interpret NNs statistically using confidence intervals and by ranking the importance of input variables and interaction effects.

A common modeling strategy in this literature involves averaging the forecasts of several ML models. The resulting hybrid model, typically referred to as an ensemble, often manages to further improve the trade-off between bias and variance. Tan, Quek, and Cheng (2011), Tsai et al. (2011), Geva and Zahavi (2014), Nuij et al. (2014), and Krauss, Do, and Huck (2017) provide examples of the application of this approach to the equity market. In a recent paper, Borghi and De Rossi (2020) experiment with an ensemble of random forest models, NN, gradient-boosted trees, and regularized regressions to predict stock returns. Their main conclusion is that a trading strategy based on model combinations tends to outperform strategies based on individual ML models. Wolff and Echterling (2020) build ML models to predict weekly returns for the constituents of the S&P 500 index. They find that an ensemble of deep NNs, random forests, long short-term memory (LSTM) NNs, and regularized regressions delivers the best risk-adjusted performance. Rasekhschaffe and Jones (2019) stress the importance of model averaging to mitigate overfitting and recommend different types of forecast combinations (across different models, training sets, and forecast horizons).

A common result in the literature is that ML-driven multifactor models tend to load predominantly on factors that generate high turnover, such as price momentum and short-term reversals. As a consequence, it is crucial to limit transaction costs when implementing such strategies. Wolff and Echterling (2020) warn that transaction costs have to be marginal for investors to be able to capitalize on the strategies. Avramov, Cheng, and Metzker (2020) reach a similar conclusion after analyzing several ML approaches to building a multifactor signal. They also argue that, particularly in the case of deep learning techniques, the profitability of the resulting signal tends to be concentrated in small, illiquid stocks or securities issued by distressed firms. In addition, the authors highlight two advantages of ML-driven strategies over traditional anomalies: They show that ML-driven strategies profit both from their long and their short positions and, unlike a number of well-established anomaly portfolios, do not suffer from a steep decline in their performance over the last 20 years.

Enhancing Single-Factor Strategies

ML methods can also be applied to signal generation by re-engineering a traditional investment factor (primarily price momentum and short-term reversal). An early example is provided by Takeuchi and Lee (2013), who propose an enhanced price momentum signal derived by using an autoencoder composed of stacked restricted Boltzmann machines. Fischer and Krauss (2018) derive a new short-term reversal signal by feeding a large number of features (each representing a lagged return for a specific window) to an NN model. One of the contributions of their paper is the application of LSTM networks to the financial prediction problem. They conclude that their data-driven approach delivers a better indicator of price reversals and outperforms the traditional indicators established in the literature. Krauss, Do, and Huck (2017) extend the analysis by employing a range of ML approaches. Varaku (2020) also uses recurrent NNs to predict stock returns based on lagged observations.

Moritz and Zimmermann (2016) propose a new method to obtain conditional portfolio sorts based on past returns. Their approach, which shares some important features with random forests, consists of averaging the forecasts of a number of shallow trees, in which splitting variables and splitting points are estimated using the data. A recent paper by Lim, Zohren, and Roberts (2019) seeks to use NNs to derive an enhanced time-series momentum signal and design trading strategies employing futures contracts. Among the approaches surveyed by the authors, LSTM networks (coupled with volatility scaling) seem to deliver the best results in terms of predictive accuracy and profitability of the resulting strategy. Booth, Gerding, and McRoarty (2014) propose the use of ML to capture seasonality effects in stock returns. In particular, the authors adopt performance-weighted ensembles of random forests and argue that the proposed methodology yields significant improvements in the traditional seasonality signals.

In a high-frequency context, Chinco, Clark-Joseph, and Ye (2019) use LASSO to predict one-minute returns of NYSE stocks using lagged returns of all available securities. Tashiro et al. (2019) adopt convolutional NNs to extract predictive signals from order-based features. A common theme among these studies is the emphasis on feature engineering, which plays a crucial role in highly data-driven forecasting procedures (Rasekhschaffe and Jones 2019). Given the low signal-to-noise ratio, it is important to incorporate domain knowledge in the process to avoid overfitting.

NLP Applications

Recent research also uses NLP tools to extract information from textual media that is not readily available in a structured form. The body of literature is vast to the point that several surveys have been published (Das 2014; Kearney and Liu 2014; Fisher, Garnsey, and Hughes 2016; Loughran and MacDonald 2016). In a recent study, Azimi and Agrawal (2019) apply deep learning to annual reports of US companies and show that it is possible to extract a sentiment indicator that predicts abnormal returns around the publication date. Earlier efforts in this field include works by Li (2010) and Loughran and McDonald (2011).

Analyst conference calls are another type of company disclosure that has received considerable attention in the literature (see Larcker and Zakolyukina 2012 and Borochin et al. 2018 for two notable examples). Most of the existing literature highlights the fact that the signals obtained from analyst conference calls have limited overlap with well-known effects, such as earnings momentum and the post–earnings announcement drift. The additional information contained in conference call transcripts is often attributed to behavioral effects. For example, a company may decide to exaggerate the losses experienced in a given period, thereby causing a significant deterioration in the company's fundamentals. However, during the conference call, it is likely that the language used by management will reflect a more positive view of the future compared to the view implied by accounting numbers. Sentiment indicators have also been derived from the language used in analyst reports (Huang, Zang, and Zheng 2014), earnings press releases (Demers and Vega 2008), and Securities and Exchange Commission comment letters (Ryans 2019).

News analytics is another notable area of interest, which can be traced back to the early work of Tetlock, Saar-Tsechansky, and Macskassy (2008). Papers in this strand of literature typically focus on short-term predictions of returns based on changes in sentiment that are detected in real time from the news coverage attracted by an issuer. Although simple techniques like bag-of-words dominate the early literature (e.g., Bartram, Brown, and Conrad 2011), recent contributions have explored more sophisticated approaches.

Schumaker and Chen (2006) consider three textual document representations: bag-of-words, noun phrases, and named entities. They use SVMs to model the impact of news articles on equity prices 20 minutes after publication. The authors conclude that noun phrase outperforms the traditional methods and that SVM is successful in capturing the impact of news on stock prices. Ke, Kelly, and Xiu (2019) attempt to predict returns directly from textual data, as opposed to building and training a sentiment indicator that can then be used as a predictor. The authors consider a practical application to Dow Jones Newswire data and argue that the proposed method yields a very effective predictive signal.

Finally, NLP methods have been applied to detecting sentiment in social media forums and internet search data. Early examples of this approach include work by Antweiler and Frank (2004) and Das and Chen (2007), who analyze large sets of postings on an internet message board. Sprenger et al. (2014) find that tweet sentiment from stock microblogs is associated with subsequent stock returns. However, authors such as Checkley, Higón, and Alles (2017) and Oliveira, Cortez, and Areal (2017) report that Twitter-based sentiment measures are weak predictors of future stock returns. The main concern in this strand of literature is the amount of noise that characterizes data extracted from platforms like Twitter. A solution advocated by Chen et al. (2014) is to focus on platforms that attract finance experts, such as StockTwits. More recently, Groß-Klußmann, König, and Ebner (2019) propose a method to identify expert users who focus mostly on financial topics. They find a strong link between their proposed directional sentiment metrics and aggregate stock index returns globally. This method can be used to enhance trend-following strategies.

PORTFOLIO CONSTRUCTION

It is commonly believed that the standard approach to portfolio construction in the financial industry is still deeply rooted in the mean–variance tradition, almost 70 years after the work of Markowitz (1952) was published. Key textbook-length works on quantitative portfolio management, such as those by Grinold and Kahn (2000), Connor, Goldberg, and Korajczyk (2010), and Qian, Hua, and Sorensen (2007), make substantial use of mean–variance methods. However, critics, such as Michaud and Michaud (2008) and Kolm, Tütüncü, and Fabozzi (2014) have pointed out that in practice the mean–variance paradigm suffers from the difficulty of estimating its main inputs, particularly expected returns. A remarkable consequence of the inaccuracy of the typical return predictions is that a simple equally weighted portfolio of all available assets, which makes no assumptions on the directionality of future returns, turns out to be a hard benchmark to beat for optimized portfolios (DeMiguel, Garlappi, and Uppal 2007). Hence, it is natural to view portfolio construction as an area in which the recent advances in ML techniques may inspire wide-ranging innovation.

A good starting point is the estimation of portfolio risk. Several recent papers have relied on ML techniques to improve the estimation of portfolio risk, in some cases dispensing with the covariance matrix altogether. An example is a study by Lopez de Prado (2016), who replaces the structure of return covariances among assets with a tree structure using hierarchical cluster analysis. Although the information processed by this method is the same as in the traditional mean–variance paradigm, it requires fewer estimates and therefore delivers better stability and robustness. The author reports that the proposed method to build a minimum variance portfolio results in a 31% improvement in the Sharpe ratio compared to the standard approach.

As mentioned earlier, imposing sparsity on the structure of dependence among financial assets is one potential avenue to address the shortcomings of the implementation of the mean–variance paradigm. Penalized regression methods are a natural choice in this context, as the extensive survey conducted by Fan, Lv, and Qi (2011) documents. The connection with LASSO is elegantly exposed by Fan, Zhang, and Yu (2012).

The so-called *econphysics* literature has also suggested various ML approaches to modeling the dependence structure of a large set of assets. Previde Massara and Aste (2019), for example, propose a topological learning algorithm called the maximally filtered clique forest. We refer the reader to the literature review in the paper for more details on this line of research.

A separate strand of literature consists of papers that attempt to use ML directly to obtain optimal portfolios. NNs seem to be a common approach in this area of research owing to their flexibility in accommodating complex rules and constraints in the decision process. Chapados and Bengio (2001), for example, use NNs to learn the optimal asset allocation subject to value-at-risk constraints. They highlight an effective use of committee methods to systematize the choice of hyperparameters during NN training. In a similar vein, Yu, Wang, and Li (2008) go beyond the first two moments by training an NN to build mean–variance-skewness efficient portfolios. Zimmermann, Neuneier, and Grothmann (2002) incorporate the Black and Littermann (1992) framework into a NN model in order to augment the set of inputs with views about future returns.

An alternative approach, based on boosting and expert weighting, is proposed by Creamer and Freund (2010). The authors develop a layered structure composed of an ML algorithm that combines trading signals to generate a number of experts, an online learning utility that selects and combines the expert forecasts, and a risk management overlay. In a recent paper, Zhang, Zohren, and Roberts (2020) suggest a deep learning approach to directly optimize a portfolio's Sharpe ratio. The advantage of this approach is that it delivers optimal portfolio weights by updating model parameters through gradient ascent without the need for a forecasting step required by the classical mean–variance framework.

Index tracking is an area of portfolio management that can significantly benefit from ML approaches. An early example is by Lowe (1994), who applies feedforward NNs to portfolio optimization under various constraints. Lowe argues that the proposed methodology is able to replicate the FTSE 100 index using a small subset of the constituents, thereby reducing transaction costs and allowing for more efficient portfolio management. Heaton, Polson, and Witte (2017) describe a procedure for data-driven portfolio selection consisting of four steps. The auto-encoding step fits the dataset of historical returns. The goal of the second step (termed the decode step) is to find a portfolio map to achieve a prespecified goal. Finally, an out-of-sample validation step is used to tune hyperparameters and, particularly, to optimize the amount of regularization needed in the first two steps. This leads to the generation of an efficient frontier that can be used in the fourth step for model selection. The paper discusses the applications of this approach to tracking an equity index and enhanced indexation.

Finally, it is worth mentioning that several papers advocate the application of evolutionary algorithms to portfolio construction. Branke et al. (2009) show that this approach can be used to incorporate complex rules, such as constraints on the number of assets in the portfolio and minimum holding thresholds. Skolpadungket, Keshav, and Napat (2016) report significant improvements in Sharpe ratios by incorporating model risk in the portfolio construction framework through evolutionary algorithms. The main goal of these papers is to exploit the flexibility of evolutionary algorithms to deal with increasingly complex optimization problems.

EXECUTION

To realign holdings with investment objectives, investment portfolios are rebalanced by executing orders based on portfolio optimization. Early studies by Almgren and Chriss (2001) and Bertsimas and Lo (1998) formalize order execution as a dynamic programming problem, in which the goal is to split trades optimally over a prespecified length of time (e.g., one day). Two main components are needed to fully characterize the problem: a market impact model and a model of the intraday dynamics of security prices. The optimal solution will then strike a balance between minimizing price risk (which can be achieved by rapidly executing trades) and minimizing market impact (which typically requires a passive execution style).

Estimating market impact, particularly in equity markets, naturally relies on ML techniques because of the vast number of available inputs, the nonlinearity of relationships, and the complex dynamics typically found in the data. Booth, Gerding, and McRoarty (2015) propose using performance-weighted random forests to build data-driven nonparametric models that predict market impact as a function of the characteristics of an order. They find that this approach significantly outperforms linear regressions, NNs, and SVMs out of sample. Park, Lee, and Son (2016) run a similar analysis and conclude that several ML models (i.e., NNs, Bayesian NNs, and Gaussian process regressions) significantly outperform a standard parametric benchmark, whereas support vector regression yields less unambiguous conclusions.

Zheng, Moulines, and Abergel (2013) use logistic regressions to investigate the relation between market impact and a large set of potential predictors. LASSO is used for variable selection. They find that trade sign, market order size, and liquidity based on best limit order prices tend to be selected as the most relevant features. Brière et al. (2019) use Bayesian networks to forecast implementation shortfall as a measure of transaction cost. This approach is particularly useful in cases of missing data because it can impute the most probable value given the available information. The authors thus incorporate net order flow imbalance as a predictor and show that the resulting model improves on the standard approaches, particularly when the order size is large and market volatility is low.

Alongside supervised methods such as the aforementioned, unsupervised models, such as cluster analysis, can be used for market impact modeling. Bloomberg's liquidity assessment tool (LQA) and the stock clustering framework developed by Goldman Sachs (2019) are examples of this approach. Cluster analysis can be used to group securities that have similar characteristics from a trade execution point of view into a small number of categories using a large set of historical microstructure features. This method has applications for trading cost analysis, anomaly detection, and market impact prediction.

Philip (2020) advocates the use of RL to estimate permanent price impact. The author shows that vector autoregression (VAR) models, which are common tools for estimating permanent price impact, can lead to incorrect inferences in the presence of nonlinear market impact dynamics. The advantage of RL is that it can learn the nonlinear relations between trades and quotes. Therefore, RL can produce significantly better predictions of permanent market impact compared to vector autoregressions.

Another topic that has attracted a great deal of attention recently is optimal execution. Rather than relying on dynamic programming, this growing body of work adopts a data-driven approach to let the algorithm learn the optimal execution strategy as a function of the evolution of the inputs. RL algorithms have proven particularly popular in this area of research. Nevmyvaka, Yi, and Kearns (2006), Kearns and Nevmyvaka (2013), and Hendricks and Wilcox (2014) provide examples of this approach. Deep RL approaches, which include RL algorithms that use deep NNs for function approximation, are successfully applied to optimal execution. Dabérius, Granat, and Karleson (2019) examine the two cutting-edge approaches of proximal policy optimization and deep double Q-network for this exercise. They show that both methods are able to outperform the time-weighted-average-price (TWAP) benchmark, one of the references used by traders. This result is mostly driven by environments in which TWAP is not optimal, such as when prices have a drift, are mean reverting, or both. In another interesting application of deep RL, Baldacci and Manziuk (2020) devise a framework for optimal partial execution of limit orders at multiple venues. This model captures the dependencies between the imbalance and the spread of venues and accounts for changing market conditions, market impact, and hidden liquidity.

Leal, Laurière, and Lehalle (2020) use a deep NN to generate optimal rules for trading using high-frequency data. The advantage of their approach is that it learns the mapping between a trader's risk aversion and the optimal trading speed. The authors provide a tool to project the learned control onto the functional space spanned by the closed-form solution to the stylized optimal control problem. This addresses the perceived lack of transparency in NN models and the resulting potential regulatory concerns.

Mounjid and Lehalle (2020) propose a methodological improvement on the RL algorithms typically adopted in the literature. Their innovation consists of introducing a dynamic optimal policy for the choice of the learning rate used in stochastic approximation. In the empirical part of their study, they demonstrate the improvement generated by their proposed methodology as applied to the optimal execution of a large number of shares.

A common problem in the application of RL to optimal execution is the need for a detailed model of the world or a realistic simulation engine (to account for the impact of an agent's trades on price dynamics). Mounjid and Lehalle (2020) propose the use of transfer learning to address this issue. In their framework, the NN is first trained on simulated trajectories, leading to a good initialization before training on historical trajectories.

A CLOSER LOOK AT RL

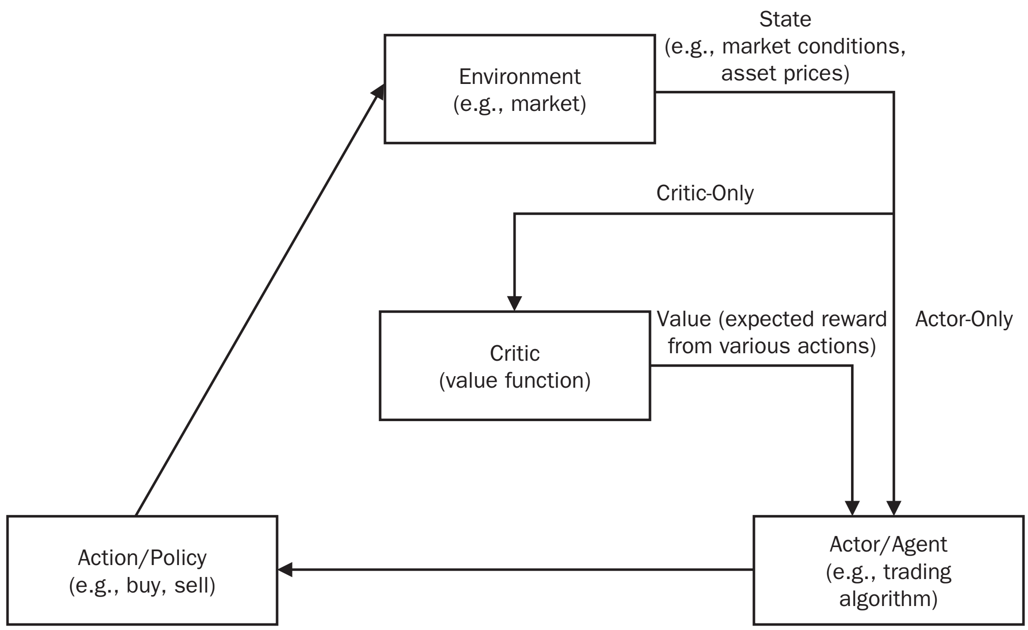
RL has three key advantages over the common supervised and unsupervised learning approaches used in finance. First, it can directly learn to maximize investors' objective functions (e.g., Sharpe ratios) rather than simply predict returns, which is what supervised learning is often used for. Second, RL, unlike most other ML approaches, can provide a convenient framework to account for market frictions, transaction costs, and liquidity constraints. Third, RL can make sequential decisions and learn from the outcomes of those decisions to improve itself. This feature makes it an ideal tool for automated trading platforms and algorithmic trading.

The recent success of DeepMind's AlphaGo Zero, the algorithm that defeated several top Go players, has generated renewed interest in RL. However, RL is currently barely used by the asset management industry. This is because these algorithms are often expensive, difficult to implement and test, and more data savvy and computationally intensive than most other ML tools (Snow 2020a). Nevertheless, RL's important advantages, as stated earlier, and rapid growth in computing power are likely to make the use of these approaches more prevalent in years to come (Snow 2020b).

Fischer (2018) categorizes RL algorithms as critic-only, actor-only, and actor-critic. Critic-only algorithms (see Nevmyvaka, Yi, and Kearns 2006; Jin and El-Saawy 2016; and Kolm and Ritter 2019) are the most extensively studied RL approaches. These models aim to learn value functions that produce the expected reward value from each action at each point in time; this allows the algorithm to choose the action with the best outcome. These algorithms are often unable to deal with many assets and can only consider discrete action spaces (e.g., buy, sell). Actor-only (see Jiang, Xu, and Liang 2017; Lim, Zohren, and Roberts 2019; Chaouki et al. 2020; Ferreira 2020) algorithms learn to map states (e.g., market conditions) to actions directly. These models are more transparent and can accommodate continuous action spaces (e.g., portfolio weights). However, they require the reward function (e.g., portfolio Sharpe ratio, investor utility) to be differentiable when the action space is continuous. Exhibit 1 depicts the structure of the actor-only and critic-only models.

EXHIBIT 1

Actor-Only and Critic-Only RL Algorithms



Actor-critic approaches (see Xiong et al. 2018 and Baldacci and Manziuk 2020) comprise two models: The first (the actor model) determines the action depending on the current state, and the second (the critic model) evaluates the performance of the chosen action. The idea is to iteratively adjust the actor model so that it maximizes the expected reward produced by the critic model. Fischer (2018) reviews a large number of studies related to each of these approaches and concludes that there is no clear winner in terms of performance.

Several papers indicate that RL has recently been adopted to build portfolios of assets directly from historical data on market-price dynamics and particular signals. The main idea is to let the algorithm learn the optimal allocation based on the available information about the market and the history of previous trades. The learning mechanism relies on reward signals received by the algorithm at each iteration in response to its actions. RL allows for highly complex path-dependent actions in dynamic environments, a feature that is potentially valuable for portfolio construction and systematic trading system designs.

The use of RL for portfolio construction dates back to the study by Moody et al. (1998). However, more recent studies explore significantly larger samples of stocks and conduct more extensive empirical analyses (Xiong et al. 2018; Cong et al. 2020; Lee et al. 2020; Wang and Zhou 2020; Zhang, Zohren, and Roberts 2020). These papers consider US financial markets and report Sharpe ratios between 0.75 and 5.5, which are greater than the S&P 500's Sharpe ratio. Furthermore, the study by Cong et al. (2020) contains two interesting ML innovations. First, it uses transformer encoders (TEs) to extract features from a list of technical and fundamental explanatory variables. TEs are particularly useful for shrinking high-dimensional panel data while preserving complex nonlinear and interaction effects. Moreover, it uses surrogate modeling and polynomial sensitivity analysis to interpret the RL algorithm's outputs and highlight the model's driving features. This is a crucial step because reinforcement algorithms are often notoriously opaque. Therefore, such interpretation approaches are necessary to address the black box issue and shed light on what the model is capturing from the data. We refer readers to Sutton and Barto (2018) for technical explanations and Fischer (2018), Zhang, Zohren, and Roberts (2019), Charpentier, Elie, and Remlinger (2020), and Kolm and Ritter (2020) for financial application surveys.

ACTIVE AI-DRIVEN ETFS

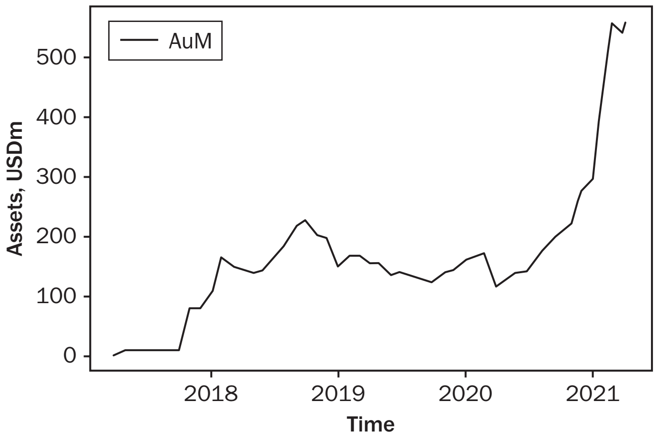
The recent launch of a number of active ETFs that claim to implement AI-driven strategies is a sign of growing investor interest in the topic. To provide a brief overview of the sector, we perform a keyword search in the description of all ETFs traded in the US market using data from ETF Global. In addition, the same keywords are used for a search in the historical Reuters/Refinitiv news feed to identify any active ETFs whose investment process is driven by AI or ML techniques. After filtering out funds that invest in companies engaged in AI, the results yield 13 funds that are analyzed using data from ETF Global and CRSP. The full list can be found in Exhibit 3.

Whereas AuM remain modest (below 1% of the total managed by active ETFs in equities), this category of funds has enjoyed significant growth since 2017, as shown in Exhibit 2. Roughly half of the assets are managed by active equity funds, whereas the rest are held by multi-asset products. Of the equity funds, all but one invest exclusively in US equities. The AI-Powered International Equity ETF (AIIQ) is the only equity fund that invests globally.

As Exhibit 4 shows, the strategies have relatively short track records, with an overall average age of 1.36 years. Equity funds exist for slightly longer, particularly if we consider the value-weighted average age (2.45 years). Two funds (i.e., BUZZ US Sentiment Leaders ETF and Rogers AI Global Macro ETF) closed down in 2019. Management fees are on average 0.75% for equity funds and slightly higher for multi-asset ones. This puts the management fees (and net expense ratios) of AI-driven ETFs toward the top of the range for ETFs in general and above the average level for active equity ETFs (0.64%).

We focus on the equity portfolios and analyze their holdings using the Axioma suite of risk models. As reported in Exhibit 4, AI-driven equity portfolios appear to be well diversified, with more than 150 holdings on average, and highly active, as suggested by the average active share of more than 80 and the tracking error above 10%. The bulk of the active risk, as analyzed through a standard risk model, can be attributed to factor exposure (i.e., 83.9% of active variance, on average). In particular, a large proportion of the active exposure seems to stem from style bets, as we would expect from an active quantitative strategy.

EXHIBIT 2
AI-Driven Active ETF Assets Under Management



NOTES: Exhibit 2 shows the trend in total AuM (in millions of US dollars) by AI-driven active ETFs. Using data from ETF Global and Refinitiv, we identify all equity ETFs listed in US markets that implement AI-driven strategies. The list of these ETFs is presented in Exhibit 3. The sample period is March 31, 2017–April 8, 2021.

EXHIBIT 3
Active AI-Driven ETFs

ETF Name	Ticker
AdvisorShares Alpha DNA Equity Sentiment ETF	SENT
AI Powered Equity ETF	AIEQ
AI Powered International Equity ETF	AIIQ
BUZZ US Sentiment Leaders ETF	BUZZ
Merlyn.AI Best-of-Breed Core Momentum ETF	BOB
Merlyn.AI Bull-Rider Bear-Fighter ETF	WIZ
Merlyn.AI Sector Surfer Momentum ETF	DUDE
Merlyn.AI Tactical Growth and Income ETF	SNUG
Qraft AI-Enhanced Next Value ETF	NVQ
QRAFT AI-Enhanced US Large Cap ETF	QRFT
QRAFT AI-Enhanced US Large Cap Momentum ETF	AMOM
Qraft AI-Enhanced US High Dividend ETF	HDIV
Rogers AI Global Macro ETF	BIKR

NOTES: Exhibit 3 presents the list of active AI-driven ETFs in our sample. To obtain the list, we performed a keyword search in the description of all ETFs traded in the US market using data from ETF Global. In addition, the same keywords were used for a search in the historical Reuters/Refinitiv news feed to identify any active ETFs whose investment process is driven by AI or, more generally, by ML techniques. Funds that invest in companies engaged in AI were filtered out from the initial results.

EXHIBIT 4

Descriptive Statistics of AI-Driven Active ETFs

	Equity Funds		All Funds	
	Simple Average	Weighted Average	Simple Average	Weighted Average
AuM, USDm	38.15	112.96	50.39	119.78
Mgmt Fee	0.76	0.75	0.81	0.91
Net Exp	0.81	0.84	0.85	0.97
Age, Years	1.68	2.45	1.36	1.54
Number of Holdings	152.14	156.94	99.73	80.31
Number of Stocks Held	145.57	152.47		
Volatility	24.04	26.97		
Tracking Error	11.14	13.36		
% Factor Active Risk	83.90	88.61		
% Style Active Risk	59.83	77.76		
% Sector Active Risk	18.56	9.41		
Active Share	86.03	81.10		

NOTES: Exhibit 4 reports descriptive statistics of AI-driven active ETFs as of April 8, 2021, listed in Exhibit 3. The ETF holdings and fund characteristics data are from ETF Global. The Axioma Suite is used to analyze the holdings and produce the risk measures. The S&P 500 index is used as the benchmark for domestic equity ETFs and international funds are benchmarked against the MSCI EAFE index. *Mgmt fee* and *Net exp* are the management fee and the total expense ratio charged by the fund, respectively. *Volatility* and *tracking error* are computed ex ante based on the Axioma Suite risk model. The ex ante tracking error is decomposed into risk factors and idiosyncratic components. The exhibit also shows the average proportion of active risk attributed to style exposures and sector exposures. Active share is defined as $\Sigma_i |w_i - w_i^B|/2$, where w_i and w_i^B are the portfolio and benchmark weights of stock *i*.

To analyze the performance of these funds, we use daily CRSP data for each fund's longest available period. Because the CRSP database does not include data for 2021 yet, we use data from Bloomberg Terminal to extend our time series to April 12, 2021. We construct two equally weighted fund portfolios and explore their performance separately. The *US-only equity funds* portfolio contains the funds that only invest in US equities, whereas the portfolio labeled *all funds* contains all 13 funds.

Panel A in Exhibit 5 reports a number of basic performance metrics. On average, the 13 ETF funds generate returns of 15.6% in excess of the risk-free rate and 3.46% in excess of the market. The Sharpe and information ratios are 0.88 and 0.42, respectively. The US-only equity funds generate a larger average excess return of 18.3%, but their Sharpe and information ratios are lower. It should be noted that the performance of the two portfolios is not directly comparable because they cover different time periods.

Panel B in Exhibit 5 reports the results of time-series factor model regressions for the US-only equity funds portfolio and the all funds portfolio. For the US-only equity portfolio, we use Fama and French's (2015) original five US factors plus momentum. For the all funds portfolio, we use the developed countries version of these factors. All factor data are sourced from Ken French's website.[2] The estimated alphas in Exhibit 5 are positive, but the corresponding t-statistics (0.01 and 0.51) are well below the critical values. These results indicate that our AI-driven ETF portfolios did not generate statistically significant abnormal returns.

The portfolio of all funds has positive exposures to the market and momentum and negative exposures to size, value, investment, and profitability factors. The portfolio of US-only funds has similar exposures, with the exception of a positive loading on the size factor and an insignificant loading on the investment factor. It is likely

[2] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

EXHIBIT 5
Performance of AI-Driven Active ETFs

	US-Only Equity Funds	All Funds
Panel A: Performance Metrics		
Average Return Minus Risk-Free Rate	18.31%	15.63%
Average Return Minus Market Return	1.54%	3.46%
Sharpe Ratio	0.84	0.88
Information Ratio	0.24	0.42
Volatility	0.22	0.18
Idiosyncratic Volatility	0.05	0.07
Number of Daily Returns	873	1,252
Sample Start Date	October 19, 2017	April 20, 2016
Sample End Date	April 12, 2021	April 12, 2021
Panel B: Factor Regressions		
Intercept (alpha)	0.03%	1.34%
	(0.01)	(0.51)
Mkt–RF	0.95***	0.97***
	(58.90)	(49.50)
SMB	0.11***	–0.21***
	(5.23)	(–5.18)
HML	–0.17***	–0.26***
	(–6.41)	(–3.98)
MOM	0.07***	0.07**
	(2.38)	(1.88)
CMA	0.03	–0.27***
	(0.80)	(–3.03)
RMW	–0.15***	–0.44***
	(–5.36)	(–5.41)
R^2	0.96	0.84

NOTES: Exhibit 5 presents the performance indicators (Panel A) and factor regression estimates (Panel B) for equally weighted portfolios of the AI-driven ETFs listed in Exhibit 3. We use daily return data from CRSP for each fund's longest available period and use data from Bloomberg Terminal to extend our time series to April 12, 2021. We construct two equally weighted fund portfolios: a US-only equity funds portfolio, containing the funds that only invest in US equities, and a portfolio labeled All Funds, containing all the 13 funds. *Average return minus risk-free rate* is the annualized average daily excess return. *Average return minus market return* is the annualized average daily return in excess of the market return. *Sharpe ratio* is the annualized Sharpe ratio of daily returns. *Information ratio* is the annualized average daily information ratio using the market index as the benchmark. *Volatility* is the annualized daily return volatility. *Idiosyncratic volatility* is the annualized volatility of the daily residuals from the five-factor model of Fama and French (2015). *Number of daily returns* is the number of available daily fund returns in our sample. *Sample start date* and *Sample end date* indicate when the sample period starts and ends for each fund. The estimates in Panel B are based on daily factor regression using the Fama and French (2015) five-factor model.

that the ML portfolios underweight value due to its poor recent performance while overweighting momentum, which has had a positive run over the same period. As we argued earlier, momentum is invariably found to be one of the key drivers of returns in the ML literature. The exposure to small-cap stocks echoes the concerns raised by Avramov, Cheng, and Metzger (2020) that ML strategies may not be scalable because they tend to concentrate on small, illiquid stocks.

CONCLUSION

A number of recent studies highlight promising applications for ML tools in active portfolio management. These tools can be used at various stages of the active portfolio management process, including signal generation, portfolio optimization, and order execution. The key advantage of ML over alternative approaches is its ability to extract information efficiently from a wide range of often large numerical and textual datasets with minimal human supervision. This is expected to make ML an integral part of active portfolio management as the speed of markets and the breadth and extent of available information make it ever more difficult for humans to keep up. Furthermore, computing power, which currently acts as the main constraint for the wider application of ML, has increased to an extent that is likely to allow more complex ML approaches, such as RL, to become more popular in practice. Such models can significantly enhance current non–ML-based automated portfolio management systems (e.g., robo-advisors and algorithmic trading systems).

The adoption of ML for active portfolio management involves various risks and challenges (see Israel, Kelly, and Moskowitz 2020). First, ML tools are highly dependent on data quality, and poor-quality, noisy data can easily result in unreliable models. By ML standards, financial time series are often very short relative to cross sections. This significantly inhibits the models' full potential to learn from the data. Even in cases in which the time-series dimension is large (e.g., high-frequency market data), the signal-to-noise ratio is typically found to be lower than in successful ML applications outside of finance. In addition, financial data evolve over time. Although the basic economic principles underlying market behaviors remain the same, the environment in which investors operate evolves owing to changes in regulation, market microstructure, accounting principles, and other institutional aspects. ML models, especially those with more flexible structures, often have difficulty distinguishing between stationary and evolving market patterns.

The second major concern with the use of ML stems from its complexity and lack of transparency. Most popular methods, such as ANN and RL, are often difficult to interpret and do not provide insights into how they generate results. This lack of interpretability makes it difficult to understand whether the model is capturing meaningful patterns or noise. The immediate consequences of this could be poor model performance and risk assessment. The latter could be a major concern because asset managers often rely on risk management and oversight procedures to gain investors' trust, especially during more turbulent times. Recently, progress has been made in so-called explainable artificial intelligence (XAI) to provide solutions for interpreting opaque ML. However, these solutions are still far more limited than the statistical inference tools available for econometric models.

In an attempt to mitigate some of the challenges associated with the use of AI and ML, the European Commission (2020) recently published a regulatory framework. This represents the first major international effort to regulate the use of AI. The key objective of the framework is to ensure the trustworthiness of AI. Eight key requirements are listed for a trustworthy AI approach: human agency and oversight, technical robustness and safety, privacy and data governance, transparency, diversity, nondiscrimination and fairness, societal and environmental well-being, and accountability. It is not yet clear how the different sectors will comply with these requirements; however, the successful implementation of these regulations can lead to other international regulatory bodies soon following suit. This is likely to reshape the future landscape of ML research and its application in active portfolio management.

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