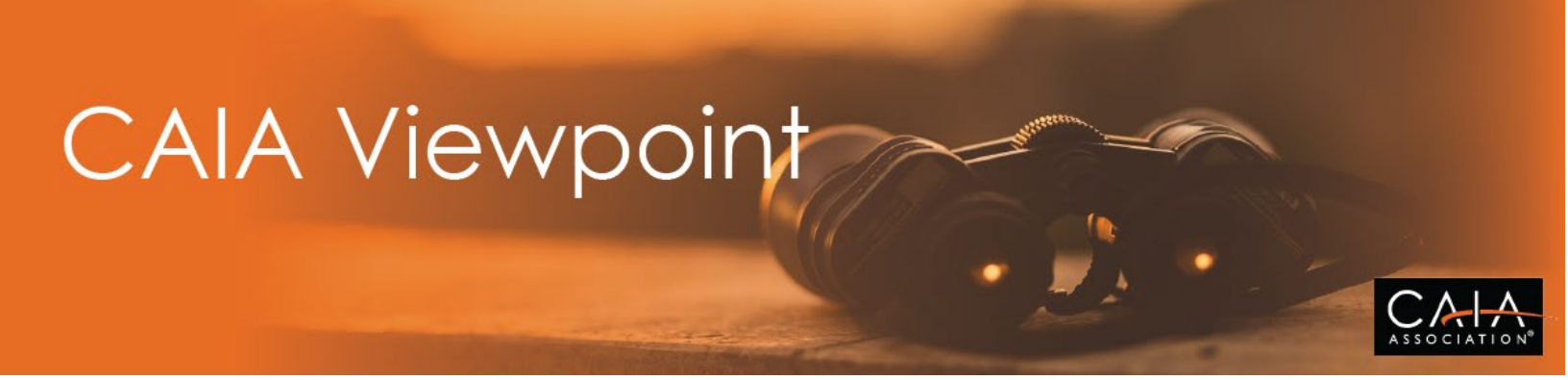

Man AND Machine

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The full article may be accessed here.

Central Issue of the Paper

Artificial intelligence has recently experienced a remarkable increase in attention, following staggering achievements in applications such as image, text and speech recognition, self-driving cars or chess and Go tournaments. It is therefore not surprising that the financial industry is ever more heavily trying to improve investment decisions by incorporating self-learning algorithms into the investment process. For that matter, the application of quantitative tools and algorithms in order to define systematic trading strategies already has a strong history in the hedge fund industry. Against this backdrop, quantitative hedge funds may provide fertile soil for the application of new machine learning techniques. But do all sectors of the asset management industry exhibit characteristics that can be exploited by artificial intelligence tools to uncover new patterns? What could be the especially relevant fields? Are there limits beyond which additional computing power and greater data availability have only marginal benefits? In "Artificial Intelligence – Chances and Challenges in Quantitative Asset Management" by Urs Schubiger, Egon Ruetsche and Fabian Dori attempt to tackle some to these burning questions.

Approach Employed by Paper

Machine learning refers to extracting knowledge from data by identifying correlated relationships without receiving prior information about what causal dependencies to seek. It combines elements from both statistics and computer science and has been in existence for many years. Most machine learning methods have been developed outside of finance and built on well-known statistical models such as linear regression or clustering techniques. Still, machine learning allows for much more flexibility, for example, by allowing for nonlinearities and feedback effects, or by completely refraining from any prior knowledge about the problem under scrutiny. It can be applied to different kinds of problems, such as classification or regression analysis. Classification algorithms group observations into a finite number of categories, whereas regression analysis estimates outcomes to problems that have an infinite number of solutions. Another method is combining supervised and unsupervised learning results in so-called reinforcement learning, where an algorithm first detects patterns on its own, and then receives feedback from an exogenous source to validate or further guide the learning process. A reward feedback is required for the algorithm to learn a certain behavior. For

instance, self-driving cars can learn collision avoidance by learning from the negative feedback received from crashing into obstacles, or computers can teach themselves the rules of games such as chess or Go. Hence, the reward feedback need not necessarily be provided by a human being.

Each sector within the financial industry uses artificial intelligence methods differently and according to their specific needs. Insurance companies, for example, use it among other applications to detect fraud in damage events. Banks count on it to assess credit quality or employ robotic process automation for middle and back office tasks. In wealth management, applications are only just emerging, with a current focus on automatically ensuring regulatory requirements, client segmentation, chatbots to deal with repetitive client requests or portfolio management based on robo-advisors.

In the investment universe, where machine learning tools may assist in identifying uncorrelated assets that provide true diversification benefits; or in the mapping of data into new representations that allow for other interpretations, such as the detection of style drifts in hedge fund strategies or, for instance, factor exposures such as momentum or value. An appropriate tool for the first task would, for example, be a dendrogram analysis; the second goal could be achieved by relying on a principal component or manifold learning analysis. In a similar manner, artificial intelligence methods can be used to proxy valuation or even the actual investment of assets for which there is only sparse historical market data or that are not eligible due to liquidity issues. In the latter case this can be achieved by substituting more liquid instruments that appropriately mimic the characteristics of the desired assets.

There are several challenges and limitations that are not necessarily new to quantitative investment managers, which may be aggravated by the flexibility of new techniques. However, despite a seemingly abundant access to data, there is only one historical price trajectory for each financial market to train a model on. This limited data availability restricts the complexity of the artificial intelligence model that can be applied and, therefore, the flexibility of the model's output when forecasting future price movements. This problem is further deteriorated by the fact that the vast majority of data for financial markets has only been collected recently. Consequently, researchers should focus on parsimonious model structures and not be misled by the mightiness of artificial intelligence models to adaptively learn the past. Despite increasing computer power and data availability, it is necessary to keep in mind that quantitative models remain a simplified transformation of the world and will only have forecasting ability that is limited to specific tasks. Additionally, the complexity of calibrating artificial models requires a diligent analysis as to where to allocate resources and model power most effectively.

Findings of the Paper

The authors highlight that machine learning tools, owing to their adaptivity and self-learning capabilities, may add value along the entire value chain of an asset manager in two specific ways. First, by more effectively using currently available data based on algorithms that learn to reveal new, nonlinear relationships or by transforming data into representations with more interpretable meanings. Second, by embracing new data sources that provide additional information, for example, based on news flow and blog posts. Machine learning will most likely not turn out to be a holy grail, but that it will help quantitative investment managers in further improving their allocation processes. Nevertheless, the use of artificial intelligence in asset management is undoubtedly still at an early stage.