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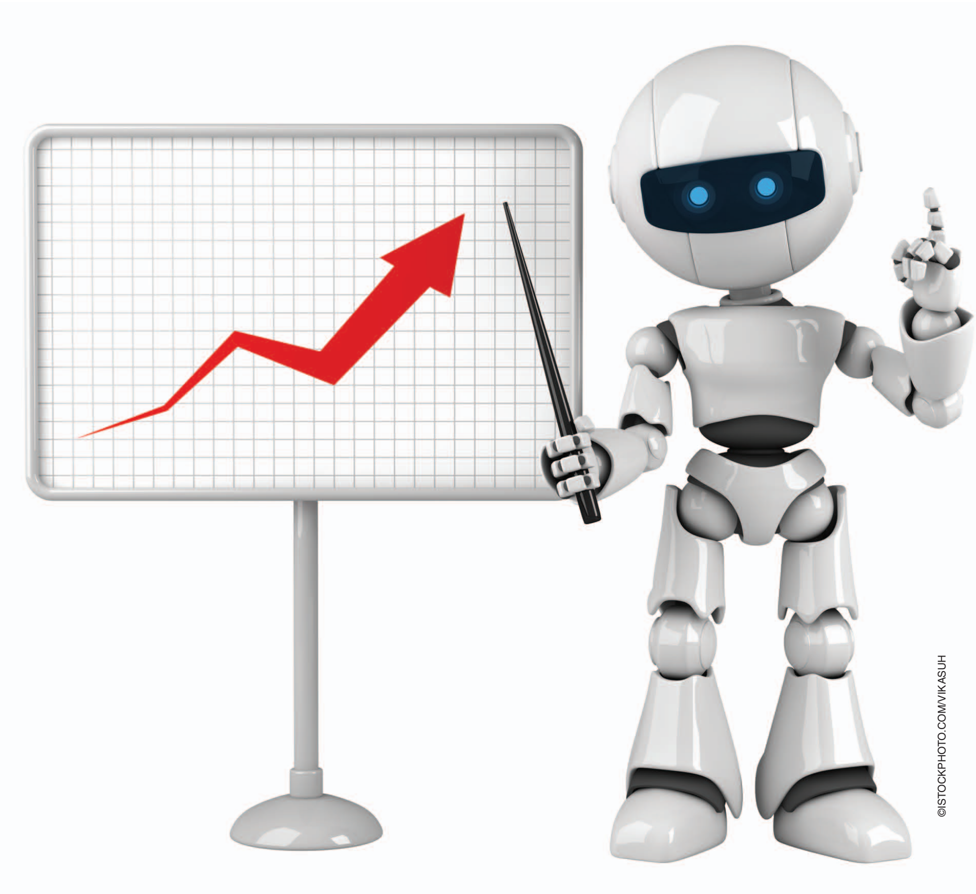
Machine learning and financial planning

John M. Mulvey

One of the top recent events in machine learning (ML) involves Google's Alpha Go System beating the world's best player Ke Jie, while experts had predicted that Go (which is considered by many to be the world's most advanced board game) was too complex to be conquered by a computer for a decade or more. What are the main ideas underlying ML algorithms? What can be expected in the area of financial planning vis-a-vis ML? Will there be major disruptions in financial services?

Today, it is common to ask a virtual assistant (VA) such as Siri to locate the nearest gas station during a holiday trip or find the fastest directions to an airport destination. These types of queries are routinely answered through ML algorithms.

We might pose a related question about suggesting a restaurant for dinner. This question implies personal information and is more subjective than travel directions; it is part of ML called *recommender systems*. The restaurant choice entails several issues: 1) the type and quality of food desired at present, 2) the price, 3) the location, and 4) other matters such as the preferences of companion travelers. To assist, the VA might ask questions to help frame the guidance including: How hungry are you? What is your budget? Decisions along these lines are operational—occurring regularly—and thereby ought to be fair game for ML. However, recommender systems have not yet had breakaway successes to date for several reasons including, among others, the lack of a commonly accepted interface platform, stable performance measures, and the inability to anticipate time-sensitive individual preferences.



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Importantly, significant financial planning problems are strategic in nature. Prominent examples include purchasing a home, saving and investing

Digital Object Identifier 10.1109/MPOT.2017.2737200
Date of publication: 10 November 2017

 0278-6648/17©2017IEEE

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for college or retirement, and setting up a life insurance policy. These decisions are solved by reference to expert advice, introspection, and, perhaps, constructing and running a decision model. For instance, to purchase a commercial real-estate property, most investors will conduct a cash-flow analysis, seek financial advice, and make a subjective personal decision. It would be considered imprudent for a VA to answer such strategic investment questions.

With notable exceptions, there is a large gap between ML classification and decision models. In most cases, the output of the ML algorithms provides inputs to the decision models (Table 1). For instance, ML might categorize individuals by their degree of risk aversion and thereby supply a reference benchmark to long-term financial planning systems. Given this insight, the planning system might suggest guidance regarding the percentage of equity in a retirement account.

Complicating the problem, many financial decisions involve multiple uncertainties. Take the case of an individual saving for retirement. Here, the list of uncertainties includes longevity and health conditions, career and salary projections, the ability to perform in the workplace, familial issues, and risk aversion, among others. Individuals must render decisions of this complexity on a regular basis. Life in modern times has transformed from a paternalistic environment to one requiring individual responsibilities, such as the shift from traditional defined-benefit pensions to defined-contribution pensions. And there are so many choices. A stroll down a supermarket lane illustrates the changes that have occurred over the past half century. Almost every consumer product is available over a wide set of variations. Making these types of decisions is part and parcel of modern life.

A brief overview of ML

Traditional applications of ML involve classification problems in the context of supervised learning. Herein, supervised learning is distinguished by the availability of a large set of previously known solutions to a classification problem, in contrast to unsupervised learning, which involves the goal of pure exploration. (The area of unsupervised learning is gaining much attention due to the collection of pervasive data throughout the world.) ML algorithms are able to decipher handwritten zip codes on mailing envelopes at a speed and accuracy far superior than by human means. How do the algorithms achieve such high performance? First, there is a training phase, wherein millions or hundreds of millions of single numbers (or complete zip codes) are analyzed. The analyzer assumes that the real digits are available for the training processes, called *supervised learning*.

The ML algorithms "learn" the significant features and the complex transformations, largely without human intervention. This shift to a small number of assumptions (assumption-free approaches are possible) by statistical inference is, perhaps, the element most difficult and troubling for many people to grasp. The computer system learns to identify a handwritten digit largely without a priori knowledge but rather with massive observations for training, efficient computational algorithms with hundreds of millions of parameters, and a skilled team

TABLE 1. Gap between ML and decision models.

ML		DECISION MODEL
Probability (heart attack)	→	Decision to install a shunt or other medical intervention
Locate short paths for deliveries	→	Optimal supply-chain network
Characterize consumer preferences	→	Design a marketing campaign
Characterize risk aversion of individuals	→	Provide guidance for investment strategies
Rank consumers on credit worthiness	→	Build a portfolio of loans for an institutional investor

FIG 1 ML identifies objects for an autonomous vehicle.

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of data scientists to conduct the ML training and evaluation.

Numerous classification problems have been solved by ML. Many of the most successful ones fit the supervised learning domain, whereby the training data contain the correct classification results. There is considerable research on identifying objects, such as whether the object crossing the street in front of a self-driving car is a human, a deer, or another automobile (Fig. 1). Clearly, this type of classification may have life-threatening consequences. Facial recognition is gaining higher accuracy, and language translation is in a similar situation, with fast recent improvements being made. These breakthroughs are generating expectations for the field, and most top universities are establishing data-science labs and programs. (There are many alternative names: ML and statistics, computer science, statistical learning, and data science, among others.)

Financial applications of machine learning

The area of finance has been relatively immune to the ML technology, except for a few exceptions such as high-frequency trading and credit scoring for loans. Significant financial decisions are made with reference to formal decision models. The first, and most famous, example is the Markowitz portfolio model. This model has been endlessly enhanced. Institutional investors build structured asset allocation and asset-liability management models for a variety of reasons, including the desire to improve performance and others, such as satisfying governance procedures. Regulators may charge institutional investors with imprudence if there is no formal analysis of their portfolio selection decisions and large losses occur. Due to the levels of uncertainties and time-lags in strategic decisions, it can be difficult to evaluate the quality of the recommendations, thus complicating the search for ML breakthroughs. Recall the need for measurements of correctness in supervised learning.

Still, there are a few applications. One involves determining factors that impact the performance of asset categories, especially the so-called *alternative assets*. Many institutional investors have shifted capital to alternatives such as hedge funds, private equity, credit funds, real assets, and others. Evaluating the performance of these assets is more complex than traditional stocks and bonds due to the presence of multiple risk factors. Think of factor selection as the task of choosing the underlying ingredients in a recipe such as in a cake mixture (Fig. 2). The selection of factors and their weightings are identical to the feature selection process in ML. The goal is to measure risks more precisely than via traditional portfolio approaches and to improve investor performance through greater diversification. Many large institutional investors are turning to factor investing approaches.

As an example, we employ the following five core factors: world equity, U.S. Treasury bonds, high-yield bonds, inflation protection, and currency protection. Next, we calculate the impact of these factors on the performance of generic asset categories. The corresponding factor loadings are determined by reference to a cross-validation approach in conjunction with a regularization term (the Lasso) as a shrinkage penalty on the size of the loadings. This approach is more robust than traditional regression models and is standard in machine learning. Figure 3 shows an illustrative case study.

A portfolio decision model takes these factor loadings as input in its search for determining an optimal asset allocation or asset-liability solution. Risks are diversified across the underlying factors, rather than solely by means of the asset categories. The goal of factor investing is to protect the investor's capital in a comprehensive fashion, especially during market crashes.

A second application of ML in financial planning involves the identification of economic regimes. Here, we partition a historical time period into "regimes," each regime possessing relatively homogenous patterns. You can interpret the regimes as conditions of the market under various environments, similar to the traffic patterns during normal periods and

FIG2 Factors underlying asset performance can be interpreted as ingredients for evaluating risks and returns (similar to ingredients in a cake recipe).

the bottlenecks that occur during rush hour periods (Fig. 4). The goal is to address the conditions of markets during crashes in a more careful manner than by assuming static conditions going forward. In contrast to normal conditions, crash periods display high volatility and correlation coefficients approaching one. This situation is called *contagion* and is treated separately in a multiregime portfolio model.

To accomplish this task, we apply a popular nonparametric ML method—trend filtering—to the historical performance of a broad stock market, in this case the S&P 500 index (Figure 5). This type of no-assumption, model-free approach is common in the ML field. The historical performance of asset categories is displayed under two regimes—normal and crash—over the period 1998–2016 (Fig. 6). We can gather interesting information by observing the performance of the assets under the two regimes. In particular, government bond returns have been a positive investment during crash periods due to their “flight to quality” characteristic. In contrast, most stock markets experienced sharp drawdowns during crash periods (over 30% drop), thus showing the need to include other types of assets besides stock in an investment portfolio to protect the investor’s capital during crash periods. Real assets have provided good performance under both regimes, and these assets have become more popular with institutional investors since the 2008 crash.

Given these regimes, we can develop a set of scenarios over future time periods that represent the market in a more accurate fashion than by assuming a static, single-regime economic environment. Thus, we can minimize worst-case risks within the financial planning systems. Again, the goal is to improve investment performance by careful risk management.

Reinforcement learning

Reinforcement learning (RL) spans the traditional areas of ML and decision models. This modeling approach has seen noteworthy successes, including Google’s Alpha Go. In the traditional set up, the modeler assumes a Markov chain for defining the evolution of the underlying environment and a discounted additive utility function. A Markov chain switches between regimes by means of a transition probability matrix. The goal is to discover a set of policy

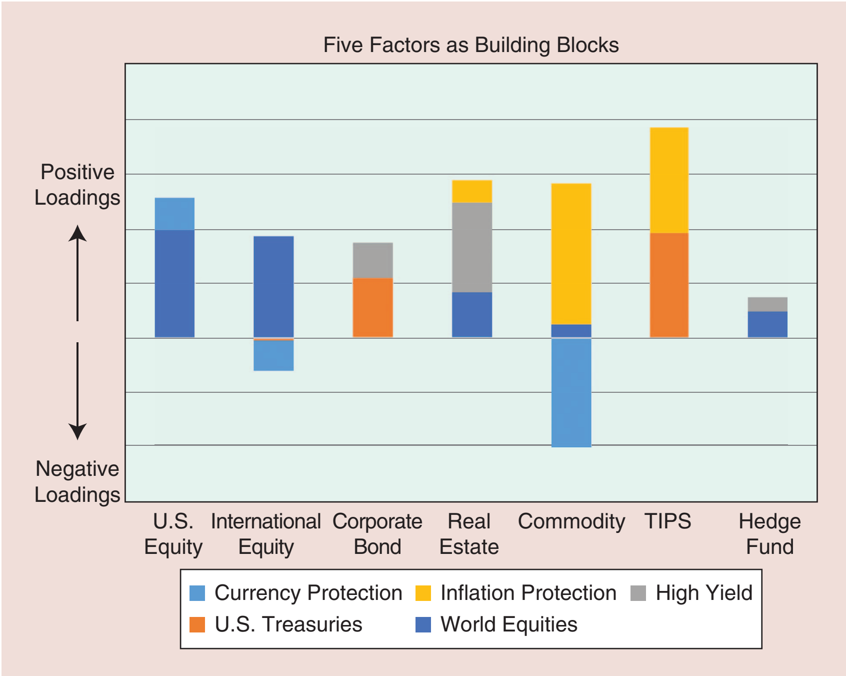

FIG3 Factors as building blocks to asset category performance (historical data: 1998–2016).

(a) (b)

FIG4 Traffic patterns under (a) normal and (b) rush period congestion in Princeton, New Jersey.

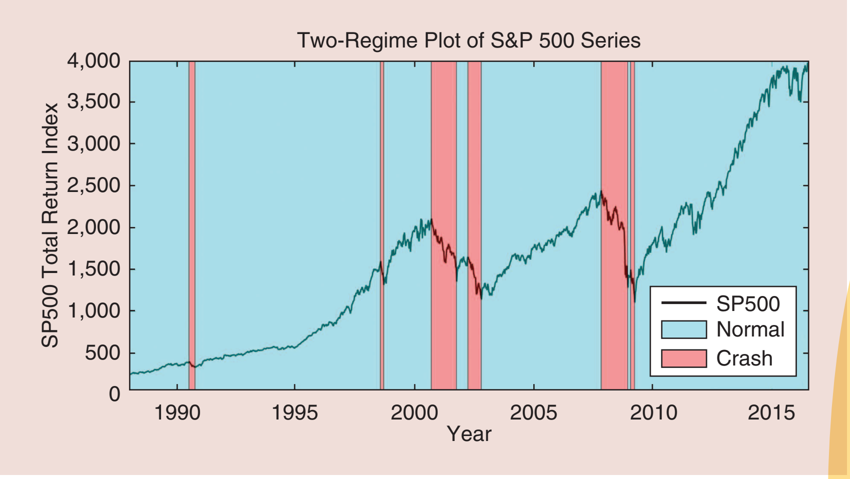

FIG5 Employing trend filtering to discover normal and crash regimes in the S&P 500 Index: 1988–2016 (blue = normal, red = contraction).

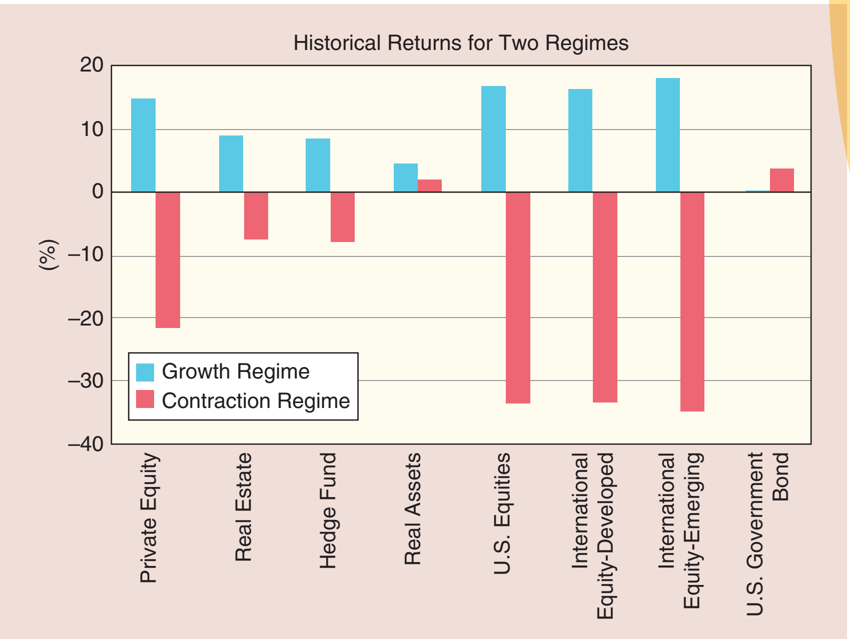

FIG6 Assets category performance is dependent upon the underlying economic regime. (The graph shows performance under two regimes: normal and crash, 1988–2016).

decisions over a planning horizon that maximizes an expected discounted objective function. The RL models fit squarely in the realm of decision models.

Markov decision models face severe limitations for financial planning. A critical barrier is the size of the state space; the curse of dimensionality limits real-world applications (Fig. 7). Approximate dynamic programming approaches have expanded the range of solvable problems. A second barrier entails estimating the environmental regimes (states) and the transition matrix across time periods. As discussed previously, we might depict a trading market as a set of economic regimes—normal and crash. Given these two regimes, we can generate scenarios over a specified planning horizon.

The first assumption in RL is the famous Markov property—path independence: period-t transition will be dictated solely by the current state at step/time t and the transition probability matrix. This assumption is identical to independent flips of a fair coin. Even if the past eight flips have been heads, there is still a 50% chance of heads for the next flip of a fair coin. An important issue involves estimating the parameters in the transition matrix. Traditionally, analysts employ econometric and related time series methods, such as maximum likelihood and method of moments.

Given the dynamic nature of economic markets over short- to mid-term periods, we might be interested in estimating the Markov transition matrix by focusing on recent market performance. Modern reinforcement learning methods address this issue through statistical sampling concepts. The parameters of the transition matrix are identified in a dynamic (online) fashion as the process evolves and the algorithm "learns." The sampling procedures require less intervention on the part of the developer. In theory, by observing the data and conducting an extensive training exercise, we can estimate the necessary parameters for solving the discounted Markov decision model in an online fashion. An extension of RL employs deep neural network algorithms to assist with the estimation process. The combination, called *deep RL*, has been employed successfully.

Future directions and challenges

The global economy is fast shifting to a data-driven environment with disruptive impacts on numerous industries. Financial services have been largely spared to date; however, several developments threaten traditional financial firms. The widespread adoption of automated financial planning systems, the so-called *robo-advisors*, will put pressure on human advisors to lower their fees and provide greater services, even for individuals with modest means. Current robo-systems are barely noticed in terms of assets under management, but there can be exponential growth of new technologies with scale.

Another potentially disruptive area involves personal credit and insurance matters through automated platforms rather than via humans at traditional banks and insurance companies. Data-driven firms can design ML algorithms that, in theory, are superior to credit evaluation carried out by humans with limited data. Likewise, there will be improvements in data-collection processes, such as avoiding long questionnaires for mortgage refinancing. What can be more time consuming and less efficient?

One of the primary challenges in financial planning entails bridging the gap between ML and decision models. The traditional classification approaches based on supervised learning can be employed as inputs to decisions models. But a tighter integration will be needed going forward.

There have been few ML implementations that focus on important financial decisions. Executives and investors need to grasp the underlying intuition behind a major decision; they rarely trust black-box algorithms. There is a need to translate the complex ML recommendations such as those generated by neural networks into understandable policy rules. These rules are critical for acceptance and implementation.

A third challenge in financial planning is to design adaptive systems. Clearly, economic conditions can change decisively and quickly during political and economy upheavals. Thereby, the online approaches can have utility in short- to mid-term planning. Recall that the reinforcement learning algorithms estimate the Markov transition matrix via sampling and thereby can address changing conditions. Further research aimed at this goal will be worth pursuing.

The area of ML in conjunction with pervasive data will continue to disrupt many industries including finance. The rapid rise of data-driven applications will certainly expand beyond repetitive and classification tasks to encompass jobs that skilled humans currently undertake. Does anyone doubt this forecast? But the long-term limits of ML/artificial intelligence for replacing human decision makers in strategic affairs remains highly uncertain at present.

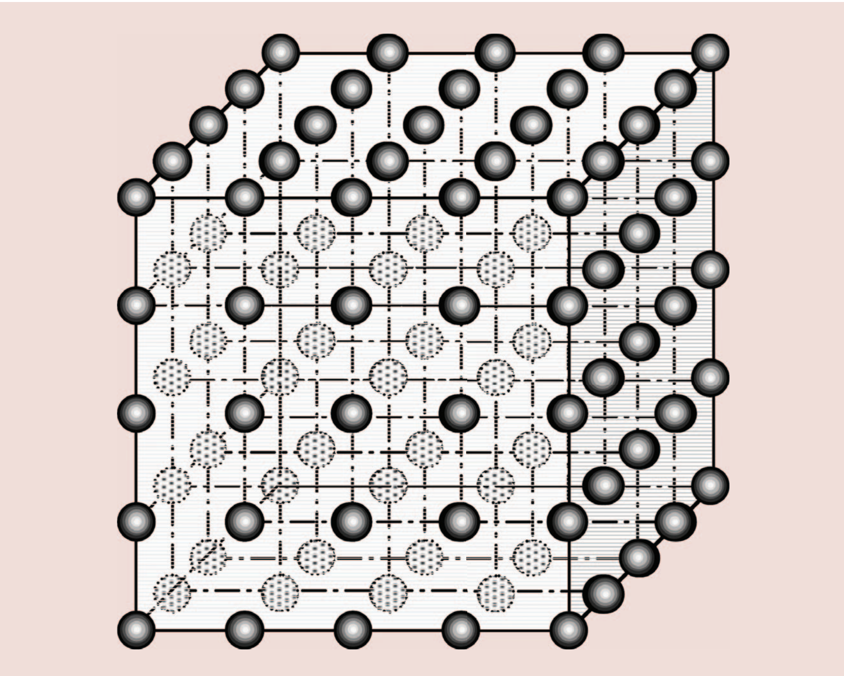

FIG7 State-space models grow exponentially in traditional reinforcement learning.

Read more about it

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About the author

John M. Mulvey (mulvey@Princeton.edu) is a founding member of the Bendheim Center for Finance in the Operations Research and Financial Engineering Department at Princeton University. He is an expert in applying financial optimization to strategic financial planning and has worked with major institutional investors including global insurance and reinsurance firms, large pension plans, multistrategy hedge funds, and others over the past 30 years. He has been a faculty member at Princeton for almost 40 years. His recent work entails applying advanced machine-learning algorithms to financial planning.