Modifying model risk management practice in the era of AI/ML

Received (in revised form): 29th May, 2020

Liming Brotcke
Sr Director — Model Validation Risk — MRM, Ally, USA

Liming Brotcke, PhD, leads the Model Validation Group at Ally. Her extensive industry finance artificial intelligence modelling and model validation experience is enriched by a deep understanding of regulatory expectations on large bank supervision, stress testing, model risk management etc. Prior to joining Ally, she worked at the Federal Reserve Bank of Chicago, Citi Group and Discover Financial Services.

440 S Church St, Charlotte NC 28202, USA
Tel: 980-312-8548; E-mail: Liming.Brotcke2@Ally.com

Abstract The model use of artificial intelligence (AI) and machine learning (ML) has caused unprecedented sensation around the wide applicability of these techniques. The rapid adoption of those alternative tools and methodologies by the heavily regulated financial sector, in areas that are outside the conventional credit lending and market participation, has posed significant challenges for model risk management professionals, including correctly defining AI and ML, properly establishing a governance framework, and, most importantly, effectively challenging AI/ML models. In this paper, the author attempts to describe the history of AI/ML, the evolution of key mathematical theories and modelling, commonalities and distinctions between statistical models and ML algorithms, and challenges of evaluation of some ML models. She discusses plausible solutions to practically address those challenges.

Keywords: *mathematical model, AI, ML, model risk, governance*

INTRODUCTION

Models and quantitative methods have been used by many banks to assist decision-making for decades. Financial market regulators, including the Federal Reserve System, the Office of Comptroller of the Currency (OCC) and the Federal Deposit Insurance Corporation (FDIC), are aware of the risk associated with model development, implementation and use and the need to mitigate potential model risk. The OCC Bulletin 2000–16 'Risk Modeling: Model Validation'[1] was the first regulation guidance that outlined key model validation principles and OCC expectations for a sound model validation process. This guidance was replaced in 2011 by OCC Bulletin 2011–12 ('Sound Practices for Model Risk Management: Supervisory Guidance on Model Risk Management') and the Board of Governors of the Federal Reserve System's (FRB) supervision and regulation letter 11-7 — 'Guidance on Model Risk Management' (SR 11-7)[2] a decade later. The FDIC later adopted the SR 11-7 in June 2017.

In recent years, advancements in financial technologies and relaxed regulatory barriers to entry have enabled FinTech firms to compete with traditional banks in the delivery of financial services. This competition forces banks to actively consider, evaluate and adopt alternative data as well as alternative approaches. Emerging technologies, including artificial intelligence (AI) and machine learning (ML), drive substantial efficiency gains in many areas of banks' operation that has caused rapid transformation of the financial services landscape. As indicated by the Financial Stability Board (FSB), AI could impact banking in several aspects including use of alternative data and algorithms for better credit evaluation, fraud identification and more effective trading strategies by the front office, enhanced customer retention and loyalty, improved risk identification, assessment, mitigation by the back-off operations, and compliance.[3]

FRB Governor Lael Brainard acknowledged the growth and potential significance of AI and ML applications for the financial services in a speech in November 2018. She emphasised that current supervisory and regulatory approaches, such as SR 11-7 and SR 13–19/CA 12–21 — 'Guidance on Managing Outsourcing Risk', are relevant guidance to apply when assessing AI/ML uses.[4] FRB's stance is similar to OCC and other regulatory agencies. This has caused ongoing industry debate over the proper application of SR 11-7 on AI and ML tools.

Financial institutions' reliance on mathematical models is a recent phenomenon of about 40 years as a result of hundreds of theoretical developments and empirical applications. Recent AI/ML sensation is also not a novel concept but rather a resurgence of continued research and progress of various fields. In this paper, the author attempts to demystify common misunderstandings of AI and ML, discuss key concepts and define their implications, and propose a reasonable governance framework to identify and manage risk related to ML models for model risk management (MRM). Section I summarises MRM evolution at large banks and new challenges brought by AI/ML. Section II is a brief discussion of the evolution of mathematical theories, followed by Section III, a history walkthrough of AL and ML, together with definitions. In Section IV, the author lays out the commonalities and distinctions between statistical model and ML algorithms, which form the foundation for a proper AI/ML governance framework. Lastly, in Section V, she discusses challenges faced by MRM and offers plausible solutions to practically address them.

MRM EVOLUTION AND NEW AI/ML CHALLENGE

Model risk has been traditionally managed by model developers with oversight from business users of the model estimates at large financial institutions. An important model was typically approved for production use after model builders and users both agreed on the conceptual soundness assessment, which typically required developers performing regression diagnostic testing, model specification evaluation and benchmarking comparison, and model users conducting additional testing on the model output when incorporating it into a business decision process.

As more models are being developed with more sophisticated techniques and integrated into more complex business processes, financial institutions are exposed to greater model risk that could lead to substantial operational losses if mismanaged. Bank regulators realised the elevation of model risk following the Great Recession and provided comprehensive guidance for banking organisations on effective MRM with the publication of the OCC Bulletin 2011-12/SR 11-7. Following the guiding principles of the regulators, large banks invested millions of dollars first building foundational elements of an effective MRM that included establishment of MRM policy and procedures, creation of a model inventory, and the formation of an independent MRM group. While most large banks have accomplished this initial setup stage, implementation and execution of the MRM framework are at various levels of maturity.

Currently, banks demonstrating leading practice have clearly defined roles and responsibilities for each MRM stakeholder that are further supported by model development, validation and annual review standards and templates. Ideally, there exists a transparent process to identify, document and prioritise new models; a centre of excellence or project management office enables consistent model development, documentation, submission across business units and timely completion of model validation. The best validation activities effectively challenge model developers and model users, add value to business operation, and promote a culture of advanced analytics sharing. Process automation related to model development and validation is also observed at some advanced firms.

Although large banks have adopted the concept of model risk life cycle management, validation activities continue to largely focus on conceptual soundness evaluation during the model development compared to model implementation and use. MRM practices can be further enhanced by addressing the following missing or challenging areas. Most large banks lack an effective approach that can translate model technical errors into business impact calculation. Developing a straightforward methodology that allows transparent quantification and reporting of model risk at the enterprise or business line level has been a daunting task for years. Review and challenge models with multiple uses continue to be a struggle for validators. Roles and responsibilities related to ongoing performance monitoring remain ambiguous and cause delayed detection of model deterioration or even ineffectiveness at addressing performance degradation at some banks. There is also marked efficiency loss when large banks continue to rely on a manual process to manage the fast-growing model inventory.

A new task related to AI/ML adoption has been recently added to the list of ongoing MRM challenges. One of the most desirable properties of AI/ML techniques is their ability to process massive volumes of data, including unstructured data, to identify hidden patterns and translate them into actionable information. When properly applied, AI/ML tools imply additional operational efficiency gain and greater competitive advantages. The current significant industry-wide uptake and an increasing acceptance of AI/ML technologies pose new challenges to the three elements of MRM defined by SR 11-–7, ie model development, implementation, and use; validation; and governance. Out of many concerns, the most frequently asked questions by risk officers include: how to define AI/ML? What are the differences between AI/ML models and conventional regressions? And what is the appropriate governance to manage AI/ML? A history review of critical mathematical theories and modelling progression can be the starting point in searching answers for those inquiries.

EVOLUTION OF KEY MATHEMATICAL THEORY AND MODELLING

Human beings' attempt to build statistical models can be dated to 100 years ago. The standard linear model was moulded in 1805, with the publication of the least square method and a rudimentary formation[5] after the key assumption of normality related to the general linear model was formed by other researchers. One of them is by de Moivre who derived the normal density formula in 1733, that became an important property of the independent and identically distributed normal model.

The central role of the normal distribution was not realised until early 19th century with work from Gauss and Laplace. It is also worth noting that the general linear model was originally proposed in the context of astronomical and geodesic observations during the 19th century. The actual derivation and application of the linear regression were done by Sir Francis Galton, a cousin of Charles Darwin and best known for his research in eugenics and human intelligence, during his pioneer study of the effects of human selective mating in late 19th century.[6] In his effort to address a problem of heredity, Galton introduced the concepts of correlation and regression when examining characteristics of the sweet pea plant. His colleague Karl Pearson further provided the mathematical framework of the Pearson Product Moment Correlation and described the genesis of the regression slope in 1930.[7]

Assumption of normality became again a focus of scholars in the early 20th century through RA Fisher's work on a small sample. Fisher claimed universal normality and applied a new treatment of the assumption in agriculture and biology data in the 1920s.[8] The modern form of linear regression became an important tool for the social sciences starting in the 1930s, assisted with development of other key concepts, such as assumptions of independence and broader applications.

Probability theory, an important branch of mathematics, began with consideration of games of chance. Origins of the probability concept date back to classical Greece. While references to games of chance in the context of gambling were present, actual calculation of probabilities of events did not yet exist. Gerolamo Cardano (1501–1576), an Italian physician, mathematician, astrologer, and gambler, presented the first systematic computation of probability in a short manual, *Liber de Ludo Aleae* (*Book on Games of Chance*) around 1564. Calculation of probabilities for the sum of the faces that show on two and three dice, multiplication rule for probabilities, along with the idea of probability ρ between 0 and 1 to an event whose outcome is random were discussed when Cardano's manual was published in 1633.[9] Cardano's contribution to the advancement of probability calculus helped lay the rudimentary foundation of probability theory.

The creation of a mathematical theory of probability came when two French mathematicians, Blaise Pascal and Pierre de Fermat, were called to resolve a gambler's dispute in 1654.[10] The underlying gambling problem was to decide whether or not to bet even money on the occurrence of at least one 'double six' during the 24 throws of a pair of dice.[11] Inspired by the work of Pascal and Fermat, Christian Huygens, a Dutch mathematician, astronomer, and physicist, presented the probability theory in *De Ratiociniis in Ludo Aleae* (*On Reasoning in Games of Chance*) in 1657.[9]

During the 18th century, probability theory rapidly developed with major contributions from Jakob Bernoulli, Abraham de Moivre, and Thomas Bayes. Bernoulli wrote the book *Ars Conjectandi* (*The Art of Conjecturing*) in 1713, presenting the famous Bernoulli theorem that later became the law of large numbers and the basic to all modern sampling theory.[9,11] De Moivre was the first scholar to define statistical independence in *The Doctrine of Chances* in 1718. He also developed the formula for the normal density.[9] Bayes established a mathematical basis for probability inference in 1763, with the publication of *Essay Towards Solving a Problem in the Doctrine of Chances*.[12] This formed the basis of Bayesian estimation, one of the major statistical estimation techniques, for calculating the probability of the validity of a proposition on the basis of a prior estimate of its probability and new relevant evidence.

Probability theory had another breakthrough when Pierre de Laplace published his book *Théorie Analytique des Probabilités* in 1812. Laplace discussed important concepts, such as asymptotic approximations, the law of large numbers for frequencies, and expectation that could be applied to practical problems. His definition of probability is still used today. Laplace also introduced two algorithms to compute the mean and the variance of two components of the solution of a linear statistical model.[13] Laplace's book established the foundation for the application of the theory of errors, actuarial mathematics, and statistical mechanics. Probability theory has since been further enriched by many scholars and influenced the formation of mathematical statistics and other branches, such as genetics, psychology, economics, and engineering.[10]

In 1919, Richard von Mises, an Austrian scientist and mathematician, published a paper on the foundation of probability theory, emphasising the stability of the long-run frequency of an outcome in a long sequence of repeated random events.[8] Although his modelling approach was not adopted, it exerted great influence on this field. The definitive formulation of the subject was formed in the 1930s, with Andrei Nikolaevich Kolmogorov publishing the *Analytical Methods in Probability Theory* in 1931, laying the foundations for the modern theory of Markov processes and discovering the famous axiomatic theory of probability in the *Foundations of the Calculus of Probabilities* two years later.

The birth of modern mathematical finance came in 1900, when Louis Bachelier derived the mathematics of Brownian motion and applied its trajectories for modelling stock price dynamics and calculating option prices.[11] Norbert Wiener further advanced the work by proving the existence of Brownian motion and constructed a measure, which described the probability distribution of Brownian motion that also became known as Wiener process. Ito's Lemma, another widely used mathematical formula, was derived by Japanese mathematician Kiyoshi Ito during his work on stochastic processes.[14] Nobel Prize laureate Harry Markowitz's paper on *Portfolio Selection* in 1952, introduced the concept of efficient frontier and showed investors how to compute the mean return and variance for a given portfolio.[15] When Fisher Black and Myron Scholes introduced a new methodology for financial instrument valuation using partial differential equation (PDE) governing the price evolution of a European call or European put in 1973, the impact on the derivative market was explosive. The Black–Scholes model is important not only because anyone can use it to assess the value of an option but also that it introduced a new way of calculating option prices from the existing approach of computing risk neutral expected value of the discounted option pay-off. Broadly speaking, the term may refer to a similar

PDE that can be derived for a variety of options, or more generally, derivatives.

HISTORY AND DEFINITIONS OF AI AND ML

In contrast, the history of AI and ML is much shorter. The ideas of AI and ML are by no mean novel. The field of AI has been studied for decades with the concept of 'artificial intelligence' first adapted by a generation of scientists, mathematicians, and philosophers during the WWII. In 1950, Alan Turing defined 'machines' and 'think' and discussed the idea that machines were able to simulate human beings and do intelligent things, such as playing a game of chess, in his paper on 'Computing Machinery and Intelligence'.[16] This research has been widely considered as laying out the logical framework for modern computers and AI. The term 'artificial intelligence' was then coined by John McCarthy in 1956, when hosting the Dartmouth Summer Research Project on Artificial Intelligence (DSRPAI) conference with Marvin Minsky.[17]

In the DSRPAI proposal, John McCarthy stated that the conference was 'to proceed on the basis of the conjecture that every aspect of learning or any other feature of intelligence can in principle be so precisely described that a machine can be made to simulate it'. Researchers participating in this two-months project represented multiple fields, including mathematics, physics, psychology, computer science, and economics. Their objective was to clarify and develop the concepts around 'thinking machines'. The brainstorming session did not lead to any breakthrough results but discussions during those eight weeks formed a foundation for future work in the next few decades.

For the next 30 years, AI research continued to advance, but the terminology remained to be largely unknown outside the computer science field. Most people associate AI as intelligence demonstrated by machines as shown in numerous science fictions. The notion of advanced robots with human-like intelligence dates back at least to 1872, with Samuel Butler and his novel Erewhon, in which the possibility that machines might develop consciousness by Darwinian selection was discussed.[18] Most of science fiction depicts AI in the dystopian scenarios, where intelligent entities created by humanity gain self-awareness, disobey human orders and attempt to destroy mankind. One of the best-known figures is the AI computer HAL 9000 from Stanley Kubrick's 1968 film *2001: A Space Odyssey*. During a space mission, HAL managed to kill the entire crew before being deactivated by the sole survivor of the exploration. A real-life but rudimentary representation of AI became known to the general mass in 1996, when IBM's Deep Blue defeated Garry Kasparov, the world champion and chess grandmaster, in game one of a six-game match.

Advancement of AI and ML has not been smooth and marked with 'AI Winter' periods during which commercial and scientific activities in AI declined dramatically.[19] The first AI winter is believed to have started in 1973, and the second around 1988. Steady progress was made from shallow neuralworks to convolutional neural networks (CNNs) to generative adversarial networks that resulted in significant development in visual pattern recognition, text categorisation, imagine classification and speech and face recognition. For example, some approaches helped the formation of ,natural language processing (NLP), another branch of AI. NLP is broadly defined as software's ability to understand, interpret and automatically manipulate human natural language, such as speech and text.

Modern dictionaries define AI as a subfield of computer science wherein machines imitate human intelligence (being human-like rather than becoming human). For instance, the Merriam Webster dictionary defines AI as (1) a branch of computer science dealing with the simulation of intelligent behaviour in computers or (2) the capability of a machine to imitate intelligent human behavior.[20] The Encyclopedia Britannica states, 'artificial intelligence (AI), the ability of a digital computer or computer-controlled robot to perform tasks commonly associated with intelligent beings'.[21] Intelligent beings are those that can adapt to changing circumstances. Similarly, the English Oxford Living Dictionary has this definition: 'The theory and development of computer systems able to perform tasks normally requiring human intelligence, such as visual perception, speech recognition, decision-making, and translation between languages'.[22]

Numerous variations of AI definitions can also be found in academic research papers as well. Authors' subject matter expertise is reflected in their definitions. According to philosophy professor Ernest Adam, AI is the field devoted to building artificial animals (or at least artificial creatures that — in suitable contexts — appear to be animals) and, for many, artificial persons (or at least artificial creatures that — in suitable contexts — appear to be persons).[23] Russel and Norvig presented AI as the field of science attempting to understand intelligent entities. While different fields such as computer science, philosophy and psychology share a common interest in AI, that is to learn more about ourselves, computer science focuses more on building the intelligent entities as well as understand them because the constructed intelligent entities are interesting and useful.[24] In 2017, the FSB introduced AI as the theory and development of computer systems able to perform tasks that traditionally have required human intelligence in its report on *FinTech and Market Structure in Financial Services: Market Developments and Potential Financial Stability Implications*.[3]

Similar to AI, there is not a universally agreed upon definition for ML. Arthur Samuel coined the term in 1959, defining it as the field of study that gives computers the ability to learn without being explicitly programmed.[25] He did pioneering work writing a checkers-playing program that made computers learn from their experience. Tom Mitchell provided a slightly different interpretation later describing ML as the study of computer algorithms that allow computer programs to automatically improve through experience.[26] According to Mitchell, a computer program is said to learn from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E. Ethem Alpaydin further defined ML as programming computers to optimise a performance criterion using example data or past experience in his book *Introduction to Machine Learning*.[27]

Early work on ML was restricted in the computer science field. ML has been generally considered a branch of AI based on the idea that systems can learn from data, identify patterns and make decisions with minimal human intervention until most recently. ML algorithms take different forms with broad practical applications. For example, some algorithms designed for data mining and regression analyses can be embedded in statistical software and require minimum coding effort. More advanced ML applications require complex computer programming that construct information filtering systems, which automatically learn users' interests.

In recent years, thanks to increased data volumes, advanced algorithms and improvements in computing power and storage, AI and ML have received unprecedented attention and coverage outside the computer science field. The most innovative use of ML algorithms of date is often to support AI applications, such as creative arts. Hence, the two terms have been used together and created a misconception that they are interchangeable. It is critical for financial market practitioners to understand what AI, ML and models have in common and where they are fundamentally different, in order to set up reasonable expectations on risk identification and risk assessment of those tools as well as establish proper governance and controls.

COMMONALITIES AND DISTINCTIONS BETWEEN MATHEMATICAL MODEL AND MACHINE LEARNING ALGORITHMS

Statistical and econometric models are rooted from fundamental mathematical theories and can be in general referenced as mathematical models. A well-known use of such models in the financial industry is credit scoring in which quantitative modelling and statistical techniques are applied to aid and automate decision-making throughout the credit life cycle. Fisher and his development of linear discriminant analysis in a 1936 paper built the foundational work for credit scoring.[28] But it was Durand who first applied the statistical technique to identify characteristics distinguishing good and bad instalment loan customers in a book published in 1941, by the National Bureau of Economic Research.[29] The automated credit scoring was first adopted by credit card lenders to cope with the volume of general-purpose card applications in the 1960s, before being applied to other retail products, such as personal loans and mortgages starting in the 1980s.[30,31] The modelling application to credit scoring that enabled lenders to leverage regressions to estimate obligors' behaviour came later. Fair Isaac Corporation (FICO) introduced the FICO score in 1989, after the company had sold its credit scoring system for more than three decades. Providian Financial Corporation and CapitalOne were the first credit card issuers involved in the early adoption of mathematical models to identify better ways to predict response for marketing in the early 1990s.[32]

Mathematical Finance is another filed that has a high dependency on numerical and quantitative models for derivative trading, risk management and portfolio management. As it became a separate discipline in the 1970s, financial engineering tools have been heavily influenced by the development of increasingly sophisticated mathematical models. The 2007–09 financial crisis made use of arcane models known to public due to their role in hedge fund trading with derivatives. It also damaged credibility of algorithmic trading as well as mathematical models developed for such purposes.

Mathematical models can be divided into two groups: parametric and nonparametric. Parametric models assume some finite set of parameters, which capture everything there is to know about the data. Therefore, future predictions are independent of the observed data, if parameters are given. An important implication of parametric models is they are incapable of capturing changes or growth of future data. Linear regression and logistic regression are the most well-known forms of parametric models. Classical time series forecasting methods, such as the autoregressive integrated moving average, the simple exponential smoothing, and the autoregressive conditional heteroscedasticity model fall into the category of parametric model. Additionally, linear support vector machines (SVMs), polynomial regression, hidden Markov models, principal component regression and mixture models are also parametric models. Parametric models can be either linear or nonlinear regressions.

Nonparametric models, on the other hand, assume the data distribution cannot be defined in terms of a finite set of parameters but instead can be represented by an infinite dimensional function. The amount of information the function captures about the data can grow as data grows. Nonparametric modelling is a learning approach that makes no assumptions about the data given the patterns observed from similar instances. Nonparametric models include decision tress, K-nearest neighbour, Gaussian processes, Dirichlet process mixtures, radial basis function kernel, and SVMs, etc.

Problems like function approximation, classification, clustering, time series analysis and feature discovery can be resolved by either parametric or nonparametric models. For example, both logistic regression and random forecast can be applied to classification problems.

In contrast, ML models and algorithms are classified into two categories: supervised and unsupervised learning. Supervised learning techniques are used to infer a function or relationship and thereby reproduce outputs known from a dataset. Classification and regression are the two types of supervised learning techniques. Supervised learning implies actual outcomes or labels associated with the data are known and available. Unsupervised learning algorithms are applied to infer patterns from a dataset without known outcomes. Clustering and association are two main techniques for unsupervised learning. Outcomes of the data or labels are not required when applying unsupervised learning.

Deep learning is a subfield of ML that concerns with algorithms inspired by the structure and function of the brain called artificial neural networks. It is also known as deep neural learning or deep neural network. Deep learning is unsupervised and imitates the workings of the human brain in processing unstructured data and creating patterns for use in decision-making. CNNs, recurrent neural network (RNN), denoising autoencoder (DAE), deep belief networks (DBNs), and long short-term memory (LSTM) are the most popular deep learning methods that have been widely used.

All existing mathematical models, statistical or econometric, can be classified as either supervised or unsupervised learning regardless of their parametric or nonparametric nature. Popular nonparametric models, such as KNN and SVM, are supervised learning while the classification and regression

(CART) decision tree can be either supervised or unsupervised. Nonparametric ML algorithms imply that coefficient estimation of population parameters in the context of an equation is not applicable. ML models have become more nonparametric with the rapid development of more advanced algorithms specific to computer science in the last decade. While mathematical underpinnings can always be identified, understood and explained, the majority of those advanced ML algorithms are developed with a deep root in computer science. Programming proficiency and operating platform knowledge are also required aside from mathematical familiarity in order to gain a comprehensive understanding of those models.

The argument that ML is just glorified statistics is probably not accurate, even if all mathematical models can find their places in different categories of ML, traces back to some mathematical theories, and can be represented by computational algorithms. The majority of ML algorithms, in particular deep learning techniques, are results of modern developments in computer science–driven AI, which require little or no statistical background.

For example, residual CNN, Monte Carlo Tree Search along with reinforcement learning form the core parts of DeepMind's AlphaGo. According to DeepMind, AlphaGo is the first computer program to defeat a professional human Go player, the first to defeat a Go world champion, and is arguably the strongest Go player in history.[33] Research across multiple disciplines with substantial overlapping between mathematical modelling and computer science support AlphaGo's improved performance and ultimate success.

Figure 1 depicts how interactions between computer science and mathematics result in the birth of AI and ML. It also reveals the fact ML algorithms are a subset of mathematical models. It is probably true that ML algorithm nomenclatures can be found for all quantitative models developed by the financial industry.

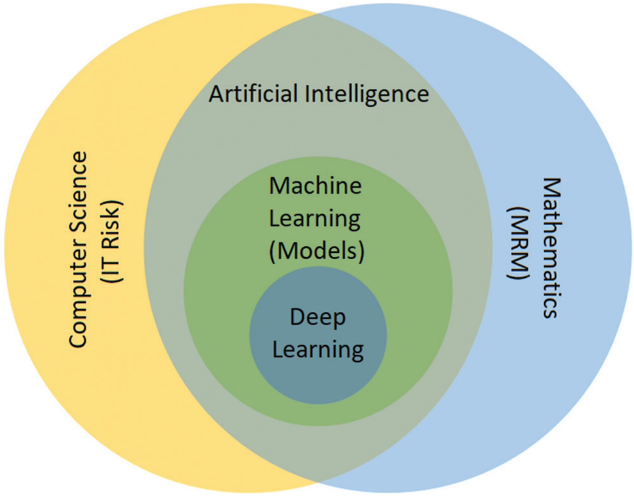

Figure 1: Artificial Intelligence, machine learning and model relations
Notes: IT, information technology; MRM, model risk management.

CHANGES AND SOLUTIONS

The recent fast adoption of nonparametric models highlights several important attractions of those solutions. First, nonparametric models are highly predictive when applied to large samples with the ability to assume an infinite parameter set and no constraint of underlying functional forms. Secondly, many software packages (R, Python, SAS, DataRobot and others) have built-in nonparametric models for developers to choose without requiring additional programming or extra work, making model development a simple exercise for everyone. Thirdly, some ML algorithms' self-learning and self-improving ability allows for timely anomaly detection, which is an extremely desirable feature when combating fraud and money laundering activities. Lastly, deep learning techniques can significantly improve operation efficiency and accuracy. Those benefits have been understood and gradually accepted by the banking industry along with rising challenges that has resulted in ongoing discussions and even debate among practitioners and with regulators.

To begin with, is there a need to revise the model definition, which is one of the foundational pieces of the MRM framework? Many large banks in the United States adopted the FRB SR 11-7 model definition, which refers 'model' to a quantitative method, system or approach that applies statistical, economic, financial or mathematical theories, techniques and assumptions to process input data into quantitative estimates.[2] Proponents of changing this definition argue that it is too narrow and does not adequately capture unique characteristics associated with alternative modelling techniques, including producing estimates without constructing relationships between inputs and outputs, and difficulty to quantify outputs' capital and liquidity impact. Their concern is further supported as expectation around model explainability and interpretability handicaps consideration and incorporation of those models, even if they outperform conventional modelling methodologies.

Both parametric and nonparametric models encompass the three key elements of a model: input, a process and estimated output although the structure of nonparametric models is assumed to change with data and not specified a priori. Therefore, the current definition is broad enough to address nonparametric ML models.

The talent pool of most large banks' model development and validation is primarily comprised of economists and statisticians — this is also true of the regulatory community. Differences in the quantitative process not only drive the level of explainability difficulty but also explain the dominant presence of economists and statisticians in the model development and validation field. The parameter identification process allows the establishment of plausible relationships between target and explanatory variables. Furthermore, such relationships can be tested over time with different data. The replicability feature associated with parametric modelling is the core of empirical analysis in economics because it fills the gap between economic theory and observed data.

Numerous mathematical theories and derivations are included in the doctoral curriculum of economic and statistical majors. One, however, requires more profound knowledge on density function, probability and optimisation theories in order to explain the mechanism of nonparametric models. Many nonparametric models are described as 'black boxes' because scientific description of those approaches cannot be further supported by business intuition like conventional regressions. Put differently, it is not a model definition problem but rather a talent acquisition and talent repurpose challenge.

When nonparametric approaches are used for process optimisation, it becomes more difficult to quantify estimates with financial figures. For instance, NLP techniques can be used for automated documentation review or for chatbot solution development to improve customer relationship. On the surface, NLP is for information extraction and finding linguistic structures that do not have much to do with model and model risk. To fulfil these primary objectives, NLP needs to solve two fundamental problems, namely tagging and parsing, which rely heavily on statistical methods and models that SR 11-7 model definition accurately captures. Similarly, even the most complex neural network-based models can be linked to generalised additive models with structured interactions.[34] A methodological review of each nonparametric machine learning (ML) algorithm will also identify the underpinning mathematical theories. It is also worth noting that this problem applies to parametric models when used for the same purpose.

Another major challenge MRM professionals face is governance around AI/ML. Can the existing MRM governance be applied to AI tools, which are built mostly with computer science knowledge and nonparametric ML algorithms without any modification? If not, what is the proper governance framework for the development and validation of those models? The answer is implied in the interactions between computer science and mathematics as depicted in Figure 1. A comprehensive review of most AI tools and advanced ML models requires information technology (IT) knowledge that most large bank's current MRM governance framework does not represent. Most model developers and validators are proficient with various statistical software and programming languages. But there is a fundamental difference between what a computer science PhD knows and what an economics PhD can command. This knowledge gap implies significant restriction on what a traditionally trained model validator can do.

Furthermore, conventional regression models are developed and validated as a standalone application without high dependence on the system they are implemented on. This is not the case for some ML models when the platform on which algorithms are built and operate is a critical component of the development. Hyperparameters that govern the training process itself and differ from input data and model parameters help achieve higher accuracy at the aggregate. Review of hyperparameters is not part of the typical model-validation activities although they enable in-time adjustments and self-learning of the algorithms. Open source platform Keras Tuner makes hyperparameter tuning easy to define a search space and leverage included algorithms to find the best hyperparameter values. Computer science expertise is needed for hyperparameter evaluation and challenge, as well as modification of the current model governance.

ML algorithms from the deep learning subset necessitate more IT expertise in order to understand the platform and context as such models operate to support a comprehensive evaluation. For instance, complex neural networks can be built on TensorFlow, a software platform and symbolic math library. Although TensorFlow is not a model, its application programming interface or system that enables development and training of ML models needs to be understood by the financial institution. The fact that many advanced deep learning algorithms have been developed by data scientists with little or no statistical background in the last decades manifests the contribution of computer science and hence the need for collaboration between MRM and IT risk.

The recent advancement of AI has added interesting flavours to model development and validation. There is no doubt that the financial sector along with other industries is embracing the alternative modelling approaches in order to improve efficiency. Whether or not these techniques will truly enhance accuracy of quantitative estimation and further optimise standard operation procedures is yet to be confirmed. In the meantime, it introduces new dynamics and new challenges for MRM to react upon.

AUTHOR'S NOTE

The views presented in this research are solely those of the author and do not necessarily represent those of the Ally Financial Inc (AFI) or any subsidiaries of AFI.

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