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MODEL BEHAVIOR. NOTHING ARTIFICIAL.

Emerging Trends in the Validation of Machine Learning and Artificial Intelligence Models

THE RISE OF MACHINE LEARNING AND ARTIFICIAL INTELLIGENCE

The world's most valuable resource? According to a recent article in "The Economist," it's not oil, it's data. To tap into the value of that data, companies are increasingly turning to machine learning (ML), which subsumes many of the fields within artificial intelligence (AI).

This new paradigm, which we call ML/AI, is no longer just for hobbyists and academics looking for a challenging problem to solve but has gone mainstream. This is not accidental. Since the early days of its study, ML/AI techniques have steadily matured and grown in sophistication. As hardware, processing power and storage capacities have rocketed into the stratosphere, so has companies' ability to solve complex, real-world business problems through the application of ML/AI techniques and algorithms.

In the financial services industry, however—one of the most data-rich industries in the world—companies have thus far only tentatively availed themselves of ML/AI capabilities. ML/AI techniques such as neural networks/deep learning have the potential to solve a wide spectrum of longstanding problems with a game-changing impact. Whether it is to find an optimal segmentation of the customer base to target new products, detect and prevent money-laundering activities, manage credit risk through sophisticated predictive analytics, or meet regulatory requirements for stress testing its balance sheet, ML/AI has emerged as a powerful tool the industry should look to adopt quickly as a significant opportunity to maintain its competitive positioning.

A key impediment to the adoption of ML/AI, however, is how to trust a particular model or algorithm—a point consistently posed to banks by their regulators as well as by their own control functions such as model validation or internal audit. The ability to explain the conceptual soundness and accuracy of such techniques is a significant challenge, not only because the tools are so new, but also because there is an inevitable "black box" nature to some of the more powerful ML/AI approaches such as deep learning.

In this document, we highlight some of the challenges the financial services industry will face on the road to ML/AI adoption, in terms of gaining comfort with the robustness of modeling techniques through meaningful models that can withstand internal and external scrutiny.

FINANCIAL SERVICES SOLUTIONS BASED ON MACHINE LEARNING AND ARTIFICIAL INTELLIGENCE

As the financial services industry has grown in complexity and sophistication, so have some of the challenges it faces.

Armed with the ability to process such complex mathematical/statistical solutions on nano-processing power with exabytes of capacity for data storage, the industry is beginning to turn to sophisticated ML/AI answers rooted in rich academic history. (For more, see sidebar: "Academic Pedigree of Machine Learning and Artificial Intelligence in Financial Services.")

The opportunities and possibilities available from ML/AI have significant implications for the financial services industry. While some traditional techniques have already been employed for certain functions, newer approaches and techniques offer much richer applications and use cases, including the following:

- **Risk Modeling:** The fields of financial risk modeling (i.e., credit, market, business and model) as well as that of non-financial modeling (i.e., operational, compliance, fraud and cyber) is and has been a natural domain of application for ML/AI techniques. Indeed, many workhorse modeling techniques in risk modeling (e.g., logistic regression, discriminant analysis, classification trees, etc.) can be viewed in fact as much more basic versions of the emerging ML/AI modeling techniques of the recent period.

  That said, there are risk types for which ML/AI has greater applicability than others. For example, one would more likely find ML/AI in data-rich environments such as retail credit risk scoring (e.g., credit card, mortgages), as compared to relatively data-poor domains such as low default credit portfolios for highly rated counterparties (e.g., sovereigns, financials, investment grade corporates). In the non-financial realm, we are seeing fruitful application in areas such as fraud analytics, where there is ample data to support ML/AI estimation.

- **Portfolio Management:** In this area algorithms are built to calibrate a financial portfolio to the goals and risk tolerance of the user. Users enter their goals (e.g., retiring at a certain age and with X amount of money in savings) and other factors (e.g., age, income, current financial assets, etc.). The advisor spreads investments across asset classes and financial instruments in order to reach the user's goals. The system then calibrates to changes in the user's goals and to real-time changes in the market, aiming always to find the best fit for the user's original goals. Commonly known as "robo-advisors," this framework has gained significant traction with younger consumers, who may be demonstrating a preference for it instead of paying higher fees for human advisors.

- **Algorithmic Trading:** Originating in the 1970s, algorithmic trading involves the use of complex ML/AI systems to make extremely fast trading decisions, often placing thousands or millions of trades in a day. This gives rise to the term "high-frequency trading," which is considered to be a subset of algorithmic trading. Most hedge funds and financial institutions do not openly disclose their ML/AI approaches to trading, but it is believed that ML/AI are playing an increasingly important role in calibrating trading decisions in real time. However, there are some noted limitations to the exclusive use of ML/AI in trading stocks and commodities, such as issues with overfitting.

- **Fraud and Misconduct Detection:** More accessible computing power, widespread use of the internet and substantial growth in the amount of valuable company data being stored online has resulted in an increase in data security risk. Although previous financial fraud detection methodologies were based on complex rule sets, modern fraud detection goes beyond this subjective risk factor scorecard to dynamically calibrate to new potential security threats. While this is the state of the art in ML/AI for addressing financial fraud, the same principles hold true for other data security problems because such systems can detect and flag anomalies. The challenge for these systems is the proliferation of false positives, which can potentially be addressed by more advanced ML/AI techniques wherein this excess sensitivity can be smoothed out.

- **Loan/Insurance Underwriting:** This is a natural field of application for ML/AI methodologies in finance, especially at large banks and publicly traded insurance firms, where such algorithms can be trained on millions of examples of consumer data (e.g., age, job, marital status) and behavior (e.g., delinquency, late payment or balance usage history). The underlying drivers of customer behaviors in banking or insurance can be assessed with algorithms and continuously analyzed to detect trends that might influence lending and insuring into the future. These results have a tremendous tangible yield for companies. At present, however, they are primarily reserved for larger companies with the resources to hire data scientists and the massive volumes of past and present data to train their ML/AI algorithms.

As ML/AI matures even further, we anticipate that many other critical functions will make significant investments and increase their dependence on such approaches. Traditional processes that carry significant operational and reputational risk and heavily rely on human judgment, such as know-your-customer, will likely see increased reliance on machine learning models that can churn through large data sets and pinpoint with high accuracy the areas that require deeper manual involvement. This should also allow less mature processes such as know-your-employee and third-party risk to benefit from such approaches.

ACADEMIC PEDIGREE OF MACHINE LEARNING AND ARTIFICIAL INTELLIGENCE IN FINANCIAL SERVICES

There is extensive academic literature in the field of ML/AI with regard to its application for financial services. Richard Bellman, the father of dynamic programming theory and optimal control, argued in his classic 1957 work that high dimensionality of data (i.e., many features associated with what someone is trying to model) is a fundamental hurdle to many scientific applications, particularly in the context of pattern classification applications where learning complexity grows at a much faster pace than the degree of dimensionality of the data (referred to as "the curse of dimensionality").[1]

Another stream of literature by Guy Wallis and Edmund Rolls (1997, 1999) discusses the motivation behind the emergence of the subfield of deep machine learning, which focuses on computational models for information representation that exhibit similar characteristics to that of the neocortex (a part of the human brain responsible for governing complex thought), finding that in addition to the spatial aspect of real-life data a temporal component also plays a key role.[2] That is, an observed sequence of patterns often conveys a meaning to the observer, whereby independent fragments of this sequence would be hard to decipher in isolation, so that meaning is often inferred from events or observations that are received close in time.

Tai Sing Lee and David Mumford (2003) and Lee, Mumford, Richard Romero and Victor Lamme (1998) examine neuroscience findings for insight into the principles governing information representation in the brain, leading to ideas for designing systems that represent information. These studies find that the neocortex associated with many cognitive abilities does not explicitly pre-process sensory signals, but rather allows them to propagate through a complex hierarchy that learns to represent observations based on the regularities they exhibit.[3]

In 2000 Richard Duda, Peter Hart and David Stork pointed out that the standard approach for dealing with this phenomenon has been data pre-processing or feature extraction algorithms that shift to a complex and rather application-dependent human-engineered process.[4] Itamar Arel, Derek Rose and Thomas Karnowski (2010) provide an overview of the mainstream deep learning approaches and research directions proposed, emphasizing the strengths and weaknesses of each approach, and present a summary of the current state of the deep ML field and some perspective into how it may evolve.[5]

Several vendors, consultancies and other financial practitioners have published white papers about ML/AI. In a 2014 white paper, the SAS Institute Inc. introduces key ML concepts and describes new SAS Institute solutions that allow data scientists to perform machine learning at scale, and shares its experiences using machine learning to differentiate a new customer loyalty program.[6]

RECENT MACHINE LEARNING AND ARTIFICIAL INTELLIGENCE ADVANCEMENTS IN FINANCIAL SERVICES

Renewed vigor in the fields of applied statistics and data sciences has resulted in highly effective methods for developing impressive, game-changing new capabilities.

- **Virtual Agents:** Agents are being deployed across compliance departments that can mine through policies, procedures, regulations and other sources to answer a wide range of queries from enterprise personnel.
- **Cognitive Robotics:** This adds a powerful dimension to automation by empowering robotics software to learn and evolve in the sophistication and accuracy of executing processes that may not be entirely repeatable and consistent.
- **Caseload Analytics:** These capabilities are empowering legal experts or fraud/anti-money-laundering functions through deployment of ML/AI methodologies to assess past cases and to make predictions about the potential success or failure of new cases.
- **Text Analytics:** This is being harnessed to parse through and analyze thousands of financial contracts in the form of legal documentation, helping to quantify and analyze the contractual risks embedded in them.
- **Video Analytics:** ML/AI has recently achieved very promising results in a wide range of areas such as computer vision, speech recognition and natural language processing. These technologies can be applied in areas such as compliance, audit and model validation in applications like the automation of report writing.
- **Unique Identity:** This application of ML/AI supervised learning can be used as a tool in a wide variety of areas (e.g., fraud detection, cyber-crime, etc.) to help risk managers in these areas monitor and manage risks that depend upon uniquely identifying entities.

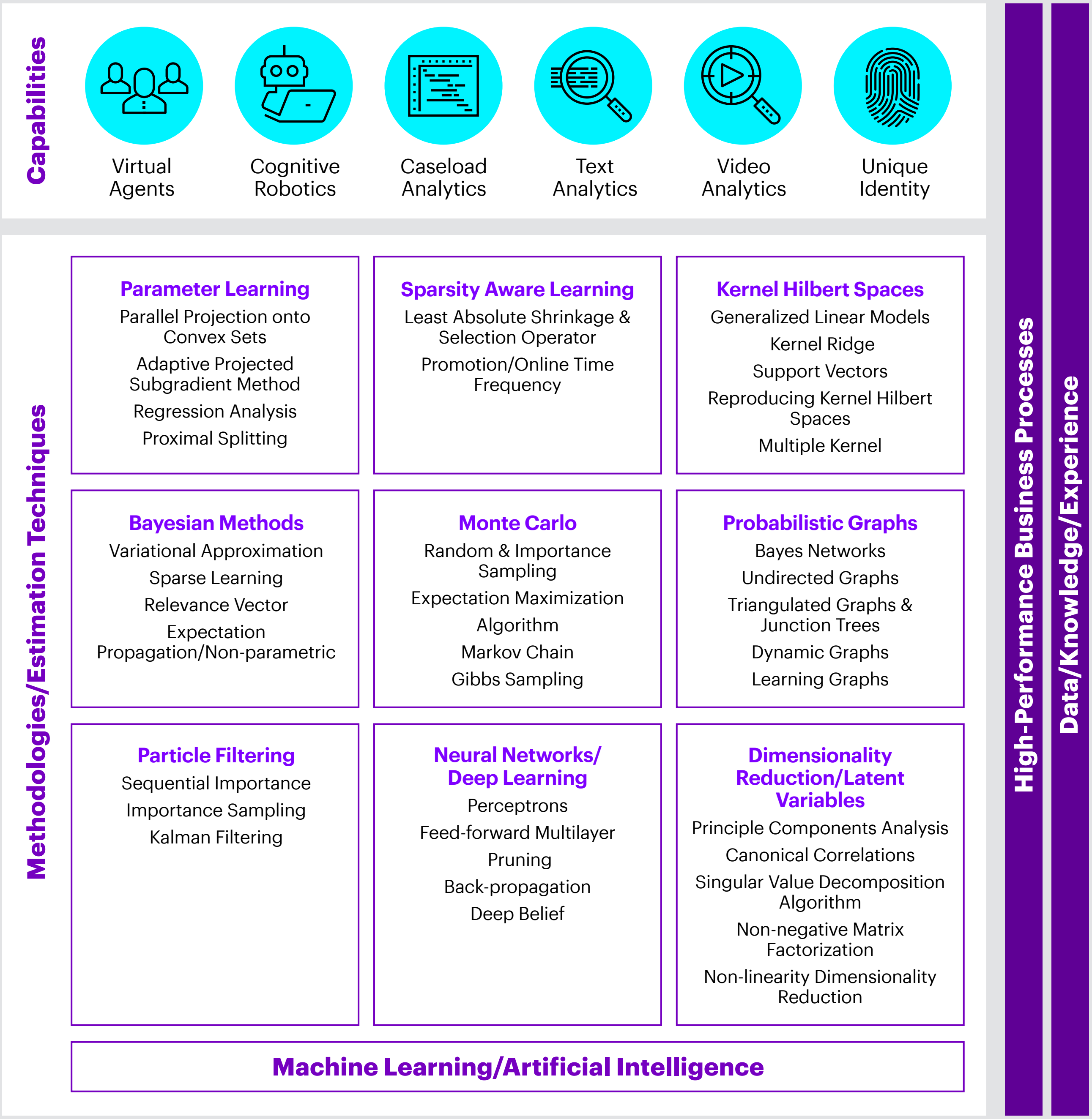
These capabilities are based on several prominent modeling techniques (see sidebar, "Modeling Techniques").

MODELING TECHNIQUES

A number of newer modeling techniques have significant potential application to financial services (also see Figure 1).

- **Sparsity-Awareness Learning (SAL)** techniques offer alternatives to the Euclidean norms as used in linear regression.
- In the **Reproducing Kernel Hilbert Spaces (RKHS)** family of approaches the emphasis is on learning non-linear models. The necessity of adopting non-linear models has been discussed extensively in the literature on classification and regression modeling.
- In contrast to other methods for parameter estimation, **Bayesian Learning** adopts a radically different viewpoint that the unknown set of parameters are treated as random variables instead of as a set of fixed but undetermined values.
- **Monte Carlo Simulation (MCS)** is a family of approximation methods based on randomly generated samples using numerical techniques, and representative of an underlying distribution, which may be of a continuous or discrete nature.
- In many everyday ML/AI applications involving multivariate statistical modeling, even simple inference tasks can easily become computationally intractable. **Graph Theory** has proved to be a powerful and elegant tool that has extensively been used in optimization and computational theory.
- **Particle Filtering** is a sequential sampling technique, where Kalman filtering is viewed in terms of probabilistic arguments and as a special case of a linear dynamic system, where the involved variables follow Gaussian distributions.
- **Parameter Learning/Convex Paths** have had a renewed interest since the 1980s, particularly in solving classical linear programming problems.
- **Dimensionality Reduction/Latent Variables (DR-LV)** has its origins in the classical principle components analysis (PCA) method, which is interpreted as a low-rank matrix factorization technique, as well as canonical correlation analysis (CCA) and its relatives such as partial least-squares (PLS).
- **Neural Networks/Deep Learning (NN-DL)** has a history that goes back to the first attempts to understand how the human brain works and how what we call "intelligence" is formed. Some of the most exciting and cutting-edge applications for ML/AI are currently being developed in the field of deep learning.

Figure 1. ML/AI Modeling Methodologies – An Evolving Analytic and Modeling Landscape



Source: Accenture, November 2017

CHALLENGES IN MODEL VALIDATION

Despite the overwhelming advantages of ML/AI technology applications in financial services, banks are expected to remain under the scrutiny of their regulators and their own control functions (some mandated by regulators themselves)—scrutiny focused on the development and execution of statistical and analytical tools employed by banking organizations following industry guidelines or their own standards and protocols.

These standards include the Federal Reserve's SR 11-7 guidance on the management of model risk, which in our view serves as the *de facto* standard for any analytical models used by banks. Most banks' control functions such as model validation emphasize conformity to such regulatory guidance and industry standards.

Figure 2 explains some of the challenges banks face by comparing model validation using traditional techniques with validation of models that employ more sophisticated ML/AI techniques. The figure depicts the model validation function as the nexus of four core components (data, methodology, processes and governance), and two dimensions in the spectrum from quantitative to qualitative validation methodologies. While many of the validation elements that have been in practice for traditional models will carry over to the ML/AI context, the differences will be in emphasis or extensions of existing techniques. The most significant challenges can be understood along the lines of the following themes (also see Figure 3):

- **Data Intensity:** The newer or more cutting-edge ML/AI modeling techniques have requirements for much greater depth and breadth of modeling data. This holds true even when compared to traditional areas such as retail credit risk scoring, where the modeling of millions of accounts has been a challenge solved over the past two decades with the advent of platforms from vendors such as SAS Institute Inc. In the ML/AI setting, not only can we be dealing with a greater volume of data, but the dimensionality of modeling features could be much larger as well, and the data could also be in a less structured format. Therefore, during validation it may be challenging to test for integrity and appropriateness, and novel tools will likely have to be developed.
- **Conceptual Soundness:** Compared with more traditional techniques, ML/AI modeling methodologies are not as widely understood by practitioners—not just the nuances of a particular technique, but also judging how fit-for-purpose a given procedure is for a particular

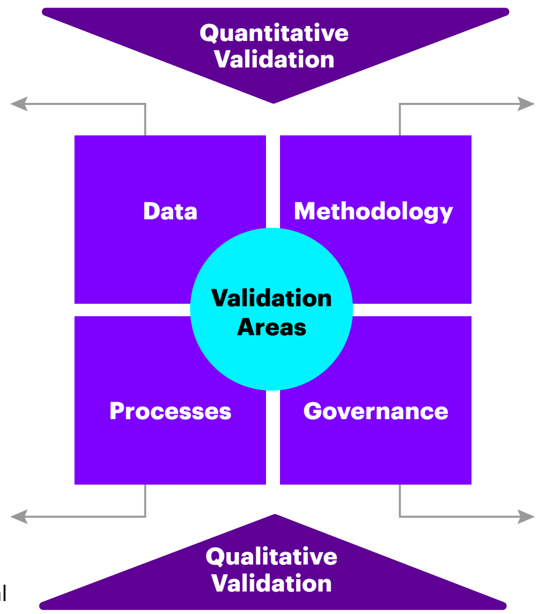
Figure 2. The Model Validation Function and Challenges in ML/AI Modeling Methodologies

Traditional Techniques
Is the development sample appropriately chosen?
Is the quality of the data sufficient enough to develop a model?
Is the data being transferred correctly between the systems?

ML/AI Techniques
Greater volume and less structure to data.
Greater computational needs for integrity testing.

Traditional Techniques
Do validation results support fit/calibration quality of the model?
Are there appropriate/relevant theories and assumptions supporting the model in place?

ML/AI Techniques
Measures of fit or discrimination may have different interpretations.
Greater emphasis on out-of-sample performance and stability metrics.



Traditional Techniques
Are the processes efficient enough to secure an effective model execution?
Is the modeling process documented with sufficient developmental evidence?

ML/AI Techniques
Greater complexity and computational overhead in model execution.
More complex algorithms and model development process to document.

Traditional Techniques
Are there robust governance policy frameworks for development, ongoing monitoring and use of the models?
Is there a set mechanism for annual review and performance monitoring?

ML/AI Techniques
It will be challenging to design policies, knowledgeable governance, of more complex development, monitoring and use.

Source: Accenture, November 2017

modeling context. That means it is going to be harder for model developers to demonstrate the suitability of the framework or theory with respect to the modeling or business context at hand.

- **Model Documentation and Code:** A critical component of model validation is an assessment of the depth and breadth of the model documentation. Ideally, the documentation should be self-contained and extensive to the degree that it would allow third-party reviewers to replicate the model without having access to the model code. While this standard is challenging to achieve even in the world of standard modeling techniques, it is an order of magnitude more challenging in the ML/AI context. This will make execution of the model validation task harder and also means that model validators are more likely to have negative assessments. For example, in the documentation for the selection of a champion model (e.g., a set of explanatory variables and an estimation technique), we find multiple challenges in the ML/AI context: high dimensionality, proliferation of subjective settings (e.g., starting values, smoothing parameters, etc.), as well as the other dimensions that we will discuss below and which will be more difficult to document in the case of ML/AI than in the standard model setting.

- **Outcomes Analysis and Model Testing:** In the context of ML/AI, banks may have to re-think standard backtesting techniques such as measures of model fit (e.g., r-squared, mean squared error, etc.), as well as other analytics such as sensitivity analysis or stability analysis. Banks may have to rely on more computationally intensive methods, such as k-fold cross validation, in order to test the accuracy and stability of ML/AI models. Because outputs may not be linked to inputs in as straightforward a manner as in traditional techniques like ordinary regression, sensitivity analysis may look rather different according to the type of model that one is considering.

- **Vendor Models:** The prevalence of vendor solutions is far higher in the ML/AI space than in the more standard areas. The current regulatory expectation is that banks will apply the same rigor in validating vendor models as they do for their in-house developed models, and this is likely to be more rigorously applied in the ML/AI context. With traditional modeling, where the proprietary nature of these models limits full-fledged validation, we have seen banks perform outcome-analyses including sensitivity and benchmarking. However, as discussed above, there are challenges associated with those standard procedures in the ML/AI context. Therefore, with vendors' ML/AI models there will be a greater reliance on "soft" forms of validation such as periodic model monitoring and review of conceptual soundness, supported by rigorous assessment of documentation on model customization, developmental evidence, and applicability of the vendor solution to the bank's portfolio.

Figure 3. Common Challenges and Potential Solutions in ML/AI Modeling Methodologies

CHALLENGES	TOOLS AND TECHNIQUES
Data Assessment for High Volume and Dimensionality	Methodologies for data access, completeness and portfolio representation – data quality tools adequate for very large or unstructured data sets may themselves be ML/AI in nature (e.g., natural language processing, big data).
Model Complexity and Conceptual Soundness	Industry benchmarks for estimation methodology, mathematical form of the model or factor selection by line of business and industry may have to borrow from applications more often, using ML/AI rather than existing simplified versions.
Model Documentation and Code Assessment	More complex and less standardized algorithms lead to challenges in documentation that necessitate fortifying the capabilities of model risk along the following dimensions: subject matter expertise (e.g., expertise in ML/AI), innovative techniques (e.g., natural language processing).
Outcomes Analysis and Model Testing	As firms may likely have to re-think standard backtesting techniques and measures of model fit and other analytics such as sensitivity/stability analysis, they would have to rely on more computationally intensive methods like k-fold cross validation. Other analyses would look rather different according to the type of model considered.
Off-the-Shelf Vendor Models	As prevalence is far higher in this space, and regulatory expectation around the rigor applied to validating in-house models is also higher, we see a greater reliance on "soft" forms of validation such as: periodic model monitoring; the review of conceptual soundness, supported by rigorous assessment of documentation on model customization; developmental evidence; and applicability to the bank's portfolio.

Source: Accenture, November 2017

CHALLENGES IN MODEL RISK MANAGEMENT

The challenges of using ML/AI models extends to the larger discourse on model risk management. As depicted in Figure 4, the management of model risk can be seen as an array of the source of the risk (data, estimation and usage) against the measurement of risk (identification, quantification and mitigation).

In terms of data, it is important to note that in the ML/AI modeling segment, sheer volume and dimensionality results in an order-of-magnitude difficulty in implementing data integrity, sensitivity and assurance processes. In the estimation of ML/AI models, identification is complicated by a more nuanced bias-variance tradeoff, stronger assumptions and greater computational complexity.

Figure 4. Emerging Trends: Quantification of Model Risk in ML/AI Modeling Methodologies

Model Risk Source	IDENTIFICATION	QUANTIFICATION	MITIGATION
Data	Finding data errors and missing variables is likely a greater challenge than insufficiency of time period or sample size.	Sensitivity of output to the exclusion of variables or data points/time periods is difficult to assess in a data-rich environment.	Data quality assurance processes are complex activities in the ML/AI context.
Estimation	The bias/variance tradeoff is more nuanced, computational complexity is higher and modeling is dependent upon stronger assumptions.	There are alternative and more nuanced measures of model fit, and while benchmark models may be more varied, it is harder to assess if appropriate.	Conservatism in inputs, estimates and outputs are hard to provide, and model backtesting or stress testing is a less straightforward task.
Usage	It is not as clear if model is re-calibrated in a timely manner in dynamic settings, and model execution error is harder to detect due to heightened computational intensity.	Measures of decay in predictive power between re-estimations are less meaningful, but the impact of not using the model can be measured.	Implementing a strict model control environment, ongoing monitoring and governance processes are a more extensive venture.

Source: Accenture, November 2017

The latter considerations flow through directly to the quantification of estimation risk, as the alternative measures of fit in the ML/AI context are more difficult to interpret. Although the universe of benchmark models may be larger, it may also be harder to identify the most appropriate benchmark.

Regarding estimation risk, in the ML/AI setting the margin of conservatism is a greater challenge to provide. Tasks such as model backtesting and stress testing are less straightforward as compared to the same tasks in the context of standard models. In the third and final dimension of model risk measurement, the added complexities of the ML/AI setting have a direct bearing on usage risk. This starts from the identification element in that determining the proper frequency of re-calibration and detection of execution error are harder to determine when models are dynamically changing at a rapid pace.

The knock-on effect of this in the estimation phase is that standard tests such as measuring decay in predictive power between re-estimations may be less meaningful if there is very frequent re-calibration. However, it is still possible to measure the impact of not using the model. Finally, in the effort to mitigate the impact of usage risk for ML/AI models, implementing the standard controls environment (i.e., ongoing monitoring and governance processes) becomes a more extensive venture.

OTHER MODEL VALIDATION AND MODEL RISK MANAGEMENT APPROACHES

We conclude our examination of model validation and model risk management approaches, a first step in the increased adoption of ML/AI models, by looking at other approaches that are also worthy of consideration.

- **Supervised Machine – GAMs:** Supervised learning has been around a long time and traditional approaches such as linear regression and logistic regression are bedrock algorithms that have been used extensively by banks in risk management applications such as credit risk modeling. One special case is the generalized additive model (GAM) which detects patterns among variables and offers greater transparency in understanding how each variable is related. GAMs have been used in several cases where it is essential to understand how an outcome is reached.

  For example, a leading technology company teamed with some hospitals in California to help doctors identify patients with combinations of symptoms that might warrant a different treatment than the one proposed for each symptom on its own. Such techniques may be necessary in financial services when a similar need for predictability is required. For example, credit scoring vendors such as FICO® (Fair Isaac Corporation) may require such techniques when predicting consumer credit scores with sufficient transparency.[7]

- **Vendor Explanation:** Several software vendors today offer a highly specialized solution built on top of ML/AI methodologies. Some of these tools (and newer ones that may be developed) may face an uphill climb in adoption from the industry because the "black box" effect of proprietary algorithms may not pass regulatory or risk control muster. A few vendors are starting to provide explanations for the model's decision making but the quality of explanations varies among vendors. For example, Sift Science, Inc. provides ML/AI models for financial services firms. They have embedded explanations (called "stories"), along with the underlying data, into their products.[8] As another example, FICO® offers a tool that provides the rationale for the decisions recommended by some of their products.[9] Although requiring vendors to provide explanations for these outcomes helps address the transparency and regulatory concerns, the "out-of-the-box" explanation may be watered down and could result in missing potentially critical information. Therefore, it is recommended that financial services firms have a dedicated resource from the vendor to provide such explanations.

- **Explainable AI (XAI):** XAI is a cutting-edge although nascent AI approach that uses the same technology to solve the problem created by the technology. In XAI, AI traverses through the code of another AI and provides an explanation for the outcomes produced by the original AI or ML model. XAI can perform an experiment and read results, then adjust the variables and repeat the experiment until satisfied that the results meet the hypothesis and finally produce a document outlining the steps taken to produce the conclusion. XAI provides the potential to readily document and translate the learning process of an ML/AI model. The technology is not yet readily available for commercial purposes and only known to be explored from an R&D perspective. For example, the Defense Advanced Research Projects Agency (DARPA) is spending $70 million to develop this technology, as they have been using ML/AI techniques in many facets of their work.[10] A large retail bank also claims to be investing in XAI for commercial purposes.

CONCLUSION: INVESTING IN EMERGING TECHNOLOGIES

As the regulatory environment stabilizes, we expect the financial sector to invest heavily in emerging technologies and methodologies that can help them be more competitive in the marketplace. ML/AI offers some of the highest potential in achieving strategic goals, as it can be employed in a myriad of areas including those that have traditionally not been good candidates for use due to regulatory or risk management standards.

Employing some of the techniques discussed in this paper can help raise the level of confidence in model risk management disciplines like model validation. It can also raise the confidence of regulators in the accuracy and appropriateness of emerging ML/AI tools in areas such as credit risk and regulatory capital management, stress testing and trade surveillance. As the vendor landscape matures in this area, financial services companies can significantly benefit from ML/AI solutions through enhanced sophistication and increased efficiency in their day-to-day business operations.

FOOTNOTES

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