



Setting The Context

The Reserve Bank of India released a circular on "Regulatory Principles for Management of Model Risks in Credit" to all the financial organizations in the country, urging all Financial Institutions which includes Commercial Banks, State Cooperative Banks & Central Cooperative Banks, Non-Banking Financial Companies (including Housing Finance Companies), All-India Financial Institution to establish board-approved risk management policies to strengthen the reliability on the credit scoring models. The central bank also suggested to validate the models using external model validation experts along with maintaining ongoing reviews of these models.

MODEL VALIDATION FRAMEWORK REQUIREMENT, AS GUIDED BY RBI

As per the circular published by RBI (DOR.STR.REC. /21.04.048/2024-25) dated 5th August 2024, Regulated Entities (REs) shall establish a model validation process and that should be independent of model development team. This team would review and evaluate the robustness of the credit risk models developed inhouse or otherwise. Every model has to be validated independently before the implementation and should be reviewed periodically i.e., at least on a yearly basis and or at the time of any amendments applied to the model owing to different events or market changes. The REs may also consider engaging external experts for validation of the models deployed by them, as mentioned under their policies.

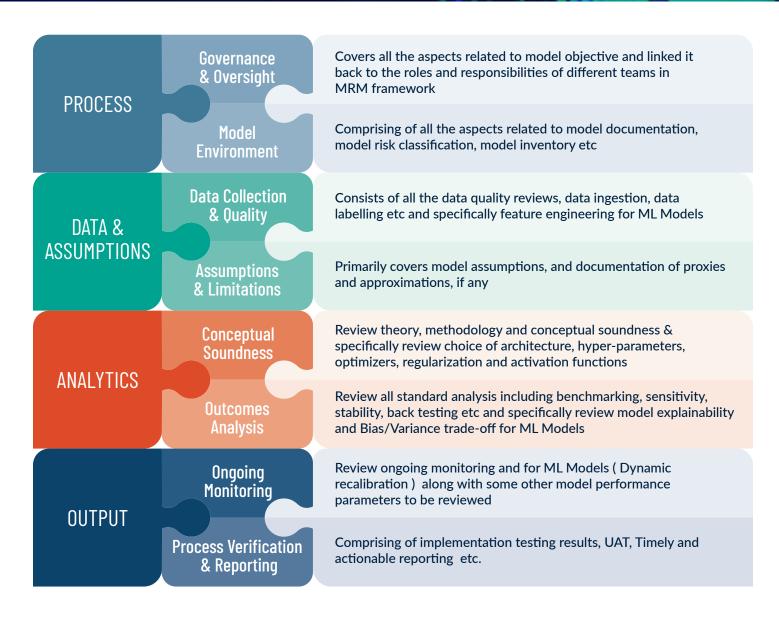
Validation outcomes should consider be in terms of suitable and easily understood before the event parameters and corresponding data elements to supplement the same. The output should be compared against benchmarks prescribed in the risk management policy framework and should be presented before the Risk Management Committee of the Board (RMCB) or the designated Sub-Committee of the Board as mentioned at clause B in RBI circular covering details of governance and oversight aspects commensurate with model materiality; processes around model development or selection; documentation for models deployed; independent vetting / ongoing validation or review processes; change control; and the monitoring and reporting framework including role of internal audit function.

The models implemented shall be subjected to supervisory review before the deployment. The Reserve Bank may also engage external experts to validate the models deployed by REs, including the external models deployed for their credit management, based on supervisory risk perception. Accordingly, wherever REs has collaborated external models in terms of clause C in RBI circular covering the broad principle of model development and deployment, such arrangements shall include appropriate contractual provisions enabling supervisory evaluation of such models either directly by the Reserve Bank officials or by other external experts as engaged by the Reserve Bank.

MODEL VALIDATION FRAMEWORK

Model validation is an integral part of Model Risk Management. All the financial organizations are required to validate the model developed by the internal team on yearly basis as guided by RBI. The models can be any type of credit risk model such as application scorecard, behaviour scorecard, fraud score, collections score. Ideally, model validation standards have to be developed as a part of regulatory requirements for model risk management and that has to be followed by model development team. Independent model validators should also consider the model validation standard while validating the model.

Model validation framework covers the below mentioned aspects aligned to the principles & directions circulated by RBI in India. The below framework covers all types of models — conventional models & ML Models. As per the framework, there are certain aspects that needs to be specifically reviewed for ML Models. As per RE, the models need to be revalidated once its redeveloped by the organizations.



POTENTIAL CHALLENGES IN MACHINE LEARNING MODEL VALIDATION

As per RBI circular, the validation exercise shall include review of assumptions underlying the model for their validity / substantiation; verification of the accuracy of data used in the model and reliability of data sources; confirming compliance with extant regulatory / statutory instructions; evaluation of model documentation for completeness and accuracy, and assessment of the efficacy of the model outcomes through back-testing. Besides, the validation exercise shall comprehensively review all the limitations and weaknesses in the models, including instances of bias or discrimination, if any, to ascertain the need for suitable corrective measures.

However, while validating ML Models the validators should review the models considering the following three critical aspects, beyond other aspects;

- · Conceptual soundness of the model & model explainability
- · Feature engineering and feature selection
- · Model stability and bias-variance trade off

Conceptual Soundness of the Model & Model Explainability

Validators should review the model methodology and the functional form to verify if it is fit for purpose for its intended use and domain of applicability, theoretically sound, and aligned with industry practices and internal and regulatory requirements. As per the industry standards, Elastic Net and Ensemble techniques (Bagging & Boosting techniques – Random Forest, Gradient Boosting) are commonly used compared to other techniques such as Neural Networks and Support Vector Machines as the outputs from these latter techniques are hard to explain.

Validators should verify that the model has been clearly explained by the developers. Local surrogate models are interpretable models that are used to explain individual predictions of black box Machine Learning models.

Feature Engineering and Feature Selection

Validators should verify the following aspects of feature engineering as Machine-learning models can incorporate a significantly larger number of inputs-

- ✓ Features created for the model should be conceptually sound and interpretable
- ✓ Features should be reviewed by domain experts or subject matter experts
- ✓ Interaction features or trend features should be inspected in the context of business objective
- ✓ Features from categorical variables should be evaluated with caution as number of categories can be grouped in multiple ways and the groups should make business sense
- ✓ Imputation method for the features with missing valued should be properly justified from the business context and features with high missing values should be omitted
- ✓ Complicated features should be avoided where business implications are not properly aligned
- ✓ Features generated from ML packages such as AutoML may lead to very high number of features and validators should review proper justification on dimension reduction processes adapted for feature engineering

Model Stability and Bias-Variance Trade-Off

Supervised machine learning model has an inherent tendency to overfit and bias-variance trade-off plays a critical role in model selection ensuring the robustness of the model across different samples. Balancing between bias and variance is a critical job for the model developers and it has to be properly examined and verified by the validators.

Error in the model has three components – bias, variance, and irreducible error. Validators should verify that the developers have taken proper measures to maintain a balance of bias and variance, including the following:

- a. Review the model complexity ensuring that its not too simple with very mess number of parameters or too complex with huge number of parameters as it would lead to high bias and high variance respectively with maintaining the balance
- b. Review the techniques such as bagging and other resampling techniques can be used to reduce the variance in model predictions
- c. Verify that the model tested on out-of-sample generates consistent result to ensure the balance between bias and variance



MACHINE LEARNING MODEL VALIDATION – BEST PRACTICES

The potential of machine learning models generates higher accuracy leading to higher value and it has been observed that the ML models create significant impact for the financial institutions over the last decade. ML models can produce significant improvements over traditional models considering the complex nonlinear use cases currently being solved by all the financial institutions. Primarily departments such as asset management, credit risk, fraud detection, and regulatory compliance has started to develop and deploy ML models and it has been rising since open source packages are available for all.

All types of model validation would require a systematic approach consisting of certain activities and sub activities and it span across all types of models i.e., conventional model, ML models. The below table depicts the detailed activities and sub activities of model validation with specifically focussing on ML Models. This can be considered as the best practice approach for conducting ML model validation.

ACTIVITIES	SUB ACTIVITIES	DETAILED VALIDATION PLAN
Planning & Current State Assessment	Model Understanding Conduct interviews with the Credit Risk Managers Review existing modeling approaches and documentation	 Understand and review the existing model objectives and ensure the alignment of the model development documentation to model risk management framework Organize interviews with the model risk managers and relevant stakeholders to understand the overall risk management policies and framework applicable for credit risk
Scorecard Validation Testing: Methodology	Conceptual Soundness Review Hyperparameter Tuning Regularization & Activation Functions Model Architecture	 Reassess the applicability and conceptual soundness of the selected model from methodology and design perspective and comparing against alternative techniques Review the theoretical soundness of the model based on research papers, industry best practice Review the key components of model development, including: Feature Selection & Feature Engineering Review Hyperparameter Tuning Techniques Review any regularization technique has been applied Review key model and data assumptions and limitations.

Scorecard Validation Testing: Design	Feature Engineering Feature Selection Soundness of model assumptions and limitations	- -	Validate the feature engineering procedures ensuring the explainability of the features and justified by SME for complex features. Review the methodologies adopted for feature selection which includes justification on feature selection / dimension reduction. Assess the sufficiency of model documentation which includes Appropriateness of target variable definitions, length of performance window, imputation method adopted for missing values and outliers, evidence to support the model selection, key assumptions and limitations, weakness, and specific mathematical calculations, model fitting result based on relevant statistics
Scorecard Validation Testing: Data	Data quality	-	Review data quality parameters used in the model development and validation and its completeness, relevancy, consistency and timeframe Review and verify all data processing logic and transformations used Review the treatments adopted for handling missing values and outliers Review sampling methodology and its justification & relevance Review data proxies (if any) Assess data for any bias (sampling bias, proxy bias, missing value treatment bias etc.) Review the soundness of the business rules applied in the procedure of data aggregation, stratification, and extraction, if applicable Review the balance between bias and variance considering the overfitting tendency of the ML algorithm
	Data Labelling and Sampling	_	
	Train/Test Split Assessment	- -	
	Bias Variance Trade-off	_	
Scorecard Validation Testing: Outcomes Analysis & Back testing	Model Replication	-	Perform an independent replication of the model construction process (where feasible).
	Discriminatory power – Relative & Absolute performance	_	Validate the model documentation and the testing results to assess the model results and outcome. Additional independent testing may be completed
	Model Back-testing	_	as necessary, such as: Sensitivity Analysis: Change in the values of the significant factors and check the impact on the
	Model Rank Ordering	_	model Discriminatory Power: Review the model performance parameters/discriminatory power
	Stability Analysis	-	Stability: Assess the model stability (population stability index) between in-sample, out-of-sample, and out-of-time samples Benchmarking: Review the results of the primary model against benchmark models to ascertain appropriateness of model output Review hyperparameter tuning methodologies Review the explainability of the model considering the black box nature of some of the ML Models such
	Sensitivity Analysis	-	
	Model Explainability	_	
	Model Benchmarking		as Neural Network
Validation Report Generation	Generate the Validation report for each of the model	_	Detailing the findings of the model validation with RYG based on the activities performed



CONCLUSION

As per RBI Guidelines, all the financial institutions should engage with independent model validators and ensure all the risk models are validated. The model should be validated once in a year along with model monitoring and governance by the respective internal risk management committee and stakeholders. The validation report should be submitted to RE ensuring compliant to the guidelines. Model Validation report should clearly highlight the gaps and breaches after notifying the stakeholders and proper action has to be taken by the organization such as recalibration of the model or redevelopment of the model.

WAY FORWARD

Financial Institutions in India may consider independent validators for validating risk models with special focus on machine learning models as ML models are now widely accepted in risk domain. Significant considerations regarding machine learning model validations cover both qualitative and quantitative aspects of model validation. Qualitative aspects are model methodology review, model design review, assessment of model data and model development testing review. Quantitative review primarily focuses on model testing i.e., Assessing the testing supporting the model development and where applicable augmenting using independent testing in terms of model replication, back testing, stability and sensitivity analysis, explainability and benchmarking

About Protiviti

Protiviti (www.protiviti.com) is a global consulting firm that delivers deep expertise, objective insights, a tailored approach and unparalleled collaboration to help leaders confidently face the future. Protiviti and its independent and locally owned member firms provide clients with consulting and managed solutions in finance, technology, operations, data, digital, legal, HR, risk and internal audit through a network of more than 90 offices in over 25 countries.

Named to the 2024 Fortune 100 Best Companies to Work For® list for the past 10 years, Protiviti has served more than 80 percent of Fortune 100 and nearly 80 percent of Fortune 500 companies. The firm also works with government agencies and smaller, growing companies, including those looking to go public. Protiviti is a wholly owned subsidiary of Robert Half Inc. (NYSE: RHI). Founded in 1948, Robert Half is a member of the S&P 500 index.

Contact

Amit Lundia Managing Director Phone: +91 9836 922 881

Email: amit.lundia@protivitiglobal.in

Acknowledgement

Kallol Kumar, from our Technology & Digital Solution Practice has contributed to this publication, which was led by Amit Lundia.

This publication has been carefully prepared, but should be seen as general guidance only. You should not act or refrain from acting, based upon the information contained in this presentation, without obtaining specific professional advice. Please contact the person listed in the publication to discuss these matters in the context of your particular circumstances. Neither Protiviti India Member Private Limited, nor the shareholders, partners, directors, managers, employees or agents of any of them make any representation or warranty, expressed or implied, as to the accuracy, reasonableness or completeness of the information contained in the publication. All such parties and entities expressly disclaim any and all liability for or based on or relating to any information contained herein, or error, or omissions from this publication or any loss incurred as a result of acting on information in this presentation, or for any decision based on it.



