WELLS FARGO

Quantitative risk management and stress test to ensure safety and soundness of financial institutions

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Together we'll go far

Stress test

- In the wake of the financial crisis, U.S. Congress enacted the Dodd-Frank Act
  - Requires the Federal Reserve to conduct an annual stress test
  - Seeks to ensure BHCs have sufficient capital to continue operations throughout times of economic and financial market stress
- Projects balance sheets, RWAs, net income, and resulting post-stress capital over a nine-quarter "planning horizon"
  - BHC stress scenario: internally generated scenarios (Baseline and Adverse) customized to idiosyncratic risk of BHC
  - Supervisory scenario: Baseline, Adverse, Severely Adverse

FRB guidance for quantitative methodologies/ models

- Stress test is a forward-looking quantitative evaluation of the impact of stressful economic and financial market conditions on BHC capital
- Specific expectations in terms of quantitative tools/models and their governance:
  - SR15-18: FRB Capital Planning Guidance
    - Use of Models and Other Estimation Approaches
    - Model Overlays
    - Use of Benchmark Models
    - Sensitivity Analysis and Assumptions Management
  - SR11-7: FRB Model Risk Management Guidance
    - Model Development, Implementation and Use
    - Model Validation
    - Model Governance, Policy, and Control

Applications of models

- Economic Scenario Generation
  - Firm-specific scenarios: specific vulnerabilities of the firm's risk profile
  - Multiple stressful conditions or events can occur simultaneously or in rapid succession
- Loss Estimation
  - Credit risk losses on loans and securities
  - Fair-value losses on loans and securities
  - Market and default risks on trading and counterparty exposures
  - Operational-risk losses

Applications of models (continued)

- Pre-Provision Net Revenue (PPNR)
  - Net interest income
  - Non-interest income
  - Non-interest expense
- Risk Weighted Asset (RWA)

Model data/input and sources

- SR15-18 Guidance
  - Disaggregated levels to capture observed variations in risk characteristics and performance across sub-portfolios/segments under changing conditions
  - Internal data to estimate Losses and PPNR when possible
- Data quality and relevance
  - Downturn historical data
  - Suitability for the model and consistent with the modeling framework
    - Included/excluded data and proxies for model development population, rationale, and impact on results
    - Representative of the bank's portfolio
    - Reconciles with general reporting information (e.g., GL) as applicable

Modeling consideration

- SR15-18 Guidance
  - Separately estimate Losses and PPNR for portfolios or business lines that are sensitive to different risk drivers
  - Qualitative Approaches are allowable in limited cases
- Model requires both accuracy and sensitivity; where the later might be more important
  - Loss forecasting: performance both for short- and long-term predictions are important
  - Stress Test: sensitivity is more important than model fit
- Proper granularity and segmentations are critical to deal with changing portfolio composition

Modeling consideration (continued)

- Beware of correlation between dynamic input or “time” dummy variables which can mute the impact of macroeconomic variables
- Treatment dynamic variables which cannot be predicted
  - Time-varying behavioral variables

Modeling framework

- Credit/PPNR Models
  - Account level modeling
    - Conditional (i.e., hazard) model/panel regression
    - Credit rating migration model
  - Pool level models: vintage, segment, or behavior pool
  - Time-series regression
  - Choice consideration: granularity to capture portfolio changes, ability to capture important drivers, data availability, resource/timing, and on-going maintenance
- Market Models
  - Full revaluation using Front Office pricing model
    - Need to evaluate the model function properly during stress condition: stability, convergence, no arbitrage
  - Approximation (Greek-based) models
  - Need Risk not in Model to deal with limitation

General modeling framework

- Let T a random time of account closing (e.g., due to default or attrition/prepayment), the hazard function is modeled as a regression with $g(.)$ link function and covariates $Z(s)$

$$\lambda\{t|Z(s)\} = g[\lambda_0(t), Z(s)]$$

- Where $\lambda_0(t)$ is the baseline hazard to represent the effects of unobserved factors and s is the observation time which can be:
  - Static such as time of origination, $s = 0$
  - Dynamics
    - Last snapshot information without future prediction
    - Including future prediction, i.e. $s = t$ and prediction model $Z(t)$ is available such as PPNR models (e.g., utilization or spend rate) or macro-economic factors

$$Z\{t|X(s)\} = h[Z_0(t), X(s)]$$

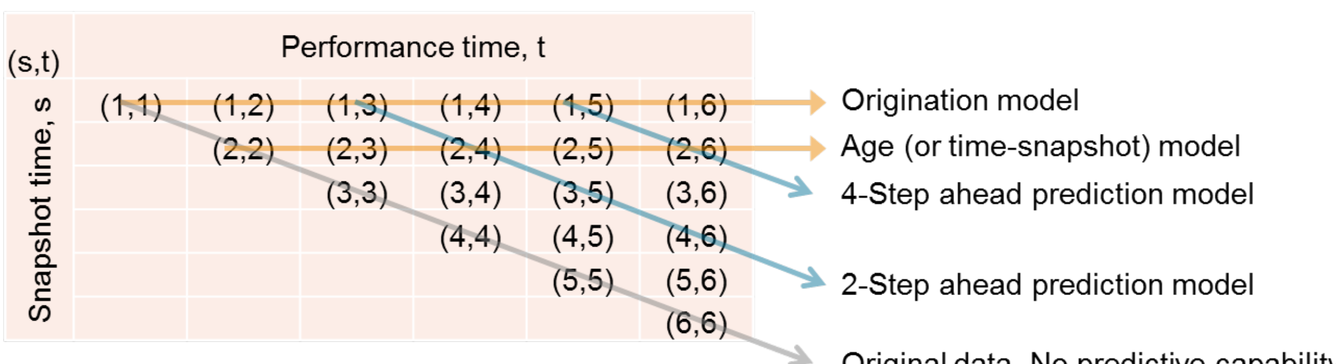
Dynamic covariates and data stacking

- Dynamic factors that no future prediction are available but they are critical such as refreshed FICO, Utilization, etc., and need to be handled through ‘data stacking’ approach

Observation Data

Snapshot Date, s	Snapshot FICO, x1	Snapshot Delinquency, x2	Performance Date, t	MOB, m	Unemployment, x3	Default	Time after snapshot, k
13-Jan(1)	675	Current	13-Jan(1)	1	7.2	0	0
13-Feb(2)	666	Current	13-Feb(2)	2	7.2	0	0
13-Mar(3)	630	30	13-Mar(3)	3	7.2	0	0
13-Apr(4)	620	60	13-Apr(4)	4	7.2	0	0
13-May(5)	620	90	13-May(5)	5	7	0	0
13-Jun(6)	620	120	13-Jun(6)	6	6.7	1	0

Dynamic Factor without future predicted values



Model validation depth and scope

- Soundness of modeling approach
  - Methodology, granularity, data quality, and treatment (coverage, proxy, etc.), parameter estimation/calibration
- Model stability under market shock
  - computational stability, parameter stability, reasonable outcome
- Rigor of model performance evaluation
  - Backtesting to previous stress condition
  - Out-of-sample and out-of-time testing
  - Sensitivity to risk varying risk drivers
    - Separation across different scenarios
    - Consistency with respect to scenarios
- Issues and limitations
  - Risk in model, risk not in model, parameter uncertainty
- Holistic approach
  - Not only focus on the targeted core models, but also include critical upstream and downstream models and tools
- Thorough documentation

Model validation:

Replication

- Independently rerunning/recoding models to confirm and evaluate model outputs
- In-sample backtesting
  - Multiple forecast starting points covering different parts of the economic cycle
  - Model performance for all segments and alternative segments.
- Out-of-sample/out-of-time performance
  - Out-of-development periods test
  - Model performance when “stress-time window” is excluded from parameter estimation
    - Appropriateness for future scenarios where such scenarios do not exist in the development sample
    - Out-of-time forecast performance
    - Parameter stability
- Sensitivity analysis and testing
  - Model sensitivity under distinct economic scenarios
  - Sensitivity to input changes

Model validation:

Benchmarking

- Distinct modeling alternatives
- Evaluate model performance when the true outcomes are unknown (i.e., Stress testing models)
- Diagnose appropriateness of modeling choice
  - Model structure including the simplification choice
  - Segmentation
  - Variable selection, non-linearity, interactions
- Model alternatives used by validators needs to be comprehensive and insightful and are likely to be more complicated and perform better than production models
  - Not constrained by the requirement for model maintenance and operational computation time

Evaluating the dynamics of stress testing models

Dynamics of Horizon Prediction:

$$\lambda_i(t|s) = \beta_0(k) + \boldsymbol{x}_i^T(s,t)\boldsymbol{\beta}(k)$$

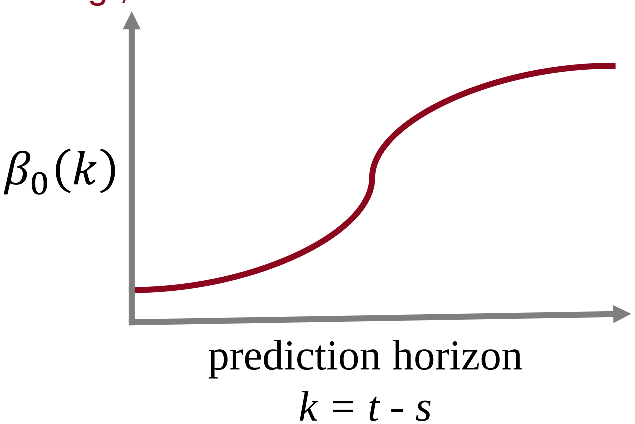
Prediction of time *t* given the 'snapshot' information at time *s*

Dynamic covariates:

- Economic factor *s*<–*t*
- Behavioral covariate *t*<–*s*

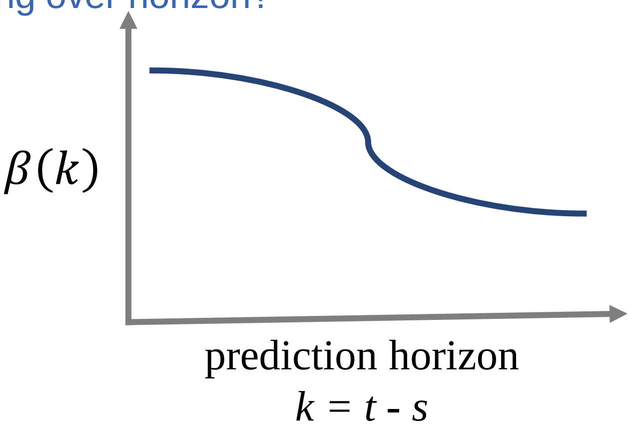
Is there effect from unobserved variables?

- e.g., baseline hazard in PD model



Is the sensitivity change over the horizon?

- e.g., is the effect of FICO at time snapshot decaying over horizon?



Machine learning for variable selections

Alternative Model: Machine Learning (ML)

Model importance ranking

- ML embedded method importance measure (e.g. gradient boosting machine(GBM), random forest)
- ML filter methods ranking(univariate and multivariate)

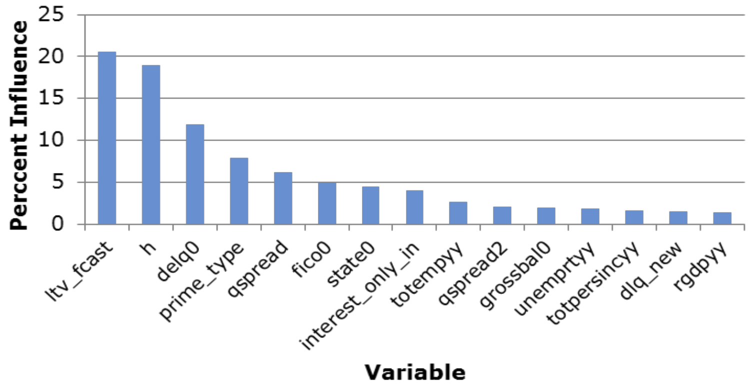
Model interaction selection

- ML H-statistics/ML 2D partial dependent plot
- GLM elastic net with regularization on interactions

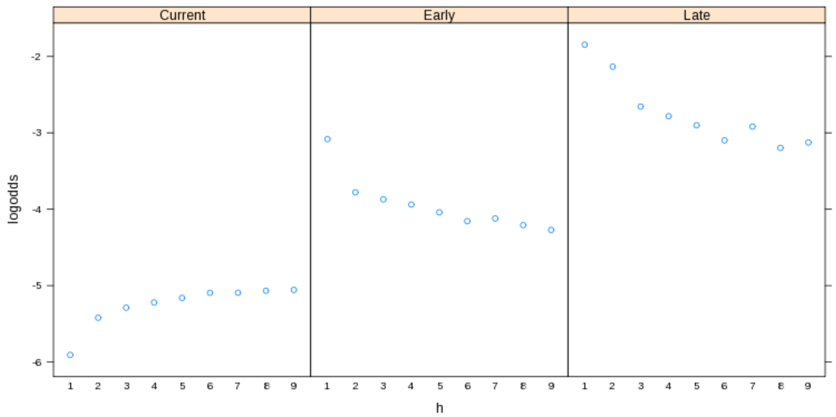
Nonlinearity detection

- ML 1D partial dependent plot

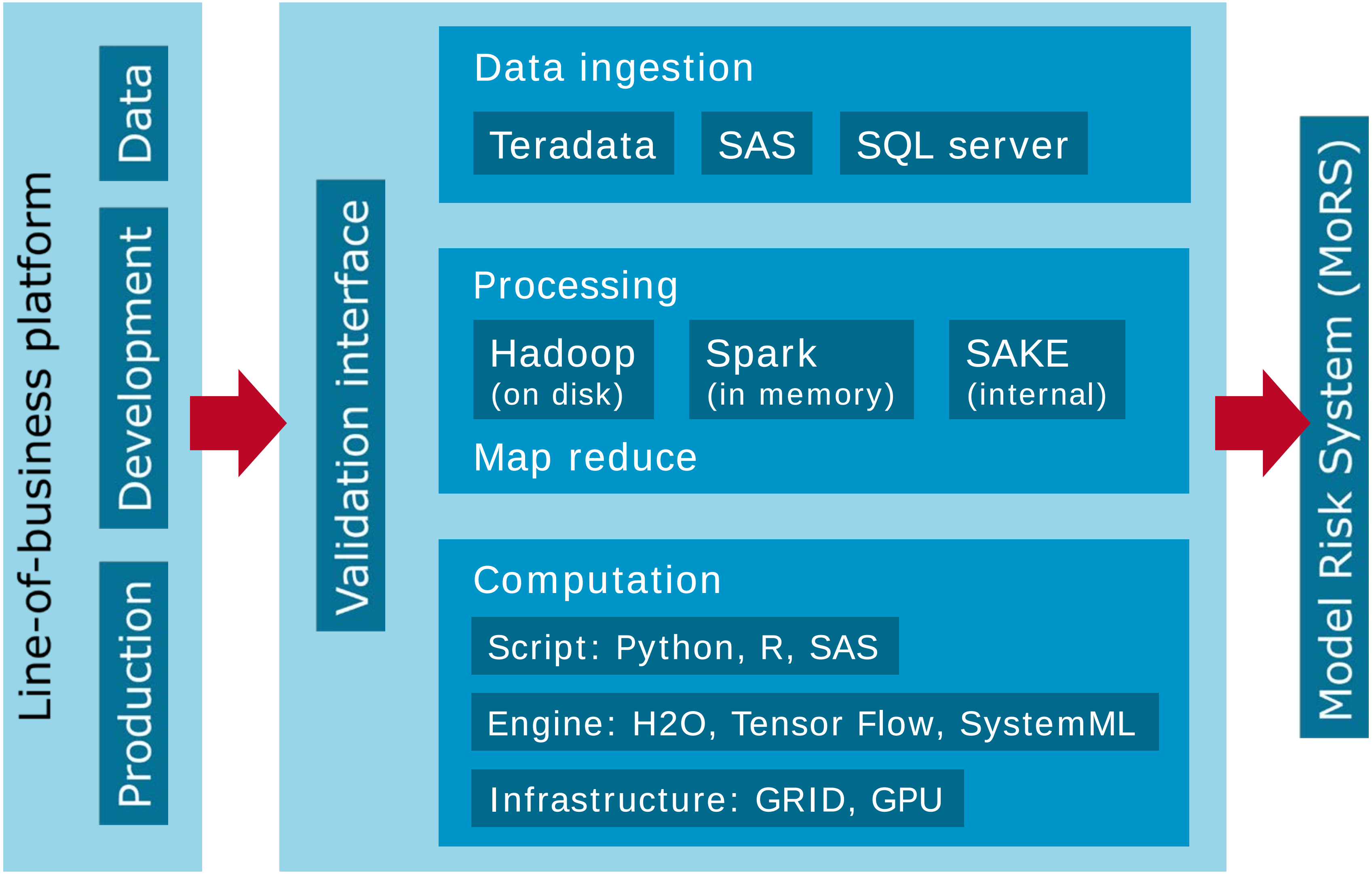
Importance ranking using GBM



Nonlinearity and Interaction



Validation platform



Compensating model weakness during usage:
Overlays

- Models are often have weakness and limitation due to:
  - Risk in Model:
    - Outstanding issues, limitations, or restriction identified during model validations or performance monitoring
    - Model dependency
      - Weakness of upstream (feeder) models
      - Uncertainty of input assumptions
  - Risk Not in Model: model limitation to capture risk drivers listed in the stress test risk identification process
    - Factors in economic scenario that are not in the models
    - Idiosyncratic factors both external events or business drivers/strategy

Compensating model weakness during usage:
Overlays

- Compensating factors such as model overlays are typically applied for model weakness
  - Quantitative overlay: model benchmark, quantitative analysis, back testing, sensitivity analysis
  - Qualitative overlay: management judgment