Webinar

Machine Learning-Based Systematic Investing in Agency Mortgage-Backed Securities

Welcome
We will begin promptly at 10 AM ET.
If you are unable to hear the speakers, please let us know in the chat box. You may enter your questions in the Q&A, we will address them at the end of the presentation. You can find a copy of the slide deck and recording of this webinar: www.fdpinstitute.org/webinars

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FDP Institute provides world class training and education to financial professionals to meet the accelerating needs of digital transformation in the industry.

Introductions

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Today's Topic:

Machine Learning-Based Systematic Investing in Agency Mortgage-Backed Securities

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Machine Learning-Based Systematic Investing in Agency Mortgage-Backed Securities

August, 2023

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Agenda

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- Introduction and Machine Learning Overview
- Fixed Income Market and Agency Mortgage-Backed Securities (MBS)
- Why Machine Learning (ML) in Agency MBS
- Tree-Based Algorithms
- Model Construction
- Model Performance
- Systematic Investment Strategy Application
- Q&A

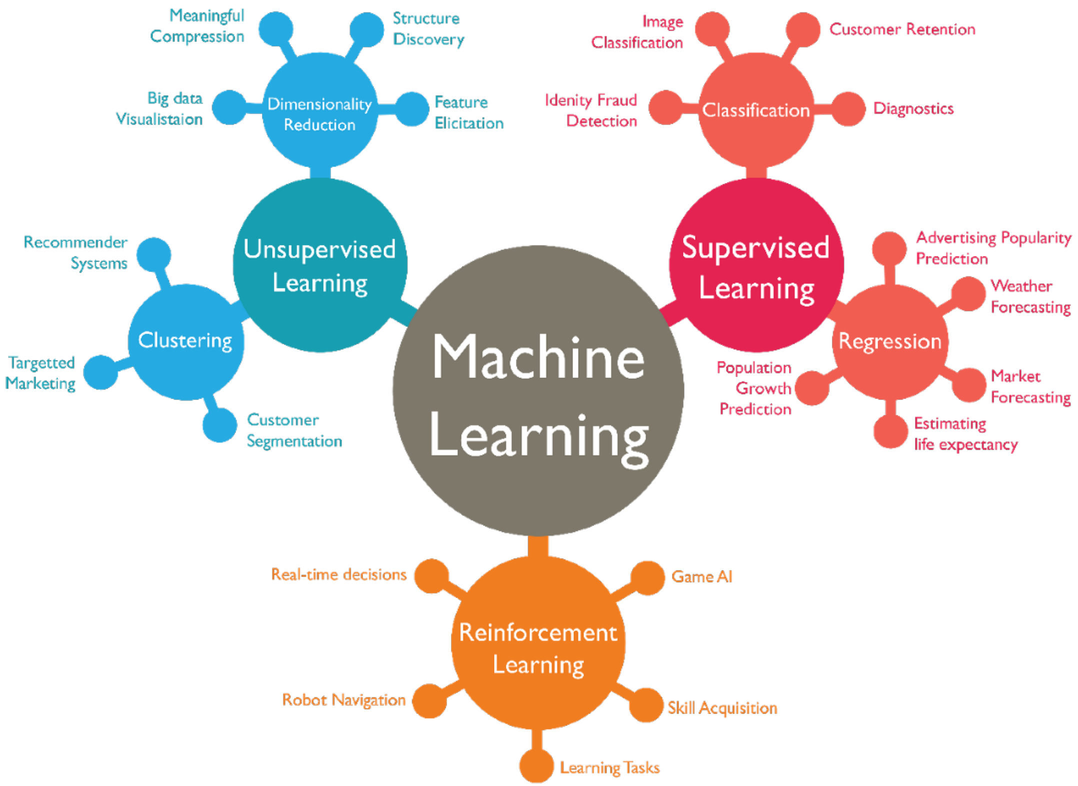
Introduction and Machine Learning Overview

Terminology and Process

Traditionally computer programs combined with human created rules can **produce answers to a problem**. Instead, machine learning uses data and answers to **discover the rules behind a problem**.

Terminology
- Dataset
- Features
- Model

Process
- Data Collection
- Data Preparation
- Training
- Evaluation
- Tuning



Source: Abdul Rahid (WordStream)

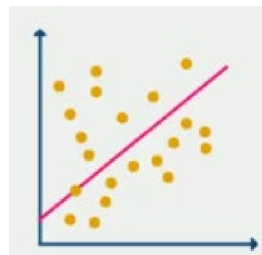
Introduction and Machine Learning Overview

Supervised Learning vs Unsupervised Learning

Based on the nature of the learning signal available ML can be roughly categorized as Supervised Learning, Unsupervised Learning and Reinforcement Learning. If based on the output, ML can also be categorized as Classification, Regression and Clustering.

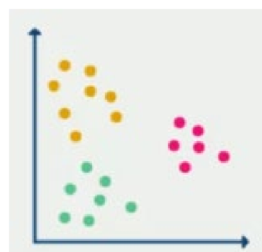
Supervised Learning

- need labeled data.



Unsupervised Learning

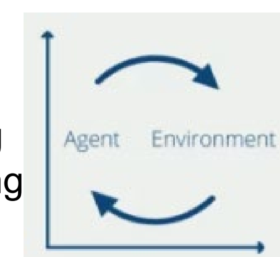
- do not need labeled data.



Minimization: minimize the fitting error of a model to the presented data

Reinforcement Learning

- Trial and error based learning most similar to human learning process.



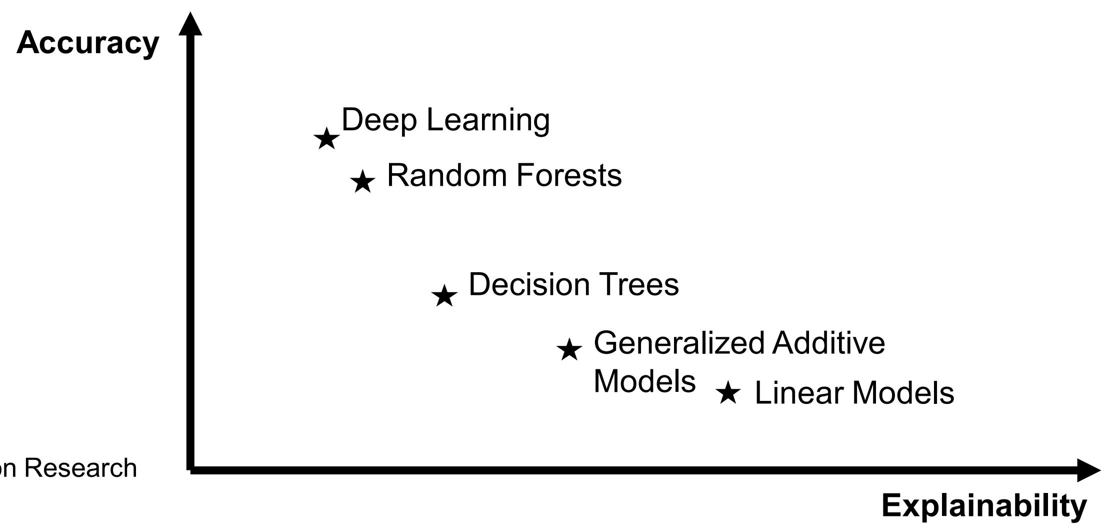
Maximization: identifies the suitable decisions to be made to maximize a well-defined objective

Source: Franklin Templeton Research

Introduction and Machine Learning Overview

Traditional Linear Model vs ML Model

	Pros	Cons
Traditional Linear Model	• Transparent • Easily interpretable • Computationally tractable	• Need to define function form specifically to capture non-linearity
Machine Learning Model	• Higher accuracy • Better capability on learning complex relationships	• Need assistance to visualize and interpret • Computational intensive



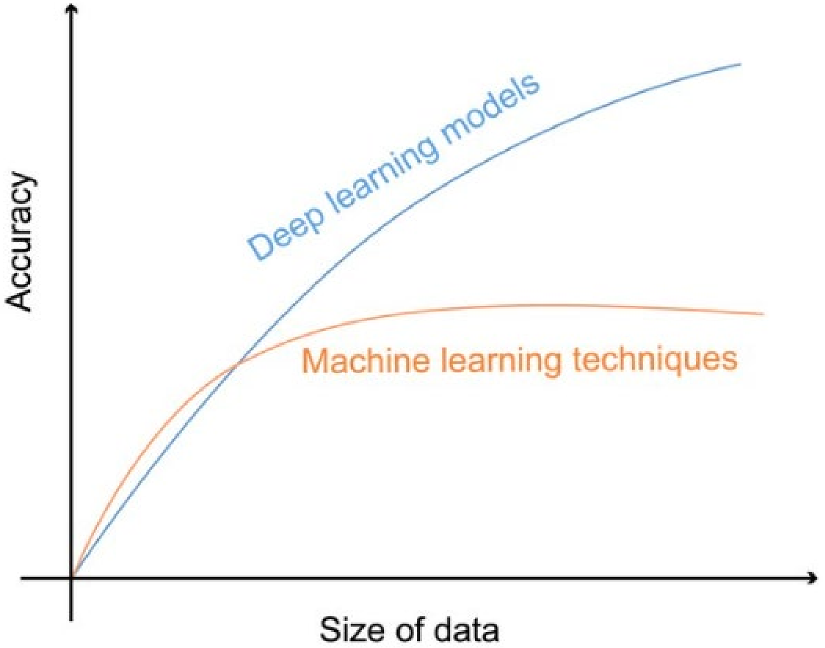
Source: Franklin Templeton Research

Introduction and Machine Learning Overview

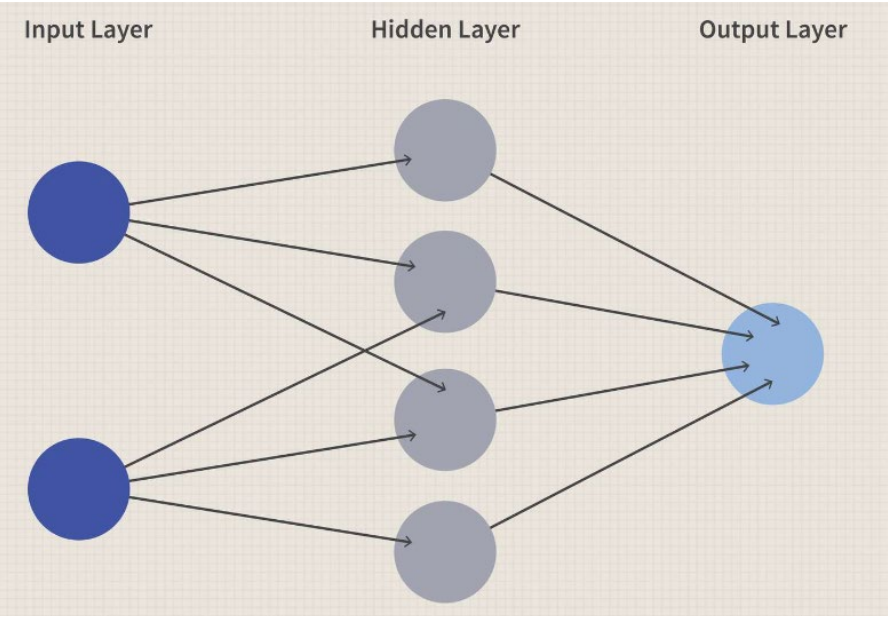
Traditional Linear Model vs ML Model

Neural Network

- Best for situations where the data is high-dimensional.



Source: Junaid Qadir

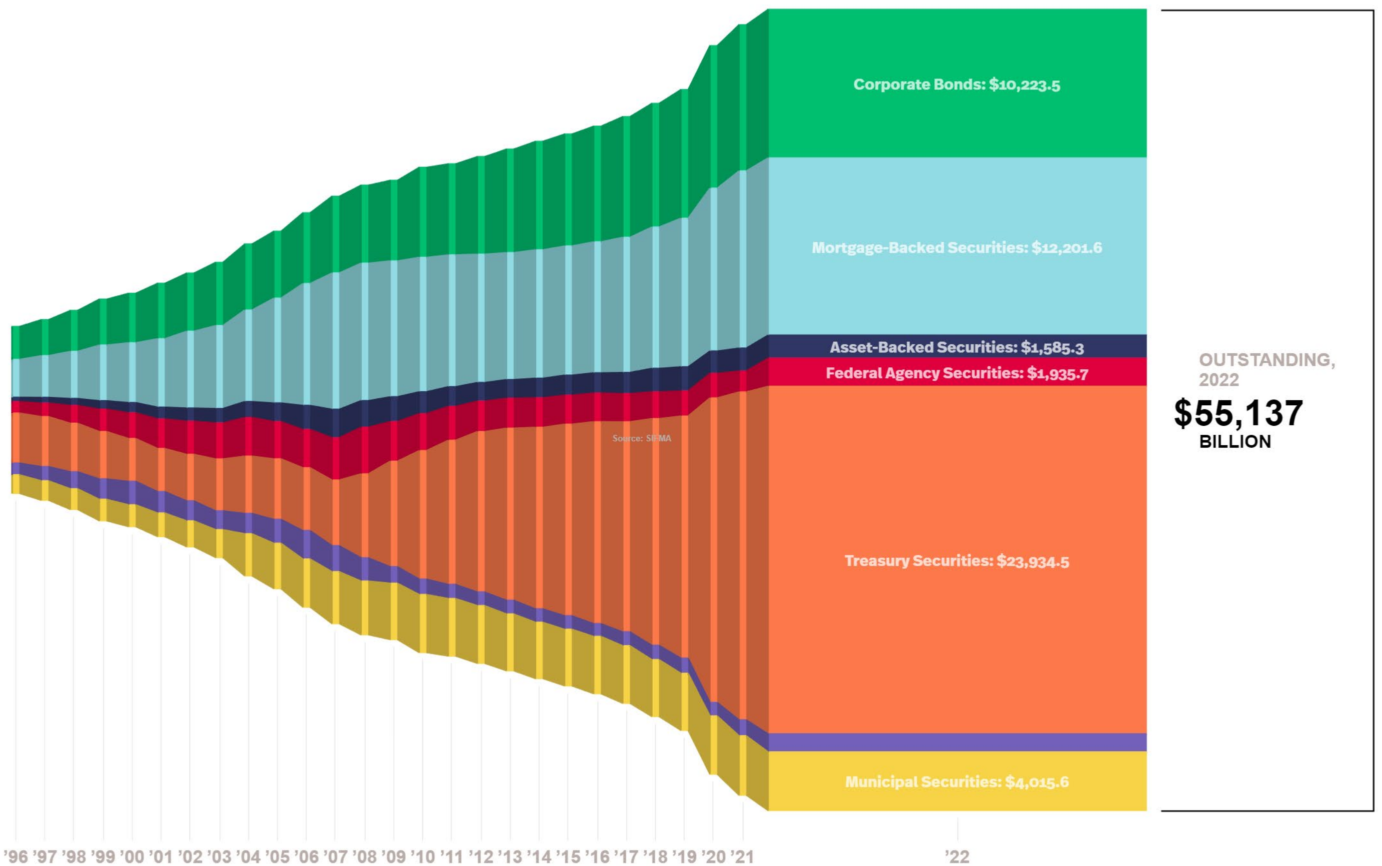


Source: Investopedia

Fixed Income Market and Agency Mortgage-Backed Securities

Fixed Income Market Overview

Mortgage-Backed Securities constitute the second largest fixed-income sector (behind Treasuries) in the US market.

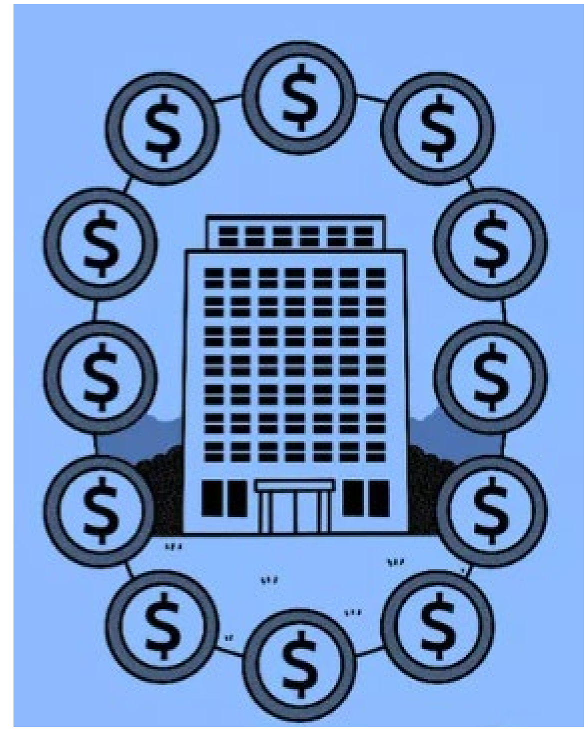


Source: Securities Industry and Financial Markets Association (SIFMA) Research as of 12/31/2022

What are Mortgage-Backed Securities (MBS)?

- A mortgage-backed security (MBS) is a fixed income security representing an ownership interest in a pool of residential mortgage loans.
- A residential mortgage is a loan issued by an originator, such as a bank, to a borrower for the purpose of purchasing a residential property.
- Residential homeowners make mortgage payments which are pooled each month, and "passed through" to MBS holders in the form of principal and interest cash flows.

MBS – A bond secured by a bundle of home loans.



Fixed Income Market and Agency Mortgage-Backed Securities

Agency Mortgage-Backed Securities

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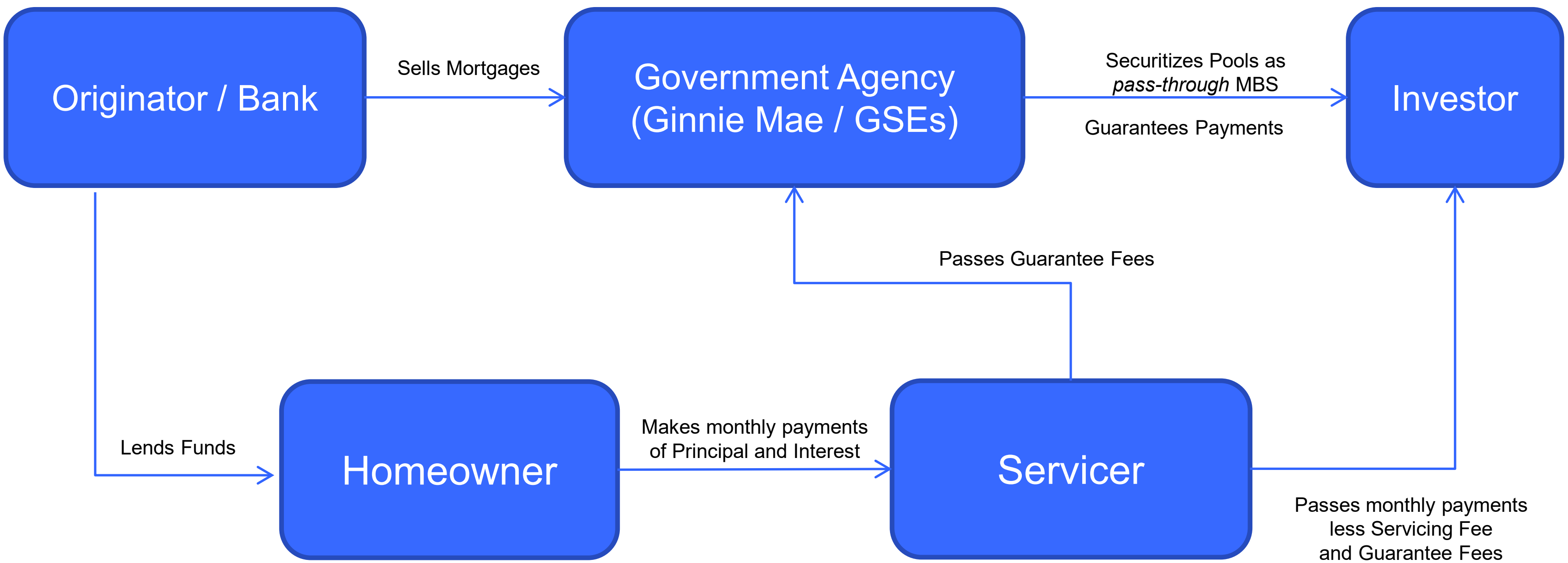
How are agency MBS created?

- To create MBS, a lending bank or originator pools together a group of mortgage loans that it has issued.
- The originator will then present the mortgage loans to a government-sponsored enterprise (GSE) designated to issue and guarantee the MBS.
- The enterprise securitizes pools across various issuers or originators into a pass-through MBS.
- MBS are sold in the global capital market to investors worldwide.



Source: Franklin Templeton Research

Fixed Income Market and Agency Mortgage-Backed Securities

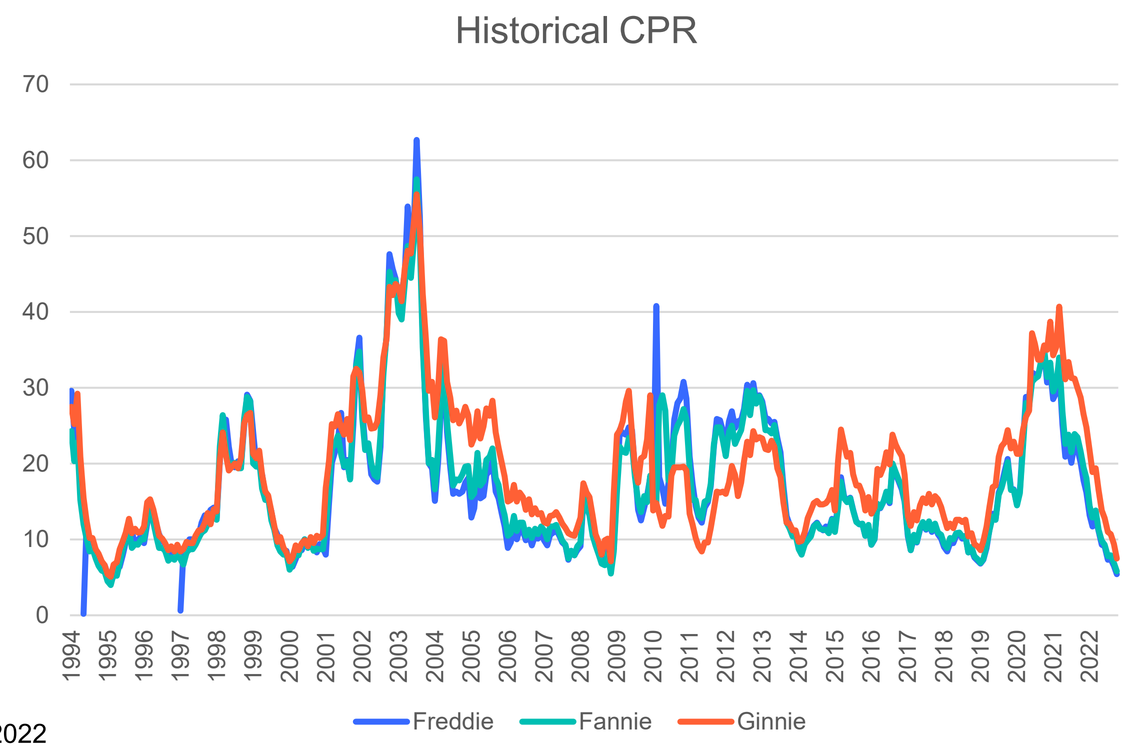
Agency Mortgage-Backed Securities

Prepayment Risk

- The primary risk in the agency MBS market is prepayment risk, the risk of uncertain cash flows caused by prepayments in the pools' underlying mortgages as most residential mortgages originated in the U.S. provide the borrower with the option to prepay some or all of their outstanding principal balance on their loans at any time.

Conditional Prepayment Rate (CPR)

- A CPR is an estimate of the percentage of a loan pool's principal that is likely to be paid off prematurely.



Source: eMBS as of 12/31/2022

Fixed Income Market and Agency Mortgage-Backed Securities

Agency Mortgage-Backed Securities

Drivers of prepayments

- Mortgage Rates
- Collateral Characteristics
- Turnover
- Seasonality
- Catastrophes / Natural Disasters
- Industry Exposure
- Servicers
- Government / Legal Reforms

Primary Mortgage Market Survey Rate

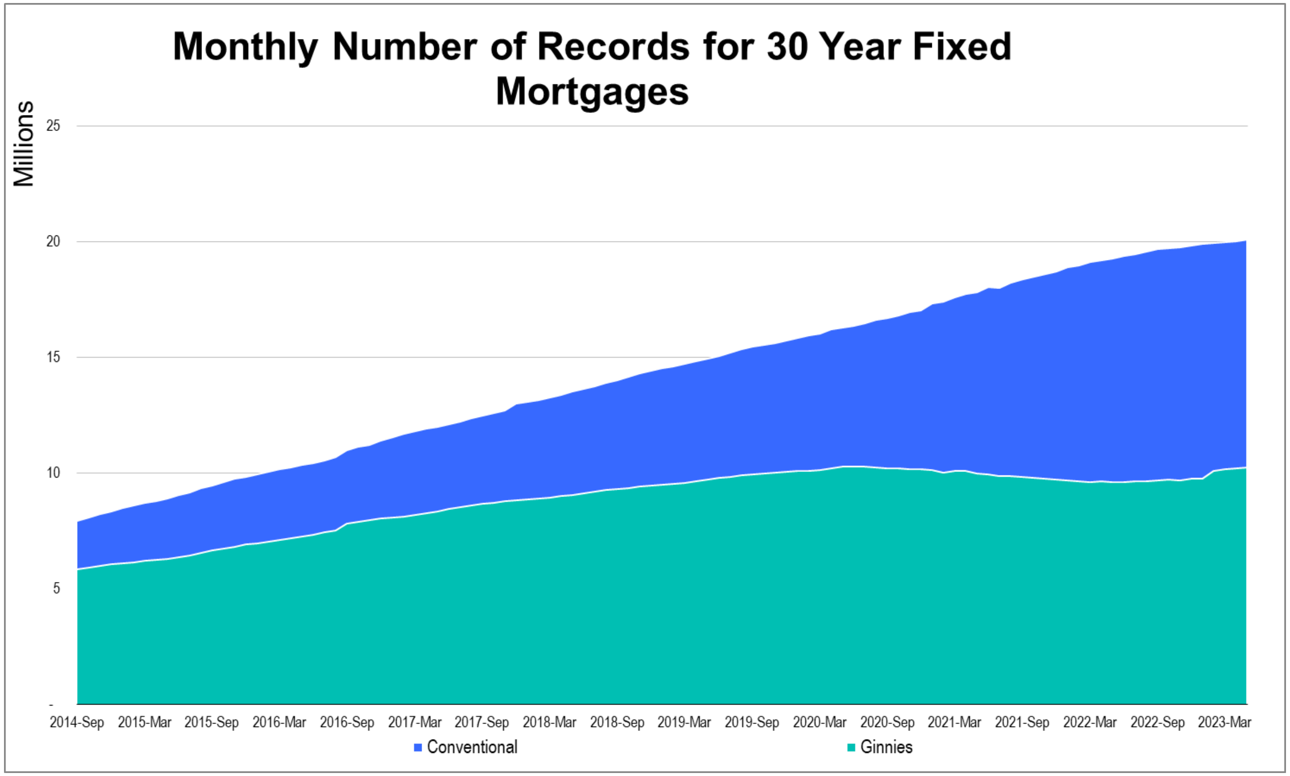
Source: Freddie Mac as of 6/30/2023

Why ML in Agency MBS

Data Availability and Scale

Long history and large amount of data

- The long. history and large amount of data available in MBS make it a prime candidate to leverage machine learning (ML) algorithms to better explain complex relationships between various macro- and microeconomic factors and MBS prepayments



Magnitude of Data

- 20 million records for Conventional
- 10 million records for Ginnies
- Over 1 billion data points.
- Long history that goes back to late 2000.

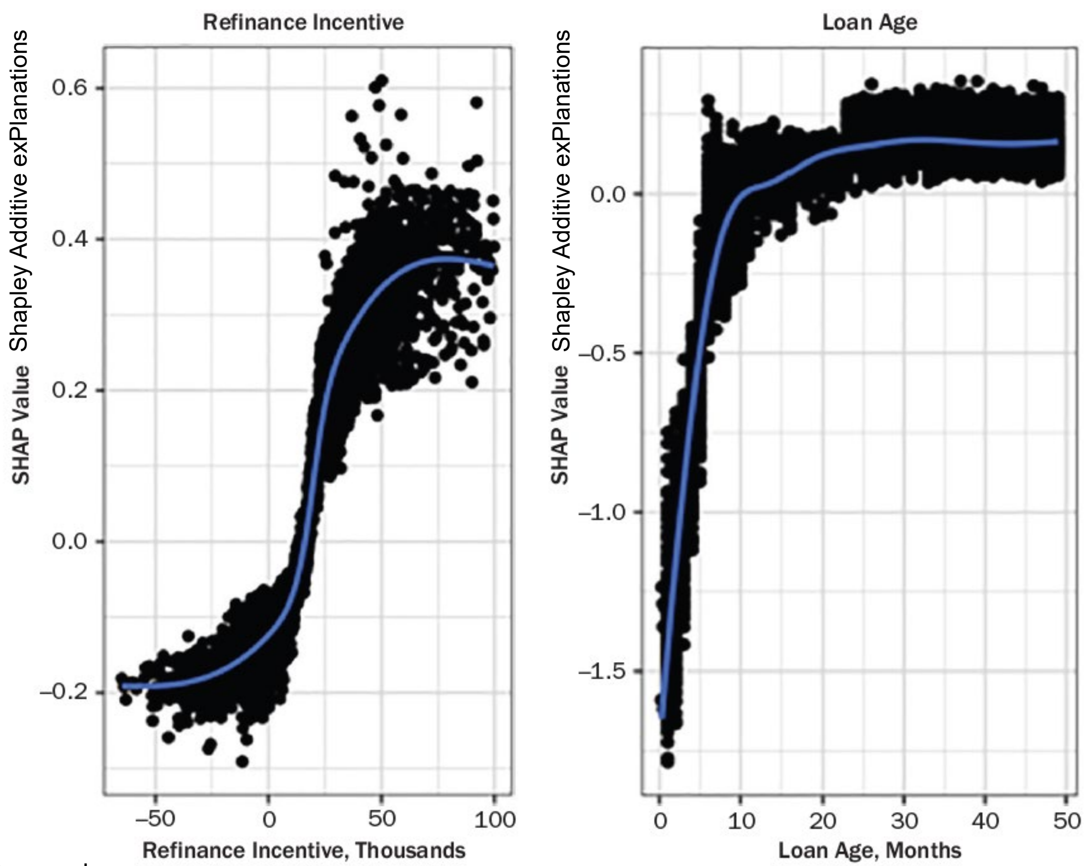
Source: eMBS from 9/2014 – 3/2023

Why ML in Agency MBS

Nonlinear Relationship

Complex and dynamic relationship

- Given the complex and dynamic relationship between pool characteristics and prepayment, an ML model should capture the nuance better, given its ability to detect nonlinear patterns and that it is not confined to a certain functional form.



Source: Franklin Templeton Research

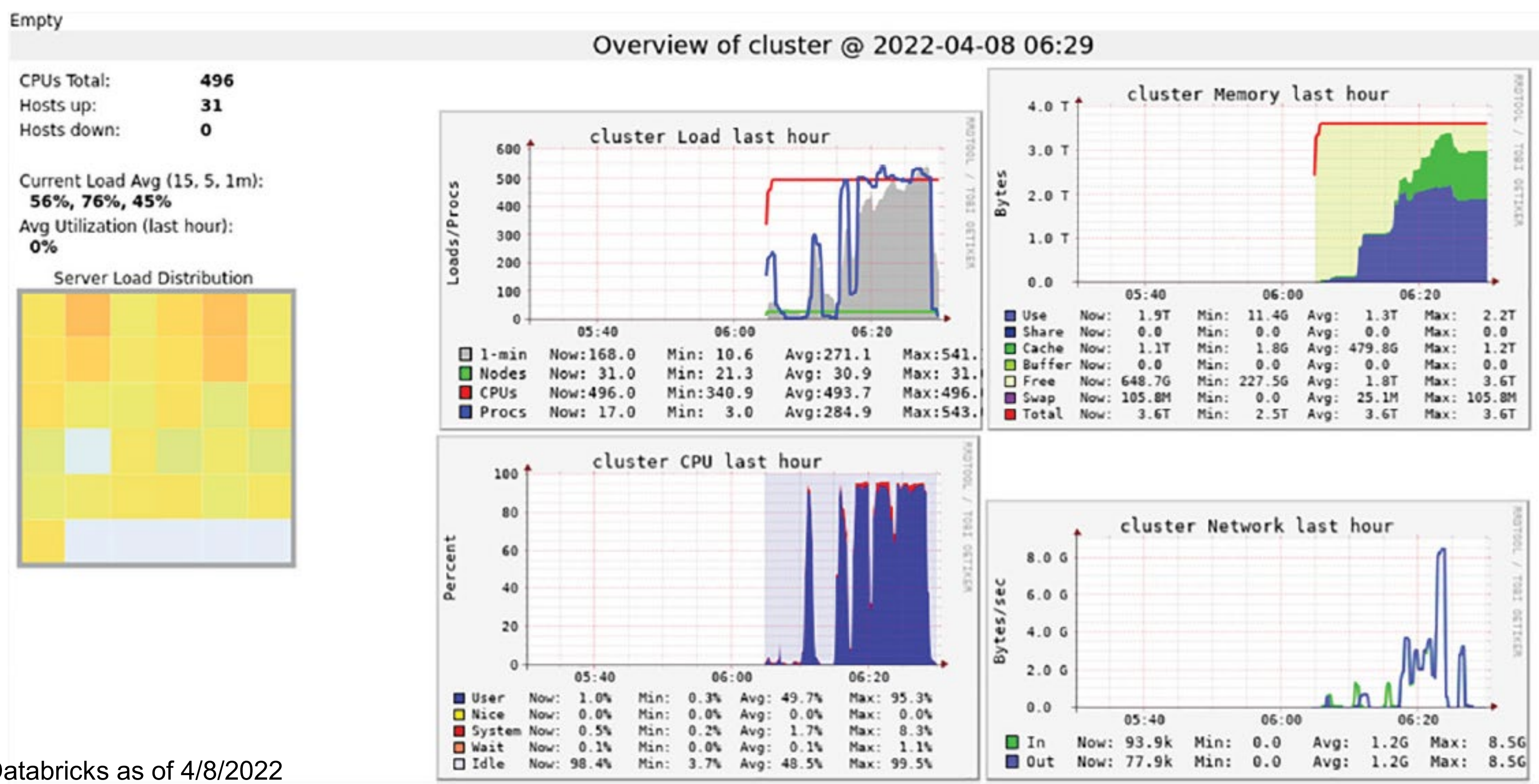
Why ML in Agency MBS

Technology Advancement

Cloud computing and parallel Computing

- Cloud computing is a relatively new paradigm in software development that facilitates broader access to parallel computing via vast, virtual computer clusters. In simple terms, parallel computing can divide larger problems into independent smaller components that can be executed simultaneously by multiple processors communicating via shared memory.

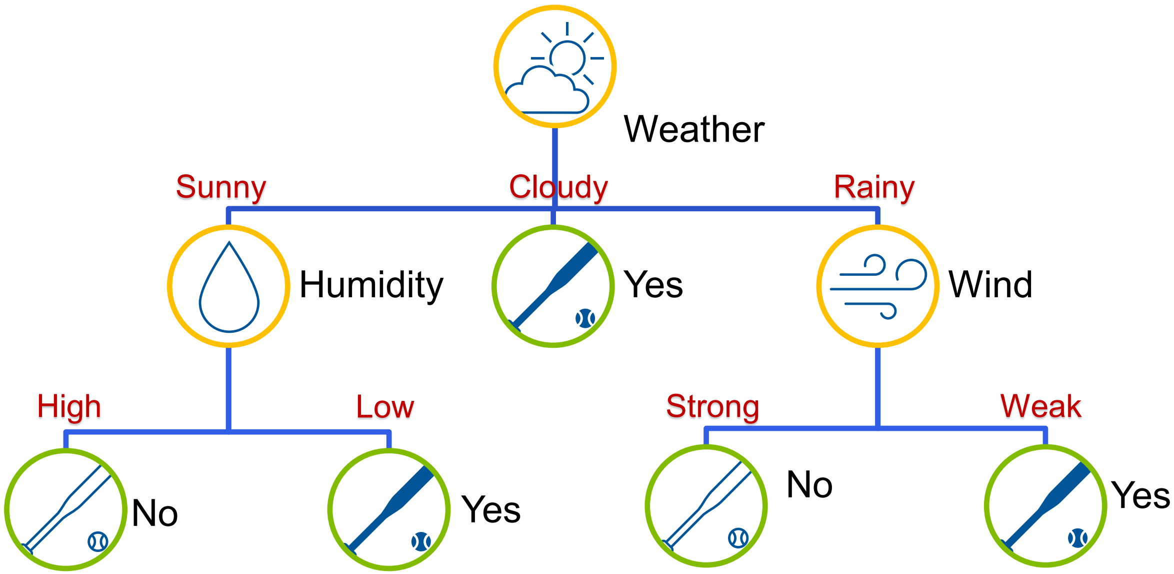
Snapshot of Cluster Overview for Cloud Computing

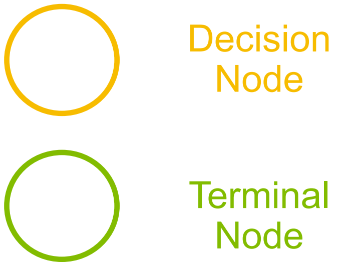


Source: Databricks as of 4/8/2022

Tree-Based Algorithms
Decision Tree

Decision tree Demo – Do we want to play baseball outside?





Attribute Selection Measures

- Entropy
- Information Gain

Source: Franklin Templeton Research

Entropy – a measure of the randomness in the information being processed. The higher the entropy, the harder it is to draw any conclusions from that information.

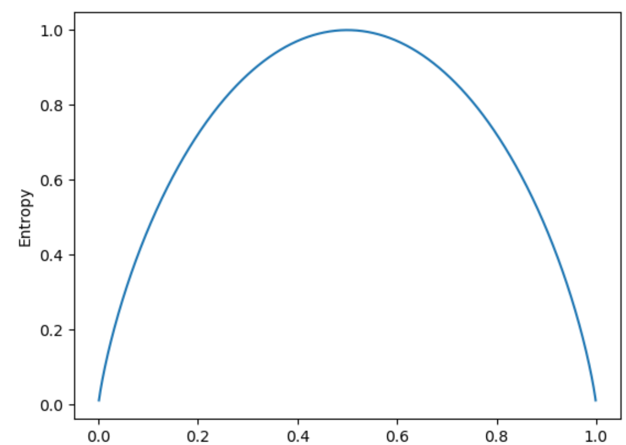
$$E(S) = \sum_{i=1}^{c} -p_i \log_2 p_i$$

Play Baseball	
Yes	No
10	6

$$E(Play\ Baseball) = -\left(\frac{10}{10+6}\right)\log_2\left(\frac{10}{10+6}\right) - \left(\frac{6}{10+6}\right)\log_2\left(\frac{6}{10+6}\right)$$
$$= -0.625\log_2 0.625 - 0.375\log_2 0.375$$
$$\approx 0.954$$

Play Baseball	
Yes	No
8	8

$$E(Play\ Baseball) = -0.5\log_2 0.5 - 0.5\log_2 0.5 = 1$$



Source: Franklin Templeton Research

Tree-Based Algorithms

Attribute Selection Measures

Information Gain – a measure on how well a given feature separates the data according to the target classification.

$$\mathrm{E}(S, X) = \sum_{i \in X} P(i)E(i)$$

		Play Baseball		Total
		Yes	No	
Weather	Sunny	4	2	6
	Cloudy	5	0	5
	Rainy	1	4	5
Total		10	6	16

$$\begin{aligned} &E(Play\ Baseball, Weather) \\ &= P(Sunny)E(4,2) \\ &\quad +P(Cloudy)E(5,0) \\ &\quad +P(Rainy)E(1,4) \\ &\approx \frac{6}{16} \times 0.918 + \frac{5}{16} \times 0 + \frac{5}{16} \times 0.722 \\ &= 0.569 \end{aligned}$$

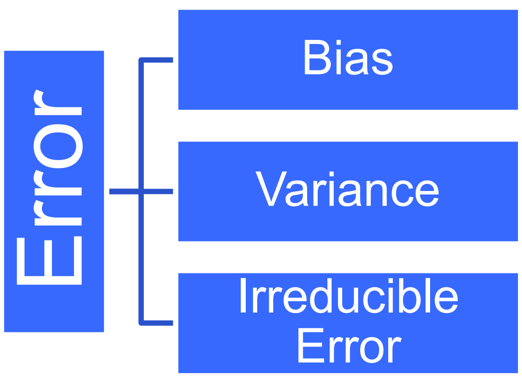
$$\boxed{\begin{aligned} &Information\ Gain(S, X) \\ &= Entropy(S) - Entropy\ (S, X) \\ &= Entropy(Before) - Entropy(After) \\ &= E(Play\ Baseball) - E(Play\ Baseball, Weather) \\ &= 0.954\ - 0.569 \\ &= 0.385 \end{aligned}}$$

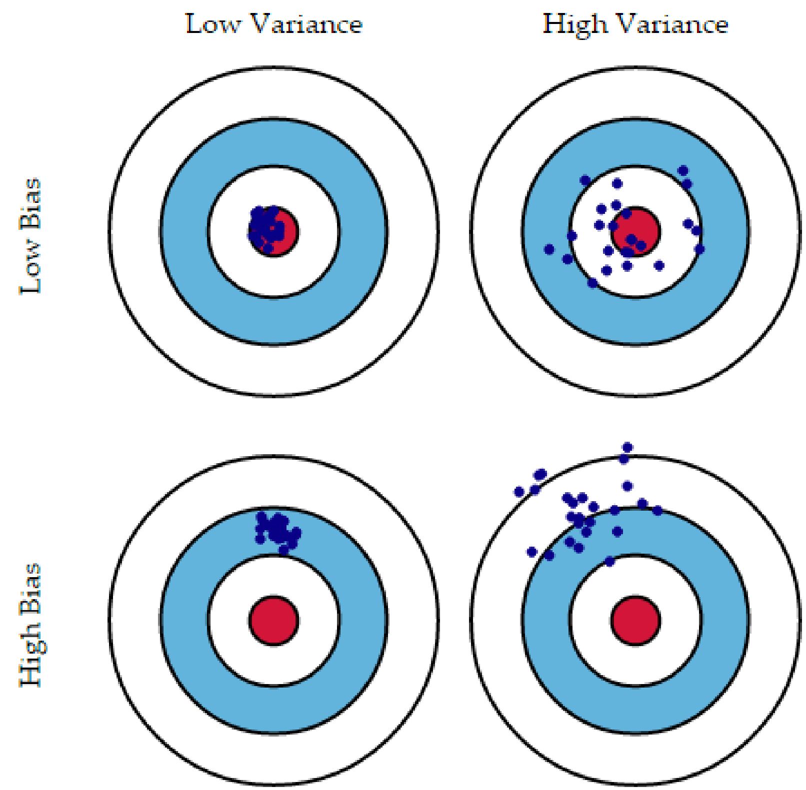
Source: Franklin Templeton Research

Tree-Based Algorithms

Ensemble Learning Methods

Ensemble Learning Methods: combines multiple algorithms to obtain better predictive performance than the one from a single model.





Source: Scott Fortmann-Roe/ BiasVariance

Model Construction

Ensemble Learning Methods

Ensemble Learning Methods: combines multiple algorithms to obtain better predictive performance than the one from a single model.

- Bagging is implemented by selecting a number of random samples of data with replacement and averaging the predictions by all the weak models trained on those sample data.
- Bagging adopts a sequential approach, where the prediction of the current model is transferred to the next one. Each model iteratively focuses attention on the observations that are misclassified by its predecessors.

	Pros	Cons
Bagging	• Significant effect on reducing variance, especially high-dimensional data • Unbiased estimate of the out-of-bag error	• Computationally intensive
Boosting	• Efficiently reduces bias • Prioritize features that increase overall accuracy, hence reducing computation time	• Not scalable • Computationally intensive

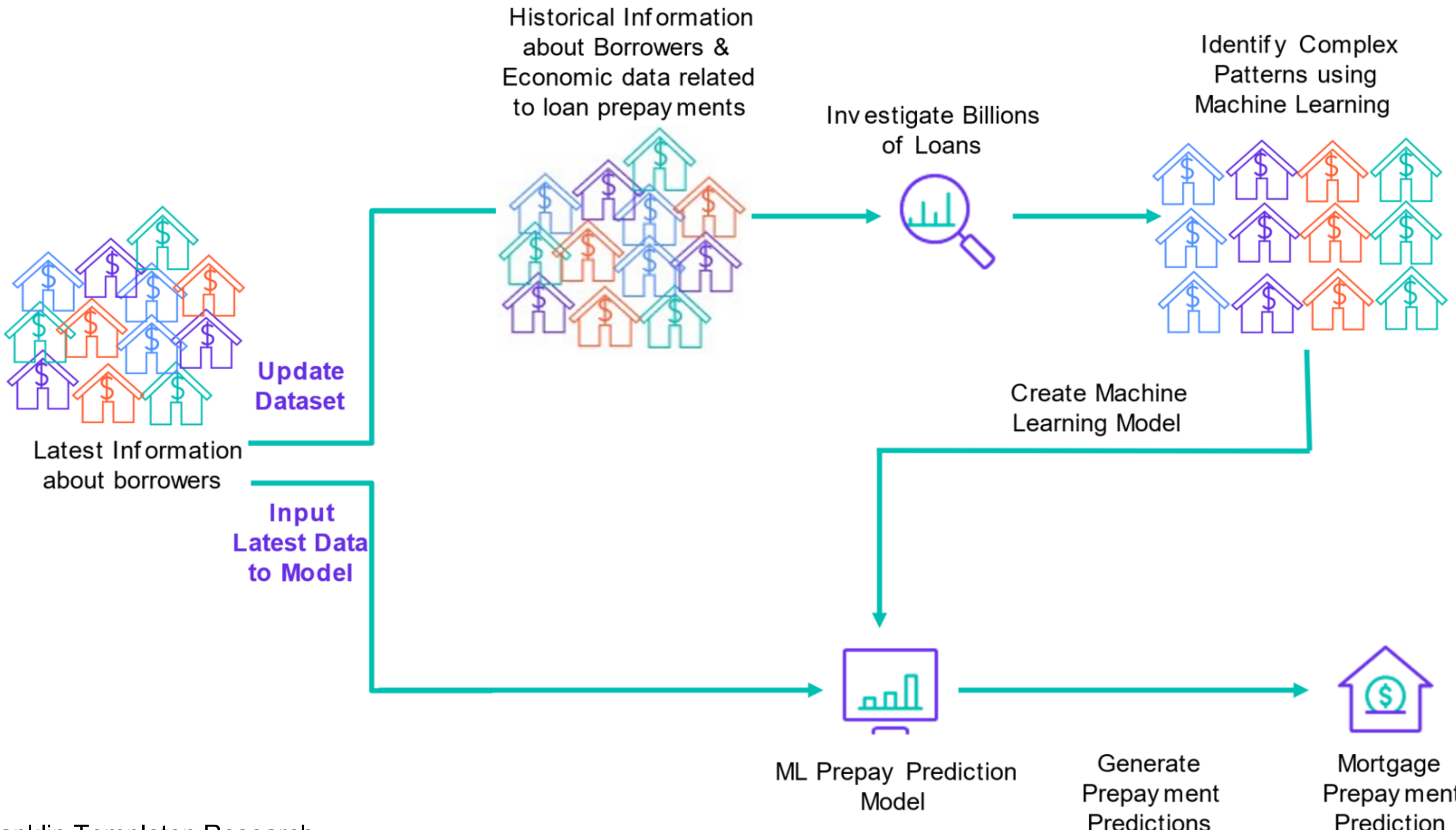
Source: Franklin Templeton Research

Model Construction

Roadmap

Data

- Macroeconomic: unemployment
- Microeconomic: application level, house value, affordability, permits issued for construction
- Loan level: remaining balance, credit score, loan to value ratio
- Unconventional data like (hit trend for certain key words)

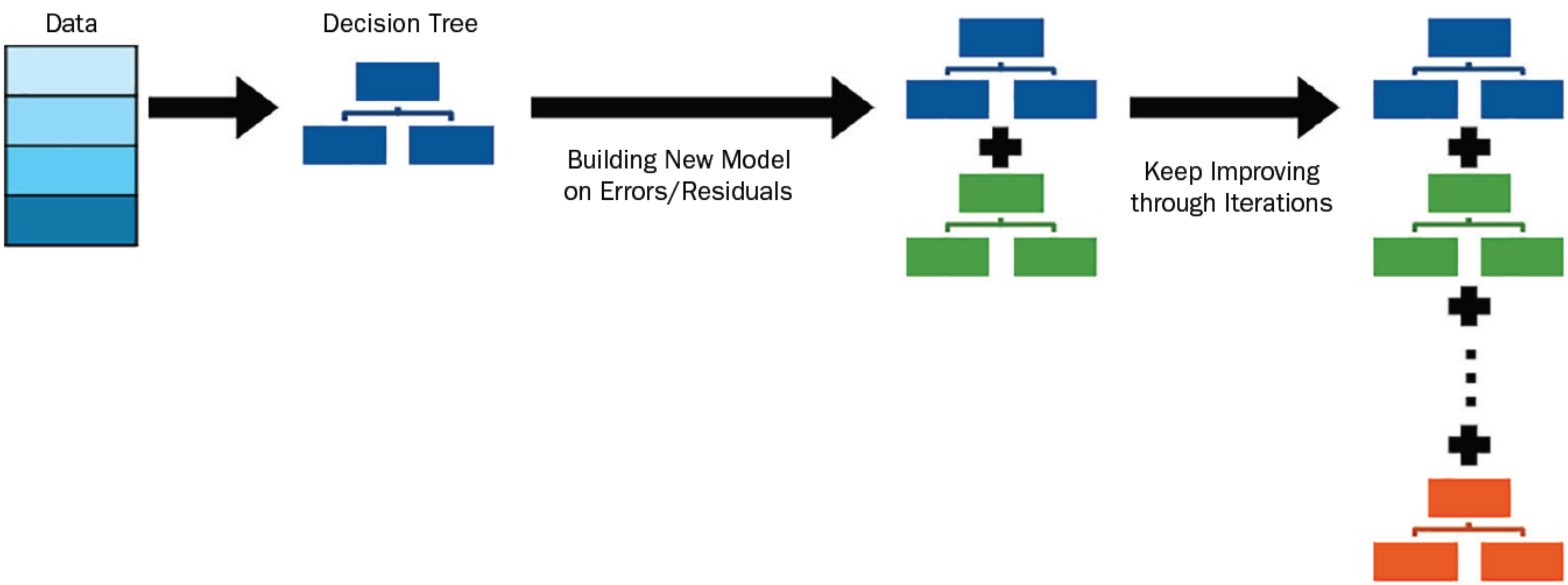


Source: Franklin Templeton Research

Model Construction
Loan Level Modeling

Loan Level Modeling

- The idea of gradient boosting is to build models sequentially, and each subsequent model tries to reduce the errors of the previous model by building a new model on the errors or residuals of the previous model.
- LightGBM uses gradient-boosting algorithms, which increases its prediction speed and accuracy, particularly with large and complex datasets.



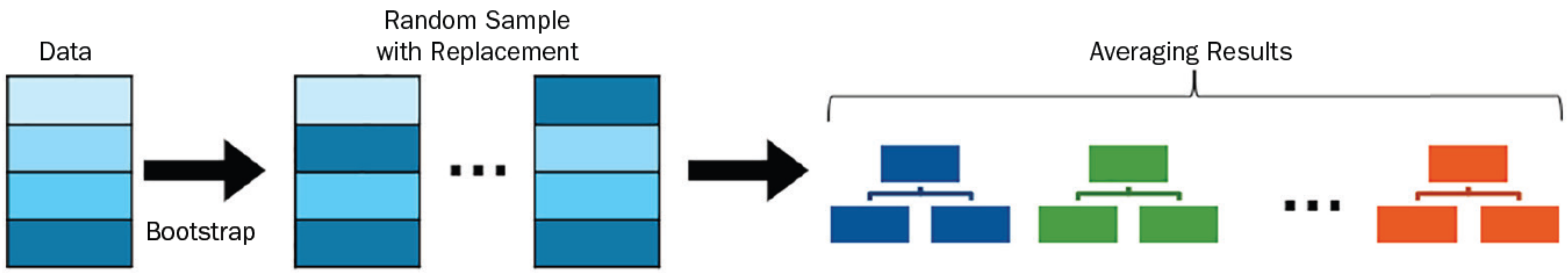
Source: Franklin Templeton Research

Model Construction

Pool Level Modeling

Pool Level Modeling

- Random Forest uses bagging, also known as bootstrap aggregation, to reduce variance and improve prediction accuracy. Bagging is implemented by selecting a number of random samples of data with replacement and averaging the predictions by all the weak models trained on those sample data.

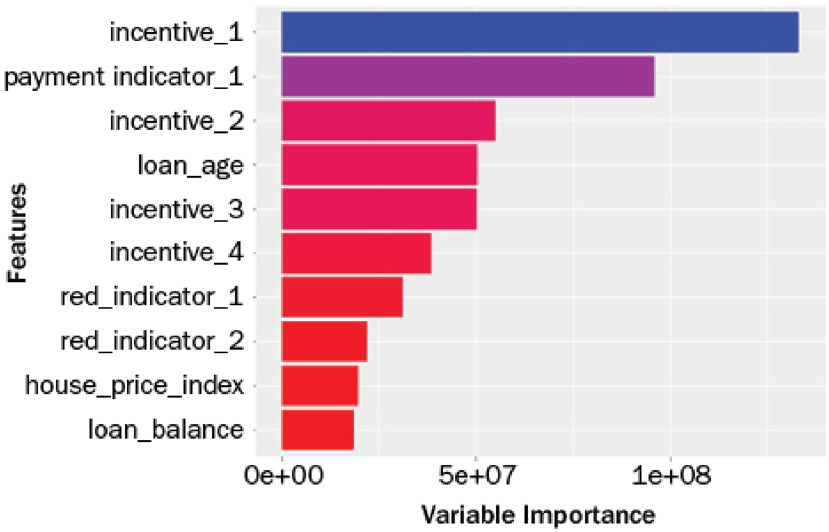


Source: Franklin Templeton Research

Model Construction

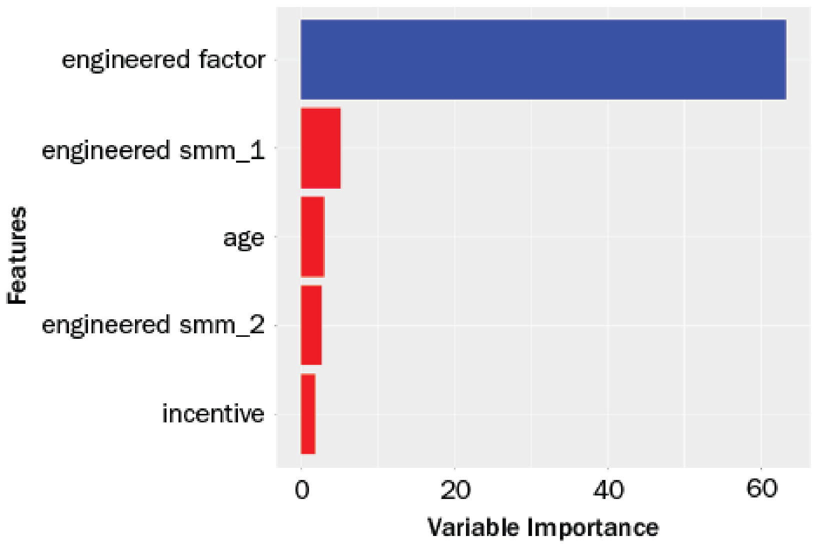
Feature Importance

Feature-Importance Ranking for Loan-Level Model



source: Franklin Templeton

Feature Importance Ranking for Pool-Level Model



Source: Franklin Templeton Research

Model Performance

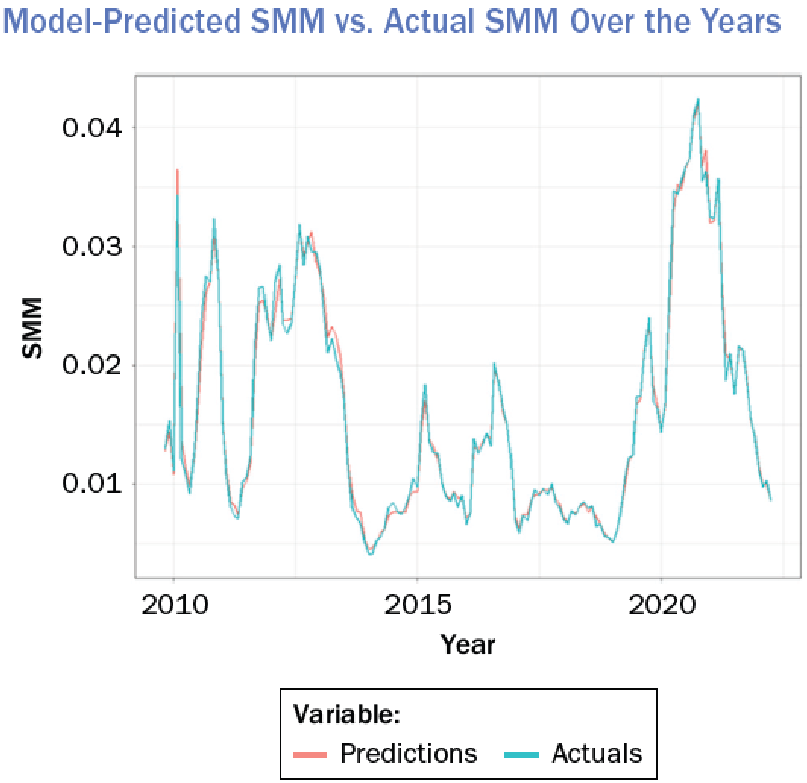
Model Performance Metrics

Single Monthly Mortality (SMM)

$$= \frac{Actual\ principal\ payments\ - Scheduled\ principal\ payments}{Beginning\ mortgage\ balance\ - Scheduled\ principal\ payment}$$

$$= \frac{Prepayment}{Outstanding\ balance}$$

$$= 1\ - (1\ - CPR)^{\frac{1}{12}}$$



Source: Franklin Templeton Research

Model Performance

Model Performance Metrics

$$\text{True Positive Rate (TPR)} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}}$$

$$\text{False Positive Rate (TPR)} = \frac{\text{False Positive}}{\text{True Negative} + \text{False Positive}}$$

Simple Example of the Calculation of TPR and FPR

Threshold = 0.5

TPR	FPR
$\frac{2}{2+0} = 100\%$	$\frac{1}{2+1} = 33\%$

Probability	Actual	Prediction (threshold = 0.5)	Prediction (threshold = 0.8)
0.9	1	1	1
0.8	1	1	1
0.5	0	1	0
0.2	0	0	0

Threshold = 0.8

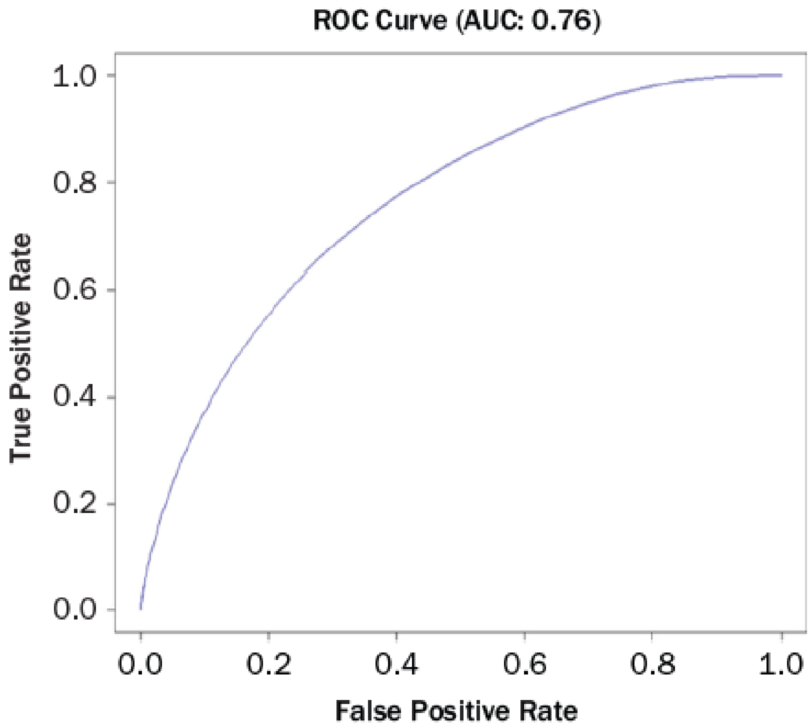
TPR	FPR
$\frac{2}{2+0} = 100\%$	$\frac{0}{2+0} = 0\%$

Source: Franklin Templeton Research

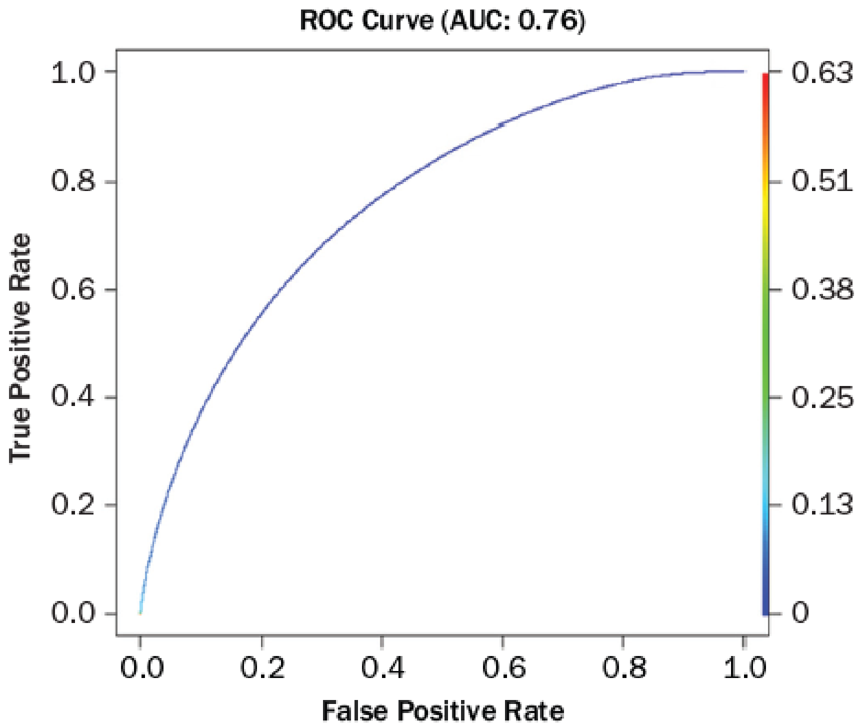
Model Performance

Model Performance Metrics

Model Performance for Loan-Level UMBS 30-Year Model (Receiver Operating Characteristic (ROC) on train data)



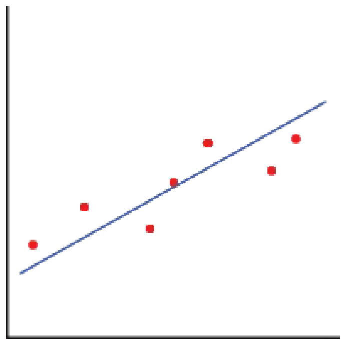
Model Performance for Loan-Level UMBS 30-Year Model (Receiver Operating Characteristic (ROC) on test data)



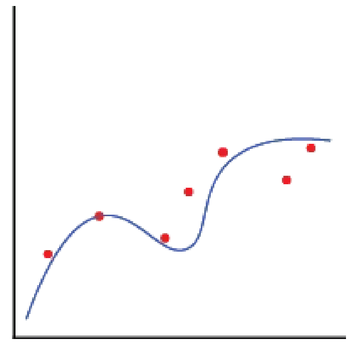
Source: Franklin Templeton Research

Model Performance

Model Performance Metrics

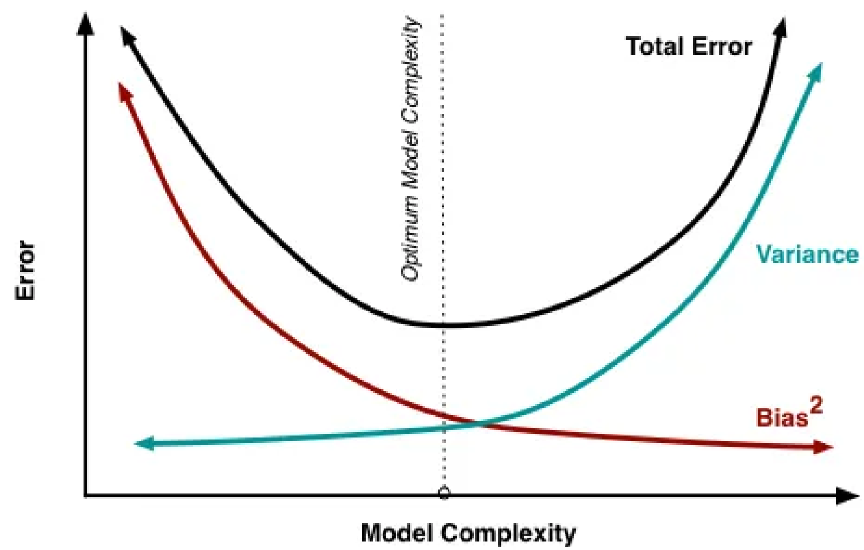


Simple model



Complex model

Make sure the model has the right amount of complexity, so it generalizes well on unseen data.



Source: Medium/Bias-Variance Tradeoff Explained as of 6/25/2020

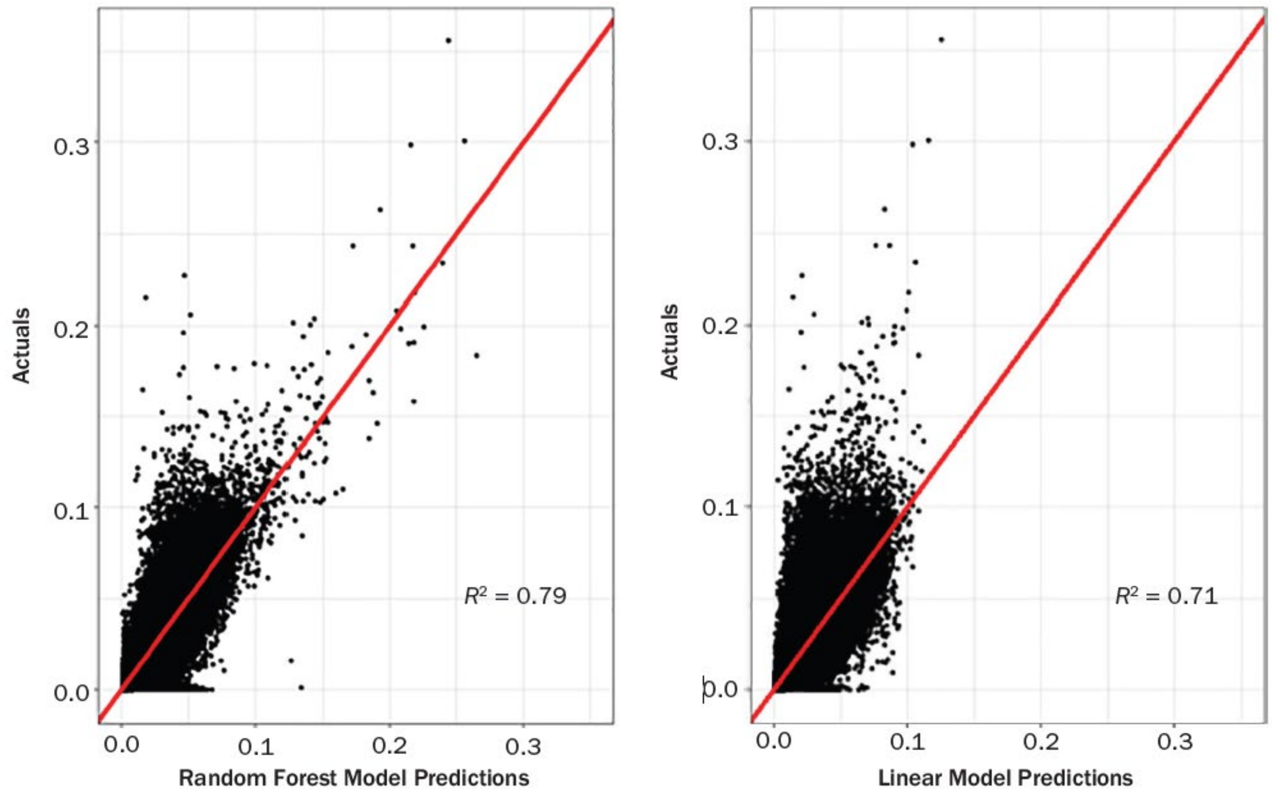
Model Performance

Model Performance Metrics

Coefficient of determination (R^2) – measures proportion of variance explained by features.

Root Mean Square Error (RMSE) – measures average deviation between the predicted and actual

Predicted SMMs vs. Actuals for both RF and Linear Models



Source: Franklin Templeton Research

Model Performance

Interpretability

Partial Dependence (PD) is calculated by fixing a specified range for the variable of interest, and then for each value in the range, predicting based on that value and all other feature values. All predictions generated for each value in the range are averaged to form a curve

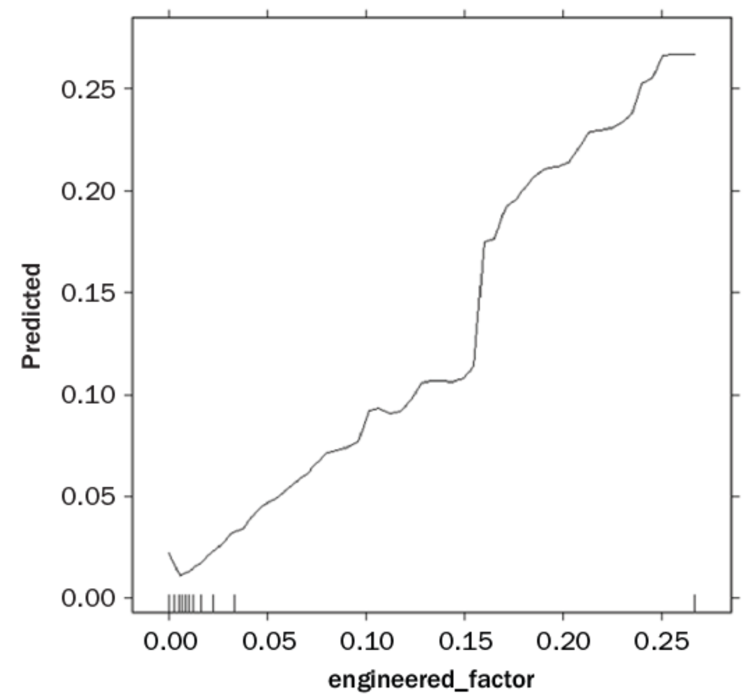
$$\text{Partial Dependence}_{x_s}(x_S) \stackrel{\text{def}}{=} \mathbb{E}_{X_c}[f(x_S, X_c)]$$

$$= \int f(x_S, x_c)p(x_c)dx_c$$

where X_S = set of input features
x_S = features in X_S
X_c = complement of X_S
x_c = features in X_c
$f(x_S, X_c)$ = model predicting function

Visualizing the average effect of a particular feature by marginalizing all other features.

Partial Dependence Plot for Engineered Factor from Loan-Level Model

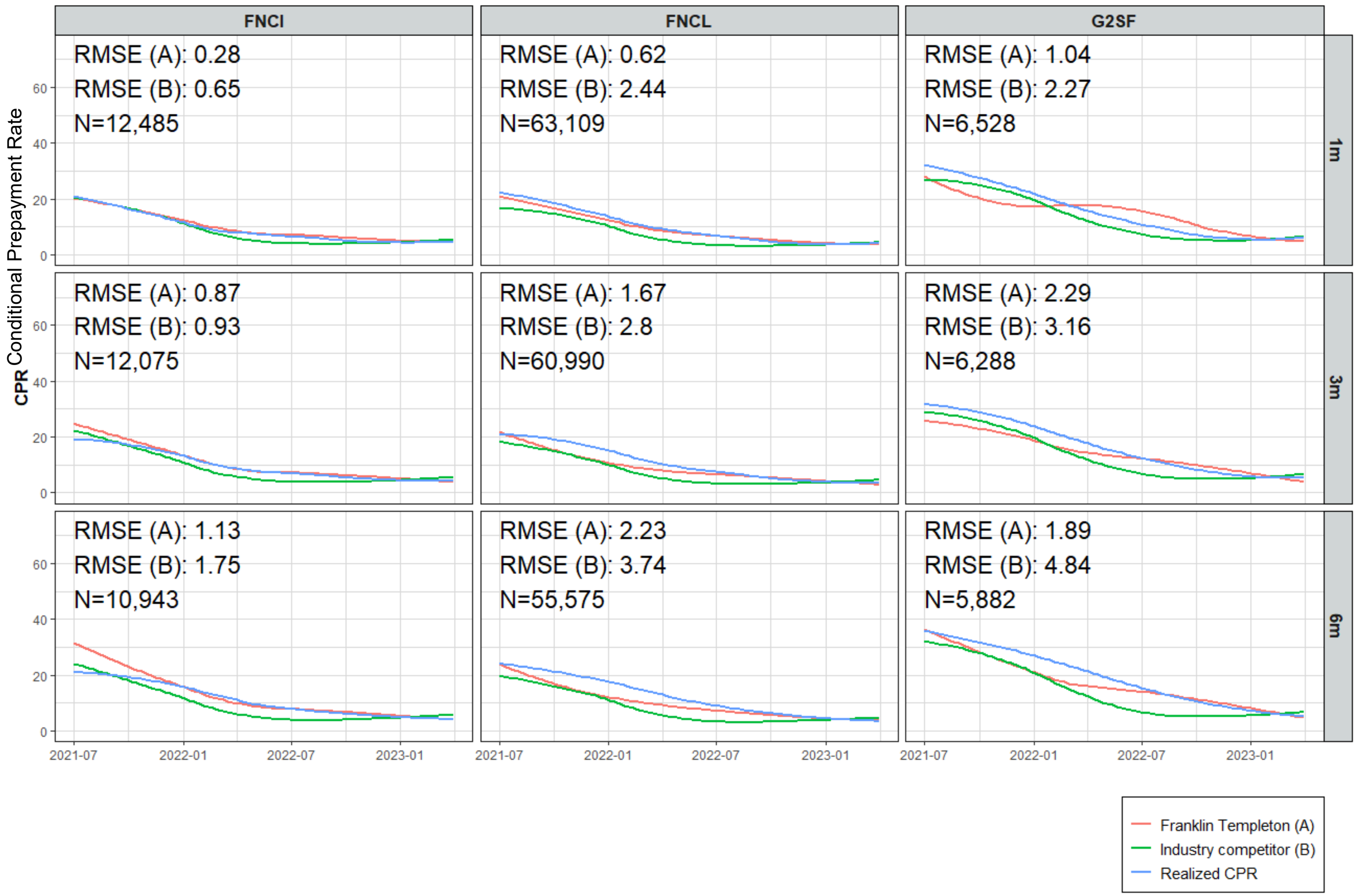


Source: Franklin Templeton Research

Model Root Mean Square Error (RMSE)

Comparison with Other Models

Model RMSE Overview

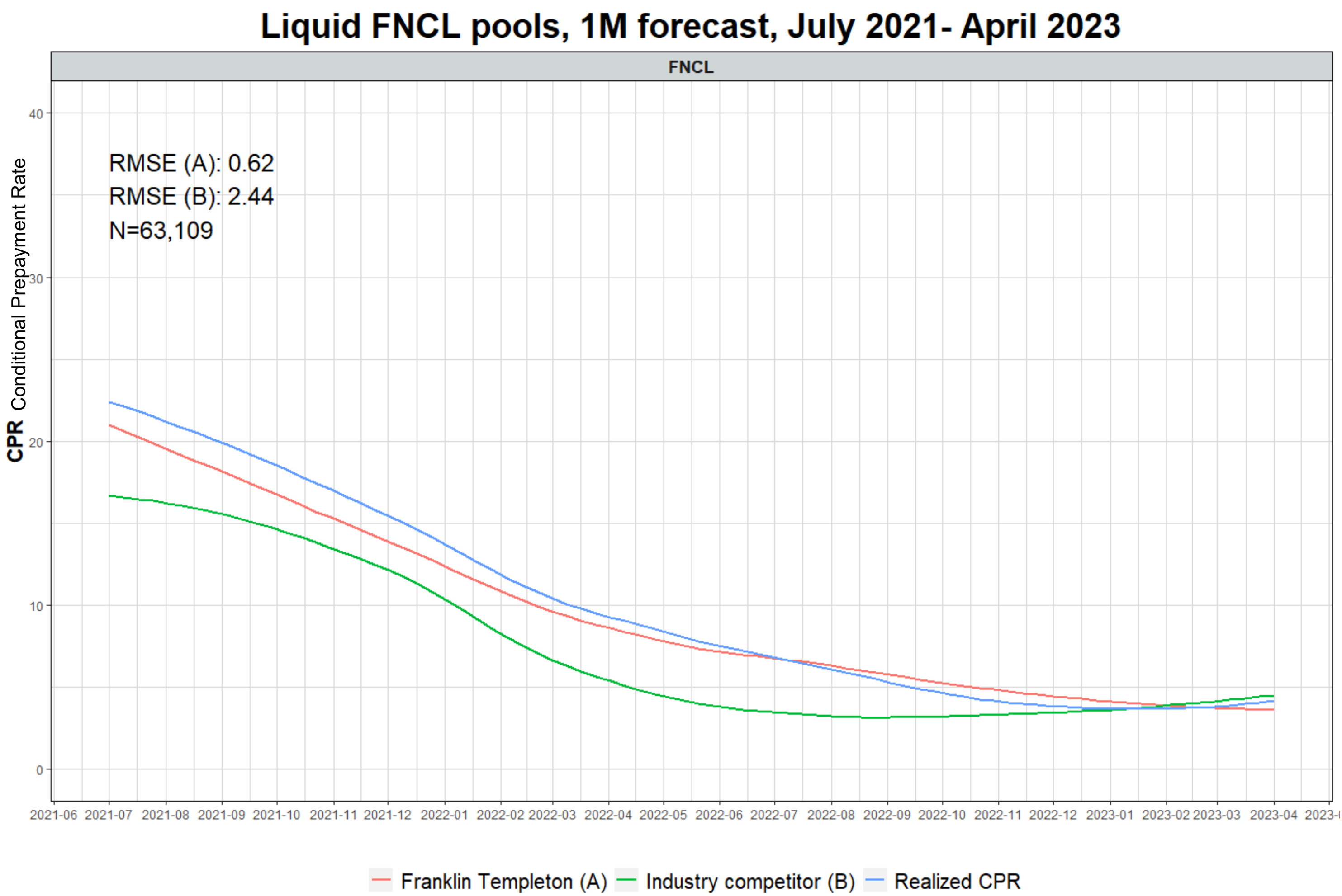


Source: Franklin Templeton Research as of 6/30/2023

Model Root Mean Square Error (RMSE)

Comparison with Other Models

Closer look on 1M horizon

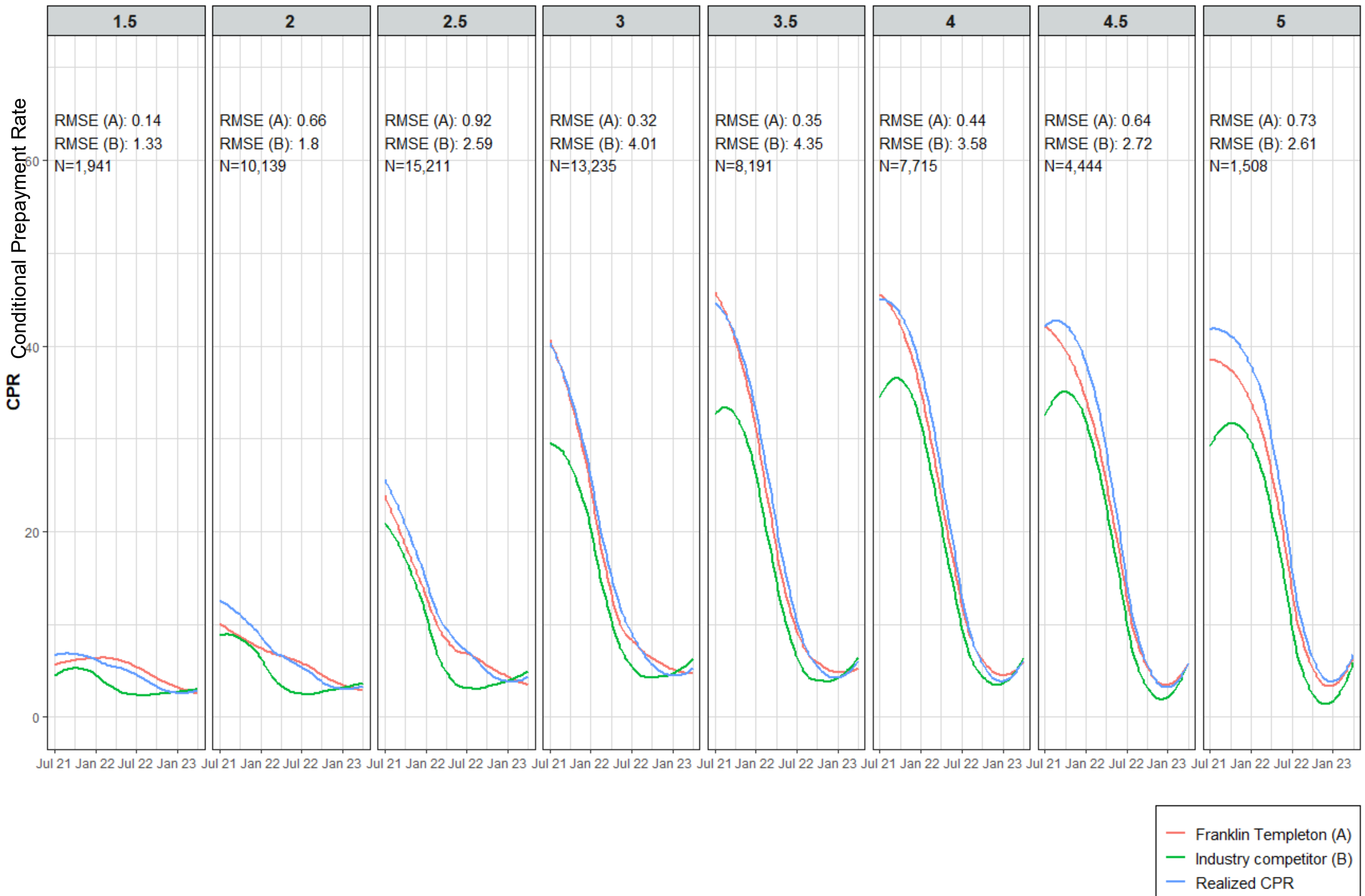


Source: Franklin Templeton Research

Model Root Mean Square Error (RMSE)

Comparison with Other Models

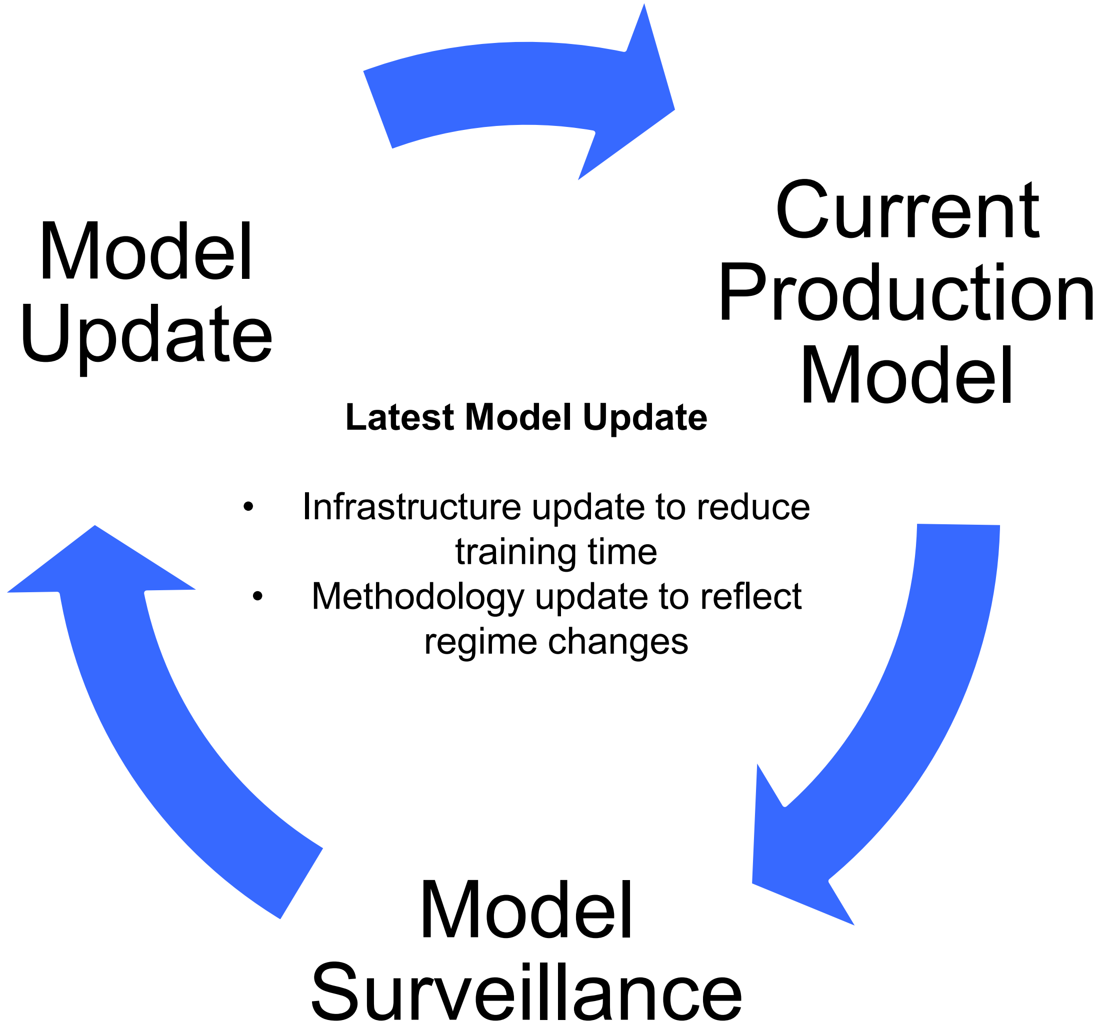
RMSE by Coupon



Source: Franklin Templeton Research June 2021 to June 2023

Model Performance

Model Surveillance & Enhancements



Latest Model Update

- Infrastructure update to reduce training time
- Methodology update to reflect regime changes

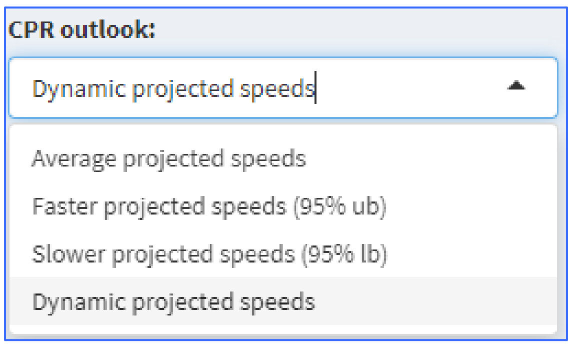
Source: Franklin Templeton Research

Systematic Investment Strategy Application

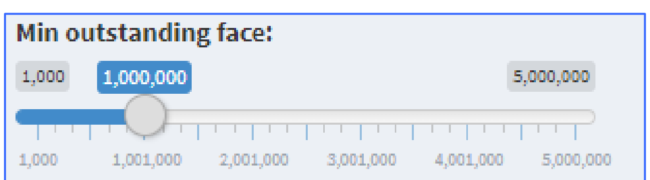
Specified Pool Optimizer

Based on CPRs generated by the ML prepayment model, we generate expected returns over a one-month horizon at a constant spread. The systematic Investment Strategy

- adopts CPRs from the ML prepayment model
- maintains same duration and convexity to the US MBS Index
- rebalances monthly
- can be configured to incorporate/adjust
  - aggressive/conservative CPR outlook



  - bid-ask spread
  - duration and convexity
  - inclusion/exclusion of certain pool characteristics



coupon	FNCI	FNCL	G2SF
2.00	13.05	15.41	11.47
2.50	13.70	2.92	1.67
3.00	13.10	15.53	0.00
3.50	0.00	8.29	0.00
4.00	0.00	3.69	0.00
4.50	0.00	0.00	0.00
5.00		0.00	0.00
5.50		0.00	0.00
6.00		1.16	0.00

For illustrative purposes only, data does not represent actual values for any investment.
Source: Franklin Templeton Research

Important information

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Q&A

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