Example of Modeling and Governance

Andre Mittag
617 840-3866
andre.wolfe.mittag@gmail.com
www.linkedin.com/in/andre-mittag/

To Prospective Hiring Manager

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Comment: Purpose of sharing this presentation with you

- This presentation is an example of the work I have done over several years. This presentation has been adjusted to preserve confidentiality, but the underlying story, methods, and layouts respect my approach.
- Ideally, I hope you to recognize a sense of how clear I attempt to make the model and the process. Any model can be built relatively quickly, but business feedback is critical to a models success.

1 Comments found in dotted text boxes, are meant as comments to assist in your reading of the presentation.

Comment: This slide outlines the point of the meeting.

Meeting Expectations

- Manager of Credit/Capital will explain **how these models can be used, their purpose**, and consider how this might help them in the future.
- Business Line/Subject Matter Expert (SME) should provide **feedback on other variables/factors options to help predict defaults.**
- Manager of Credit/Capital will explain **how the governance process will work.**

Comment: Executive Summary

Summary

- A Home Equity Line of Credit (HELOC) behavioral model is in the process of being defined. Model development needs to create a complex model to accommodate 1) complexity of mortgage products, 2) extended time horizon, 3) few defaults, and 4) pre-payments resulting in survivorship-bias.
- The model is expected to **support ongoing processes**. This includes **credit risk awareness** (loans likely to default in coming months) and thus alerting **collections** to coming workflow. Other areas that could be impacted by this are **profitability** (analysis, promotions, adjustments) and as an adjustment to reserving (**CECL**).
- The model shown here is effective at differentiating many credit risks with HELOCs based on the experiences of the 'In Sample Data'.
- A number of variables, methods, and combinations were impacted, this model was considered 'best' based on the tradeoffs required.

Comment: Executive Summary

Summary

- We have developed a complex model to accommodate 1) complexity of mortgage products, 2) extended time horizon, 3) few defaults, and 4) pre-payments resulting in survivorship-bias.
- The model is expected to support ongoing processes. This includes credit risk awareness (loans likely to default in coming months) and thus alerting collections to coming workflow. Other areas that could be impacted by this are profitability (analysis, promotions, adjustments) and as an adjustment to reserving (CECL).
- The model shown here is effective at differentiating many credit risks with HELOCs based on the experiences of the ‘In Sample Data’.
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Model Developer’s Thoughts

Comment: Transparency in governance is important to understand limitations and potential improvements.

Cons

- Challenging and complex economic and product situation.
- **No Economic Inputs, likely a function of our customer base and locations**
- Evaluation period is insufficiently short with only 24 months of out of sample. Longer ‘In Sample’ was necessary because of noted challenges to economy and product.
- *$ Losses depend on collateral values and lien position.* This will be undertaken once I have access to the proper data.

Pros

- Great performance
- Captures directly/indirectly many credit risks associated with defaults.
- Limited number of variables (inputs)
- No additional complexity (scaling) to make interpretation challenged.

Modeling Process

Comment: This is meant to help people understand where this fits in the various categories of models.

Model by Type

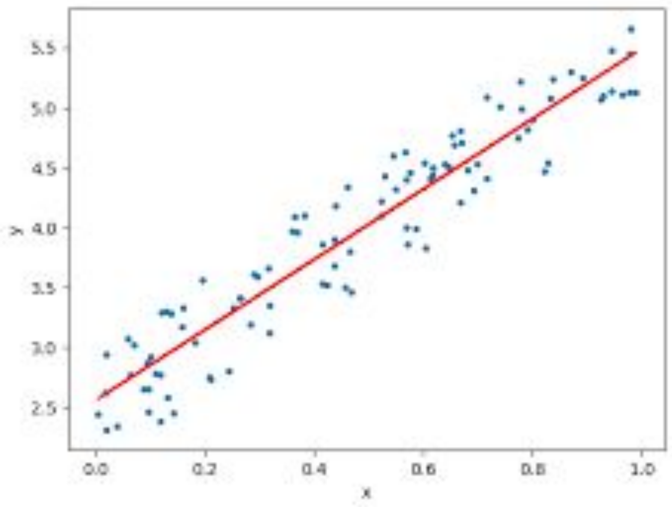
Forecasting defaults for the current portfolio without macro economic variables is a Monitoring or Behavioral PD Model.

Type	Use Cases	Question Trying to Answer	Examples of Variables in Model
Behavioral PD Model (Through the Cycle TTC)	**Monitoring Current Balance Sheet**: TTC defaults are primarily driven by changes in firms' long-run credit quality, which tends to be relatively slow and stable over time. It's results measure the firm's underlying credit trend from the macro-credit cyclical effect.	Probability of default within 1 year of current time for current loans, **given average economic environment**	Credit Scores, Direct Deposit, Negative deposit Balance
Stress Testing Model	Forecasting in different economic environments for strategic or stress testing purposes	Probability of defaulting in current quarter because of given economic environment	Monitoring PD Model + Economic factors (Unemployment Rate, Real GDP, State)
Loss Given Default Model (LGD)	Estimate Losses at Default	Loan level charge offs caused by a default	FICO, Seasoned, Collateral Value,

Comment: Outline of “what are different modeling types for this process”

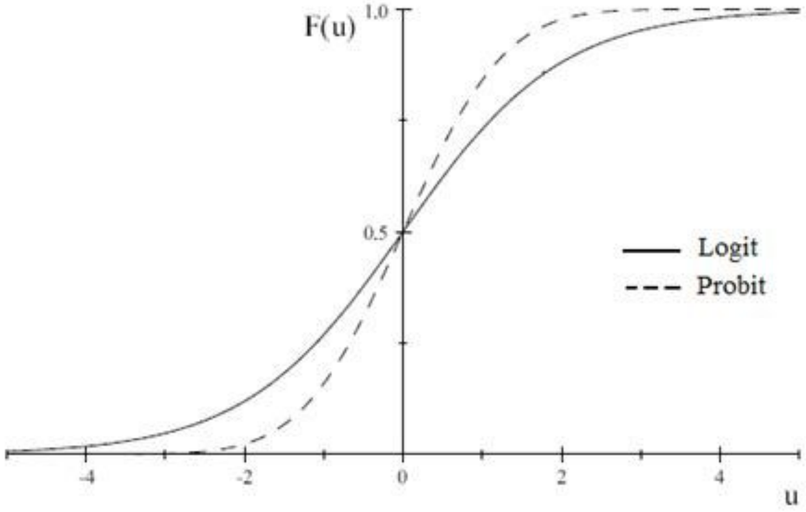
Model “Shapes”

Linear Regression



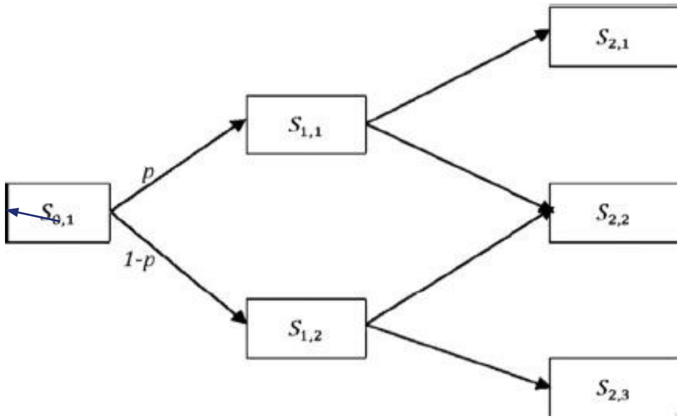
Most widely known modeling technique, but **modified to curve to meet expectations**

Probit/Logit



Fit for use with default data (0 current, 1 default)

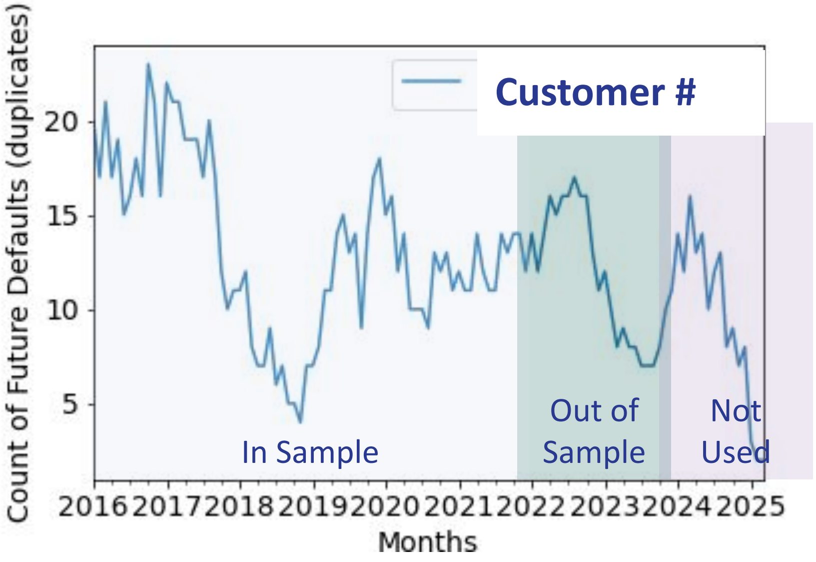
Machine Learning (Decision Trees Shown)



Can be used with default data, but has large downsides in practice (see previous page)

Data Used

Comment: The data is your model. Here there's an opportunity to discuss data or environmental anomalies



What is it: Data is pulled from the "Loan Table" in **Database**. Filtered by "2nd Mortgage" only for variable loans.

"**In Sample Data**" – Data used to build model

- Data to build the model is from January 1st 2016 - March 1st 2022 (inclusive). This is important because the economic conditions, loan and member information here will be the baseline for forecasting in the future.
- Stratification sampling provided equal number of loans from each month of the time period, regardless of the portfolio size at that time. This controls for distortions from portfolio growth. Chart above shows stratification.
- The model used 2,000 defaults in 12 months (ie default is counted more than one time). This is .24% of the used data.

"Out of Sample Data" – Data used to test the model

- Loans between March 1, 2022 - March 1, 2024 are out of sample and used to evaluate the model.
- Model predicted .2% default rate while the actual was .215%. This difference could be due to several factors including difference in consumer behavior, economic conditions, insufficient out of sample data etc.

FIXED HELOCs are considered separately

What are we forecasting?

Comment: Industry standard is to model PD separately and have that based on a consistent metric of 90 days past due or for some categories recognized impairment.

Forecasting if a HELOC will default in 1 year's time.

- Default is defined as 90 days past due. A loan can only ever default once, after that it is dropped from the data pool
- This is only looking at Credit Risk (defaults) not Fraud Risk. Where known, Fraud Risk is omitted.
- Although we are forecasting 365 days before default (275 business days), we expect that as we approach the date of actual default, the signal will grow stronger. For example, while the member is still current, in “Day 30” or “Day 0”, the credit score may drop or the member loses direct deposit (let go from employer).

Strategic Decisioning

- **Behavioral Models (just seen) gives a static view based on today's characteristics. But how should we prepare for different economic environments?**
- During a recession members will pull lines, how prepared are we for that? What can Data Services do to support you?

- **Ability to tell 'what is our risk in different economic situations'.**
- Forecast balances, payments, pre-payments, defaults, losses, utilization rates, etc by quarter
- Uses to economic, member, and loan characteristics
- Allows you to be 'comfortable' with portfolio. *If Uncomfortable*: 1) Change Origination Process, 2) Use Behavioral Model (& Knowledge) to cut lines
- Can be as complex as we want (defaults, utilization growth, origination growth, maturity, member curtailment etc)

Variables

What variables predict defaults?

Comment: Coefficients have been changed, but are directionally and magnitude corect

Variable	Definition/Rational	Relationship to PD	Complexity	Coefficient
INTERCEPT	Model Requirement: If member is bankrupt then 1 else 0	DIRECT (Higher number worse PD)	NA	7.00
CREDIT_SCORE_INT	Credit Score gives full financial picture on probability of defaulting (in general)	INVERSE (Higher number better PD)	Interpolated	-.04
NEG_DEPOSIT_BALANCE	1 if deposit balance is currently negative, 0 if otherwise	DIRECT	DUMMY	0.6
RECENT_PREPAY_DUMMY	Current Month if Paid > Payment Requirement, 1 else 0	INVERSE	DUMMY	-2.00
LOST_DEBIT_CARD_ACCESS_12M	Lost Access to Debit Card based account in the last 12 months	DIRECT	DUMMY	2.30
AVAIL_PAYMENTS_3_IN_DEPOSIT_DUMMY	If 3 payments or more is available in deposit then 1, else 0	INVERSE	DUMMY	-1.00

Variable 'Sensitivity'**

Comment: Coefficients have been changed, but are directionally and magnitude corect

1 **Good Loan: .017% PD.** Has the characteristics of a low risk loan including: 759 Credit Score, has direct deposit, has minimum of 3 available payments in deposit

2 **Risky Loan: 35.32% PD.** HELOC has a variety of negative characteristics including 620 credit score, has not recently prepaid, has a negative deposit balance and isn't the second lien (could be 1st, 3rd or unknown).

Sensitivity Analysis:** Largest drivers of PD are in red.

Variable Name	Coeff.	"Good Loan	"Bad Loan"	PD of "Good Loan" with 1 Bad Variable	Impact to PD
INTERCEPT	7.00				NA
CREDIT_SCORE_INT	-.04	759	620	0.159%	9.1X 3
NEG_DEPOSIT_BALANCE	0.6	0	1	0.031%	1.8X
RECENT_PREPAY_DUMMY	-2.00	1	0	0.058%	3.3X
LOST_DEBIT_CARD_ACCESS_12M	2.30	0	1	0.117%	6.7X
AVAIL_PAYMENTS_3_IN_deposit_D.	-1.00	1	0	0.053%	3X
	PD	**0.017%**	**35.32%**		
		1	2		

3 This swaps out a "good loan" characteristic for a "bad loan" characteristics. Where possible we used the average characteristics (noted by *).

- The biggest swap is found by Credit Score with a change of 9.1X increase in probability of default, or an increase from .017% to .159%.

**Sensitivity is a complex process; this is just to give an essence on how the model is working.
* These variables are using average values of those that defaulted and didn't default. Other variables are binomial (1 or 0) and thus averages are not consistent (.35) with how they would be used. Ignoring 'real life' we get .068% (good) vs 2.92% (bad) or ~43X increase in chance of default

Model Results

Out of Sample Examples

Comment: Using real data the model hasn't 'seen' before, we get real world feedback (Probability of Default) on a loan's risks.

Member Loan Id And DATE	Probability of Default	Model Score	Default In Future Months	Const	Credit Score Int	Neg deposit Balance	Recent Prepay Dummy	LOST_DEBIT_CARD_ACCESS_12M	Avail Payments 3 In deposit Dummy
A417-2023-02-28	81%	9	0	1	455	0	0	1	0
B7293-2023-05-31	80%	9	1	1	457	0	0	1	0
A417-2023-01-31	77%	9	0	1	469	0	0	1	0
B7626-2023-01-31	75%	9	1	1	475	0	0	1	0
B7626-2022-12-31	75%	9	1	1	477	0	0	1	0
B7293-2023-04-30	75%	9	1	1	478	0	0	1	0
B7626-2022-11-30	74%	9	1	1	480	0	0	1	0
B7626-2022-10-31	73%	9	1	1	482	0	0	1	0
A417-2022-12-31	73%	9	0	1	483	0	0	1	0
A417-2022-11-30	72%	9	0	1	487	0	0	1	0
B7626-2022-09-30	70%	9	1	1	492	0	0	1	0
B7626-2022-08-31	67%	9	1	1	502	0	0	1	0

24 Month "Out of Sample" Window

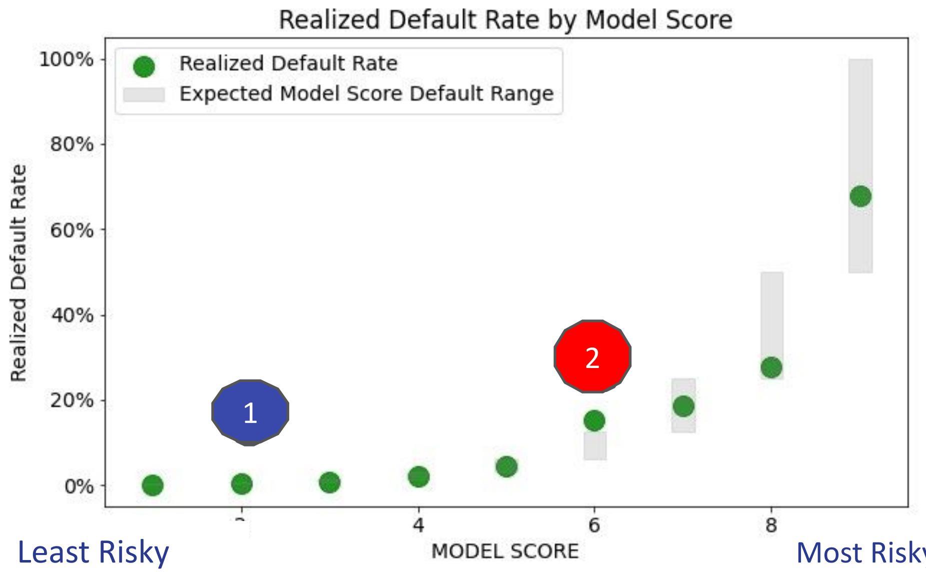
Comment: This summarizes at different 'Model Scores' how well the modeling is capturing the risks.

In each of the "out of sample" months we test "Did this loan default in the following 12 months on **data and time period the model never saw**". The 24 month "Out of Sample" Window isn't sufficient, but given COVID and complexity of Mortgage products, it's the best currently available.

1 **Good:** Model has sensitivity to factors and is appropriately capturing risks at end and beginning of range

2 **Less Well:** Model Score 6 overestimate percentage of defaults in the current environment, compared to actuals.

	Model Score	Loan Count	Default Count	Realized Default Rate	Expected Default Rate
Least Risky	1	140,202	107	0.1%	0.4%
	2	4,052	17	0.4%	0.8%
	3	2,051	17	0.8%	1.6%
	4	1,029	23	2.2%	3.1%
	5	553	25	4.5%	6.3%
	6	275	42	15.3%	12.5%
	7	119	22	18.5%	25%-12.5%
	8	83	23	27.7%	50%-25%
Most	9	31	21	67.7%	100%-50%



Least Risky

Most Risky

* Ideally we would have a similar amount of time 'in sample' vs 'out of sample'. However, this would have required several more years of data.

Quality of Model

Comment: Here I summarize using more traditional methods such as ROC/AUC and Precision Recall.

1 AUC (Area under Curve of and Receiver Operating Characteristics) are used to see how well a model prioritizes defaults. The closer to 1 i.e. the faster the blue line goes up, the better the model.

- Traditionally Model Development has shown this graph (which looks very good) and shows how good are we at forecasting right 0 or 1 (default or not defaulted). However, it loses value if defaults are very rare, which would mislead us in the quality of the model.

2 Using Precision/Recall graph answer the question: How good are you at forecasting individual defaults? Given they happen rarely. The graph here is one of the better ones produced (.179) given other modeling constraints.