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Chapter 5: The role of predictive modeling in assessing borrower risk and loan performance

5.1. Introduction

The United States is served by a diverse and competitive mortgage market of remarkable performance. Construction accounted for 6 percent of gross domestic product in 2001; one- to four-family rental and owner-occupied residential real estate outstandings exceeded 48 percent. The estimated probability of a U.S. mortgage real estate transaction experiencing a loss is measured in basis points, not percentage points. This good performance, plus continued investor and borrower interest in the product, results in a diversity of underwriting approaches, loan products, loan terms, and performance characteristics. This paper focuses on three primary themes. First, mortgage credit risk has been and is likely to continue to be assessed using the traditional financial questions faced by underwriters, plus a broad array of tools for modeling default, prepayment, and other key mortgage cash flow stimuli. Second, market participants are likely to apply new computer-driven advances in statistical techniques—predictive modeling approaches that are also used in other areas of finance and economics. These financial dimensions are also the focus of the primary prudential regulator of the Federal National Mortgage Association and the Federal Home Loan Mortgage Corporation. When conducting our safety and soundness examination, we need to apply an efficient blend of financial judgment and economic modeling.

5.1.1. Overview of the Study

Traditional credit scoring and credit risk assessment tend to focus on the likelihood of delinquency, bankruptcy, or other loan performance events given some specific profile of an applicant at the time of application. In contrast, we develop a class of predictive credit scoring tools that introduce the temporal dimension by using quarterly, monthly, or weekly performance measures to model the loan performance process and then using these models to calculate the likelihood and schedule of future loan performance events. As a distinct form of structural modeling, our approach is demonstrably better than current methods at assessing a borrower's financial stress, credit status, and performance risk at the loan origination stage, and at capturing changes in borrower behavior and performance both during good times and in periods of financial sector stress. Crucially, the model and its future performance measures can be used recursively to help select a loan portfolio, dynamically assess the credit quality of existing borrowers, determine the timing of loan workouts and resolutions, and report consistent loan performance statistics as credit conditions change.

The development of performance measures based on our hazard model permits the growth of new loan facilities and the possible extension of existing loan facilities that are consistent with the risk tolerance of the origination activity, the performance of the existing outstanding loan portfolios, and the desired capital strength of the lending institutions. Since the model is based on the performance of many loans rather than contractual or hypothetical loan characteristics, theory-driven subjectivity can also be generated efficiently and unbiasedly. The strategy makes strong use of new comprehensive credit databases and is amenable to quick updating. The application of our approach to the development of a creative practical solution to a potential major economic crisis associated with disorderly mortgage restructuring also suggests that our hazard modeling approach can make substantial positive contributions to credit and the stability of the financial system.

5.2. Understanding Predictive Modeling

The risk of lending to a borrower can be characterized by the lender and used to make more informed decisions. However, such characterization is not always straightforward and will depend on the types and amounts of information available to the lender. We develop a framework for predicting mortgage delinquencies. We later extend this predictive model to include second liens as well as alternative hybrid ARMs. Our results show that the mortgage predictive model, when combining similar types of loans into simple categories, has good overall performance characteristics when applied to first liens. Additionally, it performs at satisfactory levels in predicting the losses of first line clean-up calls within those categories. One caveat is that model performance is somewhat challenging when separating the mortgage predictions into smaller categories corresponding to different profiles of down payment and amount of credit history.

5.2.1. Definition and Overview

Mortgage lenders and underwriters use a variety of methods and tools to screen and evaluate potential borrowers and loans. One set of tools that has had recent success in predicting borrower behavior and loan performance involves the use of statistical techniques called predictive modeling. Predictive modeling uses information from borrowers' credit reports and loan applications together with performance outcomes from loans with similar borrower attributes to predict loan performance. A large number of the equations that have been estimated are functionally similar, reflecting the nested semi-collegiate structure of credit scores and reporting metrics based primarily on the borrowers' prior mortgage performance. Spurred by regulatory guidelines, several performance reports have focused on borrower and loan attributes associated with poor performance while some have also assessed the performance of non-traditional loans.

Lenders use predictive modeling techniques to screen mortgage and other loan transactions for certain borrower and loan attributes to identify segments of the loan market with borrower risks higher than would be expected based on the strength of the borrower's credit history. Some lenders also use the models to rank order applications within each attribute segment and apply their underwriting standards more flexibly for low-risk applicants. Counterbalancing the increased use of modeling techniques as a screening tool at origination is the remaining reluctance of mortgage industry participants to apply the technology to monitor loan performance post-origination. Lenders' aversion appears to reflect the perceived cost of using current statistical techniques for what lenders suggest is a basic surveillance function as well as uncertainty about just what to monitor in a mature, low-risk mortgage market.

5.2.2. Historical Context

Macroeconomic factors and underwriting criteria have historically proven to be powerful leading indicators in predicting borrower risk and loan performance. Although structured mortgage underwriting—the idea that loans made in line with set criteria can be relied upon to perform within well-defined risk parameters, and that a pool of loans may be diversified to provide stability through a variety of market cycles—is not new, the practice underneath is continually evolving to support and adapt to the mortgage industry and housing finance. The changing economic environment, borrower and loan performance trends, and loan-level data provide an opportunity to return to basics, re-examine underwriting criteria practices and the rules that support them, and focus on fundamental industry questions surrounding borrower risk and loan performance.

The goal of advanced analytics, including predictive modeling, is to provide insight to support model development and data that accurately reflects the underlying collateral attributes, so that the improved borrower and loan performance may be better delivered. Ultimately, the power of predictive modeling methodology lies with the growing set of theory, tools, and results that provide expectations for how borrowers, loans, and model neighborhoods will perform differently, and that allow for the testing and validation of presented results. The predictability-to-performance relationship is well known to be informational or logical, not mechanical, and the relationship between predictive models and the underlying borrower profiles and loan performance is inherently challenging, especially across market and economic cycles. Culminating power—the ability to work above and between advanced model-based borrower profiles and loan performance metrics, and the myriad of market experience and cycle trials that ultimately validate these findings—commonly drives model development.

Fig 5 . 1 : AI in Risk Assessment for Loans

5.2.3. Types of Predictive Models

The most widely used predictive models fall into three general categories: payment models, credit scoring models, and securitizing models. These broad categories cover a whole range of sophisticated statistical techniques, which vary from simple logit models to highly complex computer-based systems. The difference between these models lies in their primary focus, their use of dependent and independent variables, and the techniques employed to estimate the models. Essentially, a payments model focuses on the ability of borrowers to make scheduled loan repayments, a credit scoring model focuses on the likelihood that the borrower will become delinquent or explicitly default, and a securitizing model estimates the risk associated with prepayments. In general, credit scoring models draw upon more explicit credit-related information about the borrower than payment models, relying on a broader set of information than securitizing models, which are more dependent on the structure of the loan. It is not uncommon for an underwriting system to utilize a combination of models from the three different categories to assess borrower risk. While there is no optimal model, it is the combination of models used that is essential when assessing borrower and loan performance, as each model typically focuses on different information and/or risks.

5.3. The Importance of Assessing Borrower Risk

The foundation of sound bank underwriting is the identification of relevant risks associated with a loan and how those risks are mitigated. It is the interplay between the bank's risk monitoring and borrower risk that determines loan quality. Many banks have found surprises in credit portfolios as the acceleration of economic business conditions, the deterioration of a client's operations, or the increased limitations on funding have impacted other borrowers and industry sectors. Surprises are uncommon when a lender has performed timely borrower risk assessment using the techniques being discussed.

Borrower risk is determined using many of the same principles we use to evaluate capital markets. We look at cash flows, industry analysis and concentration and diversification limits, loan structure, and the sources of repayment. Predictive modeling using five years of customer-offered financial data allows the bank to provide fixed fee or low-cost fixed-rate term loans to creditworthy borrowers in strong economic sectors. Banks with limited internal models are most likely to originate short-term floating obligations to limit risk. The theme during banking crises is always the same: the loan portfolio has a credit structure and size that prevents the bank from serving as a financial intermediary. Bank regulators agree with the sentiment following each crisis that we'll all know about the bad loans a year from now; it is the current loans to the lending industry that are important. We believe that most banks have inadequate tracking and compliance procedures, lack cost-effective text-based borrower financial analysis, and do not perform regular predictive surveys on a predetermined list of problem borrowers. Even knowing this, bank regulators continue to examine only a sampling of bank loan critiques.

5.3.1. Factors Influencing Borrower Risk

By "borrower risk," we refer to the degree of initial or subsequent financial risk to the lender arising from a loan made to a borrower who may have an increased propensity for loan default or insolvency. The strategies of the lender include setting the cost or price of the loan, identifying which applicants are more or less likely to default, and developing performance improvement interventions or loan structures that mitigate borrower risk. It is likely that technology will continue to grow in importance as an element of these strategies, not only because of cost reduction imperatives but also because algorithms employing predictive modeling tools permit both close examination and relationship unlocking of borrower data characteristics that might elude our more conventional tools of inquiry. A related concern addresses the evaluation of a potential change in a loan's structure designed to enhance the relative 'safety' of the loan, such as lengthening the loan's term, increasing the loan's cost of capital, or structuring a performance-favorable variabilization of the loan's interest rate. Such inquiry, of course, deals with the ongoing risk of borrower default and requires the use of statistical analyses that estimate the likelihood of loan default over different risk ex ante time periods for the performance evaluation of such altered loan structures for similar customer profiles.

5.3.2. Consequences of Poor Risk Assessment

Lenders who provide credit to individuals are vulnerable to losing money when borrowers do not keep their promises. The inability of a lender to predict, at the time of lending, the probability of a bad outcome can lead to the offer of credit to individuals who should not, in fact, get credit. For instance, if credit is too easy, individuals may respond by borrowing too much, which may lead to insolvency and economic crises. That is why, for a very long time, banks have used rules and models that help in evaluating credit applications in an effort to differentiate potentially bad borrowers from the good ones.

Repeated violations of the laws of lending – too many bad borrowers receiving credit – have often led in countries to the supply of taxpayer-financed insurance and payment systems to support the activities of the banking sector. These repeated interventions have consequences for the virtuous bank as they can create distorted incentives and could lead to the loss of good risk management customs. For that reason, banks should invest in risk assessment methods. In the datafication era, it is perhaps a good idea to explore data-based approaches. However, because correlations between borrower/loan characteristics and future loan performance are context-specific, the accuracy of models that use data from one bank is always specific to that bank and has a limited shelf life, potentially as short as 90 days.

5.4. Data Sources for Predictive Modeling

While many other means of predicting borrower default and collateral risk are used, some of the most advanced and highest performance models are based on credit scoring. The credit scoring examples reflect attempts to model borrower risk. One firm used polynomial regression and other linear regression against a combined default numerator and pre-default denominator. The general equation of the chosen regression is: predicted risk = a + bX1 + cX2 + dX3 + ... with the extant columns of the borrower risk database representing X1, X2, X3 and the other X values. Such equations act as a set of logical sufficient conditions. However, regression analyses lack combinatorial coding, a practical rule-based approach. Such an approach leads to action.

The inaccuracies of the credit-scoring models are known but widely excused and accepted. For example, the NPV of two percent as an error sensitivity metric is known but accepted. Most lenders will take an error as long as it is beneath the loss. Therefore, the second answer to the title question is that the current data sources are inadequate in terms of original data. They, in most cases, lack specimens of borrower risk that are sufficiently homogenous and numerous to support a discriminant or regression equation with coefficients that truly discriminate, match, and consequently can be considered to have predictive capability. The same holds for the user-generated coefficients. Scalable vendor-processed databases of such homogeneity, let alone identical numeric and alphanumeric labels and categories, do not exist.

5.4.1. Credit Scores

Four main factors help us understand how predictive individual personal credit scores are of a number of loan outcomes: the percentage of observations in the population having a score of 680, 720, 750, and 780; the functions used to derive these credit scores; and the results obtained when testing the model using national data and national or lender test sets. The fair estimation results they obtain are then matched on these four percentages to get estimates of loan performance at different risk score levels. This allows all loan risk measures to be relative to the national distribution of credit scores. Finally, partial effects and probabilities of obtaining other loan outcomes by changing the risk factor can be estimated for credit score model performances having the appropriate performance links with the borrower population. Their estimated percentages with credit scores less than 620 and above 780 at loan origination were similar to their national percentages, and their average FICO at origination was also close to the average. Each matching average was about 720.

For instance, we obtained better model fit and more statistically significant and fair risk estimates for two credit score loan performance measure sets covering 90–96 percent of the population compared to the results of earlier and later issued credit score papers. We discovered that the value of the smaller consumer dataset they used was compared to what we used. After obtaining a regression model for each performance measure set, we matched national performance measures with the appropriate credit scores for the general borrower population and used functions of the average performance measures to predict other loan outcomes based on applicant/risk factor changes. The national percentage of loan applicants with credit scores less than 620 at loan origination was about 10 percent, with about 12 percent having scores less than 640. After 12, the percentages above 700 increased by 10%, with about 31% having scores above 750. The results and procedures in other recently issued homeowner risk and borrower performance papers focused on important model testing steps and modeling a number of different borrower and loan risk factors.

5.4.2. Financial History

To the extent that today's financial history is a major determinant of behavior in future years, the internal credit scoring systems that banks have built are an appropriate approach to deciding whether to originate loans with predetermined loan terms, and what those loan terms should be. Whether for small business and consumer credit, or for mortgage lending, the analysis reflects this view. Historical borrower credit reports and scores are being used today to accomplish what is currently effective scheduled repayment monitoring. Over time, credit report contents have expanded to include more categories of financial obligations, more regularly report on these obligations, and reach out to include more types of borrowers. Similarly, a consumer credit score intended for use in assessing credit risk has become increasingly sophisticated and is more widely used. The automated underwriting components of a credit decision may deny a consumer loan application, even in the absence of certain bureau-reported information, and give possible reasons for the denial. Such automatic electronic credit decision communications could represent a potential source of protected class and other fair lending problems.

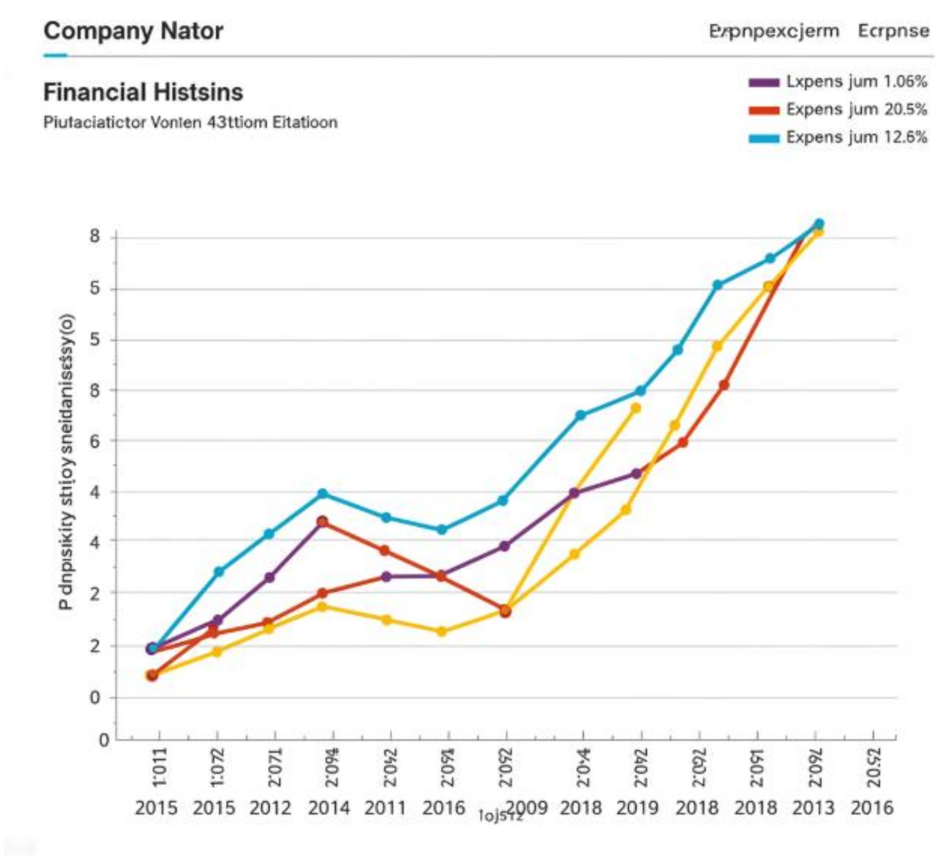

Fig 5 . 2 : Financial History

5.4.3. Demographic Data

In addition to the main numerical financial items, an additional 24 demographic fields are provided for each borrower and cosigner, if applicable. For each of the demographic fields, missing data type and frequency as well as type fields for the demographic are presented. Some examples of demographic type fields are academic, address, birthdate, cosigner, and state. An example of a type field is the 'Occupations' employer name field. Some examples of specific demographic fields include the employer name and address, the time at address, the time at employer, and the self-reported annual income. A number of demographics have been removed to reduce the risk of borrower identification and to prevent origination fraud.

There is a significant amount of missing data in a number of the demographic fields. This missing data is the reason for the majority of the missing fields in the data set. This is potentially due to the self-reported nature of the data provided by the borrowers. The users are expected to be truthful when providing the demographic information but cannot be validated and can either be falsified or simply not provided. Additionally, the team asks for a minimal amount of demographic information when connecting borrowers to money sources with the overall goal of minimizing the amount of information needed to be collected and maintained for loan origination. This is potentially reducing the information burden on the loan applicant to be submitted. Other demographic data could be historical demographic data, which has not been included in the sample.

5.5. Techniques in Predictive Modeling

To evaluate loan characteristics and to predict loan performance, a wide variety of techniques in predictive modeling can be used, with two categories broad enough to cover the approaches used in mortgage lending. In the first, the dependent variable is categorical: for example, the loan category may represent a credit quality rating, such as low, medium, and high risk. Models based on this approach, such as the discriminant function, logistic regression, linear discrimination analysis, and probit regression, are useful for modeling credit default and have been used to predict loan performance. In the second category, both dependent and independent variables can be continuously measured. The methods used may include linear regression, logit regression, and more complex econometric procedures. Traditionally, linear regression methods combine both categories by grouping the contract rate and using a quarter performance indicator. More recently, the application of more sophisticated analytical tools has been sought to incorporate credit scoring or application scoring. These tools use information on characteristics of the borrower, such as credit report data, and possibly some aggregate variables, such as interest rate or market share, in order to derive a borrower-specific estimate. Along with measures of risk-based capital, these scores are used to help determine which applicants should be approved for loans and under what terms. After the decision to initiate a loan has been made, the scores are thus applied to the portfolios, with a score being calculated at the expected time of default.

5.5.1. Regression Analysis

Ordinary least squares regression has been used to model the effect of a loan's interest rate and maturity on lender yield and other dependent variables. Multiple regression analysis models the effect of two or more independent variables upon dependent variables. The combination of yield that maximizes Sharpe ratios and other measures of performance. A variety of relationships is derived from extending this to variables other than the standard deviation and returns. A set of equations describing the joint determination of the ratio between systematic and total risk, as well as the ratio of systematic to total risk. This model recognizes that the expected returns hold uninformed and no-risk constraints. However, this model shows informed investors sometimes moving informed constraints in the same direction as no-informed constraints, thereby providing a result intermediate between no constraints and investor homogeneity.

5.5.2. Machine Learning Algorithms

In contrast, prediction is done by supervised machine learning techniques, involving building a model using historical data where the outcome is known. In the industry, machine learning techniques are used to develop credit risk models. The model is validated on a separate test dataset, and if the model is good based on predetermined criteria, it is deployed, and the future credit applicants are scored and approved or denied credit based on the model results. There are several machine learning algorithms used for credit scoring. The selection of a particular algorithm depends on the characteristics of the data, such as data size, data structure, the number of input features, interaction between input features, and the requirement of a model that is interpretable and one that is not.

Some of the commonly used algorithms are: logistic regression, decision tree, support vector machines, neural networks, k-nearest neighbor, discriminant analysis, etc. The characteristics of the various algorithms are discussed. For large structured data of low dimensions, models like logistic regression are applied. For large unstructured data, which has multiple layers of features and has plenty of data points, deep learning is incorporated. The Random Forest model is a popular classifier known to limit overfitting and has a rational degree of complexity, but lacks transparency.

5.5.3. Decision Trees

Introduced, the decision tree is flexible in form and structure and is able to handle a mixture of both continuous and categorical data. Both bagging and random forest methods involve growing multiple trees and fitting the model. These trees can be considered as grown using exhaustive search techniques, and multiple splits are applied to propose the best result. Therefore, a problem that can impact decision trees is overfitting, which reduces the predictive power of the model as it is specifically tailored to fit the data.

Viewing the decision tree model across the entire data range, researchers are interested in discovering the crucial factors while capturing their interactions with other features. Removing the insignificant variables can lead researchers to a more robust and concise model. The completion of pruning the tree transforms it into one robust and understandable model while still being descriptive due to the richness of the output. Results derived from such models can help financial representatives make investment decisions by identifying the risks and returns. The decision tree model aims to maximize good-bad customers capture, derived good-to-bad ratio, or yield obtained from the result to describe sensitive customers who are more likely to take out a loan. In financial applications, both methods called decision trees and MARS are intuitive and flexible, can handle a wide range of predictor variables, express nonlinear relationships between the predictor and the risk, and provide a mechanism for detecting interactions of the risk to the customer.

5.6. Model Validation and Testing

Model validation and testing are inherently dependent on the specificities of the underlying data and should be designed based on the intended use of the predictive model (Kaulwar, 2023; Koppolu, 2022; Kumar et al., 2025). Some of the typical steps in model validation include backtesting, stress testing, and scenario analysis. Backtesting refers to examining the historical coincidence of predictions with actual outcomes, i.e., comparing model estimates with realized experience. The model is tested to determine failures or model limitations based on comparing the model's in-sample or out-of-sample performance. There are generally two different backtesting methodologies. One uses information for point-in-time and the other uses through-the-cycle times. Models generally perform much better over in-sample, one-step ahead time periods. It is therefore important to have an out-of-sample testing period to assess the model's consistency over time in predicting economic conditions, as well as defaults.

Backtesting is also important for spotting economic and credit environment changes for undue model reliance. Regulators often encourage scenario and stress testing to assess whether the range of outcomes suggested by the model is acceptable. A severe decline in model performance at the boundaries could also suggest that the model is not robust in capturing the range of borrower behavior and therefore inadequate for decision-making. Sensitivity analysis can also be applied to probe borrower reactions to changes in economic activity, interest rates, house prices, and liquidity conditions.

5.6.1. Importance of Validation

One means of ensuring that a credit scoring model will perform well in the future is to validate the model over a time period that differs from the time period over which it was originally estimated. If a good model can be estimated on a relatively small sample of poor quality loans, the institution will have the basis for not only making better underwriting decisions, but for more quickly identifying deterioration in the quality of their loan portfolio. Ideally, a good credit scoring model should not only assist in classifying loans made at the time the model is developed, but should provide an early warning system for potential lowering of credit quality of a borrower or a loan that had been previously judged to be a good risk, but whose risk was believed to be increasing.

To date, some questions exist concerning both the appropriate test methodology and the appropriate choice of criteria for validating out-of-sample loan performance of loan performance models. Regression modeling techniques have been used to predict out-of-sample performance by basing model estimates on a random sampling of loans and then evaluating how well model estimates perform on another underwriting. Unlike the situation above, where it was difficult to test the ability of models to predict future profits, the success of out-of-sample loan performance models is known, so that their productive ability to predict the quality of new loans made, a clear set of evaluation criteria does not exist. Nonetheless, some method of validating the ability of credit scoring models to achieve their goal must be developed.

5.6.2. Common Validation Techniques

Many types of validation techniques for assessing the effectiveness of a predictive model are common among statistical techniques. The following list describes several of these commonly employed methods.

1. Sample Splitting We can achieve a direct estimate of the predictive accuracy of the model by random sampling of the data and fitting the model on a portion of the data, and calculating the average prediction error on a portion of the data that wasn’t used to fit the model. The accuracy of the model on the clusters can be used as an estimate of the predictive accuracy of the model for predicting on future and unseen clusters. This is also known as splitting the sample into estimation and validation datasets. It requires us to fit the model on half of the data and then calculate the error on the half of the data that wasn’t used to fit the model. Then we can repeat this process m times and average the prediction errors across the m samples to obtain the validation performance.

2. Cross-Validation This is essentially the same as sample splitting, except we repeatedly draw new training and validation samples from the data and iterate on the random draws of the two samples (including possibly changing the model specifications in the case of flexible models such as decision trees and random forests). Then we calculate the error in the validation set data.

5.7. Loan Performance Metrics

The use of commercial mortgage-backed securities as a capital conduit has increased the need for credible and comprehensive analytics in the placement and monitoring of loans. Investors need to know not only the probable performance of and probability of loss from loans, but also the risk-reward trade-offs implicit in different structures. Borrowers need to know the pricing and structure parameters necessary to assess the relative costs of different capital structures. Commercial mortgage originators need a reliable, quick, and inexpensive method to assess the credit risk of their clients' loans. The rating agencies need well-scrubbed and well-validated analytics to assess the probable performance of the loans and the probability of loss.

What are the building blocks of good loan performance modeling? Any loan performance model needs to take into account: The credit quality of the loan, including not only property and borrower characteristics such as LTV, DSC, and surrender value analysis, but also information about the management/liquidation process of that lender. Origination and servicing fees, if any, and the terms of the loan. Macroeconomic and local market indicators of real estate and economic performance.

5.7.1. Default Rates

A major objective of this study is to identify and evaluate the relative effectiveness of various predictive tools to assess expected loan performance. The most obvious indicator of expected loan performance is the loan default rate. The loan default rate may be a more reliable or at least a more consistent measure of risk than the input data used to predict it. For types of data that are not time-varying, it may still be possible to observe one measure of performance after an absence of more than one month without any loss of predictive power. Dollars in default or similar event variables could be used as dependent variables with a technique. However, the obvious use of the default rate as an indicator of relative predictive performance was used herein with LPM. Note that changes in the amount of dollars in default between T1 and T2 may be observed; however, without risk-specific weights being incorporated into the secondary security, these changes may not totally correspond with the alteration in the aggregate value of the portfolio of loans in default. These reasons may conflict with regulatory and the information value of the dollars in default. Future studies will assess these hypotheses using default rates.

5.7.2. Recovery Rates

Recovery rates are percentage or dollar values of the claims made by the bondholders associated with impaired loans. These payments may be made under the terms of the loan covenant either as part of the regular servicing of the loan or through the disposition of repossessed property or after the bond is liquidated. The ultimate recovery experienced on a pool of collateralized claims will be a function of the individual terms of the loans and the collateral securing the loans, the values of the loans, and the property securing the loans that underlie the claims at the time of liquidation or sale, and the terms of the security agreements.

The available literature on recovery rates in a disciplined statistical framework is limited. Investigators involved with the production of financial data manage the recovery rate parameter with data management constructs. The limited literature on recovery rate levels is largely ignored by practitioners in the analysis of default risk embedded in financial data. Default analysis conducted on the basis of recovery rate adjusted statistics carries a different message from the analysis of default risk that results when estimates of recovery rates do not enter into the construction of the value of the financial claim.

5.7.3. Profitability Analysis

Profitability analysis is concerned with what a lender will earn on loans to different quality credit risks (Singireddy, 2024; Sneha Singireddy, 2024; Kaulwar, 2023). Banks are currently spending considerable effort in specifying and estimating the profitability of different types of loan risk. The competition among banks for loan dollars can limit the ability of banks in general to earn a profit on the loans. Indeed, if banks are unable to earn a profit after meeting costs, they cannot remain in business. In addition to nonresidential real estate loans, institutions that have heavily focused on municipal bonds, business loans, or other narrowly defined business areas have experienced financial difficulties that have frequently resulted in insolvency and increased regulation. While the reasons for the problems may vary, the fact that one type of institution has experienced them within a given business area underscores the importance of assessing the implications of holding different types of assets. This suggests that lenders will need software models that will help them assess the precise nature and risk of loan holdings. Profits for each holding have to exceed the institution's marginal costs. The failure of a financial firm to maximize its profits relative to costs will dilute its rate of return to stockholders and raise their costs of capital. Capital will then flow to nonfinancial firms where expected rates of return are higher, and the financial glue that holds the economy together will be weakened.

5.8. Challenges in Predictive Modeling

There are several fundamental challenges in predictive modeling. The importance of these topics is that to the degree that models do not account for the phenomena, awareness of the fact, transparency regarding how sensitive conclusions are to these assumptions, and realizations of model mis-specification can be notably enhanced. A comprehensive review of classification algorithm properties considers computational complexity, mathematical structure, variable cost/loss function, optimality of the solution, and the amenability and a priori overfitting with forward and backward steps to interpreting the models and the variables. Each of these properties is not relevant in all contexts, and even where properties hold, they may not be of first-order concern.

The tension between prediction and model estimation and interpretation is significant. Market experience suggests that the distinction between desired accuracy and easy verbiage in the model, on the one hand, versus simple interpretations and fuller parametric models for model parameters, has conceptual importance. The implementation in the market uses two-step credit decision models, which first use accessible logit models to screen applicants, and the second step develops fuller models to predict a borrower's performance. The first model may be preferred if the requirements of the model are not overly inflated relative to the potential for default, and the result is insufficient and costly bias application inconsistency present in the second-stage estimation of the loan. Companies are continuously developing tools and other resources for understanding the models and creating the empirical basis of financial claims.

5.8.1. Data Quality Issues

Predictive modeling is used to predict how a borrower will behave in the future with respect to a loan. Typically, predictive modeling is used to predict the probability of default of a loan, the amount that might be recovered upon default, or the level of prepayment that might occur on a loan. The models are constructed using historical data, which includes the actual outcome of a borrower in terms of the behavior of the loan. The data might be examined over differing periods of time; for example, such models might predict the nature of loan performance over the first six months, after nine months, after twelve months, and so on. A model implemented to predict loan performance at a later date than originally planned might be referred to as a vintage model, and a payment made on a loan that is in advance of the normal repayment schedule is referred to as a prepayment. It is clear that historical data collected using an industry standard procedure would be useful for the construction of such models. Industry standard procedures would ensure consistency and comparability across borrowers.

The goal of predictive modeling is to maximize the information that is available about the borrower for enhancing the ability to predict loan performance using cost-effective means. In this context, for example, detailed demographic information about the borrower might be collected; but for the most part, such information would not be expected to offer anything substantive in enhancing the ability to predict how a borrower will behave with respect to a loan.

Fig 5 . 3 : Credit Risk Prediction Using Machine Learning and Deep Learning

5.8.2. Model Overfitting

Overfitting involves the development of a model that is highly complex and thus is too closely adjusted to specific training data. This occurs because of relatively large sample sizes. In the face of large sample sizes, overly complex models may appear to behave well. In other words, there are so many observations that seemingly random distinctions are made in the data with a very large set of viewing lenses that only one model fits these specific lenses. Overfitting can only be detected when applied to new datasets rather than those used for model training. The application of overfitted models to test data frequently results in a model that consistently underperforms. Despite good empirical results on the training data, it is not informative as to how the model will predict responses in future data.

There are many variations of overfit models including model noise and assessments demonstrated on random correlations, although we refer to these collectively as developed through non-training data. Models specific to training data. Such additional frictions could direct random model behavior. This in turn contributes to only asking a subset of training data that would not hold for new observations. Overfitting allows this noise to be disproportionately captured as a signal and the model to be trained excessively on irrelevant observations. Therefore, one must be skeptical of putative predictive modeling results as poor models may exhibit good performance due to untrained noise that adds to these results. However, it is a challenging task to monitor and limit model overfitting.

5.8.3. Regulatory Compliance

The growth in predictive modeling has come at a time when U.S. financial institutions and securities firms have been placed under increasing pressure to better manage the risk within their portfolios. These pressures have arisen because of renewed challenges by bank supervisors and banking regulators, who seek to ensure that banks maintain capital levels to cushion against loss once some of the recent balance sheet improvements begin to weaken. Regulatory initiatives center on making the capital requirements underpinning the supervisory process more risk-sensitive. Although stress testing is an important part of the supervisory process, banking-promulgated risk-based capital requirements have long been criticized as both pro-cyclical and too focused on balance sheet risks, with little attention paid to income statement risks. Suppose that a bank's balance sheet is supported by over-collateralized lending, with the collateral supporting a borrower relationship shifting from worthless to valuable; is the associated shrinkage of collateral risk reflected in capital relief or is the bank's risk-based capital effectively static? If protection arises from enhancing debt repayment capacity matrices as well as from equitizing income statements, is it material and does it affect risk-based capital?

Accurate and credible in-bank models of borrower risk are vital for understanding what loan terms dictate and, thereby, for enhancing protection against the income statement risks in banking. The ability to model borrower risk is vital for compliance with the forthcoming capital accord.

5.9. Conclusion

Predictive models offer a unique and informative tool in assessing borrower risk. The beneficial role of an originator's direct data strengths can be used to their fullest through the development and use of predictive models. The passage of laws designed to facilitate the collection of potentially intrusive data such as race, sex, and area median family income is likely to make model development, and the investor focus, much more intense. Tests of our predictive model showed favorable results, both in terms of the model's ability to rank order probabilities and the model's explanatory and predictive power. Internal statistical testing facilities can isolate some technical and judgmental problems, and these tests are described. Predictive modeling is likely to win the admiration of the regulators, and that is perhaps the highest compliment paid to our techniques.

5.9.1. Key Takeaways and Future Directions

This chapter offers a comprehensive overview of credit risk models, how they inform the credit function, and the use of these models across the loan life cycle. We have elaborated on the relationship between borrower, regulatory, and economic variables and loan performance, and how these variables can be considered for use at origination, through the life of the loan, and during a loan’s resolution. Model choices are shaped by the purpose of the model, the data available, the data’s quality, and the overall risk management process. There are many predictive model choices across each domain, and understanding model features and performance is paramount.

In future work, we offer the following suggestions for refinements and extensions of the types reviewed in the chapter. Reinforce the techniques used in this chapter with more in-depth modeling analyses that examine the utility of combined features, macroeconomic and regulatory variables, interactions, assumptions of model linearity, and machine learning techniques. Descriptive text is elaborated into a standardized data dictionary that contains process files, data definitions, as well as the process owner, data owner, technical data owner, and data steward. We have yet to discuss fully 'fair lending' and the impact of using different data types for underwriting or risk assessment on protected classes. After the approval of the model use, a strategic analysis is undertaken to test for sample stub periods or structural shifts as a result of artificially generated outliers or difficult-to-predict severe events. Fully operationalized into a comprehensive model scorecard.

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