Project

Summary

Wescom Credit Union wanted to revamp their risk-assessment and decision-making processes.

To increase their lending decision accuracy, Wescom went to SAS, a company known for its analytics work, to come up with a solution.

Through their analysis and implementation, SAS was able to, “increases lending decision accuracy by at least 50 percent”

They also “increased the accuracy of lending forecasts, simplified the process for meeting regulation requirements and improved portfolio response”

During my analysis I am going to speculate as to what SAS and Wescom could have possibly implemented that could lead to better classification for loans and forecasting that would reduce the overall risk of insolvent loans to better manage risk.

I believe the keys steps taken to achieve these results were:

- Implementation of a more accurate classification model
- Implementation of a forecasting model to predict the general health of the economy based on key economic indicators into the future
- Simulation of varying economic scenarios based on the forecasting predictions to ensure our forecasting model is not too optimistic and one bad year doesn’t bankrupt the credit union
- Use these predictions and simulation to assess risk

Background Information

In the credit industry, risk management is directly tied to a lender’s customers paying back their loans. Since the loan amount and interest rate (typically) are fixed, this means that the credit union can reasonably assess risk both in terms of their portfolio as well as when it comes to individual loans.

When it comes to risk as it pertains to credit, there are three main components.

1. Probability of Default (PD)
2. Exposure at Default (EAD)
3. Loss Given Default (LGD)

Expected Loss (of a loan) = PD x EAD x LGD

Expected Loss (of a portfolio of loans) = SUM(PD x EAD x LGD) - the sum of the Expected Loss of every single loan in the portfolio

The Expected Loss (and some of the components within) are dynamic; changing month by month with each new payment and based on the Probability of Default changing based on the macroeconomic picture changing from the issuance of the loan compared to the completion of it,.

Methodology

1.) Implementation of a more accurate classification model

In the article, there is reference to how the credit union used to classify loans based on a "voting" methodology but with the help of SAS, they have now switched to a "weighing" methodology with a resulting "scorecard".

How I interpreted the article is that Wescom has been taking data from all applicants and in order to be approved, an applicant would have to check every single "box" to be approved.

For example, the hard cut-off under the old "voting" methodology might be:
- Income over $75,000 a year
- Credit score greater than 700
- Debt-to-Income Ratio less than 35%

Under the above methodology, an applicant with an income of $1,000,000 a year, credit score of 500, and a Debt-to-Income of 0% may be denied for a loan.

While there is certainly still inherent risk with the hypothetical applicant, they would have been denied under the old way.

New Model:

Given:

Historical loan data (paid/unpaid)

Individual Characteristics:
- Income
- Credit Score
- Debt-to-Income Ratio

Economic Indicators:
- GDP
- Interest Rate
- Unemployment Rate
- Inflation Rate
- Effective Federal Funds Rate (as it corresponds to the aggregate credit cycle)
- Housing information for housing cycle

Use: Logistic Regression

To: Train a model that will give the probability as to whether or not current and potential new loans will be paid or not. Economic indicators are included in the model because economic and credit cycles will ultimately have an impact on whether or not loans will be repaid and will thus affect the probability of the loan default.

The response from this model will be the Probability of Default (PD) that can be used to dynamically assess the risk of this loan as well as how it ties into the overall portfolio. The article refers to this as the “scorecard” that can be rank-ordered compared to other loan applicants.

While individual factors (such as income, credit score, debt-to-income ratio) arguably have a greater effect on whether or not an individual repays a loan, overall economic health would have an impact as well.

This new approach allows for a lot more flexibility and accuracy. In better financial times the credit union can give out riskier loans and in worse times the credit union can use the scorecard to give out loans with less Expected Loss/risk.

The threshold would be dependent on Wescom Board of Director’s risk tolerance that they set monthly.

2.) Implementation of a forecasting model

Since loans have varying durations (typically anywhere between 1 year and 5 years), to accurately assess risk it is important to attempt to try and envision the big picture from a macroeconomic standpoint as that affects our risk.

The article makes mention that “Wescom updates loan loss forecasts each month for a “rolling 60-month view.””, with “economic impacts (econometric cycles) and quality adjustments (credit cycles) over this timeframe” factored in.

The article also mentions that the forecasting model uses, “2.5 million records” with “350 economic indexes with 30 years’ worth of data stored on SAS servers, ready for use.”

I want to be transparent that I will be summarizing the “2.5 million records” and “350 economic indexes”. The following “given” is a guess and nowhere being inclusive as that would involve much more rigorous data exploration.

Given:

Economic Indicators:
- GDP
- Interest Rate
- Unemployment Rate
- Inflation Rate
- Effective Federal Funds Rate (as it corresponds to the aggregate credit cycle)
- Housing information for housing cycle

Use: ARIMA

To: Create a forecasting model for each of our economic indicators that can forecast economic indicators at times into the future.

By forecasting what the future will look like from an economic perspective, we can better assess the risk of our portfolio as a whole.

There would likely be a strong correlation with economic downturn and increase in portfolio risk due to increased Probability of Default.

Conversely, there would be a correlation between good economic times and a decrease in portfolio risk.

This model attempts to capture trends (especially cyclical) from historical data and better predict what will happen in the future.

3.) Simulate different economic scenarios to ensure we adequately assess risk

The article mentions that the credit union “now closely pairs its risk appetite… to its portfolio risk levels on a monthly basis” and can forecast “five years out, and mitigate excess loan losses”

Frankly, being able to forecast five years out on anything is pretty difficult. An ARIMA model does an adequate job of giving us a roughly mean prediction into the future, but doesn’t quite assess for worst-case scenarios that could bankrupt the credit union.

A Monte Carlo simulation allows us to load in our past ARIMA predictions and the simulation can add variation to our predictions that we can then use to assess the risk of our portfolio.

For each variation in economic indicators, those indicators would be plugged back into the logistic regression to give us a simulated Probability of Default (PD).

The Monte Carlo simulation will also simulate variation in our Loss Given Default (LGD).

Loss Given Default (LGD) for the sake of this simulation will be normally distributed and the data set would reveal the mean and standard deviation.

Exposure at Default (EAD) will be the amount of the initial loan.

Given: ARIMA Projected Macroeconomic Indicators, our logistic regression model, Probability of Default (PD), Loss Given Default (LGD) (mean and standard deviation), Exposure at Default (EAD) (associated with each loan)

Use: Simulation (Monte Carlo), previous Logistic Regression Model

To: Simulate variation in our predicted economic indicators and credit variables to capture the possibility of different scenarios of economic conditions. Then multiply the simulated variation components to get each loan’s Expected Loss. The sum of each individual loan’s Expected Loss can be aggregated to get the portfolio’s total Expected Loss.

The simulation can be run 10,000 times over a timeline of 5 years into the future, updated monthly.

The output of the Monte Carlo will provide to us a distribution for the portfolio’s Expected Loss based on probability.

The article makes mention that the Board of Directors will provide us with a risk threshold represented as a dollar amount. Let’s say for example the Board wants the risk to be no more than $1,000,000 in the next year.

We can then take that dollar amount and compare it to the distribution from the Monte Carlo simulation and figure out in what percentage of simulations the Expected Loss was above that value.

All in all, this simulation could give us better insight as to the risk of the portfolio. For example, the Monte Carlo simulation may reveal to us that there is a 1% chance that the Expected Loss is greater than $1,000,000 in the next year given our current portfolio.

Bibliography

https://www.sas.com/en_us/customers/wescom-credit-union.html