ECO353 Final Paper: Transparent Credit Risk Modeling

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Abstract

The ability to accurately evaluate companies is critical for making informed investment decisions, which then have far-reaching implications for a nation's economic progress. One of the most vital aspects of this assessment is gauging an entity's creditworthiness, in order to inform the investment decision of extending capital. Credit Rating Agencies (CRAs) play a crucial role in this process, providing grade ratings that are intended to be indicative of default probability. However, despite regulatory reforms in the aftermath of financial crises, the existing rating models and how they function remain obscured and unknown. Our research seeks to address this problem by constructing a transparent and interpretable credit rating model that produces comparable or superior predictions to the existing models. Towards this goal, we construct a predictive model that estimates a company's probability of default, and then translate these probabilities to align with the rating schematics of the CRAs. We then compare the results and find that our model performs just as well as the CRA models, with the primary benefit and advantage of having full transparency in the credit rating derivation process.

Introduction

Initially focusing on rating municipal and railroad bonds, CRAs have since evolved into respected institutions that assess corporate bonds, structured finance products, and sovereign debt. The ratings published by the CRAs are widely used by investors and financial institutions, with agencies having considerable influence over financial markets by shaping investor beliefs and influencing capital flows. For example, research has shown that a country's credit rating is significantly related to the level of capital investment that the country receives.[1] Intuitively, investors are more inclined to invest in and lend money to companies, or countries, that they believe to be capable of meeting their financial obligations. Credit Ratings thus act as a valuable indicator to inform investment decisions, providing critical information that may otherwise not be easily attainable. Effectively, Ratings published by CRAs serve to alleviate the issue of asymmetric information in capital markets by providing standardized assessments of credit risk, and thereby enhancing market efficiency by promoting informed decision making. Challenges from asymmetric information lead to market distortions and suboptimal outcomes, and CRAs mitigate these challenges by providing vital information. Credit ratings also facilitate price discovery in financial markets by influencing the pricing of debt securities, with empirical studies documenting the impact of credit rating changes on bond yields that highlights the role of CRAs in shaping market outcomes.[2]

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[1] De. et. al., 2020
[2] Gonzalez et. al., 2004

Although we can imagine the ideal, CRAs have been widely criticized on issues relating to the reliability and integrity of their ratings, as well as their possible anti-competitiveness practices. The modern credit rating industry consists of three dominant agencies; Standard & Poor's, Moody's Investor Services, and Fitch Ratings. This concentration of power is a cause of concern when we consider the critical role that these agencies fulfill, where 'consensus' ratings have the potential to be skewed and non-representative. For example, many agree that these CRAs failures were at the center of the 2007-2008 financial crisis as a result of conflicts of interests and inaccurate ratings published that ultimately misinformed investors. As experienced, inaccurate or biased ratings can distort market perceptions and contribute to asset bubbles. The accuracy and reliability of credit ratings are crucial for maintaining financial stability and mitigating systemic risks, as demonstrated by the swift regulatory responses in the aftermath of the financial crisis. Although regulatory reforms such as the Dodd-Frank Act have been implemented to enhance transparency, accountability, and competition within the credit rating industry, research has shown that these reforms have failed to respond to the shortcomings of CRAs[3]. As we agree, one of the major inadequacies of CRAs is the lack of transparency in the credit ratings they publish. Rousseau has similarly suggested that CRAs lack accountability towards market participants, arguing that a disclosure-based approach would be effective in guiding regulatory policy.[4]

Given their critical role in the financial system and their influence on economic outcomes, it is useful to understand how CRAs have arrived at their published assessments of credit ratings. Essentially, these credit ratings reflect the probability that an entity will default, with letter grades indicating the respective probabilities. Generally, their predictions are based on publicly-available financial data, industry trends, and qualitative factors. However, there remains considerable mystery behind the mechanics behind their models, with researchers having argued for a more transparent approach.

Our research aims to construct a transparent and interpretable model for assigning credit ratings. Specifically, we predict a company's probability of default and then translate these probabilities to the grade rating schematics of CRAs in order to make our comparisons. As an added result, we also estimate the relationships between a company's financial metrics and their creditworthiness. Ultimately however, we seek to produce similar or better predictions than the existing models, but with the primary benefit and advantage of full transparency in deriving these ratings.

[3] Partnoy, 2017
[4] Rousseau, 2005

Literature Review

The importance and impact of credit ratings has been well-documented and studied. (Gonzalez et. al., 2004) discuss the expanding use of credit ratings and the economic rationale for using them. Specifically, they argue that CRAs provide information economies of scale and contribute to solving principal-agent problems like asymmetric information. Moreover, they emphasize that the interest in credit rating services has significantly increased over the recent decades, alongside the influence of CRAs on securities markets; ratings now function as benchmarks and creditworthiness standards, and have become ubiquitous in financial markets. In studying the market dynamics associated with credit ratings, (Gonzalez et. al., 2004) examine the relationship between bond yields and ratings, confirming that bond ratings changes do cause price changes of bonds as well as stock returns. These findings further emphasize the influence that CRAs have over shaping market outcomes.

Similarly, De. et al. (2020) examine the influence of sovereign credit ratings on private capital flows, finding that a nation's credit rating is considerably related to the level of private investment they receive. Intuitively, investors are more willing to extend capital to entities with greater creditworthiness, with the understanding that their investments are relatively less risky given the ability of the borrower to meet their financial obligations. However, such findings highlight the importance of accurate and reliable credit ratings, and the impact of ratings on the larger economy. Countries with positive ratings are thus more likely to experience greater economic growth as investors become more willing to extend capital, but the quality of these ratings are significant towards determining where the most efficient use of capital investments are.

Given the considerable influence of CRAs, it is useful to gain a clear understanding of their operations and results. In the aftermath of financial crises, regulatory reforms have been implemented with the aim of increasing transparency and accountability within the credit rating industry. However, (Partnoy, 2017) found that these regulatory changes have had little or no impact on the overall functionality of CRAs; arguing that "the same credit rating-related dangers, market distortions, and inefficient allocations of capital that led to the 2007-08 global financial crisis potentially remain today" (Partnoy, 2017). Along the same lines, (Rousseau, 2005) claims that CRAs still lack accountability towards market participants, suggesting that a disclosure-based approach would be more effective in guiding regulatory policy. Furthermore, she highlights the issue of reliability in ratings, given the concentrated market power in the credit rating industry. As she argues, a disclosure-based approach related to the CRAs methods of analysis can be useful policy guidance towards increasing the reliability and accountability of CRAs.

Two studies by Kammoun et al. (2015) and Whalen (2016) emphasize that the underlying issue with credit rating agencies is the moral hazard of the *"Issuer-Pays"* model. This model refers to the conflict of interest that arises from the primary customers of credit agencies, financial firms, also issue credit that the agencies are responsible for rating. The dynamics of this market create an imbalance of power where the customer maintains excessive purchasing power, where financial firms can *rate shop* for whichever CRA offers the most advantageous rating. Ultimately, the accuracy of credit ratings becomes compromised to protect the top line of CRAs.

The evaluation and management of credit risk remain paramount concerns for financial institutions, as evidenced by three distinct yet interconnected scholarly papers. The first paper delves into the application of accounting data in long-term credit management, scrutinizing the utility of financial ratios for predicting corporate bond ratings. It challenges the efficacy of such ratios, advocating for their transformation through multivariate analysis to enhance accuracy and address the criticisms commonly associated with financial accounting data. Jayadev (2006)

Moving from the critique of traditional accounting practices, the second paper introduces the application of Rough Set Theory (RST) complemented by Genetic Algorithms (GA) to navigate the often flawed real-life data characterized by redundancies and inconsistencies. This innovative approach not only refines the forecasting models but also expedites computation processes, ultimately benefiting decision-makers through simplified, logical knowledge representations derived from the data. The practicality of this method is demonstrated through its application to a Taiwanese credit rating dataset, yielding impressive results that signify a leap in forecasting performance. Lee & Lin (2014)

They then extend the discussion by assessing three default prediction models: the market-based KMV model, the Z-score model employing discriminant analysis, and the logit model. This study broadens the predictive scope beyond financial ratios to include an array of factors like macroeconomic indicators, corporate governance, and firm-specific variables, leading to a nuanced understanding of default risk. It underscores the dichotomy between accounting-based and market-based models, recognizing the forward-looking insights provided by the former and the comprehensive data analysis facilitated by the latter. Moreover, it brings to light the critical role of financial disclosures in identifying default risk and curbing "creative accounting" practices. (Horrigan, 1966)

Methodology

The development of econometric models for predicting a company's credit rating incorporates external financial variables that significantly impact their creditworthiness and ability to meet future financial obligations. Publicly available data for most publicly traded companies can be found in databases like Bloomberg, which also provides ratings from major credit rating agencies (CRAs).

The variables utilized in these models vary and include:

- Company Size Variables: These include total sales revenue, short-term and long-term debt, net income, total assets, and non-current assets.
- Economic Activity Variables: Variables such as net profits, inventories, cash, and short-term investments.
- Financial Metrics: This includes PBITDA, PBIT, return on assets (ROA), return on equity (ROE), earnings per share (EPS), cash flow from operations (CFO), funds from operations (FFO), net interest expenses, total equity, cash flow from ordinary operations, total capital expenditures, returns to shareholders, and various operating expenses.
- Market Variables: These encompass current market capitalization, interest paid relative to total expenses, or sales.
- Leverage and Liquidity Data: This includes ratios like cash flow to total debt or total assets, short-term and long-term debt ratios, liquidity ratios, sales growth, and stock market capitalization.

Prominent researchers like Jayadev (2006) suggest employing financial ratios as external causal variables. Historically, the most indicative variable of a company's rating has been its size, as measured by total equity and other size metrics as noted by various studies (Horrigan, 1966; Maher & Sen, 1997; Huang et al., 2004). These studies have linked larger company size with a greater ability to manage financial downturns, suggesting a higher credit rating.

Activity-related variables often focus on the speed and efficiency of a company's operations, such as sales ratios or growth rates, and indicate how effectively ongoing projects can fund commitments. Financial structure is commonly examined through ratios of debt to total assets or equity, and liquidity ratios that analyze current assets against liabilities or as a proportion of total capital or assets. Advanced methods like genetic algorithms and double ensemble methods have also been explored for rating predictions by researchers like Lee & Lin (2014). The analysis of liquidity ratios is crucial as it provides insights into a company's immediate financial health and its structure of financing.

Profitability measures over specific time frames are also vital, assessing efficiency through income statement items or investment returns. The volatility of a company's stock prices, as discussed by researchers like Kaplan & Urwitz (1979) and Maher & Sen (1997), serves to gauge market uncertainty reflected in the company's stock prices, although this might also capture effects beyond credit quality due to broader capital market fluctuations.

Overview of Companies' Credit Ratings

Standard & Poor's (S&P) employ a systematic classification of credit ratings, which correlates with the estimated probability of a company defaulting on its debt obligations. These classifications are generally aligned and are represented by a series of letters and numbers, detailed in Table 1 alongside their respective default probabilities.

S&P categorizes prime rates into ten levels (ranging from AAA to BBB), matched by Moody's ratings from AAA to Baa. For non-prime ratings, S&P identifies 13 categories (from BB to D), whereas Moody's distinguishes 11 categories (from Ba to C, with an additional category – or Ca, corresponding to S&P's D); Fitch also uses 11 ratings. These classifications pertain to long-term assessments, with separate classifications for short-term evaluations. Additionally, ratings may include a plus or minus sign to indicate potential future adjustments. Each rating agency employs its unique methodology, using publicly available financial data and qualitative data that consider business strategies and industry changes.

This study utilizes historical annual financial data, which are publicly accessible for each company. These data, combined with the calculated ratings from S&P are used to develop models to predict actual ratings. The models' results closely align with the final ratings issued by these agencies.

The study incorporates several well-established financial ratios derived from selected financial variables (measured in millions of euros), including sales revenues, working capital / total assets , retained earnings / total assets, interest expenses, net income , total assets , non-current assets, inventories, cash and short-term investments , short- and long-term debt, total equity, cash flow from operation, capital expenditures , dividends paid , and current market capitalization . From these, key economic-financial ratios are calculated, such as the EBITDA margin over sales), EBIT margin , and others. These ratios are valuable for forecasting ratings, although it has been observed that the original variables often provide more useful insights.

The objective is to predict the companies' ratings as assessed by the CRAs: S&P rating (Y1). These ratings are ordinal, although the rating companies initially compute them numerically before categorizing them within defined intervals. In their final assessments, apart from economic-financial data, CRAs also consider other types of information including opinions and rumors, and notably, the previous valuation level, which sometimes leads to unexpected outcomes.

Data Samples for Credit Rating Analysis

Two random samples were selected from the Bloomberg and Keggle financial database, encompassing companies across various sectors. The first sample consists of 1,324 companies, with data from fiscal year 2014. The second sample comprises 1,094 firms with data spanning five years, from 2010 to 2014. These selections were made post the 2008 financial crisis to ensure the impacts were considered, samples include the companies' S&P ratings.

The distribution of ratings within these samples typically ranges from A+ to BB+, indicating recommended investment grades. Companies rated BB or below are considered non-prime but are still included in the sample. Fewer companies are found in the C and D categories due to their higher failure rates, while higher rating categories contain fewer companies, reflecting a distribution that mirrors the broader market assessed by the rating agencies.

To begin with, the S&P ratings, spanning across 20 categories from AAA (or Aaa) to D (or Ca), will serve as the dependent variable in both the Artificial Neural Network (ANN) and Ridge Regression models (RRM). Consolidating the rating categories tends to enhance the models' predictive accuracy by reducing the complexity of the classification task. With fewer distinct categories, the models can focus on capturing broader patterns and trends in the data, rather than getting bogged down by the nuances of individual rating levels. This simplification helps mitigate the risk of overfitting and improves the generalization ability of the models, ultimately resulting in more robust predictions.

The data includes both economic-financial variables (X) and derived ratios (R), detailed in subsequent tables with basic descriptive statistics. Previous studies often prioritize financial ratios; however, in our ANN model and RRM model, these ratios become less relevant when the X variables are included directly.

Our models aim to forecast a full spectrum of ratings, differing from previous models that simplified ratings into fewer categories. Initially grouping the ratings into two categories—stable and speculative—shows that 57.9% of companies are rated BBB- or higher, while 42.1% fall into speculative (non-prime) categories. This distribution is detailed further in Table 6.

Individual analysis of the X variables indicates none can serve as a definitive benchmark for rating predictions. Sector-specific behaviors vary; for instance, the EBITDA performance in the utilities sector contrasts with other sectors. Similarly, the behavior of interest expenses and net income varies, with no direct correlation to ratings observable across different sectors. Other financial indicators such as total assets, non-current assets, inventory levels, and short- and long-term debt also show inconsistent relationships with credit ratings. Even cash flow and market capitalization do not consistently correlate with ratings.

Similar patterns are observed in the second sample, confirming that no single variable distinctly correlates with ratings when analyzed independently. Furthermore, temporal analysis of these variables does not reveal a straightforward relationship with ratings, underscoring the necessity for multivariate analytical methods to effectively predict credit ratings using comprehensive financial data from each firm.

Models for Predicting Company Ratings

In this study the modeling approach for company ratings in both data samples begins with Artificial Neural Network (ANN) techniques. ANNs, modeled after the human brain's structure, consist of interconnected nodes organized in layers. These networks excel in capturing complex, non-linear relationships among variables, making them particularly suitable for predicting the comprehensive, non-aggregated ratings of companies.The study then uses Ridge Regression Model (RRM), a variant of linear regression, incorporates a penalty term for large coefficients, making it adept at handling multicollinearity and overfitting. This method provides a robust solution in scenarios where predictors are correlated.While other multivariate statistical methods, such as multinomial logistic models or discriminant analysis, are available, their efficacy is limited in this context. These methods struggle to handle non-linear relationships among variables, which are common in the assessment of company ratings. Therefore, starting with ANN techniques and complementing them with RRM

The first basic model that is created by incorporating the basic bankruptcy prediction model that is based on Edward I. Altman's seminal work involving the Z-score formula. Altman's method ((Altman)) assess the financial health and bankruptcy risk of companies through a set of five financial ratios. The first ratio, working capital to total assets (X1), assesses liquidity and short-term financial stability. The second, retained earnings to total assets (X2), reflects the company's age and the extent of reinvested earnings. The third, earnings before interest and taxes to total assets (X3), measures profitability independent of tax and interest obligations. The fourth, market value of equity to total liabilities (X4), contrasts the market's valuation of the company's equity with its liabilities, serving as an indicator of financial leverage and potential distress. Lastly, sales to total assets (X5) gauges asset efficiency and turnover. Together, these ratios form the Z-score, which categorizes firms into those at high risk of bankruptcy, those for which the risk is indeterminate, and those at low risk, thus providing a quantitative measure of financial distress likelihood.

Then the amended model, a Ridge Regression Model, was constructed based on the principles of Altman's Model. To enhance the model's predictive capability, additional variables were incorporated based on incorporating additional variables in the data set. Subsequently, an Akaike Information Criterion (AIC) selection process was conducted to streamline the model by selecting the most statistically significant variables from the financial data.The model underwent further refinement using a dilute function, which likely served to adjust or mitigate the influence of certain variables, ensuring the model's robustness and improving its predictive accuracy. After this step, the Amended Model was finalized using the GLM Net approach. In the final stages of the methodology, the model was employed to identify the probability of default of external companies, indicating its practical application in assessing credit risk. Furthermore, the model outcomes, specifically the mapped probabilities, were juxtaposed with actual credit ratings to identify any discrepancies, which could signal potential over- or underestimation of financial risk by current credit rating mechanisms. This comprehensive approach signifies a diligent and multi-phased effort to develop a refined statistical model for financial prediction.

The Artificial Neural Network employed in this study adopts a Multilayer Perceptron (MLP) architecture comprising 64 inputs, 32 hidden neurons, and 1 output, with the hyperbolic tangent activation function. Among the 787 valid cases, 537 were allocated for training, while 250 were earmarked for validation purposes. Remarkably, the network exhibits commendable predictive accuracy, achieving a 97% correct classification rate for precise ratings. Moreover, its performance further excels when accounting for adjacent rating categories, underscoring its robustness and efficacy in rating estimation.

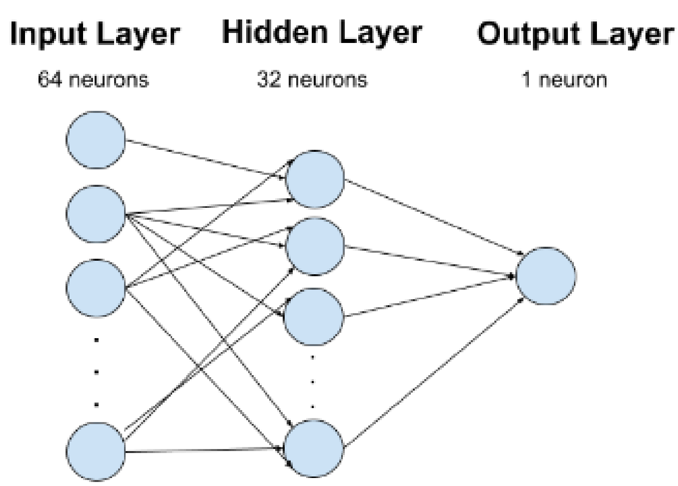


Figure 1: The architecture behind the neural network. Composed of 64 neurons in the input layers, 32 neurons in the hidden layer, and 1 neuron with the credit rating in the output layer.

Performance of the Prediction Models

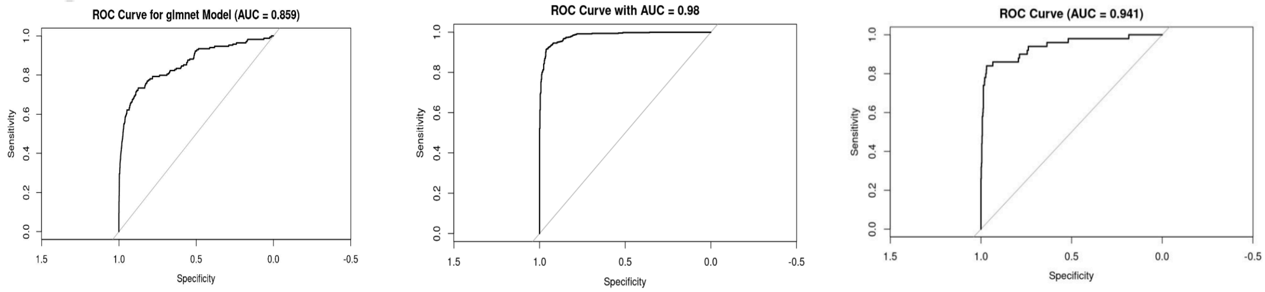
For dynamic rating predictions, we utilized Sample II, which allows for the analysis of a more comprehensive data set spanning from 2010 to 2014. The Basic Model demonstrates a pronounced capacity for the identification of true positives, as evidenced by its sensitivity value of 0.9978. This characteristic suggests a robust model performance in the accurate classification of instances that are indeed subject to the event of interest—in this case, company defaults. However, this model exhibits a notably deficient specificity measure of 0.0710, indicating a propensity for the misclassification of negative instances as positive (i.e., a high rate of false positives). While the model achieves an accuracy rate of 0.93, this figure must be interpreted with caution. Accuracy, as a standalone metric, may not reliably represent model efficacy, particularly in scenarios characterized by class imbalances. The Basic Model's ROC Curve, with an AUC of 0.859, falls within the acceptable range but does not reach the threshold of excellence.

Conversely, the Amended Model shows a marginally superior sensitivity (0.9992) and a substantial enhancement in specificity (0.7805), indicating significant advancements in the model's ability to correctly identify true negatives. Such an improvement underscores the model's refined capability to discern non-defaulting entities, thus reducing the likelihood of false positive classifications. The accuracy metric for the Amended Model registers at 0.96, a reflection of the overall performance uplift. The ROC Curve corresponding to this model achieves an AUC of 0.941, a value that denotes an exceptional level of class separability, thus reinforcing the model's discriminative power.

The sophisticated architecture of the artificial neural network, comprising multiple layers with distinct configurations, significantly contributes to its predictive capabilities, which are quantitatively encapsulated in the Receiver Operating Characteristic (ROC) curve. The network boasts a remarkable Area Under the Curve (AUC) of 0.98, evidencing its nuanced discriminative power in classifying credit default risks. Within this architecture, Layer 1 initiates the model's processing with a weight matrix of shape (64, 74) and employs the ReLU activation function to introduce non-linearity. Subsequently, Layer 2 continues the transformation with a weight configuration of (32, 64), also utilizing the ReLU function for activation. The final stage, Layer 3, culminates the network's output with a weight matrix of shape (1, 32) and adopts a linear activation function, refining the network's output for predictive assessment.

The calibrated neural network demonstrates a high sensitivity value of 0.994, affirming its adeptness in accurately identifying true positive instances of default, and a specificity of 0.8989, underscoring its precision in negating false identifications of default. These characteristics, combined with an overall accuracy rate of 0.9899, delineate a robust classification framework across the rating continuum.

Graph 1 : ROC curve (1 Basic model) , (2nd artificial neural network) and (3rd amended model)



Results and Discussion

The results from the model revealed fascinating information. The model evaluated ten companies, five of which have gone bankrupt and five within the Standard and Poor's determination of the top 500 companies by market capitalization (i.e. S&P 500). In the figure below, the first five and last 5 refer to the former and later categorizations.

Company Name (Ticker)	S&P Rating	Our Model Rating
Silicon Valley Bank (SVB)	BBB	B
Loyalty Ventures Inc. (LYLT)	BB	CCC
Diamond Sports Group (SBGI*)	CCC	CC
Ascena Retail Group (ASNA)	CCC	CC
Sears Holdings Corps (SEE.HM)	CCC	CC
Apple Inc. (AAPL)	AA	AA
Microsoft Corp. (MSFT)	AAA	AA
Cardinal Health Inc. (CAH)	BBB	BB
Wells Fargo & Co. (WFC)	BBB	BBB
Netflix Inc. (NFLX)	BB	BB

*Parent company ticker, analysis was done on the financials of the subsidiary

Figure 2: The results of the model conducted on 10 companies; first 5 firms have declared bankruptcy and 5 are financially sound.

A primary focus point from the findings is the discrepancy between the model and S&P Global's ratings. Although the model was consistent with the S&P ratings of the five financially healthy companies, it determined a significantly harsher rating for the five companies that declared bankruptcy. By extension, this implies that the model rating was, in fact, more accurate than the S&P rating, particularly within more financially at-risk companies.

Firstly, the potential practice of rating inflation. Although the CRA industry faced stricter regulations following 2008, much of the modeling lacks transparency. Per Krämer and Güttler's analysis, neither S&P nor Moody's rating models were superior across all tests, which suggests the complexity of their models and inconsistencies between even two of the major agencies within the industry.[5]

Secondly, this model takes a purely quantitative approach to understanding risk. This implies that the model does not factor in any qualitative analysis, unlike CRAs that use them to supplement quantitative findings. This allows the model to act on numerical facts but implies that it will lack any further rationalization to the rating- removing the risk of bias at the cost of some level of accuracy.

Due to the black-box nature of these rating models employed by CRAs, it is more complex to understand the difference in findings precisely. However, the results and the historical evidence support that rating agencies favor giving higher ratings than lower ones.

Conclusion

Though vital, the credit rating industry has been under heavy scrutiny following the events of 2008. However, it is important to consider that the business model of credit agencies creates inherent moral hazard challenges. The issuer-pays model is built into the very essence of the industry, as rating agencies serve to rate credit that financial institutions issue. Furthermore, rating inflation and malpractice concerns have lingered since the financial crisis, and there is criticism of overly lenient regulatory efforts.

One method of addressing the moral hazard within the credit rating industry is by significantly increasing regulation. By creating firm requirements for model transparency and methodology disclosure, the black-box nature of credit ratings can be eradicated, and the agencies can be held accountable for their work. Furthermore, more severe judiciary consequences can disincentivize and lessen the risk of caving to moral hazard.

Kammoun and Louizi (2015) suggest reforming the entire credit rating industry. They suggest that one method to alleviate the current concerns can be through establishing publicly owned CRAs. The open nature of a social institution will eliminate profit-driven bias faced by firms. Another proposed method is to implement third-party mediation within the current system, with the idea being that an unbiased entity without any other agenda can help ensure that financial relationships with issuers do not influence the ratings.

All in all, the ethical issues within the credit risk industry continue to challenge the reliability of the credit risk agencies' work and ultimately jeopardize the welfare of society as a whole without prompt and sufficient intervention for transparency and strict regulation.

[5] Walter, Andre (2003)

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Appendix

Model Coefficients

Basic Model

```
Variable Name | Coefficient Value
--------------------------------
Constant      | -0.318762388
X1            | -0.001179271
X2            | 0.029383000
X3            | 0.374972000
X4            | -8.701390600
X5            | 0.005789567
```

Amended Model

```
Variable Name               | Coefficient Value
----------------------------------------------
Constant                    | -1.33132
Shareholders/Assets         | -6.05558
Borrowings/Assets           | 0.00217
PBDITA/Income               | 0.00789
CashProfit/Income           | -0.03995
PBDITA/Income               | 0.00789
CashProfit/Income           | -0.03995
PAT/NetWorth                | -0.03429
ContLiabilities/Assets      | 0.01291
PAT/NetWorth                | -0.03429
ContLiabilities/Assets      | 0.01291
ContLiabilities/NetWorth    | 0.00191
TotalCapital/Assets         | 0.11031
ContLiabilities/NetWorth    | 0.00191
TotalCapital/Assets         | 0.11031
X4                          | 0.00668
X5                          | -0.06379
X3                          | 0.00161
X1                          | 0.00668
X2                          | -0.06379
GDP Growth Rate             | 0.00161
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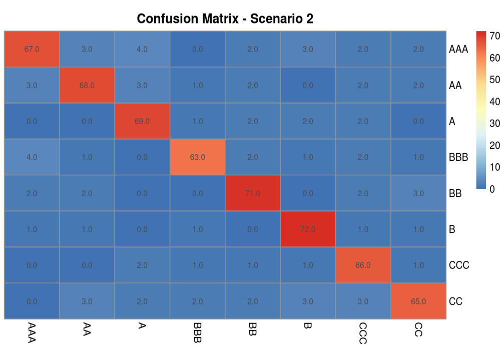
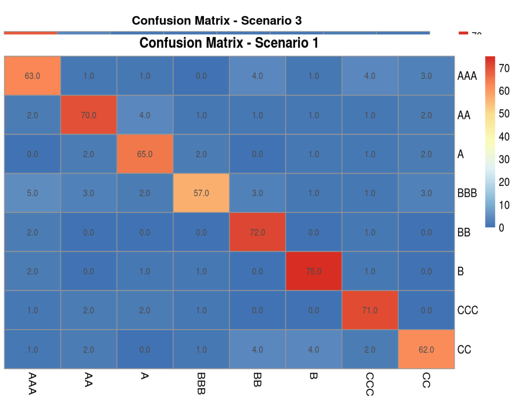
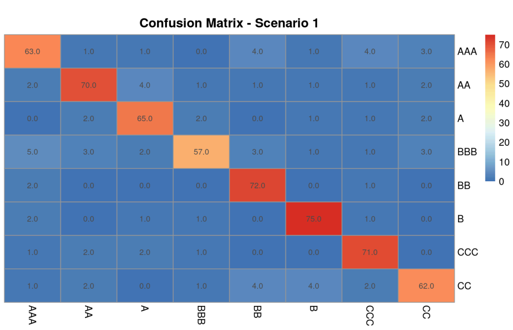


:*Amended model*



:*Artificial neural network*



: *Basic model*