TRADING & QUANTITATIVE RESEARCH REPORT

Predicting Credit Ratings

Credit Rating Forecasting in the Nordic Market Using Machine Learning

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OQAM

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Theory & Data

Introduction

For the past two years, the world has seen the steepest series of interest rate increases since 1980 (IMF, 2023). This has led to a shift from the era of very low-interest rates and has heightened the importance of discerning credit risks as businesses face increased debt servicing challenges. A stronger emphasis on corporate financial health makes corporate fundamentals and balance sheets more impactful. Thus, predicting credit ratings through data science has become a compelling field of study.

This paper explores the possibility of forecasting a company's future credit ratings using a machine learning algorithm. The algorithm is built on carefully selected publicly available financial metrics and one of the leading rating agencies, Moody’s, assessments. Such an analytical tool that gives a portfolio manager an accurate credit forecast on corporate bonds would lead to more informed decisions in managing and allocating risk.

Theory

Credit ratings measure a company's financial health and reflect its ability to meet financial obligations and repay debt. Assigned by credit rating agencies, these ratings can be given directly to entities and individual debt issuances like corporate bonds. When entities are looking to issue bonds, they can pay an agency to rate the entity itself or the issuance. The ratings help potential investors make informed decisions, and the ratings significantly influence the rate that the borrowing party has to pay (John, Lynch, & Puri, 2003).

An issuance may also choose not to publish or cancel its credit rating before it gets published (Moody's, 2016). However, this can lead to skepticism among investors and potentially limit a company's access to capital markets, as it may signal financial instability or concerns about the entity's creditworthiness in the long run. Openly disclosing a low credit rating, on the other hand, may be part of a larger strategy to renegotiate terms with lenders or attract new capital under specific conditions, indicating a recognized challenge the rated entity is willing to address.

Obtaining a credit rating can also be expensive, which leads to some smaller companies having infrequent or absent ratings. This has made it even more crucial for investors to make so-called "shadow ratings". Shadow ratings are private evaluations that are not officially released and are assigned by investors or other entities without access to companies' confidential data.

Credit rating agencies sometimes issue unsolicited ratings due to market interest in improving transparency and risk analysis or meeting regulatory requirements. Both unsolicited and shadow ratings from third parties rely on public data, such as the company's financial reports, to construct their assessments. (Moody's, 2021)

Definition & Scope

The project aimed to develop a credit rating forecast model for the Nordic markets using machine learning techniques. It was done in collaboration with and under the supervision of the quantitative asset management company OQAM. The goal of the model's performance was to find companies on the brink of being downgraded or upgraded or to find discrepancies between their assessed rating and their current market pricing. This project's asset universe encompasses public Nordic companies within the investment grade rating from Moody's.

The sensitivity of senior unsecured corporate bonds to credit rating changes and the resulting valuation impacts is the focus of this project. Unlike secured bonds, unsecured bonds do not have collateral backing. This means that although these bondholders have a privileged position in payout order, they are not tied to a specific asset on which other secured bondholders have a claim in case of a company default. In turn, this may lead to senior unsecured bond prices having a higher correlation with credit rating changes. (Jark, 2022)

Data

A comprehensive review was conducted of all Nordic companies that have received a long-term debt rating from Moody's from 1/1/2000 to 31/12/2023. Companies that only had affirmations as rating actions in this period were filtered out since the model is trained on rating changes. With this filter, 45 Nordic companies (Appendix I) were gathered from Moody's. Historical quarterly report data and stock data were downloaded from Bloomberg for each of the Nordic companies. 27 financial metrics from quarterly report data were selected based on Wallis M, Kumar K, and Gepp A's research, which identified these as key explanatory variables for a company's wealth and ability to pay long-term debt (2019).

Data & Method

Seven other metrics incorporated from the quarterly reports were chosen since they provide insights into the companies' operational efficiency, liquidity status, and market position. In addition to the financial report data, "Bloomberg 5-Year Default Probability" and "Bloomberg 1-Year Default Probability" were included as estimation features. In total, 34 quarterly metrics, two forward-looking Bloomberg (BBG) analytical estimates, and four index and stock-related metrics (Appendix I) were gathered.

One of the index metrics chosen for the model was three-month index volatility. Analyzing the impact of this metric on credit rating trends could show how market fluctuations influence an investor's behavior and an issuer's creditworthiness. Standard and Poor's Global Ratings (2022) analyzed the impact of increasing market volatility on credit trends, which suggests there could be an indirect effect. Underlying factors of market volatility, such as financing costs and inflation, may influence credit ratings through their impact on a company's financial health and financing ability. This could potentially lead to negative credit rating actions on corporate bonds. (S&P Global Ratings, 2022)

Hypothesis

The analysts hypothesize that it is possible to generate an accurate estimate of Moody's ratings on Nordic-rated entities and their outstanding long-term senior unsecured bonds. Crucially, one could predict a rating change before Moody's published an official rating action. Therefore, the time discrepancy between the model's forecasted rating change and the official rating assignment would allow a portfolio manager to generate excess returns by being more informed than other market participants.

Data Management

The quarterly report data was converted to a percentage difference of the trailing 12 months (TTM) compared to the same value last quarter. This was done in order to stabilize the data and reduce the noise observed when only looking at quarter-over-quarter (QoQ) changes. By disregarding QoQ noise and focusing on the percentage differences of TTM for each feature, the model can better identify the fundamental changes within the underlying company. Seasonal differences in the data can also be omitted using this methodology.

Some quarterly data had missing values, which had to be dealt with. If data was missing for a particular quarter, the missing data was replaced with the most recent quarterly data available. If a company had no data for a specific metric, the missing data was replaced with zeros, equivalent to no change between two TTM quarters. The stock data used was benchmarked against the respective country's main stock index. The indices used were OMXS30, OSEBX, OMXC20, and OMXH25. The relative performance over a 3-month period compared to the respective index was used as a feature. The 3-month volatility for stocks and stock indices was calculated and used as a feature as well. Some of the initially gathered metrics had a lot of missing data for most companies and were therefore not used in the model. Out of the 40 metrics obtained, 34 metrics were used in the final model.

The ratings from Moody's were mapped to the data closest to the previous quarterly report, see Figure 1. The motivation for this mapping is to look at what data Moody's had available when assessing the rating. Mapping the rating to the closest future quarter would remove the possibility of predicting and exploiting knowledge about an upcoming rating since the rating would have already occurred. The features from the last TTM were then grouped, and the mapped ratings were labeled as either an "Upgrade", "Affirmation", or "Downgrade" according to the rating agency's assigned rating. This resulted in 333 quarters with ratings divided into training and validation data (90%) and test data (10%). The data split was done with stratification to maintain the class distribution in both data sets.

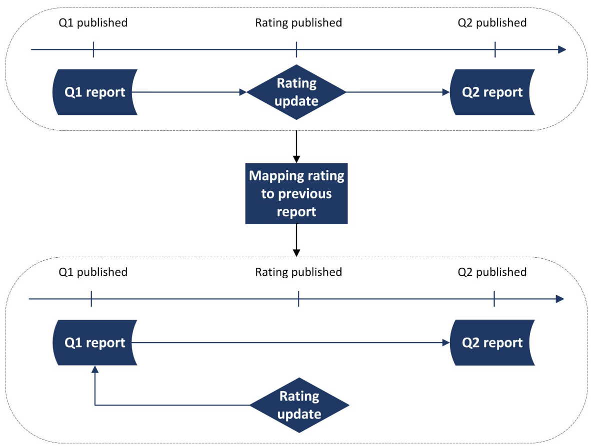

Figure 1: Mapping of rating update.

Method

Modelling

To make predictions on credit ratings, supervised machine learning was used. For this project, the model was trained on the quarterly metrics to predict a company's next credit rating update. Different machine learning algorithms were considered to make predictions on the rating changes. When choosing a model, it is crucial to consider the number of features available and the risk of overfitting. Since many features were available for each quarter, the analysts decided to use the Random Forest Classifier, a robust model that does not require much data preprocessing.

Random Forest utilizes a "bagging" technique (bootstrap aggregating) as illustrated in Figure 2. Bootstrapping means creating multiple subsets of the data set by randomly selecting samples, with replacements, from the original data set. A decision tree is trained on each subset of the data by using a random subset of features for each level in the tree. When each decision tree is trained, the random forest predicts by aggregating all decision trees. In this case, all decision trees are aggregated by majority voting from each decision tree's class prediction. While an individual decision tree might be overfitted due to using a bootstrapped data set and a random subset of features, the majority-voted prediction has reduced overfitting compared to using a single decision tree with the original data. The reason for this is that by introducing randomness and diversity among the decision trees, the trees become less correlated and more varied in the decision-making.

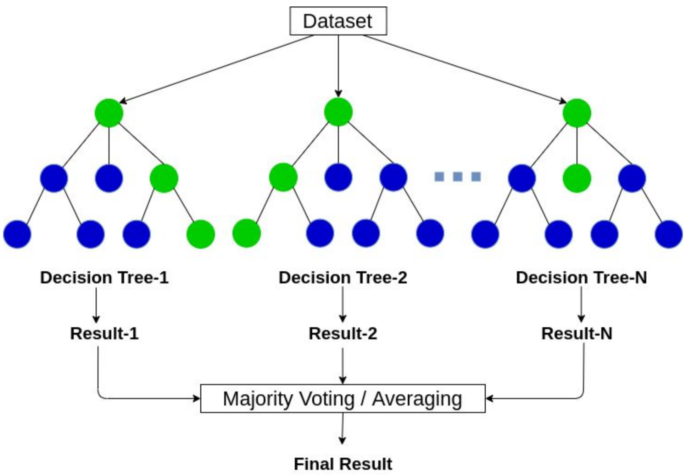

Figure 2: Random forest algorithm (Brital, 2021).

To train the model, Cross-validation was used with 5-fold cross-validation based on the 90% training and validation data, see Figure 3. Different combinations of the following hyperparameters were iteratively tested with the 5-fold cross-validation: max features, minimum samples split, and max depth. The combination with the highest accuracy on the cross-validation data was chosen. The test data was used as a final test to see the model's accuracy on unforeseen data.

A time series model was also implemented by training on all available data except for a specific company to test the potential of predicting credit ratings further. This model's test data consisted of all gathered quarterly data rather than just the quarters with ratings mapped to it. The idea was to create a time series of prediction probabilities to see if there was any trend among the prediction probabilities before a rating change. The specific company was chosen based on the number of rating changes in general and upgrades and downgrades in particular. This led to choosing SEB as the specific company.

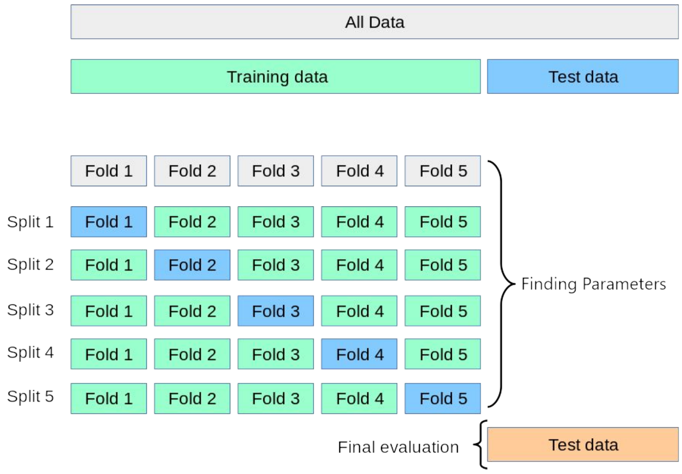

Figure 3: Cross-validation scheme (Pedregosa et al., 2011).

Results

Results

The classifier model had a prediction accuracy of 64.7% on the test data. Table 1, Table 2, and Figure 4 presents results based on the test data for the first model. Table 1 presents performance metrics for classification. Precision represents the ratio of true positive predictions to the total number of positive predictions made by the model, while recall signifies the ratio of true positive predictions to the total number of actual positive instances in the dataset. F1-score, being the harmonic mean of precision and recall, provides a balanced measure of a model's performance. Support denotes the actual count of instances for each class in the dataset.

Table 1: Prediction benchmarks on test data.

	Precision	Recall	F1-score	Support
"Downgrade"	0.500	0.167	0.250	6
"Affirmation"	0.656	0.955	0.778	22
"Upgrade"	0.000	0.000	0.000	6
Accuracy			0.647	34
Macro avg	0.385	0.374	0.343	34
Weighted avg	0.513	0.647	0.547	34

For a detailed examination of the model's predictions, refer to the confusion matrix depicted in Figure 4. Additionally, Table 2 illustrates the feature importance of each predictor variable in the model. Feature importance is determined by each feature's contribution to reducing impurity, thereby indicating their influence on the model's predictions. Features with higher importance are deemed more influential in driving the model's decisions.

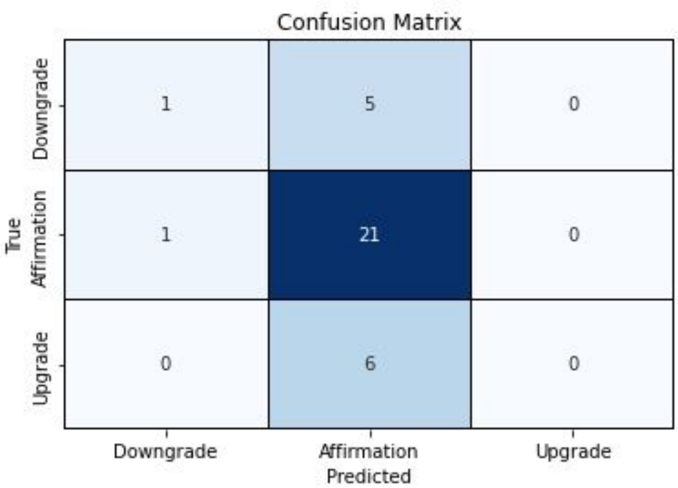

Figure 4: Confusion matrix of predictions on test data.

Table 2: Feature Importance of the 34 features used in the model, 2.94% is the neutral importance.

Feature	Importance (%)
Index Volatility 3 Months	4.16
Total Debt to EBIT	4.13
Return on Investment Capital	3.97
Retained Earnings to Total Asset	3.95
3 Month Performance vs Index	3.92
Long-term Debt to Total Asset	3.90
Sales to Total Asset	3.83
Bloomberg 5 Year Default Probability	3.69
Best Sales	3.52
Short-term debt	3.30
Relative 3 Month Performance	3.29
Cash to Total Asset	3.22
Total Debt to Total Equity	3.11
Number of Employees	3.03
Operating Margin	3.01
Operating Income to Net Sales	2.99
Common Equity to Total Capital	2.94
Total Liabilities to Total Liabilities and Equity	2.94
Cash Flow from Disposed Fixed Assets	2.91
Balance Sheet Total Assets	2.86
Common Equity to Total Asset	2.77
Pretax Margin	2.76
Return on Asset	2.75
Stock Volatility 3 Months	2.71
Bloomberg 1 Year Default Probability	2.64
Asset Turnover	2.63
Net Fixed Asset to Total Asset	2.58
Inventory to Sales	2.41
Inventory to Current Assets	2.06
Cash Ratio	1.80
Accounts Receivable to Sales	1.62
Current Asset to Total Asset	1.56
Current Ratio	1.55
Quick Ratio	1.51

Results & Analysis

Figure 5 presents the time series model's outcome applied to one of the companies studied SEB AB. The figure illustrates the forecasted probabilities of "Downgrade", "Upgrade," and "Affirmation", alongside Moody's rating.

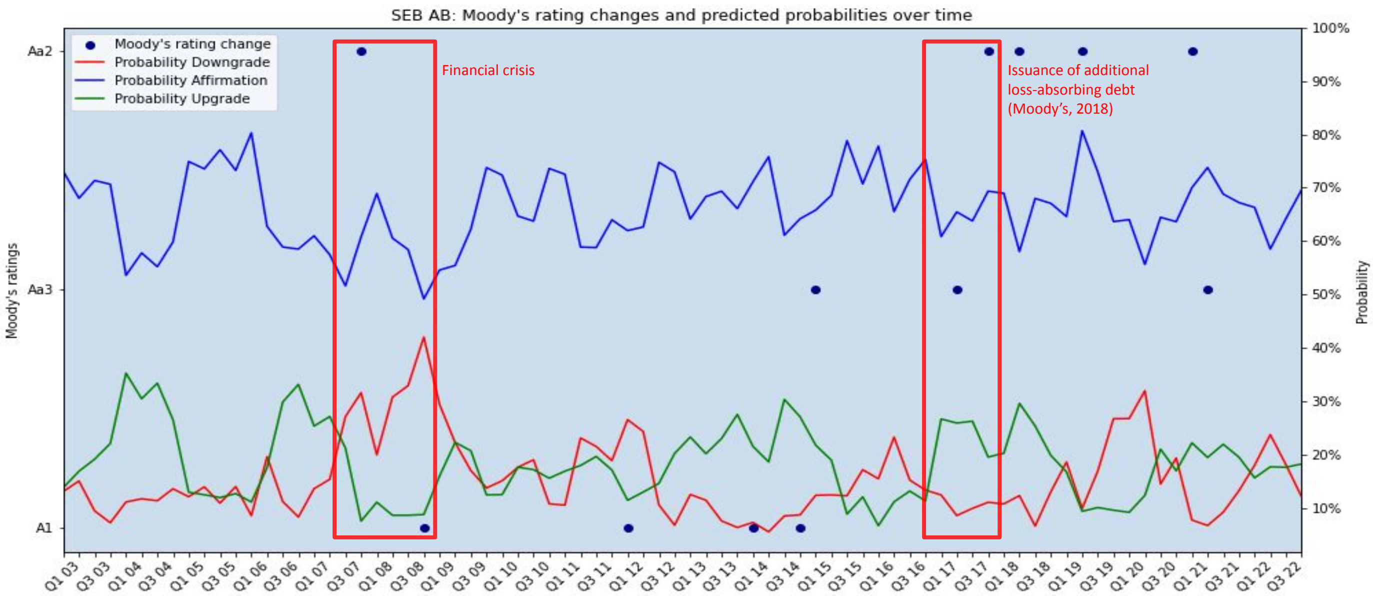

Figure 5: SEB AB rating change probabilities and actual rating changes from Moody's.

Analysis

Figure 4 illustrates that the model predominantly predicts "Affirmations". This bias stemmed from the training data, in which a considerable majority of feature vectors were classified as "Affirmations". For the "Affirmations" the precision, recall, and F1-score were high which indicates a low false positive rate, few missed instances of "Affirmations" and a robust performance respectively, see Table 1. The model only predicted one "Downgrade" correctly resulting in a low recall and F1-score. The "Upgrades" were all zero for the benchmarks meaning that the model did not classify any of the "Downgrades" or "Upgrades" correctly. The overall accuracy was 64.7% which in itself could be decent, but considering the low macro average of precision, recall and F1-score the model performance was poor. However, as seen in Figure 4, the model never predicted the opposite rating change, which can be considered a success.

In an effort to get more data points, an alternative model underwent testing. Instead of only mapping the ratings from Moody's to the previous quarterly report, the four following quarters after an official Moody's rating were also assigned the same rating. This procedure was done unless another official rating occurred within the four following quarters. The four following quarterly data was then compared with the quarterly data previous to the official rating instead of the most recent previous quarter.

The motivation behind this mapping is that the ratings of interest are long-term, i.e. more than a year and Moody's is monitoring all outstanding bonds they have rated (Moody's, 2016). Consequently, this approach yielded a substantially larger dataset of 1192 data points, in contrast to the current dataset comprising 333 data points. The results from the alternative model are included in Appendix II. This alternative model only predicted "Affirmation" on the test data and the overall accuracy was 58.8% which is lower than what the model included in the report achieved. The underperformance of the alternative model could indicate a reduced likelihood or incentive for Moody's to adjust ratings within a year following an update. However, further investigations with more data for both models is required to draw any final conclusions of which the best model is.

There is potential in the field of credit forecasting, and a well-crafted model with more data can be of use. When testing the model on the Swedish bank SEB the probability of downgrade increased before an actual downgrade and equivalent for actual upgrades, see Figure 5. The probability for affirmation is still superior but, using the increase in probability of downgrade and upgrade as indicators of rating change could be useful for a portfolio manager. As seen in Figure 5, the most significant surge in downgrade probability occurred in 2007-2008, coinciding with the onset of the global financial crisis. Being able to spot these trends before a crisis would be crucial for risk management.

Analysis & Conclusion

As with all machine learning models, the quantity of data is crucial. The model can never give more insight than the data it is trained on. The defined asset universe within the project inherently imposed a ceiling on the volume of data that the analysts could collect. There are only a certain number of Nordic companies that rating agencies rate and these companies only have a certain number of historical rating changes. As previously specified in the scope, all data for the relevant companies was gathered. Despite this, the dataset likely needs to be revised to create a more reliable model. For example, the train-test split was 90/10 to achieve a substantial amount of training data. However, given that only 333 data points were available, this results in a quite small set of data which makes the results susceptible to higher variability and potentially less generalizability. For this dataset, an 80/20 or 70/30 split would make the results more reliable.

One way to get more ratings data would be to include companies outside the Nordic that have ratings on Moody's in the model. This would, however, require an assumption that companies outside the Nordic are comparable with Nordic companies, which is not a trivial assumption to make. Another way to get more data points would be to include Nordic companies with ratings from another rating firm, e.g. S&P or Fitch, assuming that these ratings are comparable. While these ways would increase the data quantity, the quality must be taken into consideration. Making trades based on the wrong predictions increases the risk of the strategy.

It is important to also consider the quality of the features being used. In this project the features mostly consisted of quarterly metrics which can describe a company's well being, but it is also important to consider macroeconomic indicators. While all metrics similarly contributed to the model's performance, the four macroeconomic indicators performed well, and the most important feature was the three-month index volatility metric, see Table 2. This result supports the Standard and Poor's Global Ratings' emphasis on indirect changes in underlying economic or financial factors correlating with market volatility.

Although a large number of features can enhance the model, it's crucial to take into account the dimensionality. Random Forest, due to its 'bagging' technique, generally thrives with a substantial feature set, and adding more macro indicators could improve the performance of the model. Nonetheless, in this instance, the dimensionality is notably high, prompting consideration for feature selection or dimensionality reduction to enhance the model further. Combining dimensionality reduction with a more qualitative machine learning model for comparison would also be interesting.

Conclusion

The infrequency of Moody's ratings for Nordic public companies heavily limited the amount of training data the model could use. This caused the machine learning model to achieve relatively low overall accuracy with a high misclassification rate for downgrade and upgrade.

Notably, it consistently avoided misclassifying the opposite classification, e.g. classifying an "Upgrade" as a "Downgrade", emphasizing reliability and underscoring its potential for accurate predictions. Although the model's performance indicates the need for refinement and expansion of data sources, the fundamental premise of the hypothesis remains intact.

A further topic to explore is the correlation between credit ratings for international companies and ratings in the Nordics. If the correlation is high, it would open up the possibility of training the model using international quarterly and ratings data to achieve more accurate rating forecasts in the Nordic markets.

The transition from a low-interest era underscores the criticality of examining credit risk and delving into methodologies for forecasting credit ratings. Whether the aim is to anticipate ratings assigned by credit agencies or monitoring shifts in probabilities concerning upgrades and downgrades, the model's potential utility for portfolio managers in effectively allocating assets is evident.

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Appendix I - Companies and financial metrics

Table 3: List of Nordic companies with credit ratings.

Companies
A.P. Moller-Maersk A/S
AB SKF
AB Sagax
AB Volvo
Aker BP ASA
Castellum AB
Dometic Group AB
Elisa Corporation
Entra ASA
Equinor ASA
Fabege AB
Fortum Oyj
Investor AB
Kungsleden AB
Metsa Board Corporation
Nokia Oyj
Norsk Hydro ASA
SAS AB
TDC Holding A/S
Telefonaktiebolaget LM Ericsson
Telenor ASA
Telia Company AB
UPM-Kymmene
Vestas Wind Systems A/S
B2 Impact ASA
DLR Kredit A/S
DNB Bank ASA
Danske Bank A/S
Eika Boligkreditt AS
Intrum AB (publ)
Jyske Bank A/S
Nordea Bank AB
Nykredit Bank A/S
OP Corporate Bank plc
Ringkjobing Landbobank A/S
SBAB Bank AB (publ)
SR-Boligkreditt AS
Santander Consumer Bank AS
Skandinaviska Enskilda Banken AB
Spar Nord Bank A/S
Svenska Handelsbanken AB
Swedbank AB
Sydbank A/S
Sampo Plc
Storebrand ASA
Lansforsakringar Bank AB (publ)

Table 4: List of financial metrics.

Financial Metrics
Operating Margin
Pretax Margin
Return on Investment Capital
Return on Asset
Current Ratio
Quick Ratio
Current Asset to Total Asset
Operating Income to Net Sales
Retained Earnings to Total Asset
Accounts Receivable to Sales
Inventory to Sales
Sales to Total Asset
Net Fixed Asset to Total Asset
Long-term Debt to Total Asset
Total Liabilities to Total Liabilities and Equity
Number of Employees
Cash Flow from Disposed Fixed Assets
Best Sales
Balance Sheet Total Assets
Inventory to Current Assets
Total Debt to Total Equity
Cash Ratio
Cash to Total Asset
Asset Turnover
Common Equity to Total Capital
Common Equity to Total Asset
Total Debt to EBIT
Balance Sheet Short-term Borrowings
Interest Coverage Ratio*
Total Debt Weighted Average Maturity*
Unsecured Debt Weighted Average Maturity*
Real Estate Vacancy Rate Commercial*
Real Estate Vacancy Rate Residential*
Short-term debt*
Total Capital Expenditures*
Bloomberg 5 Year Default Probability**
Bloomberg 1 Year Default Probability**
3 Month Performance vs Index***
Relative 3 Month Performance***
Index Volatility 3 Months***
Stock Volatility 3 Months***

Metrics outside the scope of Kumar et al.
* Bloomberg metric
** Bloomberg estimate
*** Economic indicator

Appendix II - Results for alternative implementation

The alternative model had a prediction accuracy of 58.8% on the test data. Table 5, Table 6, and Figure 7 presents results based on the test data for the initial implementation. Table 1 presents performance metrics for classification. Figure 7 depicts a confusion matrix of the predictions. Table 6 lists the feature importance of each feature used in the model.

Table 5: Prediction benchmarks on test data.

	Precision	Recall	F1-score	Support
"Downgrade"	0.000	0.000	0.000	25
“Affirmation"	0.588	1.000	0.741	70
“Upgrade"	0.000	0.000	0.000	24
Accuracy			0.588	119
Macro avg	0.196	0.333	0.247	119
Weighted avg	0.346	0.588	0.436	199

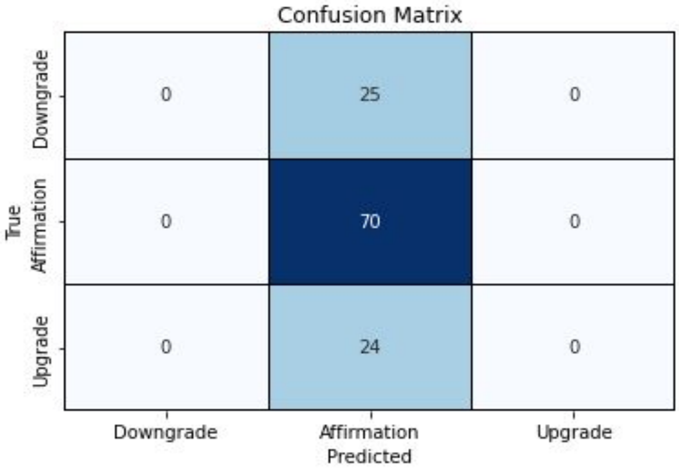

Figure 6: Confusion matrix of predictions on test data.

Table 6: Feature importance of the 34 features used in the model, 2.94% is the neutral importance.

Feature	Importance (%)
Index Volatility 3 Months	6.38
Relative 3 Month Performance	4.20
Number of Employees	4.14
Stock Volatility 3 Months	3.78
Total Liabilities to Total Liabilities and Equity	3.78
Asset Turnover	3.46
Retained Earnings to Total Asset	3.34
Short-term debt	3.22
3 Month Performance vs Index	3.21
Common Equity to Total Asset	3.19
Return on Investment Capital	3.17
Bloomberg 1 Year Default Probability	3.03
Total Debt to Total Equity	2.99
Operating Income to Net Sales	2.95
Net Fixed Asset to Total Asset	2.91
Return on Asset	2.91
Sales to Total Asset	2.89
Bloomberg 5 Year Default Probability	2.85
Long-term Debt to Total Asset	2.84
Best Sales	2.82
Operating Margin	2.81
Cash to Total Asset	2.71
Common Equity to Total Capital	2.66
Pretax Margin	2.66
Total Debt to EBIT	2.65
Balance Sheet Total Assets	2.59
Cash Ratio	2.49
Cash Flow from Disposed Fixed Assets	2.44
Current Ratio	2.38
Accounts Receivable to Sales	1.89
Inventory to Current Assets	1.80
Quick Ratio	1.71
Current Asset to Total Asset	1.64
Inventory to Sales	1.51

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