Textual Analysis and Financial Statements

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March 31, 2024

Introduction

Corporate credit ratings represent professional estimations of the default risk carried by company debt. These ratings represent critical information for investors - not just institutional investors and financially sophisticated bondholders, but also stockholders, who may be wiped out completely in the event of bankruptcy. Analyzing ways to predict ratings can offer substantial value to a variety of stakeholders. Predictive models may be useful for investors without access to data, companies or potential lenders that seek information about influential factors (there is evidence suggesting financial factors and projections have a causal impact on ratings and are not manipulated by companies in response to forecasted rating changes (He, 2018)), and by any parties seeking interpolated ratings for companies that do not have them.

In this project, we seek to fully leverage the text of earnings calls, along with traditional financial measures and variables, to improve predictions of corporate credit ratings for any given company and quarter and better understand the importance of various influences. Textual features such as pre-trained language model vector embeddings (Araci, 2019) and analyses of sentiment accompany tabular variables as inputs to a variety of supervised machine learning techniques for classification from logistic regression to tree-based methods. If time allows, we will also incorporate advances in the study of graph neural networks to create additional embeddings modelling linkages between firms (Das et al., 2023) implied by calls.

Though much literature has focused on financial statements and reports and credit ratings (as just one example, see Makwana et al. (2022)), our paper takes a relatively underexplored approach, instead incorporating earnings call transcripts. We believe calls offer a richer picture of a firm's financial prospects because they include two-way conversation between company management and financial analysts in form of a Q and A section. This section incorporates the broader beliefs and concerns of the financial community into our predictions. Additionally, in contrast to financial statements, which must be (noisily) parsed to identify sections relevant to management analysis, earnings calls provide more directly valuable and readily available information.

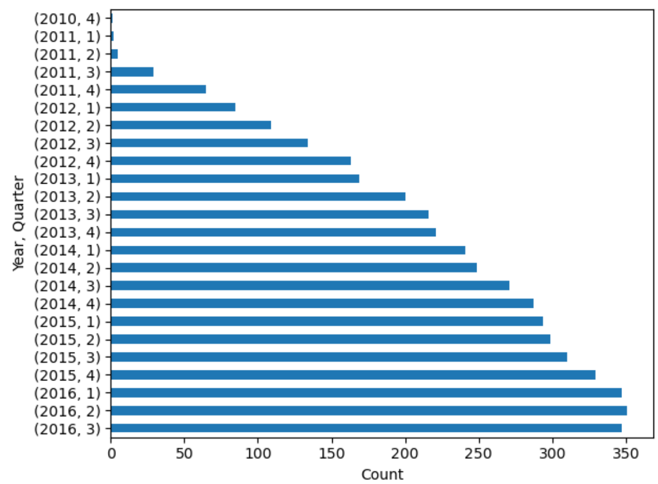
To the best of our knowledge, the closest prior work to ours is Donovan et al. (2021), which leverages the textual content of earnings calls and financial statements to predict credit events such as bankruptcies, interest spread changes, and rating downgrades using unigram and bigram frequencies and the supervised machine learning techniques of Support Vector Regression, Latent Dirichlet Allocation, and Random Forests. The coefficient on a constructed textual measure of credit risk was found to be significant up the 1% level. In contrast to this approach, we focus on predicting the credit ratings themselves, and integrate more techniques from machine learning such as the power of pre-trained language models and a wider variety of algorithms for classification.

Data and Exploratory Data Analysis

We combine a wide variety of data sources to support our predictions of credit ratings - merging rating data with company earnings calls, financial statement variables, and industry sector. In our final dataset, each observation represents a fixed quarter date (1/1, 4/1, 7/1, 10/1) for a company, with the company's most recent credit rating, earnings call and associated financial statement variables, and sector attached.

Our scope of interest is publicly traded companies from 2010-2016 (a limitation due to the availability of credit rating data). The data is temporally unbalanced, with many companies entering the dataset in later years, after they first receive an observable credit rating (Figure 1).

Figure 1: Observations by Quarter and Year



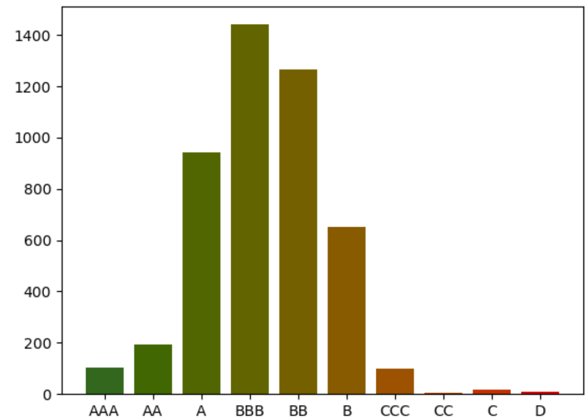
To ensure comparability, we drop items missing any predictor variable. In all, we have 4724 quarters for 387 unique companies.

Credit Ratings

We make use of long-term credit rating issuances from S and P Rating Services, provided from a combination of two credit rating datasets downloaded in CSV and Excel format from Kaggle (Gewerc, 2020; Makwana, Bhatt and Delwadia, 2022). Each issuance be a change in rating (upgrade, downgrade) or reaffirmation - they occur at ad-hoc intervals. We reshape these rating issuances to a dataset of ratings for each company on each fixed quarter date by creating a rating end date variable that is the date of the next issuance, and joining a list of the fixed quarter dates on the condition that the fixed quarter date is between the issuance date and the end date.

Figure 2 shows the distribution of rating grades used in our final dataset. Finer grades (+, -) are sometimes assigned by agencies, but these grades were removed for this project. Ratings of BBB and above are considered investment grade - these bonds carry empirical one-year default rates of 0 to 1%. Ratings below that are classified as junk, with default rates from 1 to 30, 40, or even 50% for some years (S and P Global Ratings, 2024). Most company-quarters have ratings around the BBB threshold, with very few cases on the extreme ends of the spectrum.

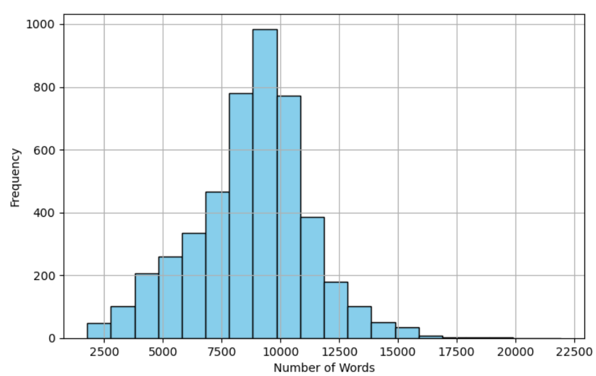
Figure 2: Credit Ratings



Earnings Calls

Our earnings call data comes from the Financial Modelling Prep API (Financial Modeling Prep, 2024), a trusted source widely used in industry. We remove all calls that happened more than 250 days prior and after the year and quarter they are supposed to discuss the results from. Including both prepared remarks and analyst Q and A sessions, the overall average call length in our final data stands at 8,776.18 words.

Figure 3: Number of Words in Earnings Calls



Financial Statements

Our financial statement variables are also retrieved using the Financial Modelling Prep API. We make use of items from company balance sheets, cash flow statements, and income statements, as well as company market capitalization. We include 124 variables in total, such as revenue, total liabilities, net income, EBITDA.

Drop cases where dates do not agree between not agree between tabular financial sources

Drop cases where filing date falls outside of fixed quarter

Drop cases hwere filing date more than 45 days after earnings call

To prepare the data, we limit our observations to items reported in USD, check for and correct items off by a factor of 1,000 as a result of parsing (if last few digits are 000.00 and the item is above or below 2.5% and 97.5% quantile, divide by 1,000), and check some accounting identities in Das et al. (2023), setting failing variables to missing.

In some of our models, we make use of Altman's Z-score, a traditional measure of bankruptcy risk (Altman, 1968). As in Das et al. (2023), the components of the Z-score are as follows:

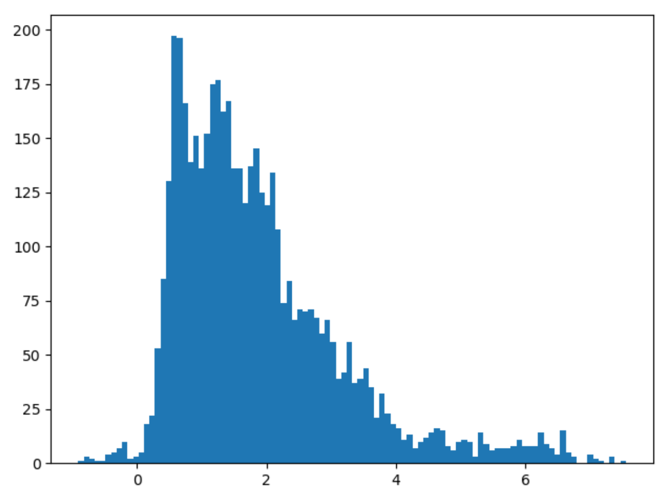
- A: EBIT / Total Assets
- B: Net Sales / Total Assets
- C: Market Capitalization / Total Liabilities
- D: Working Capital / Total Assets
- E: Retained Earnings / Total Assets

These are combined via the following equation:

$$\text{Z-Score} = 3.3A + 0.99B + 0.6C + 1.2D + 1.4E$$

We Winsorize extreme values of Ratio A, B, D, and E by setting the top and bottom 2.5% of values to the 97.5 and 2.5 percentile, respectively. Due to the presence of additional outliers and the sourcing of market capitalization from a different dataset than the rest of the variables, Ratio C is instead Winsorized over the top and bottom 5% of values. Figure 4 shows the distribution of adjusted Z-scores in our dataset. Though interpretations of the score vary, traditionally, values above 3.0 have been considered safe, while those below 1.8 are considered to have a high chance of bankruptcy. Though such an interpretation is potentially overly pessimistic for our data, we do have some companies on both ends of the spectrum.

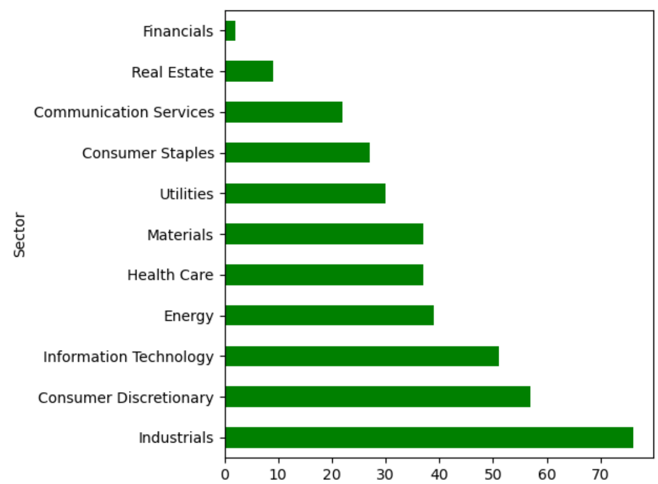
Figure 4: Altman Z-Score



Sector

The GCIS industry classification standard divides companies into 11 major industry sectors (there are finer groupings as well, but this data was not easily obtainable for our project) (S and P and MSCI, 2024). It is widely used in the financial community, and was developed in part by S and P, the same company responsible for our credit ratings. We obtained classifications from Kaggle in CSV format and supplemented them with manual lookup (Kozlov, 2022). Figure 5 shows the unfortunate sectoral imbalance present in our data, with a large share of firms in consumer, industrial, and technology sectors, relative to very few in the distinctly different financials and real estate sectors.

Figure 5: Firms by Sector



Quality Control

Our data preparation was subject to rigorous quality control standards. We extensively code reviewed all data cleaning code. Our exploratory analyses identified data quality issues such as extreme values in financial statement variables, which we handled by winsorizing, and date gaps between quarters, earnings calls, and financial statements, which we dropped in the case of aggregiously mismatched observations. We carefully removed companies that only provided annual reporting. We also removed all observations for Peabody Energy (ticker BTU), the only company in our dataset to declare bankruptcy (April 13, 2016) due to substantial concern about missing data leading up to the event.

NLP Features

In general, average call length in words appears to be positively correlated with credit rating, with the companies with the highest ratings having the longest calls, as shown in Figure 6.

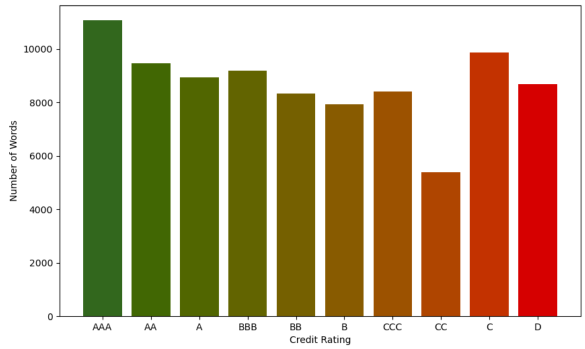
Things to Include

outliers and errors

correlations and patterns

identification of good machine learning methods

Figure 6: Average Call Length by Credit Rating



Modelling

Our overall model architecture is of the form

$$\text{Predicted Credit Rating} = f(\text{Financial Statement Variables}, \text{Sector}, \text{NLP Features})$$

Our first model is a simple logistic regression

XXX logistic regression predictors

multinomial, balanced class weights, l1 penalty

table of predictions

fitting and output

assumptions

interpretation

Next Steps

We've begun using the AutoML library Autogluon to explore a wider variety of classifiers. Autogluon runs a wide variety of state-of-the-art prediction algorithms and performs hyperparameter tuning. The results, shown in Table 1 can provide a good starting point for our further modelling choices.

Ensembling and Auto-ML

more classifiers

first steps using AutoML

a good starting point for diving deep on more algorithms

algorithms and accuracy from them

outputted feature importance

Graph Neural Network incorporating the relationships between companies, trained end-to-end with both tabular financial data and NLP features

Table 1: Autogluon Leaderboard

Model	Test Accuracy
ExtraTreesGini	0.929844
XGBoost	0.928731
CatBoost	0.928731
LightGBM	0.927617
LightGBMXT	0.927617
WeightedEnsembleL2	0.927617
LightGBMLarge	0.927617
RandomForestEntr	0.926503
ExtraTreesEntr	0.925390
RandomForestGini	0.925390
NeuralNetTorch	0.920935
NeuralNetFastAI	0.920935
KNeighborsUnif	0.250557
KNeighborsDist	0.247216

Fine tune the pre-trained LLMs for NLP feature construction

References

Altman, Edward I. 1968. "Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy." *The Journal of Finance*, 23(4): 589–609. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1540-6261.1968.tb00843.x.

Araci, Dogu. 2019. "FinBERT: Financial Sentiment Analysis with Pre-trained Language Models." arXiv:1908.10063 [cs].

Das, Sanjiv, Xin Huang, Soji Adeshina, Patrick Yang, and Leonardo Bachega. 2023. "Credit Risk Modeling with Graph Machine Learning." *INFORMS Journal on Data Science*, 2(2): 197–217. Publisher: INFORMS.

Donovan, John, Jared Jennings, Kevin Koharki, and Joshua Lee. 2021. "Measuring credit risk using qualitative disclosure." *Review of Accounting Studies*, 26(2): 815–863.

Financial Modeling Prep. 2024. "Financial Modeling Prep - FinancialModelingPrep."

Gewerc, Alan. 2020. "Corporate Credit Rating with Financial Ratios."

He, Guanming. 2018. "The Impact of Impending Credit Rating Changes on Management Earnings Forecasts." *Global Journal of Management and Business Research*, 18: 1–18.

Kozlov, Alex. 2022. "US public companies classification."

Makwana, Ravi, Dhruvil Bhatt, and Kirtan Delwadia. 2022. "Corporate Credit Rating."

Makwana, Ravi, Dhruvil Bhatt, Kirtan Delwadia, Agam Shah, and Bhaskar Chaudhury. 2022. "Understanding and Attaining an Investment Grade Rating in the Age of Explainable AI."

S and P, and MSCI. 2024. "GICS® - Global Industry Classification Standard."

S and P Global Ratings. 2024. "S and P Global Ratings."