Textual Analysis and Financial Statements

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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 individual 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,[1] 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.[2] Features capturing call readability, transparency, and engagement join classical and pre-trained language model representations of sentiment (Araci, 2019) and traditional tabular variables as inputs to a variety of supervised machine learning techniques for classification from logistic regression to tree-based methods. We also make use of advances in the study of graph neural networks to model linkages between firms (Das et al., 2023), in our case implied by mentions in calls.

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. Unigram and bigram word frequencies were used with 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 to the 1% level. In contrast to this approach, we focus on predicting the credit ratings themselves, and integrate more recent techniques such as neural language models and a wider variety of algorithms for classification.

Data and Exploratory Data Analysis

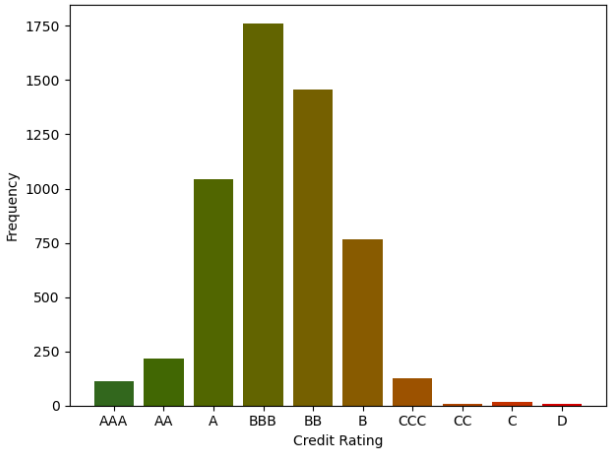
We combine a wide variety of data sources to support our predictions of credit ratings - merging rating data with company earnings calls, financial statement variables, and industry sector. In our combined dataset, each observation represents a fixed quarter date (1/1, 4/1, 7/1, 10/1) for a company,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

[1] 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).

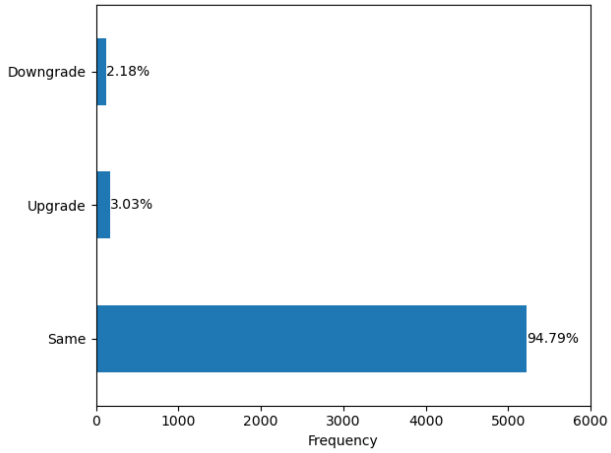
[2] Though much literature has focused on financial statements and reports and credit ratings (as just one example, see Makwana et al. (2022)), our paper takes a relatively underexplored approach, instead incorporating earnings call transcripts. We believe calls offer a richer picture of a firm's financial 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.

Figure 1: Credit Ratings

(a) Distribution



(b) Change Between Fixed Quarter Dates



credit rating, earnings call and associated financial statement variables, and sector attached. An example of many of the variables for a company by fixed quarter date can be found in Appendix Section A.1.

Our scope of interest is publicly traded companies from 2010-2016 (a limitation due to the availability of credit rating data) - the distribution of call year and quarters can be found in Appendix Figure A.2. We took many steps to remove or Winsorize errors and outliers - details of our data cleaning and filtering steps can be found in Appendix Section A.3. In all, we have 5,509 quarters for 429 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 can 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 or end of data, 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.

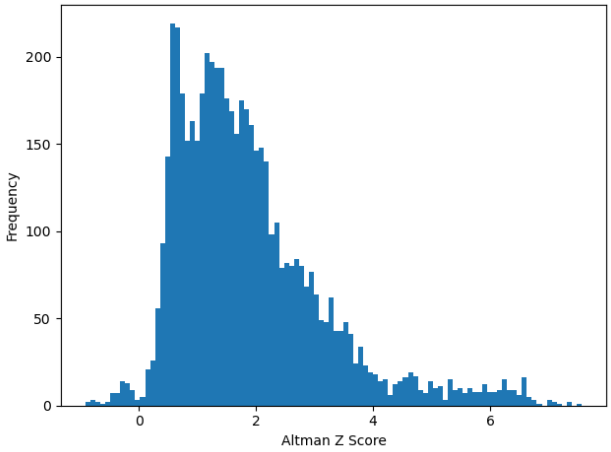
Figure 1 shows the distribution of rating grades used in our final dataset. Finer grades (AA+, CCC-, etc.) are sometimes assigned by agencies, but these grades were converted by dropping the +/- for this project. Ratings of BBB and above are considered investment grade - these bonds carry empirical one-year 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. Ratings also tend to be constant over time. Relative to the previous fixed quarter date, 94.79% of ratings remain the same. When available, rating on the previous fixed quarter date can thus be an extremely strong predictor.

Earnings Calls

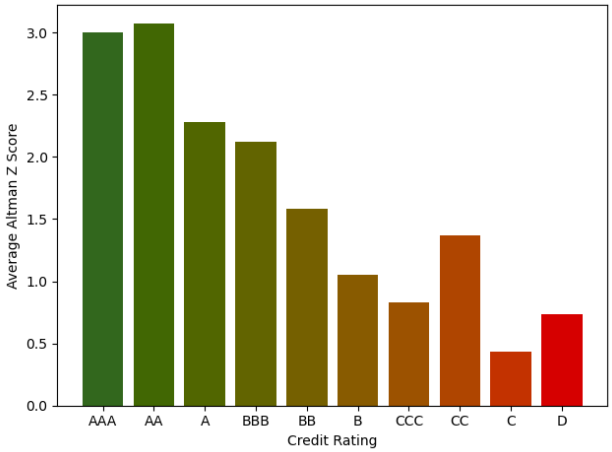
Our earnings call data comes from the Financial Modelling Prep API (Financial Modeling Prep, 2024), a trusted source widely used in industry. Including both prepared remarks and analyst Q and A sessions, the overall average call length in our final data stands at 8,759.68 words.

Figure 2: Altman Z-Score

(a) Distribution



(b) Average by Rating



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 also calculated and included a wide variety of ratios and combinations of levels of variables (for a list, see Appendix Section A.4).

In some of our models, we make use of Altman's Z-score (Altman, 1968), a traditional measure of bankruptcy risk that accounts for company earnings, equity, and assets and liabilities (for details on the construction of the score, see Appendix Section A.5). Figure 2 shows the distribution of Z-scores in our dataset. Traditionally, values above 3.0 have been considered safe, while those below 1.8 are considered to imply a high chance of bankruptcy. The average scores for each rating in our data seem to align well with this interpretation, with high scores being associated with higher ratings in a linear manner. Though our distribution of scores is skewed, with a long right tail, and though the relationship between ratings and average scores breaks down on the ends of the rating spectrum (where not many companies and ratings are available), Z-Score demonstrated potential as a predictor.

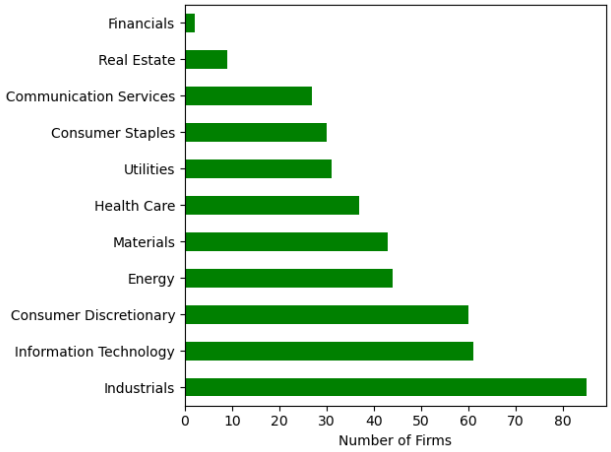
Sector

The GCIS industry classification standard divides companies into 11 major industry sectors (S and P and MSCI, 2024).[3] 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 (Kozlov, 2022) and supplemented them with manual lookup. Figure 3 shows the sectoral imbalance present in our data, with a large share of firms in consumer, industrial, and technology sectors. However, when we quantify ratings and compute average values by sector, we do not see large differences, suggesting our results still may provide some generalizability. Though it was not clear that sector alone provided enough useful variation in rating to be a useful predictor, we still included it in our models based on its potential to improve models including other controls or interactions.

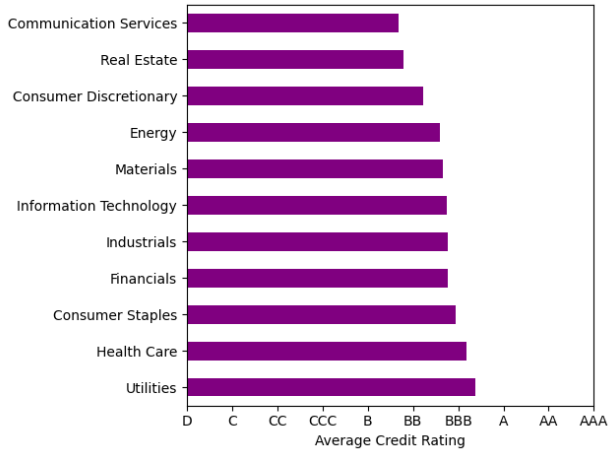
[3]There are finer groupings as well, but this data was not easily obtainable for our project.

Figure 3: Sector

(a) Firms by Sector



(b) Average Rating by Sector



NLP Features

We make use of techniques from Natural Language Processing (NLP) to create features to capture the transparency of discussion, level of engagement, and overall sentiment of calls.

- Numeric Transparency - Ratio of numbers to words in the word-tokenized call
- Readability - We construct the Gunning-Fog grade-level readability score (Gunning, 1952) as

$$0.4 \times \left(\frac{\text{Words}}{\text{Sentences}} + 100 \times \frac{\text{3+ Syllable Words}}{\text{Words}}\right)$$

- Word Count
- Normalized Number of Questions - Count of question marks, divided by call word count
- Tone - Following Price et al. (2012), we use the Harvard IV Psychosocial dictionary to count words falling in various categories (Positive, Negative, Active, Passive, etc.).[4] Then we construct tone using the first principal component of the matrix with each call as a row and each column as one of the following:

$$\frac{\text{Positive}}{\text{Negative}}, \frac{\text{Active}}{\text{Passive}}, \frac{\text{Strong}}{\text{Weak}}, \frac{\text{Overstated}}{\text{Understated}}$$

- FinBERT Positivity Score - We use FinBERT, a version of the transformer-model BERT finetuned for the financial domain to determine the tone (positive, negative, neutral) of sentences in each call.[5] (Huang, Wang and Yang, 2023) In line with Kantos et al. (2022), we then calculate a positivity score for the call as:

$$\text{FinBERT Positivity Score} = log_{10}\frac{\text{Count Positive} + 1}{\text{Count Negative} + 1}$$

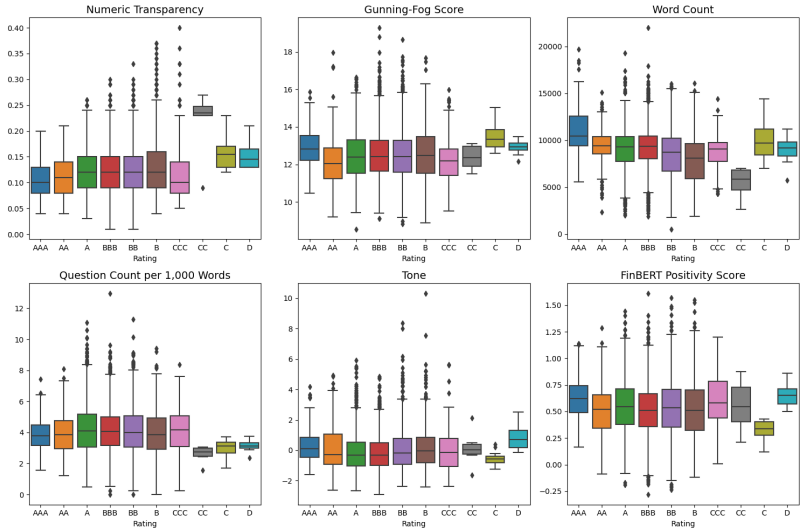
Examples for readability and tone can be found in Appendix Section A.6, and the distribution of each NLP feature by rating is shown in Figure 4 below. Lower quality companies seem to provide more numbers with less

[4] In addition to the tone feature described, we also incorporate these counts as individual features.

[5] We originally considered directly incorporating FinBERT embeddings into our models, or creating an end-to-end classifier making use of a BERT model. Our calls, however, are too long for readily available transformer embeddings or models to efficiently and effectively represent.

commentary. It appears to be the case that higher quality companies tend to have longer calls. Though somewhat noisy, our FinBERT positivity score does seem to correlate with higher ratings.

Figure 4: Distribution of NLP Features by Rating



Network of Firms

In addition to our standard NLP features, which already capture a rich representation, we also created a network graph representing the connections between firms based on mentions within calls. We deployed transformer-based named-entity recognition (spaCy, 2024) to identify company names in the text, then cleaned and matched these names to standardized versions.[6] An interactive visualization of our entire network of firms (aggregating mentions up from the call level - where we also have a network) can be found at https://sites.google.com/view/isaac-liu/company-mentions-network, and a 50% sample of nodes (faster load time) can be found at https://sites.google.com/view/isaac-liu/co-mentions-50-node-sample.

Modelling

Our overall model architecture is of the form

$$\text{Predicted Credit Rating} = f(\text{Altman's Z}, \text{Financial Variables}, \text{Sector}, \text{NLP Features})$$

We performed an 80-20 train-test split on our data (4,391 train, 1,118 test), and used 5-fold cross validation to select hyperparameters for the Logistic Regression and XGBoost models.

Logistic Regression

Table 1 shows prediction statistics for our initial set of classifiers - simple and interpretable logistic regression models aiming to predict ratings. In the main section of this paper, we do not include the rating on the previous

[6] Interestingly, we found that simple code to remove words such as "Company", "Inc.", etc. followed by an exact match ignoring case outperformed fuzzy matching algorithms such as Levenshtein distance and q-gram similarity.

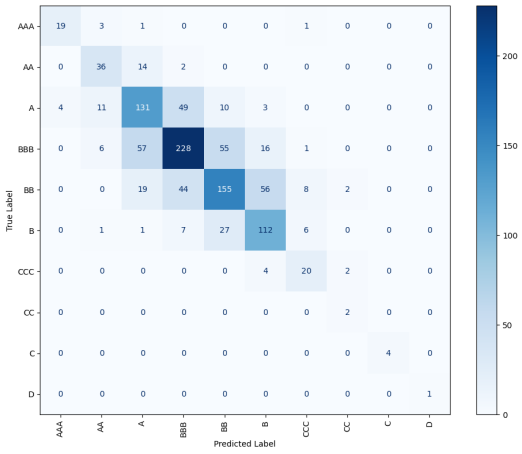
fixed quarter date (for those results, see Appendix Section A.7). For predicting changes in rating, see Appendix Section A.8.

Table 1: Logistic Regression Model Comparison

Model/Baseline	Accuracy	Share ≤ 1 Rating From Actual
Altman's Z	0.1923	0.4633
Financial Variables and Sector	0.6225	0.9186
Financial Variables, Sector, and NLP Features	0.6333	0.9267
Most Common Class Baseline	0.3247	

Altman's Z-Score alone performs poorly - worse than simply assuming each rating belonged to the most common class.[7] Substantial improvement can be attained by instead using underlying and additional financial variables (for a list, see Table A.1) as well as sector, and a slight further improvement by adding our NLP features - though this second improvement is not statistically significant (we made use of McNemar's test for all significance checks in this paper - see Appendix Section A.9). These models including financial variables very frequently bring the predicted rating one rating or less away from the actual.

Table 2: Confusion Matrix and Permutation Importance - Most Complex Logistic Regression Model



Permuted Feature	Mean Accuracy Drop	Standard Deviation
Ratio E	0.070625	0.009156
Passive Tone	0.056786	0.007741
Sector: Utilities	0.043208	0.005661
Interest Expense	0.043019	0.007802
Ratio D	0.041765	0.007607
Ratio C	0.040578	0.008042
Depreciation and Amortization (Income Statement)	0.038593	0.007163
Net Receivables	0.036435	0.007130
Word Count	0.035743	0.007747
Long-Term Debt	0.035463	0.007198
Market Capitalization	0.031103	0.006867
Goodwill and Intangible Assets	0.030084	0.007430
Gross Profit	0.027059	0.006837
Total Debt	0.026485	0.007413
Net Debt	0.025156	0.007661

The left side of Table 2 shows that our most complex model with financial and NLP features generally performs well across all classes (for details, see Appendix Section A.10). This is in large part due to our use of balanced class weighting to handle rare classes. We also found via grid search that an Elastic Net penalty (which collapses to entirely a LASSO penalty) with a slight amount of regularization (C) effectively handles the large number of variables present in our data. The right side of Table 2 shows the 15 most important individual features as determined by the average drop in test accuracy when the feature is permuted 1,000 times. Financial features appear to be the most important, with some contributions from our NLP features considering tone and word count.

XGBoost

In Table 3, we used the popular gradient boosting algorithm XGBoost to predict ratings, finding significant success. With the ability to model complex interactions between variables, we are able to attain substantially higher accuracy when including financial variables, and NLP features provide a statistically significant additional benefit. At around 90% accuracy, our best model attains a level of performance slightly exceeding that in Das et al.

[7]This model also does not significantly outperform a random guess model based on the distribution or ratings in the training dataset, which achieved an accuracy of 0.2245.

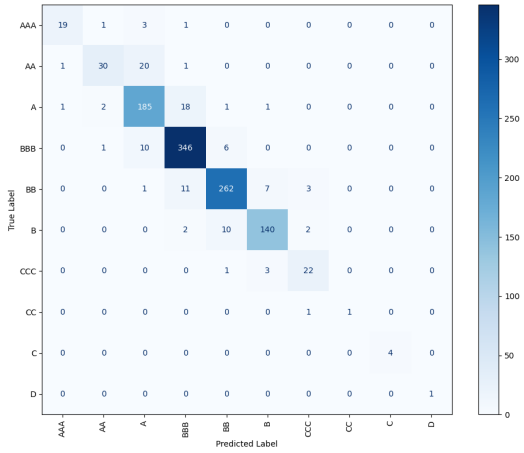
(2023), with the substantially harder prediction task of predicting from among 10 different ratings (rather than a binary investment grade versus junk classification), and without the affordances of a graph neural network or more complex ensembling. Our model is near perfect in placing ratings within a very close neighborhood of their actual values.

Table 3: XGBoost Model Comparison

Model/Baseline	Accuracy	Share ≤ 1 Rating From Actual
Altman's Z	0.3855	0.7657
Financial Variables and Sector	0.7630	0.9597
Financial Variables, Sector, and NLP Features	0.9034	0.9857
Most Common Class Baseline	0.3247	

Table 4 demonstrates that this strong performance by our most complex model is consistent across all classes. Our selected hyperparameters, described in detail in Appendix Section A.11, appear to have worked well on this dataset. Financial features appear to be the most important individual variables, though NLP features also contribute in aggregate (FinBERT positivity, the negative and understated components of tone, and numeric transparency contribute substantially at rank 42, 39, and 52 respectively - word count less so, at rank 135).[8] Relative to prior work, our addition of far more financial factors, in combination with complex and transformer-based NLP features, in our large dataset, appears to greatly improve performance.

Table 4: Confusion Matrix and Permutation Importance - Most Complex XGBoost Model



Permuted Feature	Mean Accuracy Drop	Standard Deviation
Retained Earnings	0.043819	0.005761
Market Capitalization	0.035169	0.005735
Dividends Paid	0.021455	0.004481
Debt Ratio	0.009987	0.003413
Common Stock	0.009693	0.002248
Ratio E	0.009535	0.003463
Other Total Stockholders' Equity	0.009288	0.003028
Total Current Liabilities	0.006888	0.002785
Inventory (Balance Sheet)	0.006802	0.002994
Total Current Assets	0.006684	0.003243
Selling General and Administrative Expenses	0.006031	0.002395
Interest Expense	0.005973	0.002740
Net Property Plant Equipment	0.005729	0.001915
Ratio C	0.005677	0.002476
Total Non-Current Assets	0.005589	0.003420

Graph Neural Network

We make use of the network of company mentions within earnings calls to train an end-to-end graph neural network for classification. Graph Neural Networks construct powerful representations of nodes/entities in a network of relationships by using message passing to aggregate features from neighboring nodes. In this work, we use a GraphSAGE (Hamilton, Ying and Leskovec, 2018) Graph Convolutional Network (GCN) implemented via the Deep Graph Library. For details concerning our network architecture, see Appendix Section A.12.

To initialize our network, we form an unweighted and undirected edge connection between nodes of firm by fixed quarters based on the full firm to firm graph (which was aggregated across quarters) discussed earlier. Our network consists of subgraphs for each fixed quarter date. If two firms are ever connected via a mention, their nodes are always connected within each fixed quarter date. When we include only nodes that are connected to

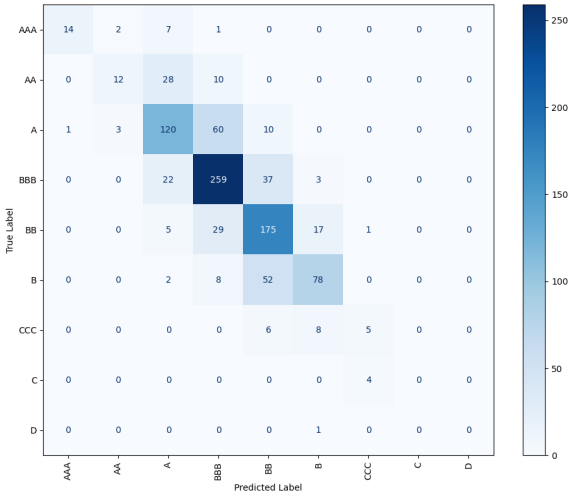
[8]Given that our specific tone components are counts of words, they may have absorbed some of the predictive power of the word count feature in this case.

others, and nodes for rating classes with more than one value in the training data, we are left with 4,829 nodes (3,849 training, 980 test) falling into 9 rating classes, and 12,922 edges between these company-quarters. The average degree of the network is 5.02 connections.

For reference, we also constructed comparisons with our other classifiers including financial and NLP features on the graph neural network's dataset. Logistic regression and XGBoost achieved an accuracies of 0.6469 and 0.9071 on the graph neural network's test set. A possibly fairer comparison are the accuracies we achieved on this set after fully retraining these classifiers (albeit with the same hyperparameters as earlier) on the graph neural network's training set, which were 0.6398 and 0.9031.

Table 5: Transductive Graph Neural Network Model Comparison and Confusion Matrix for Most Complex Model

Model/Baseline	Accuracy
Altman's Z	0.3571
Financial Variables and Sector	0.6633
Financial Variables, Sector, and NLP Features	0.6765
Most Common Class Baseline	0.3276



Graph Neural Networks for node classification may be trained transductively or inductively. In the transductive setting, the entire graph of firms - the training and test dataset, and their associated features - is visible to the model for training, but the labels for the test dataset are masked. Therefore, the model is retrained when a new node for which a prediction is to be made is added. The performance for our transductive models is shown in Table 5. Our performance is slightly better than that of logistic regression (statistically significant relative to the retrained, though not pretrained version) but trails that of XGBoost,[9] and similar to the logistic case, NLP features do not clearly contribute.

In the inductive setting, introduced in Hamilton, Ying and Leskovec (2018) with GraphSAGE, the model can only see the network of nodes in the training dataset, and uses this to learn general functions for embedding nodes. This makes the model easier to adapt to new data, but may come at some cost to performance. Our inductive results are shown in Table 6, and are similar to (and not significantly different from) the transductive case, though differences with both logistic regression models are now significant.

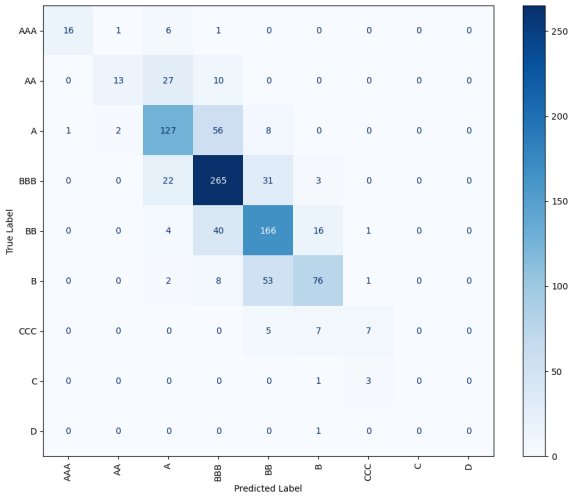
Conclusion

In this paper we demonstrated methods to incorporate the text of earnings call transcripts to improve predictions of corporate credit ratings. Simple logistic regression achieves middling accuracy on the difficult task of rating prediction, which is not signficantly improved by the addition of NLP features. When we implement XGBoost to better account for interactions between variables, however, performance reaches state-of-the-art/near-state-of-

[9]It is sometimes stated that XGBoost and tree-based algorithms can outperform neural networks on heterogenous data - our diverse collection of variables from a variety of sources fall in line with such an explanation.

Table 6: Inductive Graph Neural Network Model Comparison and Confusion Matrix for Most Complex Model

Model/Baseline	Accuracy
Altman's Z	0.3551
Financial Variables and Sector	0.6653
Financial Variables, Sector, and NLP Features	0.6837
Most Common Class Baseline	0.3276



the-art levels, with a substantial contribution from NLP features. Our experimental graph neural network based on mentions of other companies calls behaved somewhat in-between these two methods. We have a moderate degree of evidence that NLP features are important within our specific setup when used with a sufficiently capable classifier, and most of them (particularly aspects of tone, positivity, numeric transparency, and word count) contribute in at least some models.

There remains substantial opportunity for future improvements to this project. We would have liked to incorporate more metadata for our calls and financial information into predictions, leveraging date and time series components. Though our XGBoost classifier already performs well, with more time we would have liked to explore more hyperparameters to further improve accuracy.[10] There are other potential modifications to our network of firms and graph neural network that might be good to explore. We could have experimented with the use of Doc2Vec embeddings and cosine similarities for network construction on our data, which seemed to work well in Das et al. (2023). A different foundational approach would be to extract graph node embeddings and use them with another classifier (likely XGBoost). We might make specific adjustments to architecture to handle individual fixed quarter date subgraphs, and incorporate weighted edges for the number of actual mentions.[11] Overall, it seems likely that mastery of credit rating prediction (especially when including rich representations of text from earnings calls) is within reach.

Acknowledgements

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[10] We based our initial hyperparameter settings and grid in part on optimal results from the Autogluon AutoML library (Erickson, 2024) for a model similar to our most complex one, but we would have loved to explore more specifications for our exact final model also using Bayesian optimization (and potentially from other libraries).

[11] We might also consider forming connections between nodes for the same company across time, though these sorts of temporal impacts may already be addressed with our inclusion of changes in ratios and level. Such a modification may also introduce undesired heterogeneity in the meaning of an edge.

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A Appendix

A.1 Example of One Observation in Final Data

Figure A.1 shows some variables for Apple Inc. for the fixed quarter date of October 1, 2014. Apple had a strong rating of AA at this time. This was supported, in part, by a relatively high Altman Z-Score, capturing the company's excellent financial condition. Sentiment and tone of the earnings call for this quarter were generally positive, numeric transparency indicates there was a relatively high share of words to numbers (indicating more potentially bold commentary), and word count/call length was around average.

Figure A.1: Apple Inc., October 1, 2014

Metadata, Rating, and NLP Features

ticker	AAPL
fixed_quarter_date	2014-10-01
earnings_call_date	2014-07-22
Rating	AA
rating_date	2014-05-27
pos_score_finbert	0.765917
num_transparency	0.1
gf_score	12.781526
word_count	7587.0
num_questions	29.0
Positiv	298.0
Negativ	54.0
Strong	641.0
Weak	42.0
Active	495.0
Passive	186.0
Ovrst	364.0
Undrst	131.0
PN	5.518519
SW	15.261905
AP	2.66129
OU	2.778626
tone	3.188264

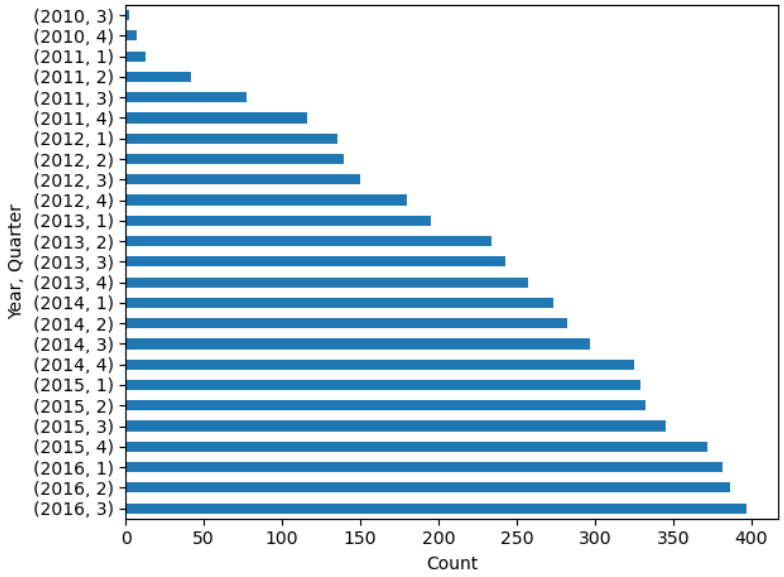
Financial Data

Altman_Z	4.324703
filingDate	2014-07-23
currentRatio	1.470598
quickRatio	0.000609
cashRatio	0.280857
	...

A.2 Observations by Quarter and Year

Figure A.2 demonstrates that the data is temporally unbalanced, with many companies entering the dataset in later years, after they first receive an observable credit rating.

Figure A.2: Observations by Quarter and Year



A.3 Data Cleaning Steps

To ensure comparability, we dropped items missing any predictor variable, as well as some companies with only a few (3 or less) quarters.

We identified one bankruptcy in our data - Peabody Energy on April 13, 2016 - and on further investigation, deleted some quarters with incorrect ratings.

We removed all calls that happened more than 250 days prior and after the first day of the year and quarter they are supposed to discuss the results from, as well as calls for companies that hold them on an annual, rather than quarterly basis.

For our financial data, we limited our observations to items reported in USD, checked for and corrected values off by a factor of 1,000 as a result of parsing,[12] and checked some accounting identities in Das et al. (2023),[13] setting failing variables to missing. We also discarded observations where statement filing dates did not agree between the three types of statements (income statement, balance sheet, and cash flow statement), where the filing date fell outside of the fixed quarter matched on via earnings call date, and where the filing date was more than 45 days after the earnings call date.

We removed observations with outliers for any NLP feature, produced, for example, as a result of zeroes or low values in denominators.

[12] If the last few digits were 000.00 and the item was above or below the 2.5% and 97.5% quantile, we divided by 1,000.

[13] We checked total liabilities were greater than current liabilities, total assets were greater than total current assets, and net sales (revenue) was greater than EBIT. We originally also checked that total assets were greater than or equal to total equity + retained earnings + total liabilities, but this proved to be too restrictive.

A.4 Summary Statistics for Financial Variables

Table A.1 shows summary statistics for the financial variables we include in our models (including sub-components of Altman's Z Score) in our final prepared data.[14] Other important variables are explained in the main text.

Table A.1: Financial Variable Summary Statistics

Variable Name	Mean	Minimum	Median	Maximum	Standard Deviation	Variable Type
Cash Per Share	4.57	0.00	2.13	69.91	9.64	Additional Ratios
Cash Ratio	1.21	0.00	0.28	53.17	6.23	Additional Ratios
Current Ratio	1.93	0.35	1.58	7.93	1.33	Additional Ratios
Debt Ratio	0.35	0.00	0.32	0.94	0.19	Additional Ratios
Debt Ratio (Alternative Definition)	0.65	0.28	0.64	1.22	0.17	Additional Ratios
Debt to Equity Ratio	-34.63	-1,890.41	1.70	25.40	256.02	Additional Ratios
EBIT to Revenue	0.12	-0.26	0.11	0.47	0.12	Additional Ratios
Enterprise Value Multiplier	59.08	-309.75	40.67	727.20	125.93	Additional Ratios
Equity Multiplier	-22.79	-1,270.10	2.71	22.64	175.08	Additional Ratios
Free Cash Flow Per Share	0.57	-2.98	0.39	7.70	1.52	Additional Ratios
Free Cash Flow to Operating Cash Flow	0.72	-2.42	0.66	10.98	1.86	Additional Ratios
Operating Cash Flow Per Share	1.48	-0.98	1.04	11.82	1.92	Additional Ratios
Operating Cash Flow to Sales	0.16	-0.15	0.14	0.64	0.15	Additional Ratios
Quick Ratio	1.36	0.00	1.15	6.12	0.98	Additional Ratios
Return on Assets	0.01	-0.03	0.01	0.06	0.02	Additional Ratios
Return on Capital Employed	0.03	-0.03	0.02	0.11	0.03	Additional Ratios
Return on Equity	0.01	-1.32	0.03	0.78	0.25	Additional Ratios
Common Plus Preferred Stock	338,752,830.58	-74,100.00	6,000,000.00	9,817,134,000.00	926,606,262.05	Constructed for Altman's Z
EBIT	304,424,183.99	-1,364,004,000.00	122,944,000.00	4,334,000,000.00	556,409,802.60	Constructed for Altman's Z
Ratio A	0.02	-0.02	0.02	0.08	0.02	Constructed for Altman's Z
Ratio B	0.21	0.04	0.18	0.70	0.15	Constructed for Altman's Z
Ratio C	1.87	0.29	1.42	8.06	1.55	Constructed for Altman's Z
Ratio D	0.13	-0.13	0.10	0.57	0.15	Constructed for Altman's Z
Ratio E	0.23	-0.74	0.21	1.01	0.32	Constructed for Altman's Z
Working Capital	1,125,108,587.77	-28,931,855,000.00	543,614,000.00	39,464,552,600.00	3,845,915,891.90	Constructed for Altman's Z
Accounts Payable (Balance Sheet)	957,290,323.93	-237,651,171.00	356,700,000.00	11,433,000,000.00	1,551,108,353.02	Financial Statements
Accounts Payable (Cash Flow Statement)	5,154,565.15	-321,769,000.00	0.00	1,789,652,000.00	82,110,968.91	Financial Statements
Accounts Receivables	-11,478,236.25	-544,000,000.00	0.00	325,000,000.00	91,535,961.30	Financial Statements
Accumulated Other Comprehensive Income (Loss)	-404,483,300.22	-5,290,000,000.00	-77,514,000.00	431,595,000.00	874,353,108.41	Financial Statements
Capital Expenditure	-192,514,484.47	-1,867,000,000.00	-60,129,000.00	412,700.00	310,057,440.27	Financial Statements
Capital Lease Obligations	24,642,498.79	0.00	0.00	9,056,234,000.00	228,328,885.18	Financial Statements
Cash and Cash Equivalents	862,135,865.07	0.00	333,000,000.00	9,223,000,000.00	1,366,595,243.17	Financial Statements
Cash and Short Term Investments	1,060,086,810.64	0.00	363,008,000.00	15,601,000,000.00	1,890,682,420.93	Financial Statements
Cash at Beginning of Period	867,410,489.82	-2,556,000.00	334,000,000.00	9,610,000,000.00	1,388,834,800.13	Financial Statements
Cash at End of Period	871,017,693.39	-154,400.00	335,469,000.00	9,743,000,000.00	1,394,641,397.30	Financial Statements
Change in Working Capital	-17,557,103.20	-870,000,000.00	-2,384,000.00	753,000,000.00	183,788,257.05	Financial Statements
Common Stock	329,277,684.36	-539,800.00	3,800,000.00	9,817,134,000.00	925,626,949.20	Financial Statements
Common Stock Issued	44,672,509.36	-3,572,000.00	43,000.00	1,111,490,728.00	124,027,450.20	Financial Statements
Common Stock Repurchased	-78,527,033.90	-2,086,545,366.00	-773,000.00	545,656,614.52	188,219,352.34	Financial Statements
Cost and Expenses	2,317,513,877.07	-2,495,000.00	1,121,064,000.00	22,769,000,000.00	3,357,899,606.58	Financial Statements
Cost of Revenue	1,624,233,369.18	-3,094,000.00	787,700,000.00	18,303,000,000.00	2,405,765,370.43	Financial Statements
Debt Repayment	-247,880,234.24	-3,001,000,000.00	-33,400,000.00	200.00	471,724,050.37	Financial Statements
Deferred Income Tax	6,154,669.54	-253,000,000.00	64,000.00	1,850,454,000.00	58,927,713.28	Financial Statements
Deferred Revenue	310,000,739.66	-116,912,000.00	50,066,000.00	4,918,100,000.00	642,489,899.31	Financial Statements
Depreciation and Amortization (Cash Flow Statement)	141,811,048.14	-675,312.00	53,551,000.00	1,529,000,000.00	210,315,836.18	Financial Statements
Depreciation and Amortization (Income Statement)	140,571,212.83	-1,550,000.00	54,507,000.00	1,371,000,000.00	203,167,331.44	Financial Statements
Diluted EPS	0.51	-156.36	0.51	49.73	3.31	Financial Statements
Dividends Paid	-91,357,096.76	-1,233,000,000.00	-21,054,000.00	0.00	182,429,714.55	Financial Statements
EBITDA	444,995,396.82	-66,200,000.00	193,000,000.00	4,410,000,000.00	644,706,471.62	Financial Statements
EBITDA Ratio	0.20	-5.77	0.17	2.16	0.22	Financial Statements
EPS	0.52	-156.36	0.52	53.75	3.33	Financial Statements
Effect of Foreign Exchange Changes on Cash	-1,697,085.83	-65,000,000.00	0.00	52,000,000.00	11,200,007.88	Financial Statements
Free Cash Flow	156,892,657.81	-541,000,000.00	51,691,000.00	2,683,000,000.00	389,666,937.19	Financial Statements
General and Administrative Expenses	153,933,016.99	-2,738,500.00	33,768,000.00	2,007,000,000.00	303,900,948.38	Financial Statements
Goodwill	2,009,260,205.06	-202,702,100.00	636,039,000.00	23,389,000,000.00	3,554,057,246.39	Financial Statements
Goodwill and Intangible Assets	3,102,882,804.88	-1,618,944,000.00	970,000,000.00	37,123,000,000.00	5,639,038,312.52	Financial Statements
Gross Profit	861,821,178.07	-7,195,000.00	378,500,000.00	9,223,000,000.00	1,365,410,717.45	Financial Statements
Gross Profit Ratio	0.37	-5.65	0.34	2.32	0.26	Financial Statements
Income Before Tax	255,351,974.53	-353,153,000.00	91,900,000.00	2,951,000,000.00	434,623,029.43	Financial Statements
Income Before Tax Ratio	0.07	-9.38	0.09	2.68	0.35	Financial Statements
Income Tax Expense	69,444,774.33	-119,131,000.00	22,100,000.00	736,000,000.00	121,681,731.43	Financial Statements
Intangible Assets	835,940,509.51	-421,000.00	170,197,000.00	14,110,100,000.00	1,785,542,119.17	Financial Statements
Interest Expense	46,568,508.69	-16,400,000.00	23,000,000.00	386,000,000.00	61,712,161.15	Financial Statements
Interest Income	2,372,725.23	-62,900.00	0.00	69,000,000.00	6,859,086.75	Financial Statements
Inventory (Balance Sheet)	933,043,177.40	-19,626,000.00	403,789,000.00	8,328,000,000.00	1,398,934,358.21	Financial Statements
Inventory (Cash Flow Statement)	-10,302,495.14	-420,000,000.00	0.00	289,000,000.00	70,374,129.32	Financial Statements
Investments in Property, Plants, and Equipment	-193,897,744.95	-1,921,864,000.00	-60,373,000.00	412,700.00	313,436,441.14	Financial Statements
Long-Term Debt	4,159,473,460.27	-651,718.00	1,822,139,000.00	31,359,000,000.00	5,574,538,232.32	Financial Statements
Long-Term Investments	494,196,440.41	-490,677,000.00	12,449,000.00	10,981,000,000.00	1,359,571,399.50	Financial Statements
Minority Interest	90,043,651.07	-20,252,654.04	1,600,000.00	2,316,406,000.00	268,200,905.93	Financial Statements
Net Acquisitions	-32,878,764.18	-805,960,000.00	0.00	249,000,000.00	116,107,004.20	Financial Statements
Net Cash Provided by Operating Activities	352,446,106.81	-179,404,000.00	143,626,000.00	3,870,000,000.00	545,602,564.63	Financial Statements

Continued on next page

[14] We did not Winsorize all of our financial ratios (though we could have) due to general agreement on even extreme values with Das et al. (2023).

Table A.1: Financial Variable Summary Statistics

Variable Name	Mean	Minimum	Median	Maximum	Standard Deviation	Variable Type
Net Cash Used for Investing Activities	-252,575,304.44	-2,840,033,000.00	-71,100,000.00	325,900,000.00	443,647,871.52	Financial Statements
Net Cash Used or Provided by Financing Activities	-114,570,062.00	-2,444,000,000.00	-29,157,000.00	1,094,000,000.00	399,330,481.52	Financial Statements
Net Change in Cash	3,933,018.18	-1,161,000,000.00	573,000.00	1,401,000,000.00	269,005,283.68	Financial Statements
Net Debt	3,597,141,664.59	-1,044,500,000.00	1,508,594,000.00	30,761,000,000.00	5,338,457,121.62	Financial Statements
Net Income (Cash Flow Statement)	189,122,176.12	-327,000,000.00	66,190,000.00	2,402,000,000.00	336,635,167.35	Financial Statements
Net Income (Income Statement)	185,944,828.27	-329,864,000.00	66,389,000.00	2,340,000,000.00	330,952,161.49	Financial Statements
Net Income Ratio	0.05	-8.88	0.07	2.72	0.29	Financial Statements
Net Property Plant Equipment	4,931,687,321.78	0.00	1,389,600,000.00	44,441,000,000.00	7,885,938,319.99	Financial Statements
Net Receivables	1,276,905,848.63	-4,199,600.00	570,338,000.00	12,116,000,000.00	1,776,578,353.43	Financial Statements
Non-Current Deferred Revenue	248,840,448.23	-500,933,000.00	0.00	5,778,000,000.00	723,186,467.01	Financial Statements
Non-Current Deferred Tax Liabilities	702,874,797.74	-3,818,507.00	135,597,000.00	8,306,000,000.00	1,400,029,509.57	Financial Statements
Operating Cash Flow	352,446,106.81	-179,404,000.00	143,626,000.00	3,870,000,000.00	545,602,564.63	Financial Statements
Operating Expenses	538,189,512.49	-13,530,000.00	221,700,000.00	6,252,000,000.00	918,426,909.60	Financial Statements
Operating Income	302,231,079.76	-208,377,000.00	122,000,000.00	3,294,000,000.00	475,077,278.15	Financial Statements
Operating Income Ratio	0.11	-9.71	0.12	2.86	0.31	Financial Statements
Other Assets	5,662.39	-19,834,700.00	0.00	8,948,000.00	421,776.93	Financial Statements
Other Current Assets	370,526,390.88	-98,000.00	119,600,000.00	4,968,950,000.00	664,643,317.21	Financial Statements
Other Current Liabilities	955,075,890.93	-48,317,000.00	322,800,000.00	12,137,000,000.00	1,782,231,297.37	Financial Statements
Other Expenses	50,749,806.82	-64,000,000.00	585,000.00	16,189,674,590.00	342,110,629.66	Financial Statements
Other Financing Activities	217,421,866.42	-975,168,999.00	8,000,000.00	3,297,501,000.00	515,334,960.45	Financial Statements
Other Investing Activities	4,573,739.09	-448,000,000.00	106,000.00	3,060,433,659.00	96,736,267.62	Financial Statements
Other Liabilities	95,902.58	-3,063,000.00	0.00	51,076,000.00	1,967,227.53	Financial Statements
Other Non-Cash Items	15,325,139.75	-1,848,719,007.00	1,621,000.00	703,000,000.00	109,294,805.79	Financial Statements
Other Non-Current Assets	506,778,121.04	-75,012,534,818.00	158,696,000.00	8,037,000,000.00	1,778,143,597.09	Financial Statements
Other Non-Current Liabilities	975,892,048.39	-286,041,895.00	327,700,000.00	11,890,564,000.00	1,686,827,873.95	Financial Statements
Other Total Stockholders' Equity	1,135,331,510.72	-12,393,000,000.00	427,000,000.00	34,030,400,000.00	3,586,435,863.55	Financial Statements
Other Working Capital	21,414,823.22	-1,788,851,160.00	0.00	40,341,689,407.00	786,599,061.35	Financial Statements
Preferred Stock	9,475,146.22	0.00	0.00	401,500,000.00	42,785,110.93	Financial Statements
Purchases of Investments	-104,151,034.82	-11,997,654,000.00	0.00	81,823,000.00	346,711,949.30	Financial Statements
Research and Development Expenses	28,169,938.85	-214,000.00	0.00	893,000,000.00	94,071,513.75	Financial Statements
Retained Earnings	3,628,393,969.72	-4,839,000,000.00	1,293,100,000.00	37,899,000,000.00	6,424,744,717.89	Financial Statements
Revenue	2,728,749,857.76	-4,273,000.00	1,297,700,000.00	25,420,000,000.00	3,959,362,594.26	Financial Statements
Sales and Maturities of Investments	99,796,411.86	-9,409,000.00	0.00	8,936,406,000.00	311,292,561.88	Financial Statements
Selling General and Administrative Expenses	296,899,615.00	-5,054,000.00	119,600,000.00	3,343,000,000.00	486,131,457.73	Financial Statements
Selling and Marketing Expenses	25,431,647.83	-3,003,000.00	0.00	876,761,000.00	97,367,023.08	Financial Statements
Short Term Investments	182,988,242.55	-515,000.00	0.00	6,178,000,000.00	599,747,024.65	Financial Statements
Short-Term Debt	465,870,869.02	-655,561.00	83,800,000.00	5,363,000,000.00	885,210,679.51	Financial Statements
Stock-Based Compensation	14,496,292.55	-36,000,000.00	5,106,000.00	254,000,000.00	29,968,462.79	Financial Statements
Tax Assets	378,132,518.58	-2,310,712,000.00	48,963,000.00	6,535,000,000.00	909,237,680.35	Financial Statements
Tax Payable	60,670,669.07	-87,400.00	2,810,000.00	1,187,000,000.00	150,628,980.40	Financial Statements
Total Assets	15,592,495,985.55	123,279.00	7,048,475,000.00	131,119,000,000.00	21,911,032,910.64	Financial Statements
Total Current Assets	3,937,085,272.11	29,954.00	1,933,750,000.00	41,276,000,000.00	5,729,273,613.69	Financial Statements
Total Current Liabilities	2,811,976,684.34	24,083.00	1,138,200,000.00	29,919,000,000.00	4,247,045,840.39	Financial Statements
Total Debt	4,593,265,532.66	0.00	2,019,244,000.00	37,124,000,000.00	6,254,194,800.16	Financial Statements
Total Equity	4,968,502,543.29	-501,467,000.00	2,095,000,000.00	49,975,000,000.00	7,272,421,518.55	Financial Statements
Total Investments	729,199,594.64	-334,673,000.00	43,275,000.00	19,331,000,000.00	1,944,649,108.26	Financial Statements
Total Liabilities	9,817,545,124.72	79,283.00	4,308,693,000.00	87,293,000,000.00	13,527,062,565.42	Financial Statements
Total Liabilities and Stockholders' Equity	15,556,696,866.65	123,279.00	7,043,426,000.00	131,119,000,000.00	21,905,884,302.05	Financial Statements
Total Liabilities and Total Equity	15,556,696,866.65	123,279.00	7,043,426,000.00	131,119,000,000.00	21,905,884,302.05	Financial Statements
Total Non-Current Assets	11,011,964,229.49	49,861.00	4,119,200,000.00	104,263,000,000.00	15,994,777,583.25	Financial Statements
Total Non-Current Liabilities	6,639,451,321.63	53,696.00	2,809,300,000.00	54,300,000,000.00	9,424,654,097.47	Financial Statements
Total Other Income Expenses Net	-13,134,652.92	-503,976,000.00	-920,000.00	286,000,000.00	72,414,124.07	Financial Statements
Total Stockholders' Equity	4,933,321,107.00	-526,491,000.00	2,088,608,000.00	49,269,000,000.00	7,194,176,771.15	Financial Statements
Weighted Average Shares Outstanding	352,790,171.17	0.00	146,000,000.00	13,751,391,147.00	720,460,888.99	Financial Statements
Weighted Average Shares Outstanding (Diluted)	316,630,108.94	0.00	145,951,913.00	13,986,214,405.00	547,337,219.46	Financial Statements
Market Capitalization	18,996,749,034.57	106,422.00	6,409,459,125.00	726,320,349,360.00	44,246,873,159.19	Market Capitalization

A.5 Altman's Z-Score

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

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.

The ratios are combined via the following equation:

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

A.6 Examples of NLP Features

A.6.1 Readability: Gunning-Fog Index

"Gale Klappa: We are looking here. Yes.

Ted Hayden – Point State Capital: Okay. And the equity ratio is like 53? It's a sliding scale I guess, right?

Gale Klappa: Pat, we had 52.2%, 53% up in utilities?

Patrick Keyes: 53.5 is the high end. We were underneath that.

Frederick Kuester: Midpoint is 51.

Gale Klappa: Yeah, our allowed range is 51% to 53.5%. As Pat said we were just under the 53.5%."

Gunning-Fog: 8.5

"We've reduced our group stores value by more than $50 million and that's in spite of the significant growth that our operations have being through in that period, and I think the other thing that's key is the fact that our managers on our mines have risen to the challenge and certainly both the owned skills as far as our desire to see that all our operations manage their business as a commercially on - and with sound commercial decisions, as well as technically, and also treat our operations as if they were the owned and that's something that we believe we have invested quite significantly over the last couple of years and we are confident that we will continue to be able to streamline decisions and optimize their efficiency and running our businesses because we do it with top executives on start."

Gunning-Fog: 19.3

A.6.2 Tone (Principal Component)

"We had one disappointment with the second well in terms of the zone not really being present in terms of what we were looking for."

Tone: -2.9

"We see a great runway still ahead given the fragmented global landscape in concert, management, and ticketing."

Tone: 10.3

A.7 Including Previous Rating

As a reminder, 94.79% of ratings remain the same from one fixed quarter date to the next (95.35% in our test dataset). Therefore, including rating on the previous fixed quarter date in our predictions leads it to far outweigh the impact of other variables. Table A.2 demonstrates our accuracy performance is anchored around the share of ratings that remain the same (with the strange exception of Logistic Regression with Altman Z-Scores only). NLP Features do not add value.

Table A.2: Model Comparison Including Previous Rating

Model/Baseline	Accuracy
Altman's Z	0.7442
Financial Variables and Sector	0.9508
Financial Variables, Sector, and NLP Features	0.9508
Most Common Class Baseline	0.3247

Logistic Regression

Model/Baseline	Accuracy
Altman's Z	0.9517
Financial Variables and Sector	0.9535
Financial Variables, Sector, and NLP Features	0.9535
Most Common Class Baseline	0.3247

XGBoost

Table A.3 substantiates the dominance of previous rating, showing that shuffling its constituent variables leads to large drops in accuracy. Financial variables round out the list of important contributing features, and contribute far less information.

Table A.3: Permutation Importance Including Previous Rating - Most Complex Model

Permuted Feature	Mean Accuracy Drop	Standard Deviation
Rating on Previous Fixed Quarter Date BB	0.256178	0.009675
Rating on Previous Fixed Quarter Date BBB	0.233306	0.008979
Rating on Previous Fixed Quarter Date A	0.111181	0.006236
Rating on Previous Fixed Quarter Date B	0.064464	0.003919
Rating on Previous Fixed Quarter Date CCC	0.013557	0.001143
Rating on Previous Fixed Quarter Date AA	0.010714	0.001722
Rating on Previous Fixed Quarter Date D	0.001829	0.000050
Ratio D	0.000866	0.000799
Weighted Average Shares Outstanding (Diluted)	0.000849	0.000249
Other Expenses	0.000840	0.000262
Net Income Ratio	0.000713	0.000779
Numeric Transparency	0.000703	0.000566
EBITDA	0.000681	0.000428
Ratio C	0.000412	0.000538
Ratio B	0.000130	0.000340

Logistic Regression

Permuted Feature	Mean Accuracy Drop	Standard Deviation
Rating on Previous Fixed Quarter Date BB	0.276554	0.010192
Rating on Previous Fixed Quarter Date BBB	0.257352	0.010267
Rating on Previous Fixed Quarter Date B	0.080826	0.004940
Rating on Previous Fixed Quarter Date A	0.047979	0.004233
Rating on Previous Fixed Quarter Date AA	0.036817	0.001890
Rating on Previous Fixed Quarter Date CCC	0.025477	0.002348
Rating on Previous Fixed Quarter Date AAA	0.021269	0.002349
Net Property Plant Equipment	0.001779	0.000093
Rating on Previous Fixed Quarter Date C	0.000900	0.000098
Cash Per Share	0.000834	0.000225
Return on Capital Employed	0.000024	0.000150
Market Capitalization	0.000022	0.000140
Operating Cash Flow to Sales	0.000020	0.000131
Cash at Beginning of Period	0.000000	0.000000
Interest Income	0.000000	0.000000

XGBoost

Previous rating might be available in some real-world prediction scenarios, but absent in others. For predictions for ratings for unrated or entirely new companies or for investors without any rating data, it would not be present, though in standard scenarios concerning movements from quarter to quarter for well-known companies with significant history, it could be.

A.8 Predicting Changes in Rating

As shown in Figure 1, 94.79% of ratings remain the same from one fixed quarter date to the next (95.35% in our test dataset). This poses a serious challenge for predicting changes, a task easily dominated by the majority class. We implemented SMOTE (Synthetic Minority Over-sampling Technique) (Chawla et al., 2002) to create synthetic observations in the minority classes in the training data (between existing data points) and balance the dataset, adding 2,000 additional observations. We also differenced all financial variables that were ratios in order to get useful changes from quarter to quarter (many of our level variables, such as quarterly revenue or income, are already quarterly changes in a company's financial position).

Table A.4 shows that SMOTE decreases the accuracy of our models relative to simply predicting the majority class, but increases the recall of the minority classes slightly in some cases (Figure A.3).[15] We were not able to find a specification that greatly improved our predictions of minority classes. Improvements in accuracy when adding NLP features are small and insignificant.

Table A.4: Rating Changes Model Comparison

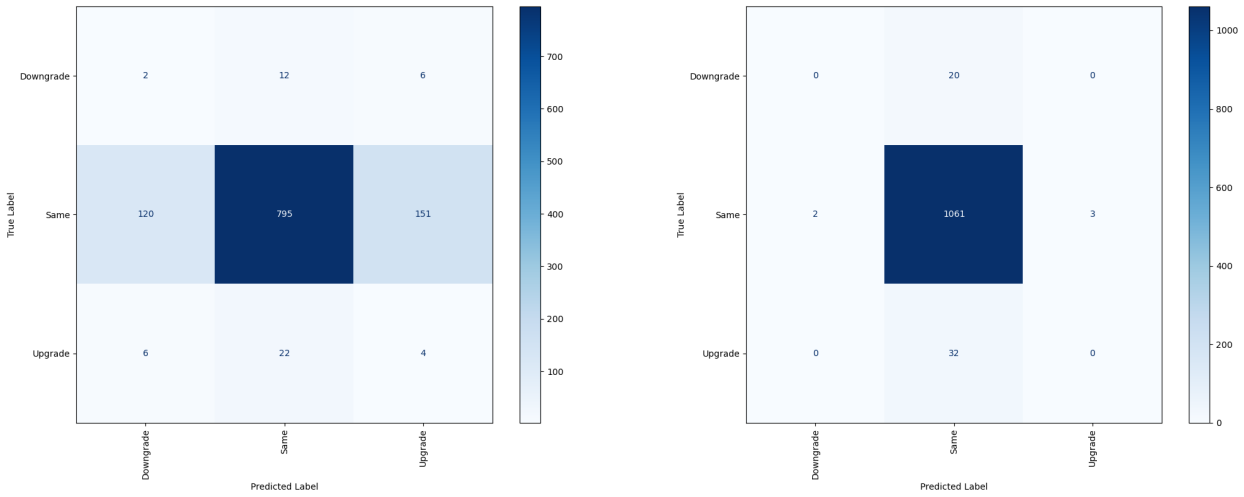
Model/Baseline	Accuracy
Altman's Z	0.5608
Financial Variables and Sector	0.7004
Financial Variables, Sector, and NLP Features	0.7165
Most Common Class Baseline	0.9535

Logistic Regression

Model/Baseline	Accuracy
Altman's Z	0.7415
Financial Variables and Sector	0.9436
Financial Variables, Sector, and NLP Features	0.9490
Most Common Class Baseline	0.9535

XGBoost

Figure A.3: Rating Changes Confusion Matrices - Most Complex Model



Logistic Regression

XGBoost

[15] A random guess model for rating changes received an accuracy of 0.898, better than most of our models, except for the two most complex XGBoost specifications.

A.9 McNemar's Test

We make use of McNemar's Test to check for statistically significant differences between our models (usually those without NLP features and including NLP features).

This test makes use of the following contingency table using counts over observations in our test dataset:

	Model Y Correct	Model Y Incorrect	Row Total
Model X Correct	a	b	$a+b$
Model X Incorrect	c	d	$c+d$
Column Total	$a+c$	$b+d$	n

Under the null hypothesis of identical performance, the marginal probabilities of each model being correct and incorrect are the same:

$$p_a + p_b = p_a + p_c$$

$$p_c + p_d = p_b + p_d$$

which reduces to

$$H_0 : p_b = p_c$$

$$H_1 : p_b \neq p_c$$

The test statistic is

$$\frac{(b-c)^2}{b+c} \sim \chi_1^2$$

(chi-squared with one degree of freedom) under H_0, for sufficiently large b and c (heuristically, at least 10 for each). For a derivation (similar to that for the standard Chi-Squared test), see McNemar (1947) or Rice (2006). We can then compute p-values and assess significance at the 5% level.

There are modifications of the test to perform continuity correction, as well as to handle small values of $b+c$ by making it exact with a binomial distribution, but for our purposes these versions always produced the same conclusions regarding significance at 5%.

McNemar's test is paired, enabling us to effectively make comparisons between our models when they both face the same observations in the test dataset. At the same time, it operates on counts of the data (our counts correct and incorrect) and is non-parametric, without normality or other distributional assumptions. (Note: the test does still assume independence across observations, but it is difficult to perform testing without this.)

The results of our tests are shown in Table A.5 below. p-values are rounded to two decimal places. Items are dashed where there was no difference in accuracy.

Table A.5: p-values for McNemar's Test

Model X	Model Y	p, Non-Exact	p, Non-Exact, Continuity Corrected	p, Exact
Logistic - Exclude Previous Rating, Altman-Z Only	Rating Random Guess Model	0.06	0.07	0.07
Logistic - Exclude Previous Rating - Fin Only	Logistic - Exclude Previous Rating - Fin + NLP	0.31	0.35	0.35
Logistic - Include Previous Rating - Fin Only	Logistic - Include Previous Rating - Fin + NLP	-	-	-
Logistic - SMOTE Rating Change - Fin Only	Logistic - SMOTE Rating Change - Fin + NLP	0.17	0.19	0.19
XGBoost - Exclude Previous Rating - Fin Only	XGBoost - Exclude Previous Rating - Fin + NLP	0.0	0.0	0.0
XGBoost - Include Previous Rating - Fin Only	XGBoost - Include Previous Rating - Fin + NLP	-	-	-
XGBoost - SMOTE Rating Change - Fin Only	XGBoost - SMOTE Rating Change - Fin + NLP	0.06	0.11	0.11
XGBoost - SMOTE Rating Change - Fin Only	Change Random Guess Model	0.0	0.0	0.0
XGBoost - SMOTE Rating Change - Fin + NLP	Change Random Guess Model	0.0	0.0	0.0
GNN - Transductive - Fin + NLP	Logistic Regression - Retrain on GNN Data - Fin + NLP	0.03	0.03	0.03
GNN - Transductive - Fin + NLP	Logistic Regression - Pretrained, on GNN Data - Fin + NLP	0.08	0.09	0.09
GNN - Transductive - Fin + NLP	XGBoost - Retrain on GNN Data - Fin + NLP	0.0	0.0	0.0
GNN - Transductive - Fin + NLP	XGBoost - Pretrained, on GNN Data - Fin + NLP	0.0	0.0	0.0
GNN - Transductive - Fin Only	GNN - Transductive - Fin + NLP	0.17	0.21	0.21
GNN - Transductive - Fin Only	GNN - Inductive - Fin Only	0.83	0.92	0.92
GNN - Transductive - Fin + NLP	GNN - Inductive - Fin + NLP	0.48	0.55	0.55
GNN - Inductive - Fin + NLP	Logistic Regression - Retrain on GNN Data - Fin + NLP	0.01	0.01	0.01
GNN - Inductive - Fin + NLP	Logistic Regression - Pretrained, on GNN Data - Fin + NLP	0.03	0.04	0.04
GNN - Inductive - Fin + NLP	XGBoost - Retrain on GNN Data - Fin + NLP	0.0	0.0	0.0
GNN - Inductive - Fin + NLP	XGBoost - Pretrained, on GNN Data - Fin + NLP	0.0	0.0	0.0
GNN - Inductive - Fin Only	GNN - Inductive - Fin + NLP	0.1	0.12	0.12

A.10 Logistic Regression - Most Complex Model - Additional Details

Table A.6 shows our detailed classification report for our logistic regression model incorporating all of the financial and NLP features. Our use of balanced class weighting enables the model to perform fairly well, even for rare classes.

Table A.6: Classification Report - Most Complex Logistic Regression Model

Rating	Precision	Recall	F1-Score	Support
AAA	0.8261	0.7917	0.8085	24
AA	0.6316	0.6923	0.6606	52
A	0.5874	0.6298	0.6079	208
BBB	0.6909	0.6281	0.6580	363
BB	0.6275	0.5458	0.5838	284
B	0.5864	0.7273	0.6493	154
CCC	0.5556	0.7692	0.6452	26
CC	0.3333	1.0000	0.5000	2
C	1.0000	1.0000	1.0000	4
D	1.0000	1.0000	1.0000	1

In addition to this, Table A.7 shows all the optimal hyperparameters we were able to find via grid search. We are able to handle our high-dimensional data with hundreds of variables effectively by using Elastic Net (which collapses to entirely a LASSO penalty) with a slight amount of regularization (C). A one versus rest multiclass prediction setup is used, where a binary is/is not logistic regression probability is estimated for each class, and the class with the highest score is taken.

Table A.7: Best Hyperparameters - Most Complex Logistic Regression Model

C	Class Weighting Strategy	L1 Ratio	Multi-Class Strategy	Penalty	Solver
0.10	Balanced	1.00	One vs Rest	Elastic Net	SAGA

A.11 XGBoost - Most Complex Model - Additional Details

Table A.8 shows our detailed classification report for our XGBoost model incorporating all features. Though we do not use balanced class weighting, recall for small classes is usually very good.

Table A.8: Classification Report - Most Complex XGBoost Model

Rating	Precision	Recall	F1-Score	Support
AAA	0.9048	0.7917	0.8444	24
AA	0.8824	0.5769	0.6977	52
A	0.8447	0.8894	0.8665	208
BBB	0.9129	0.9532	0.9326	363
BB	0.9357	0.9225	0.9291	284
B	0.9272	0.9091	0.9180	154
CCC	0.7857	0.8462	0.8148	26
CC	1.0000	0.5000	0.6667	2
C	1.0000	1.0000	1.0000	4
D	1.0000	1.0000	1.0000	1

Table A.9 displays the optimal hyperparameters for our XGBoost model incorporating all financial and NLP features. To minimize risk of overfitting, we employed a gamma parameter to control the minimum loss reduction required to make further leaf nodes, in addition to limitations on maximum tree depth and the minimum weight needed to make a further split. We used a fairly high number of estimators to create our predictions.

Table A.9: Best Hyperparameters - Most Complex XGBoost Model

Gamma	Learning Rate	Max Depth	Min Child Weight	Number of Estimators
0.10	0.10	20	5	1,000

A.12 Graph Neural Network Architecture

A GraphSage GCN is trained across a number of timesteps (here indexed by r) which progressively mix information from the embeddings of more and more distant neighbors. Creating these embeddings for a given timestep is a two-step process.

First, in the AGG step, the embeddings of the node's direct neighbors are aggregated. We use what is referred to as pool or pooling aggregation: for node h, with neighborhood $N(i)$, at timestep r,

$$h_{N(i)}^{(r)} = max[\sigma(W_{pool} h_j^{(r-1)} + b), \forall j \in N(i)]$$

meaning the neighboring embeddings from the previous timestep are fed through a fully connected neural network (weights W_{pool}, bias b, ReLU activation σ), and then the elementwise maximum across the new neighbor representations is taken as the aggregated vector.

Next, during the update (or COMBINE) step, we concatenate the representation of our node of interest from the previous timestep with this aggregated vector, then apply another set of weights and activation (in our case, ReLU again) to get a fully updated node representation.

$$h_i^{(r)} = \sigma(W^{(r)} * CONCAT[h_i^{(r-1)}, h_{N(i)}^{(r)}])$$

The operations for each timestep ultimately represent a layer of the neural network - a SAGEConv layer, of which we have 3. For our classification task, the last of these produces output with dimension of the number of classes (for each node), while we use vectors of size 128 for intermediate h values. Our implementation includes a bias term after the weight application in the update step, and the update step of our last layer does not have an activation function.

Our entire process is trained end-to-end with cross entropy loss for rating classification. We perform weight decay at rate 1e-2, dropout at rate 0.4, and train for 300 epochs at a learning rate of 0.01, using a class stratified 80-20 train-val split and selecting the model state from the epoch with the highest validation accuracy.