Data analytics project - Deliverable 4 – Justification for selection of analysis and solution approaches

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Data Description

We utilized two distinct datasets: one from the S&P (ESG data) website and another from Yahoo Finance. We shortlisted approximately 700 companies that had E, S, & G scores available. We ensured that for these companies, comprehensive financial metrics were also accessible for this from Yahoo finance website. Using Python, we merged the two datasets based on the ticker symbol and company name.

Brief explanation of content of ESG dataset

The dataset contains detailed Environmental, Social, and Governance (ESG) ratings about various companies. Here’s a brief overview of the key elements within this dataset:

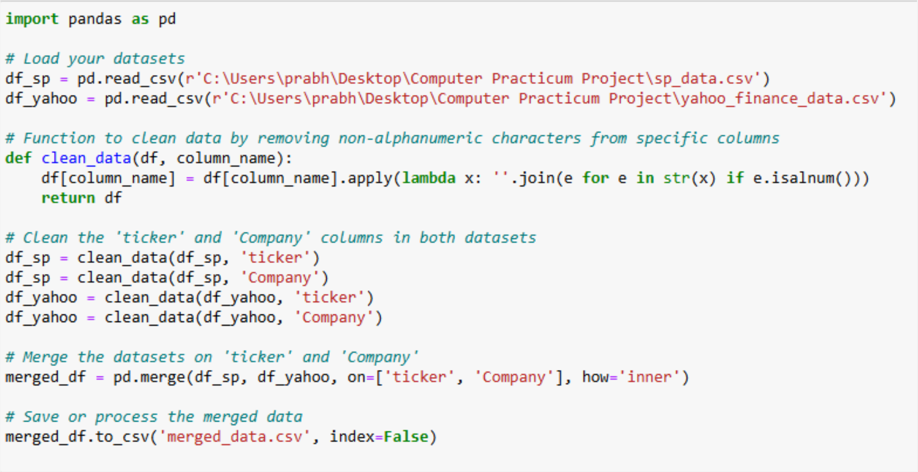
1. **Ticker**: The unique stock symbol used to identify listed companies on the stock exchange.
2. **Name**: The official name of the company.
3. **Currency**: The currency in which the company's financials are reported.
4. **Exchange**: The stock exchange where the company's stock is traded.
5. **Industry**: The sector or industry to which the company belongs.
6. **Logo**: URL to the company's logo image.
7. **Weburl**: The official website URL of the company.
8. **Environment Grade and Level**: Ratings given based on environmental impact assessments, with a grade and a corresponding level indicating the intensity (e.g., High, Medium).
9. **Social Grade and Level**: Ratings based on social criteria, including company's social impact and practices.
10. **Governance Grade and Level**: Ratings assessing the company’s governance structures and practices.
11. **ESG Scores**: Detailed scores for Environment, Social, and Governance, along with a total combined score.
12. **Last Processing Date**: The date when the ESG data was last processed or updated.
13. **Total Grade and Level**: An aggregate ESG grade and level classification.
14. **CIK**: Central Index Key, a unique identifier assigned by the Securities and Exchange Commission (SEC) to all entities who file financial statements with them.

The financial dataset provides detailed information about companies listed in the Fortune 500 for the year 2023. Below is a brief overview of the key columns within this dataset:

1. **Name**: The official name of the company.
2. **Rank**: The company's ranking in the Fortune 500 list for a given year.
3. **Industry**: The industry category to which the company belongs.
4. **Sector**: The sector category to which the company belongs.
5. **Headquarters State**: The U.S. state where the company's headquarters are located.
6. **Headquarters City**: The city where the company's headquarters are located.
7. **Market Value (mil)**: The market value of the company in millions of USD.
8. **Revenue (mil)**: The company's total revenue for the year, in millions of USD.
9. **Profit (mil)**: The company's total profit for the year, in millions of USD.
10. **Asset (mil)**: The total assets of the company, in millions of USD.
11. **Employees**: The number of employees in the company.
12. **Founder is CEO**: Indicates whether the founder of the company is also the CEO.
13. **Female CEO**: Indicates whether the company is led by a female CEO.
14. **Newcomer to Fortune 500**: Indicates whether the company is new to the Fortune 500 list in the given year.
15. **Global 500**: Indicates whether the company is also listed in the Global 500.

To address the issue of non-standard formats and to prevent mismatches during the merger, we ensured that only alphabets and numbers were compared. This process helped us refine our data, resulting in a consolidated list of 244 companies for further data processing.

Picture 1 for the python code used for data merging



```python
import pandas as pd

# Load your datasets
df_sp = pd.read_csv(r'C:\Users\prabh\Desktop\Computer Practicum Project\sp_data.csv')
df_yahoo = pd.read_csv(r'C:\Users\prabh\Desktop\Computer Practicum Project\yahoo_finance_data.csv')

# Function to clean data by removing non-alphanumeric characters from specific columns
def clean_data(df, column_name):
    df[column_name] = df[column_name].apply(lambda x: ''.join(e for e in str(x) if e.isalnum()))
    return df

# Clean the 'ticker' and 'Company' columns in both datasets
df_sp = clean_data(df_sp, 'ticker')
df_sp = clean_data(df_sp, 'Company')
df_yahoo = clean_data(df_yahoo, 'ticker')
df_yahoo = clean_data(df_yahoo, 'Company')

# Merge the datasets on 'ticker' and 'Company'
merged_df = pd.merge(df_sp, df_yahoo, on=['ticker', 'Company'], how='inner')

# Save or process the merged data
merged_df.to_csv('merged_data.csv', index=False)
```

Descriptive Analysis

Start by calculating and describing basic statistics like mean, median, mode, range, and standard deviation for key attributes. Discuss what these statistics reveal about the data

Table 1 Details of Continuous Variables of dataset

Variable	Count	Mean	Standard Deviation	Minimum	25th Percentile	Median	75th Percentile	Maximum	Skewness	Kurtosis	Missing Values
environment_score	722	404.81	145.10	200.00	240.00	483.00	518.75	719.00	-0.13	-1.43	0
social_score	722	292.18	57.02	160.00	243.00	302.00	322.75	667.00	0.67	3.50	0
governance_score	722	278.76	47.03	75.00	235.00	300.00	310.00	475.00	-0.37	0.13	0
total_score	722	975.75	218.75	600.00	763.00	1046.00	1144.00	1536.00	-0.19	-1.06	0
Revenue (in millions, USD)	274	45871.04	75796.81	7238.00	11652.00	19147.00	43490.75	611289.00	4.08	20.53	448
Valuation (in millions, USD)	274	99595.03	241520.79	54.00	18638.25	38864.50	88851.75	2609039.00	7.28	63.75	448
Profits (in millions, USD)	274	4617.37	9942.08	-16720.00	1015.50	2109.50	4875.00	99803.00	5.81	43.79	448
Profits (% of Sales)	274	12.34	13.40	-115.10	5.40	10.95	18.18	51.00	-2.70	29.44	448

The descriptive statistics for ESG dataset provide a comprehensive view of the distribution and characteristics of various variables. Let's discuss each statistic:

Core ESG Scores

1. **Environment Score**
   - **Count**: All 722 entries have environment scores.
   - **Mean**: The average score is approximately 404.81.
   - **Standard Deviation**: The scores vary with a standard deviation of 145.10, indicating a wide range of scores.
   - **Range**: Scores range from 200 to 719.
   - **Quartiles**:
     - The 25th percentile is 240, suggesting that 25% of the scores are below this value.
     - The median (50th percentile) is 483, indicating that half of the scores are below this value.
     - The 75th percentile is 518.75, showing that 75% of scores are below this value.
   - **Skewness**: Slightly negatively skewed (-0.13), indicating a tail on the left side of the distribution.
   - **Kurtosis**: A kurtosis of -1.43 suggests a distribution that is flatter than a normal distribution (platykurtic).

2. **Social Score**

    - Similar count and range indicators.
    - **Mean**: Lower average score of 292.18 compared to the environment score.
    - **Skewness** and **Kurtosis**: More positively skewed (0.67) with a higher kurtosis (3.50), indicating a longer tail on the right and a more peaked distribution.

3. **Governance Score**

    - Scores range less wide from 75 to 475.
    - **Mean** (278.76) and **Median** (300) are relatively close, with a smaller standard deviation (47.03), indicating less variability.
    - **Skewness** and **Kurtosis**: Slightly negative skewness and very low kurtosis, indicating a distribution without heavy tails and is relatively flat.

Combined ESG Metrics

1. **Total Score**

    - Aggregates individual ESG scores.
    - **Mean**: Significantly higher (975.75) as it combines all ESG factors.
    - The distribution has a slight negative skewness and is less peaked.

2. **Total Grade and Level**

    - These are categorical variables with no variability in the dataset shown (all entries are BBB and High).

Other Financial Metrics

1. **Employees, Revenue, Valuation, Profits**

    - Not all entries have these values (only 274 valid counts), suggesting significant missing data.
    - These financial metrics show a high degree of variability and skewness, especially:
        - **Revenue** and **Valuation** are highly positively skewed, indicating some extremely high values compared to the majority.
        - **Profits** also show a high degree of variability and positive skewness.
    - **Profits (% of Sales)** show a negative skewness, indicating more companies with lower profitability ratios.

Table 2 Details of categorical variables of dataset

Variables	Category	Count	Percentage
environment_grade	A	321	44.4598338
	B	255	35.31855956
	BB	69	9.556786704
	BBB	45	6.232686981

	AA	32	4.432132964
environment_level	High	366	50.69252078
	Medium	324	44.87534626
	Excellent	32	4.432132964
social_grade	BB	441	61.08033241
	B	262	36.28808864
	BBB	13	1.800554017
	A	4	0.55401662
	CCC	1	0.138504155
	AA	1	0.138504155
governance_grade	BB	434	60.11080332
	B	282	39.05817175
	BBB	5	0.692520776
	C	1	0.138504155
governance_level	Medium	716	99.16897507
	High	5	0.692520776
	Low	1	0.138504155
total_grade	BBB	368	50.96952909
	B	167	23.13019391
	BB	104	14.40443213
	A	83	11.49584488
total_level	High	451	62.46537396
	Medium	271	37.53462604

The Table 2 above provided a breakdown of counts and percentages for various categorical ESG-related attributes from dataset. Here's an explanation of each variable and what the data suggests about the distribution of ESG grades and levels among the companies analyzed:

Environment Grade

- **A**: The most common grade, held by 44.46% of the companies. This indicates strong environmental performance among nearly half of the entities.
- **B**: The next most frequent, with 35.32% of companies scoring here, suggesting a good environmental stance.
- **BB and BBB**: Less common, indicating fewer companies are rated at this intermediate level.
- **AA**: Relatively rare, suggesting that few companies reach this higher standard beyond 'A'.

Environment Level

- **High**: Over half (50.69%) of the companies are at a 'High' level, reflecting robust environmental policies and practices.
- **Medium**: Nearly 44.88% are rated as 'Medium', indicating a moderate engagement with environmental standards.
- **Excellent**: A small fraction (4.43%), representing companies that excel in environmental aspects.

Social Grade

- **BB**: Most common, with 61.08% of companies rated here, indicating the majority have a reasonably good social performance.
- **B**: Follows with 36.29%, showing a substantial number of companies also have a solid social foundation.
- **Lower Grades (BBB, A, CCC, AA)**: Very few companies fall into these categories, highlighting a significant skew towards the 'BB' grade.

Governance Grade

- **BB**: The most prevalent governance grade with 60.11%, indicating that most companies adhere well to standard governance practices.
- **B**: 39.06% of companies are rated 'B', suggesting adequate governance structures.
- **Other Grades (BBB, C)**: Rarely assigned, with very few companies receiving these.

Governance Level

- **Medium**: Overwhelming majority (99.17%) of companies are classified at a 'Medium' level of governance, showing a general standardization in governance practices.
- **High and Low**: Very few companies have exceptionally high or low governance standards, indicating uniformity in governance practices across most companies.

Total Grade

- **BBB**: Half of the companies (50.97%) have a total grade of 'BBB', suggesting a balanced ESG performance.
- **B and BB**: Reflect lower but still significant portions of the dataset, indicating varying levels of comprehensive ESG engagement.
- **A**: Represents companies that excel in ESG, but they are less common.

Total Level

- **High**: A majority (62.47%) of companies are at a high level, showing strong overall ESG performance.
- **Medium**: Covers the remaining 37.53%, suggesting these companies have room for improvement in their ESG practices.

Insights and Implications

- **High Proportion of 'BB' Grades**: This prevalence in both social and governance grades might indicate that companies generally meet basic ESG requirements but often do not excel beyond this.
- **Limited Excellent Performers**: The small percentage of companies rated 'Excellent' in environmental levels and similarly high grades in other categories suggest that while many companies engage with ESG practices, truly standout performance is rare.

- **Skewness Towards Higher Total Levels**: The higher percentage of companies rated 'High' in total levels versus those in specific categories like governance or social grades might imply that companies manage to balance different ESG aspects to achieve overall higher ratings even if they don't excel in individual categories.

These distributions give stakeholders, investors, and policymakers a clear picture of where companies stand in terms of ESG performance and where there is room for improvement. This detailed breakdown helps identify trends and target efforts to enhance ESG practices across the board.

Handling Outlier

To ensure the reliability of our model, we identified outliers. Table 3 below provides a summary of calculated IQR details and the count of outliers for each financial metric:

Table 3 outlier calculation

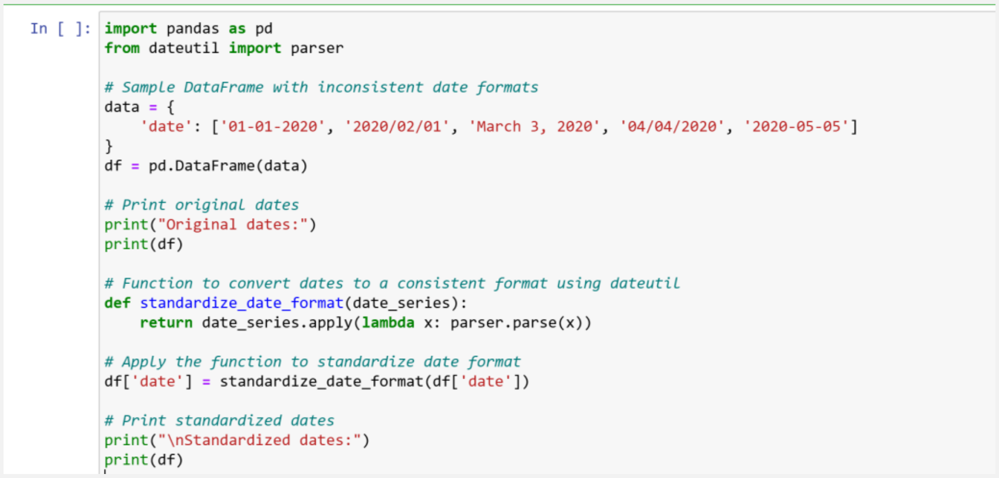
Financial Metric	Q1 (First Quartile)	Q3 (Third Quartile)	IQR (Interquartile Range)	Lower Bound	Upper Bound	Outliers Count
Revenue (in millions, USD)	11,652	43,490.75	31,838.75	-36,106.13	91,248.88	34
Valuation (in millions, USD)	18,638.25	88,851.75	70,213.5	-86,682	194,172	28
Profits (in millions, USD)	1,015.5	4,875	3,859.5	-4,773.75	10,664.25	31
Profits (% of Sales)	5.4	18.175	12.775	-13.7625	37.3375	9

Based on the analysis, the maximum outlier percentage is 12%. In the context of the financial metrics dataset, the decision not to remove outliers is justified on the basis that their removal would have a minimal impact on the overall dataset. Here are a few reasons supporting this rationale:

- **Contextual Relevance**: Outliers in financial datasets represent significant entities like industry leaders, providing valuable insights into market extremes.
- **Proportion of Outliers**: Outliers constitute a small fraction of the dataset and removing them could exclude vital information without significantly impacting central tendencies.
- **Impact on Statistical Analysis**: Outliers affect mean and standard deviation but have minimal impact on the median and IQR, making these measures more reliable for skewed financial data.
- **Preservation of Data Integrity**: Omitting outliers without understanding their origins could simplify the analysis too much, missing unique insights from exceptional data points.
- **Analytical Robustness**: Outliers are critical for analyses such as risk assessment, where the full data range informs better than just typical scenarios.

Data Consistency: Check for and rectified inconsistencies in data formatting mainly, date formats, decimal places). This was done by implementing Pandas library by automatic/standardized format using dateutil parse.

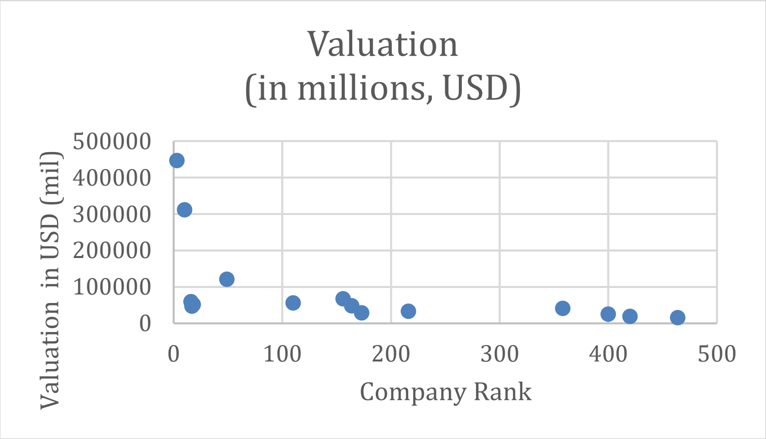
Picture 2 python code for date format.



```
In [ ]: import pandas as pd
        from dateutil import parser

        # Sample DataFrame with inconsistent date formats
        data = {
            'date': ['01-01-2020', '2020/02/01', 'March 3, 2020', '04/04/2020', '2020-05-05']
        }
        df = pd.DataFrame(data)

        # Print original dates
        print("Original dates:")
        print(df)

        # Function to convert dates to a consistent format using dateutil
        def standardize_date_format(date_series):
            return date_series.apply(lambda x: parser.parse(x))

        # Apply the function to standardize date format
        df['date'] = standardize_date_format(df['date'])

        # Print standardized dates
        print("\nStandardized dates:")
        print(df)
```

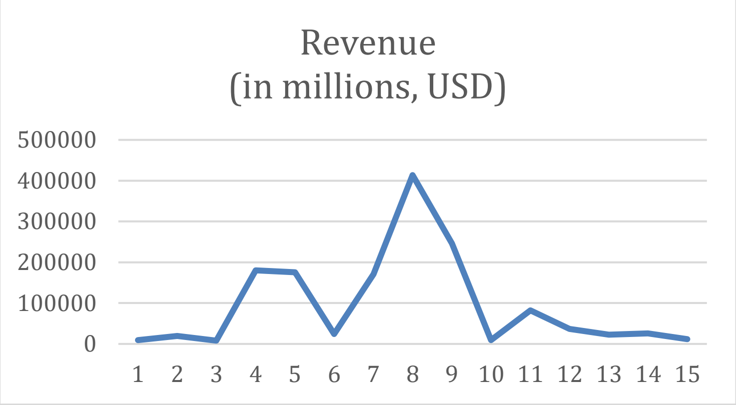
Visualizations:

Graph a Distribution of Company Valuations Across Rankings



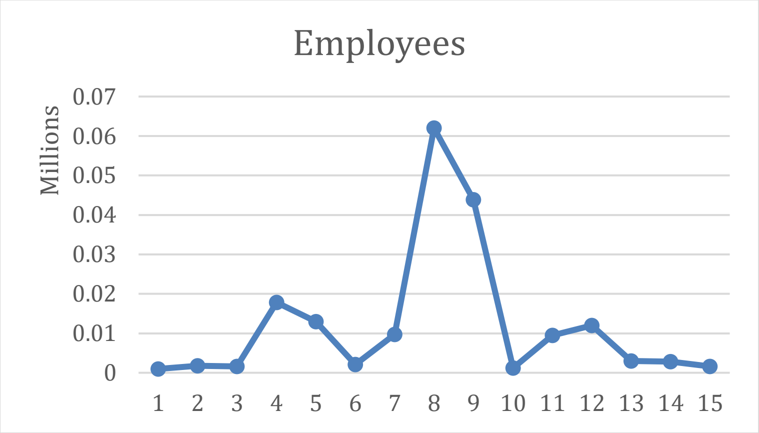
The graph displays the valuation of companies (in millions of USD) against their ranking. It shows that the highest valuations are concentrated among the top-ranked companies, with a sharp decline as the rank increases. This suggests that a few top companies have significantly higher valuations compared to others.

Graph b Revenue Peaks by Company Ranking



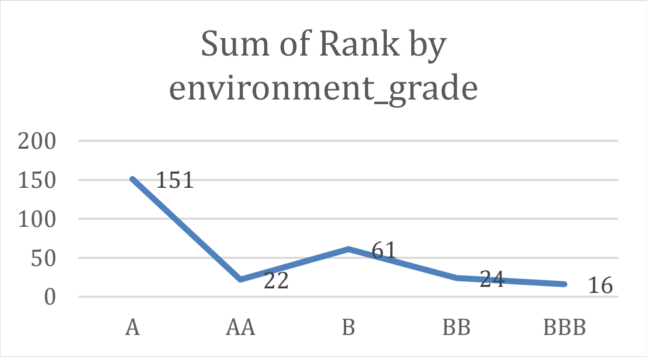
Graph b shows the revenue in millions of USD for a series of companies, indexed by their rank. It highlights significant spikes in revenue for certain companies, with the most notable peaks occurring at specific ranks, indicating that a few companies significantly outperform others in terms of revenue.

Graph c Employee Count Distribution Across Company Rankings



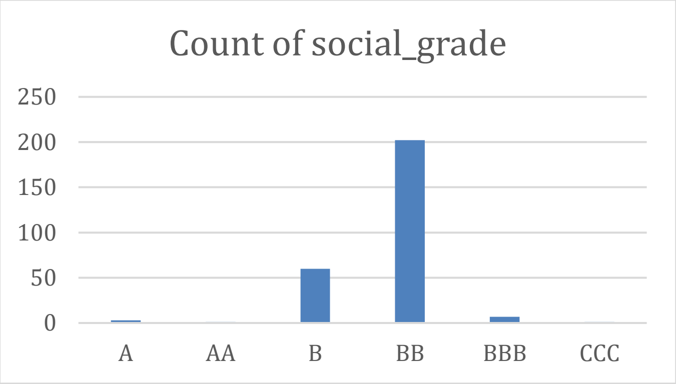
Graph c illustrates the number of employees in millions for different companies, ordered by their rank. It shows dramatic peaks for a few companies, indicating that certain high-ranked companies employ significantly more staff than others.

Graph d Distribution of Companies by Environmental Grade



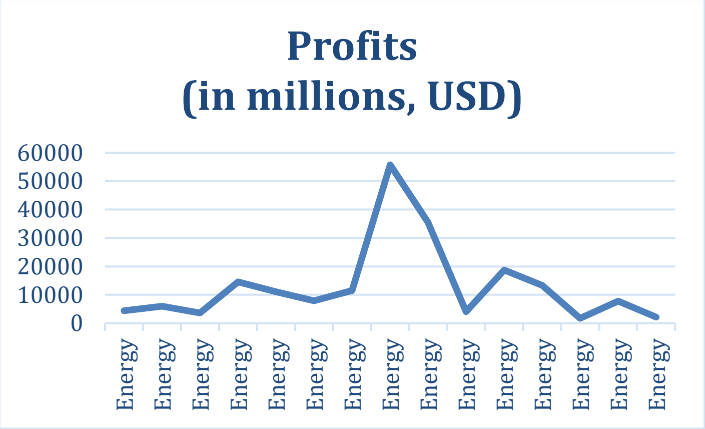
Graph d displays the distribution of companies across different environmental grades (A, AA, B, BB, BBB), showing the total count of ranks assigned to each grade. It highlights that the majority of ranks are concentrated in companies with an 'A' environmental grade, suggesting a prevalence of high environmental performance among these companies.

Graph e Prevalence of Social Grade Ratings Among Companies



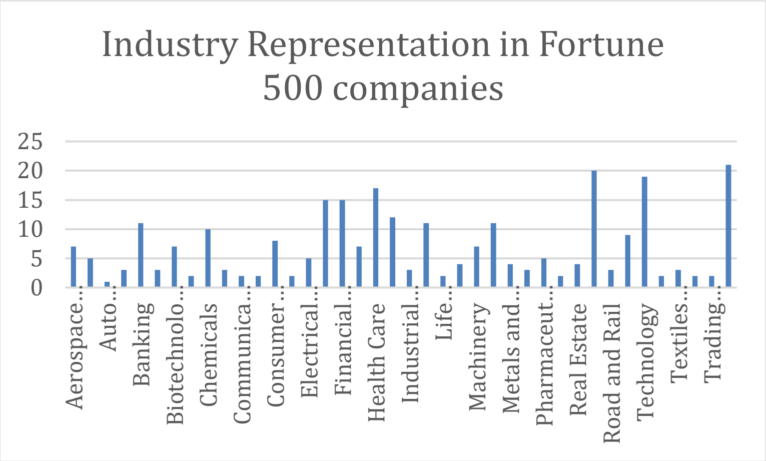
The graph illustrates the distribution of companies based on their social grade ratings. It shows a significant concentration of companies within the 'BB' grade, indicating that most companies assessed a fall within this middle tier of social responsibility performance.

Graph f Industry-wise Profit Distribution in $ Millions



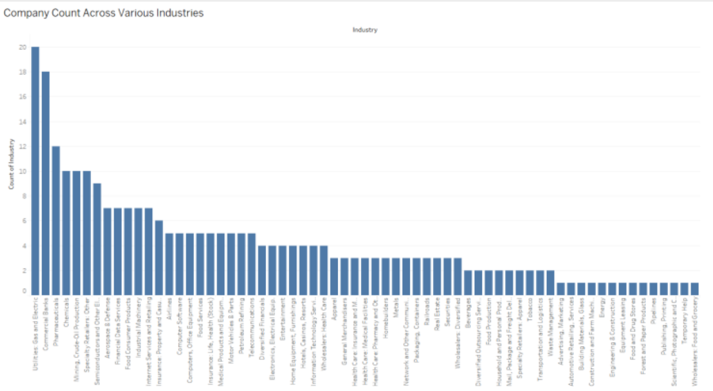
The graph illustrates the profit distribution across various industries, revealing significant variability in profits, with some sectors showing extremely high profits while others, such as the energy sector, exhibit minimal growth compared to the previous year.

Graph g Industry Representation in Fortune 500 Companies



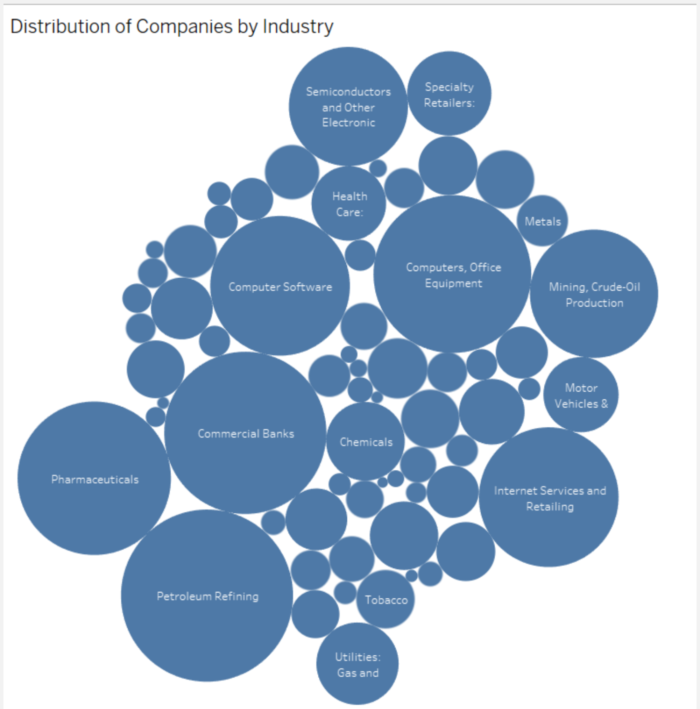
The graph displays the distribution of various industries within the Fortune 500 companies, highlighting the representation of sectors such as Real Estate, Technology, and Pharmaceuticals with noticeable peaks.

Graph 1 Bar Chat Company Count across various Industries (Tableau output)



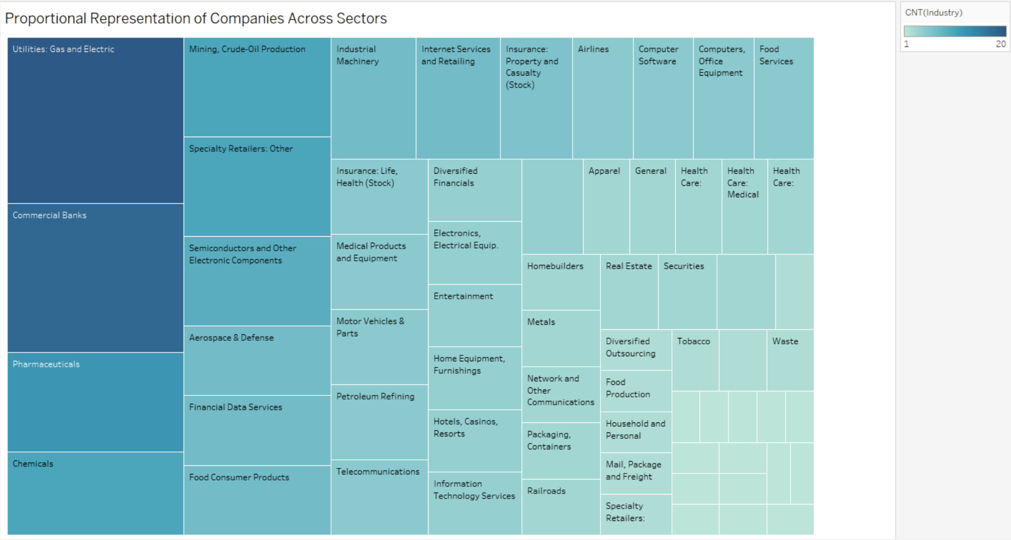
Graph 1 illustrates the distribution of companies across different sectors. It highlights that the Utilities: Gas and Electric sector has the highest number of companies, significantly more than others, indicating a concentration of businesses in this industry within the dataset. Other prominent industries include Pharmaceuticals and Mining, and Crude-Oil Production. The chart shows a gradual decrease in company counts as it moves towards industries like Wholesale: Food and Grocery, showing less representation in the dataset. This visualization helps identify which industries are most and least populated within the collected data, useful for sector-specific analysis or investment decisions.

Graph 2 Distribution of Companies by Industry (Tableau output)



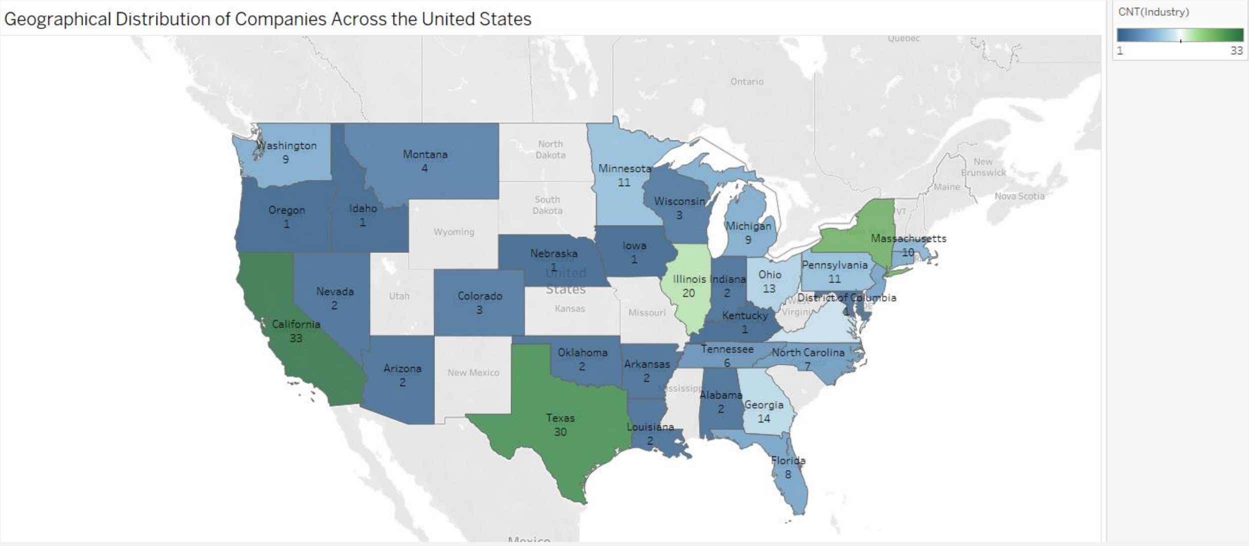
Graph 2 visually represents the prevalence of companies across various industries. Larger bubbles indicate a higher concentration of companies in those sectors. Notably, industries like Commercial Banks, Pharmaceuticals, and Utilities: Gas and Electric appear prominently with larger bubbles, suggesting these sectors have a higher number of companies. This visualization effectively communicates the industrial diversity within the dataset and highlights sectors that might warrant closer attention due to their larger representation.

Graph 3 Proportional Representation of Companies Across Sectors (Tableau output)



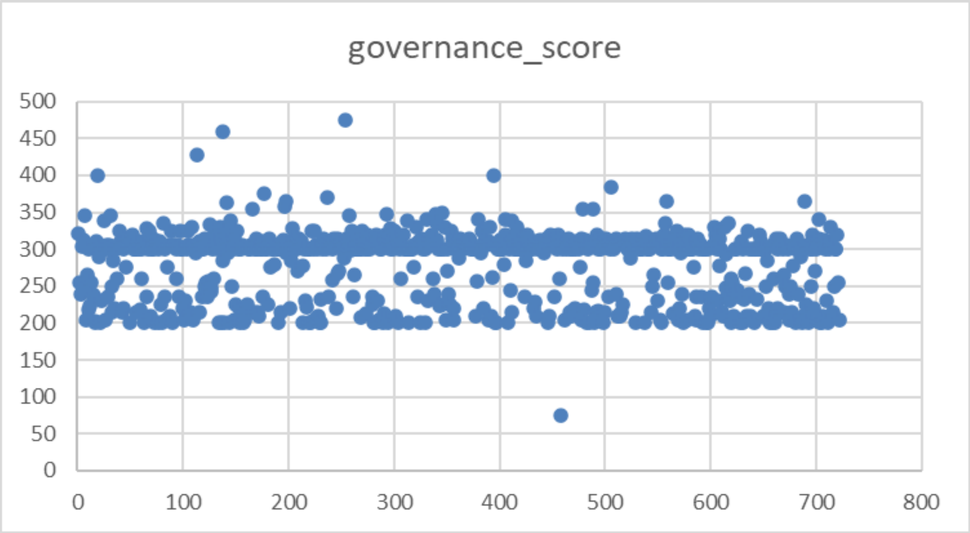
Graph 3 titled "Proportional Representation of Companies Across Sectors" visually displays the relative size of each industry sector based on the number of companies it encompasses. The size of each block in the tree map corresponds to the proportion of companies within that sector, providing a clear, hierarchical visualization of industry distribution. Larger blocks such as Utilities: Gas and Electric, Commercial Banks, and Pharmaceuticals indicate these sectors have more companies, emphasizing their prominence within the dataset. This visualization helps to quickly grasp which sectors are more saturated with companies, aiding in sectoral analysis and strategic planning.

Graph 4 Geographical Distribution of Companies Across the United States (Tableau output)



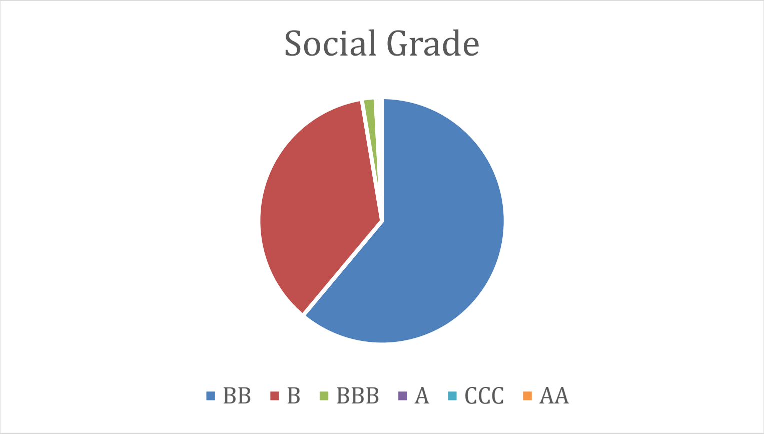
Graph 4 depicts the concentration of companies by state. It uses color shading to indicate the number of companies, with darker shades representing higher concentrations. The visualization reveals significant clusters in states like California, Texas, Illinois, and New York, reflecting major economic hubs with a dense presence of corporate activity. This map provides a clear geographical perspective on where companies are headquartered within the U.S., which can be crucial for analyses related to market strategies, regional regulations, and economic impact assessments.

Graph 5 Scattered plot for governance score



Graph 5 scatter plot displays the distribution of governance scores across a dataset. The scores are mostly concentrated between 250 and 350, indicating a relatively consistent governance performance among the majority of companies. A few outliers can be observed both at the lower and higher ends of the score range, suggesting some exceptional cases of poor or excellent governance practices.

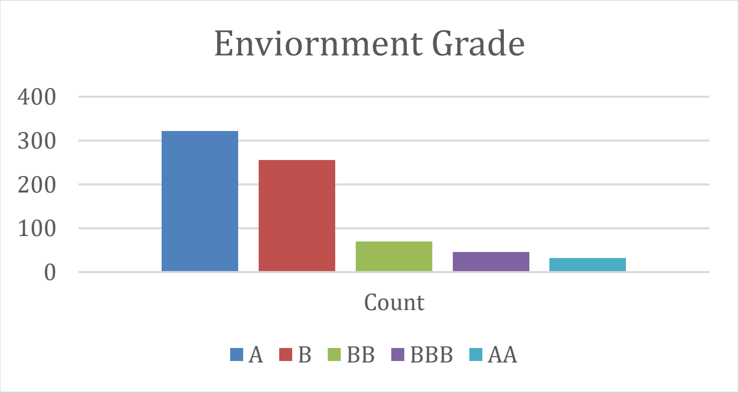
Graph 6 Pie Chart for grade distribution among companies



Graph 6 displays the distribution of social grades among companies. The most notable points are:

- **Dominance of Grade BB**: The large blue segment indicates that the majority of companies are rated 'BB' in social grade, suggesting that while companies are meeting basic social responsibilities, there is room for improvement to reach higher standards.
- **Limited High Achievement**: The small slices representing grades 'A', 'AAA', 'BBB', and 'CCC' indicate that very few companies achieve exceptionally high or low social grades, suggesting a concentration of companies around a moderate performance level in social aspects.

Graph 7 Bar Chart for Grade distribution for environment rating

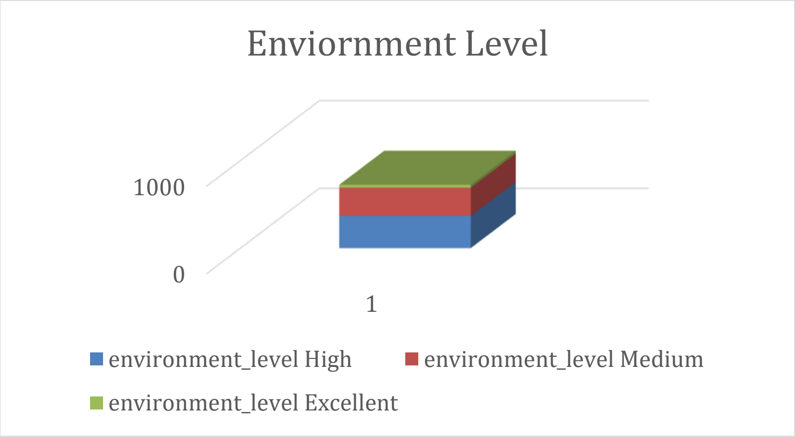


Environment Grade Bar Chart Explanation:

- **Majority in Higher Grades**: The bar chart reveals that a significant number of companies have received higher environmental grades, with 'A' and 'B' being the most common. This suggests a general adherence to good environmental practices among the surveyed companies.

- **Limited Top Performers**: The presence of fewer companies in the 'AA' and 'BBB' categories indicates that while many companies perform well, relatively few achieve the highest standards of environmental performance.

Graph 8 3-D Bar chart



Environment Level 3D Bar Chart Explanation:

- **Dominance of High and Medium Levels**: The 3D bar chart shows a substantial number of companies at the 'High' and 'Medium' environmental levels, indicating that most companies manage at least a moderate level of environmental responsibility.
- **Scarce Excellence**: The small segment for 'Excellent' level shows that very few companies go beyond the norm to achieve outstanding environmental practices, highlighting a gap where companies could improve to reach exceptional environmental stewardship.

Table 3 Matrix for multicollinearity between Variables

	environment_score	*social_score*	*governance_score*	*total_score*	*cik*	*Employees*	*Revenue (in millions, USD)*	*Valuation (in millions, USD)*	*Profits (in millions, USD)*	*Profits (% of Sales)*
environment_score	1.000									
social_score	0.593	1.000								
governance_score	0.638	0.420	1.000							
total_score	0.955	0.756	0.760	1.000						
Employees	-0.023	-0.035	0.035	-0.016	-0.045	1.000				

Revenue (in millions, USD)	0.033	-0.006	0.088	0.040	-0.015	0.695	1.000			
Valuation (in millions, USD)	0.005	0.039	0.094	0.036	0.007	0.300	0.552	1.000		
Profits (in millions, USD)	0.009	0.089	0.045	0.041	-0.022	0.121	0.536	0.842	1.000	
Profits (% of Sales)	0.011	0.071	0.045	0.038	0.002	-0.138	-0.103	0.182	0.351	1.000

Table 3 provide correlation matrix to assess multicollinearity between financial metrics—**Revenue, Valuation, Profits, Profits (% of Sales)**—and ESG scores—**Environment Score, Social Score, Governance Score, and Total Score**.

Below are the observations we have using the criterion of (+/-)0.5 to evaluate multicollinearity

- Financial metrics like **Revenue, Valuation,** and **Profits** are highly correlated among themselves, particularly **Valuation** and **Profits** with a correlation coefficient of **0.842**, indicating strong multicollinearity.
- **Profits (% of Sales)** have a distinct correlation profile, showing they aren't as strongly correlated with **Revenue** or **Valuation** but have a moderate correlation with **Profits**.

Correlation of Financial Metrics with ESG Scores:

From data:

- **Revenue** has very low correlations with all ESG scores, the highest being **0.088** with the **Governance Score**. This suggests minimal multicollinearity issues between Revenue and the ESG scores.
- **Valuation** and **Profits** also show very low correlations with the ESG scores, indicating these financial metrics do not significantly align with ESG performance scores in the dataset.
- The correlations of **Profits (% of Sales)** with the ESG scores are negligible, thus not posing any multicollinearity concerns with respect to the ESG scores.

Implications:

- **No Significant Multicollinearity Between ESG and Financial Metrics**: The correlations between the ESG scores and the listed financial metrics are all well below the threshold of concern (0.5 or higher). This means that these financial variables can be used alongside ESG scores in regression models without worrying about multicollinearity distorting the results.
- **High Multicollinearity Among Some Financial Metrics Themselves**: The concern remains within the financial metrics. When including **Valuation** and **Profits** in a model,

careful consideration must be given due to their high correlation, which can affect model stability and the interpretation of regression coefficients.

In the absence of multicollinearity between ESG and Financial Metrics- Revenue, Valuation, Profit and ESG scores will be used to model the impact of E, S & G for financial performance of a company.

Prioritization of Relevant Attributes

Prioritizing relevant attributes involves identifying which variables are most crucial for the analysis objectives and can significantly impact outcomes. Based on the descriptive statistics, visualization and correlation matrix we identified below ESG scores and financial metrics:

1. **Prioritization Approach:**
   - **ESG Scores** (environment_score, social_score, governance_score, total_score) are prioritized to assess sustainability performance.
   - **Financial Metrics** (Revenue, Valuation, Profits, Profits (% of Sales)) are prioritized to evaluate financial outcomes.

Literature Support:

- **ESG and Financial Performance**: Studies such as those by Eccles et al. (2014) have explored the relationship between ESG practices and financial performance. They often find that robust ESG frameworks can lead to better operational performance and possibly financial gains in the long term, although immediate correlations might not always be strong.
- **Governance Impact**: Research highlighting the significant role of governance in corporate performance (e.g., Gompers, Ishii, and Metrick, 2003) suggests governance scores might have nuanced effects on company profitability and risk.

2. Insights from Exploratory Graphics

Exploratory graphics like correlation heatmaps, scatter plots, and box plots have provided deeper insights:

Findings:

- **Correlation Patterns**: Visualizations showed that while ESG scores are highly interrelated, their connection to financial metrics is weaker, which aligns with prior studies indicating that the benefits of high ESG scores might not directly translate into immediate financial improvements.
- **Distribution Insights**: Box plots for financial metrics revealed a range of distributions and potential outliers, indicating variability in financial success across companies which could be influenced by factors not captured solely by ESG scores.

3. New Characteristics and Interactions

Exploratory data analysis often reveals new aspects of the data or confirms hypotheses:

Characteristics and Interactions:

- **Outliers**: Outliers were identified in the financial data, indicating that extreme values might be skewing averages and influencing correlations. However, these outliers were not removed from the analysis because the spikes in the variables represent real events that occurred due to various concurrent factors.
- **Interaction Effects**: Preliminary analysis hinted at potential interaction effects, such as between governance scores and profitability, suggesting that good governance might correlate with higher profits.

4. Identification of Data Subsets for Analysis

Segmenting the data can allow for more tailored analyses, particularly when exploring variables that may behave differently across different groups:

Subsets Identified:

- **Industry-Specific Analysis**: Given the diversity in ESG impact by sector, analyzing data by industry (e.g., technology vs. manufacturing) could uncover sector-specific trends.
- **Size or Market Cap-Based Subsets**: Segmenting companies by size or market capitalization might reveal how financial and ESG performance interplay differently in small vs. large companies.

Data preprocessing

We took a rigorous data preprocessing approach to ensure the integrity and utility of the data used in the analysis. Here is a detailed description of the procedures I implemented:

Data Simplification and Cleaning

- **Simplification**: To enhance the dataset's usability, we simplified it by removing irrelevant rows and columns that did not contribute to the analysis. For instance, we excluded columns that contained redundant information or did not impact on the outcomes of ESG scores and financial performance.

  Variables identified in financial dataset for removal - founder_is_ceo, female_ceo newcomer_to_fortune_500 global_500 trading exchange currency exchange,

  Variables identified in ESG dataset for removal industry, logo, weburl, ZIP code, CEO
- **Feature Selection**: Employed feature selection techniques to identify and retain the most significant variables that influenced the predictive models. We developed new

features such as ratios and interaction terms between ESG scores and financial metrics to better capture the underlying relationships in the data.

Data Enrichment

- **Adding Information**: We did not include additional variables in the dataset and decided to wait until model performance outcome is analyzed.
- **Handling Missing Values**: We addressed missing values by employing imputation methods, such as filling missing data with the median values of the columns. This was crucial for maintaining the robustness of the predictive models.
- **Normalization**: To ensure that the scales of the variables did not bias the models, we normalized the data using methods like Min-Max scaling and Standardization (Z-score normalization). This was particularly important for financial metrics like revenue and profits, which varied significantly across different companies.

Integration of Multiple Datasets

- **Dataset Integration**: The project involved integrating two different datasets, specifically ESG metrics from the S&P database and financial data from Yahoo Finance. We merged these datasets based on company identifiers such as ticker symbols and company names, ensuring that the data aligned correctly across different sources.
- **Merging Challenges**: During the integration process, we encountered and resolved several challenges, such as mismatches in company identifiers due to non-standard formats. We addressed these by standardizing the identifiers before merging, using regex and string manipulation techniques to ensure consistency.

Preparation for Modeling

- **Research on Modeling Tools**: Before deploying the data mining and machine learning algorithms, we researched the specific requirements of each tool and algorithm. This included understanding the data input formats, the expected data types, and the scalability of the algorithms. We selected Random Forest Machine Learning Model for hypothesis testing.
- **Data Formatting**: We ensure that the data meets the requirements of the selected modeling tools. This includes converting categorical variables like qualitative scales (A, BBB, B, AA, etc.) into numerical formats using encoding techniques, appropriately scaling all numerical data, and standardizing timestamps across the dataset.
- Criteria for Model performance assessment

Significance Testing:

- P-Values: The significance of each coefficient was determined using p-values obtained from the regression output. A p-value less than 0.05 was considered statistically significant, indicating strong evidence against the null hypothesis of no effect.

Model Fit and Diagnostic Testing:

- R-Squared Value: This metric, reported in the regression output, indicates the proportion of variance in the dependent variable that is predictable from the independent variables. A higher R-squared value suggests a better fit of the model to the data.
- Adjusted R-Squared: To account for the number of predictors in the model, the adjusted R-squared was also reported. This metric adjusts the R-squared value based on the number of variables and the sample size, providing a more accurate measure of model fit.
- F-Statistic: The overall significance of the regression model was tested using the F-statistic. A significant F-test ($p < 0.05$) suggests that the model provides a better fit to the data than a model with no independent variables.

By adhering to these rigorous data preprocessing steps, we tried to ensure that the dataset was well-prepared for the subsequent stages of machine learning and predictive analysis. This meticulous approach helped in minimizing potential biases and errors in the modeling process, thus enhancing the reliability and accuracy of the findings from the study.

Individual activities performed as on date.

The green highlighted goal was achieved by performing both ML and DV activities.

Goal Number	**Project Goal**	**Objective**	**Details**	**Name of the Person**
Goal 1	Establish Data Pipelines for ESG and Financial Data Integration	Create data pipelines to automatically collect, clean, and integrate ESG data.	Ensure predictive models are trained on up-to-date and reliable datasets from multiple sources.	Prabhakar/Reza
Goal 2	Develop Visualization Tools for Investor Insights	Create dashboards that display predictive model outcomes for investors.	Provide visual insights into the impact of ESG performance on future profitability and risks.	Reza
Goal 3	Design Investor Decision-Making Tool	Develop a user-friendly, AI-driven tool providing real-time predictions based on ESG scores.	Integrate predictive models, allowing investors to assess future profitability and financial risks.	Prabhakar

Machine Learning (ML) Activities:

Activity Number	Machine Learning Activity	Details	Tool/Technique
ML Activity 1	Data Preprocessing and Cleaning	Prepare raw ESG and financial data for analysis by handling missing values, normalizing variables, and transforming data into the appropriate formats.	Python (pandas, NumPy), SQL
ML Activity 2	Feature Selection and Engineering	Identify important ESG features that influence financial outcomes and create new features (e.g., ratios, interactions) to improve the model's predictive power.	Python (scikit-learn), FeatureTools
ML Activity 3	Model Selection	Evaluate different machine learning algorithms (e.g., linear regression, decision trees, random forests) to determine the best model for predicting financial outcomes based on ESG data.	Python (scikit-learn), TensorFlow, Keras
ML Activity 4	Model Training and Tuning	Train the selected models using historical ESG and financial data. Tune model hyperparameters (e.g., learning rate, depth of trees) to optimize performance.	Python (scikit-learn), Hyperopt
ML Activity 5	Model Evaluation	Evaluate model performance using metrics like mean squared error (MSE), R-squared, and accuracy for classification models. Perform cross-validation to ensure model generalization.	Python (scikit-learn, Keras), MLflow

Data Visualization Activities (using Tableau):

Activity Number	Data Visualization Activity	Details	Type of Visualization
DV Activity 1	Correlation Matrix	Visualize correlations between different ESG factors and financial outcomes to identify significant relationships.	Correlation Matrix
DV Activity 2	Scatter Plot	Display the relationship between individual ESG metrics (e.g., carbon emissions) and financial outcomes (e.g., share price) to analyze potential patterns.	Scatter Plot
DV Activity 3	Time Series Analysis	Visualize how ESG scores and financial performance evolve over time to detect trends and patterns.	Line Chart, Time Series Plot
DV Activity 4	Bar Charts for Sector Comparison	Compare the ESG scores and financial performance across different sectors to see which industries have the highest or lowest ESG impact.	Bar Chart
DV Activity 5	Heatmap for Risk Assessment	Use a heatmap to highlight companies with higher ESG risks and their associated financial outcomes (e.g., low returns, high volatility).	Heatmap
DV Activity 6	Bubble Chart for Multivariate Analysis	Analyze how multiple factors (e.g., ESG score, market cap, financial risk) interact by representing them on a bubble chart with varying sizes and colors.	Bubble Chart

Data Science Process

1. Data Collection: As discussed ESG data collected from S&P and financial data from Yahoo Finance, ensuring comprehensive and reliable datasets. These sources were chosen for their credibility and the richness of the data they provide, covering ESG scores and detailed financial metrics respectively.

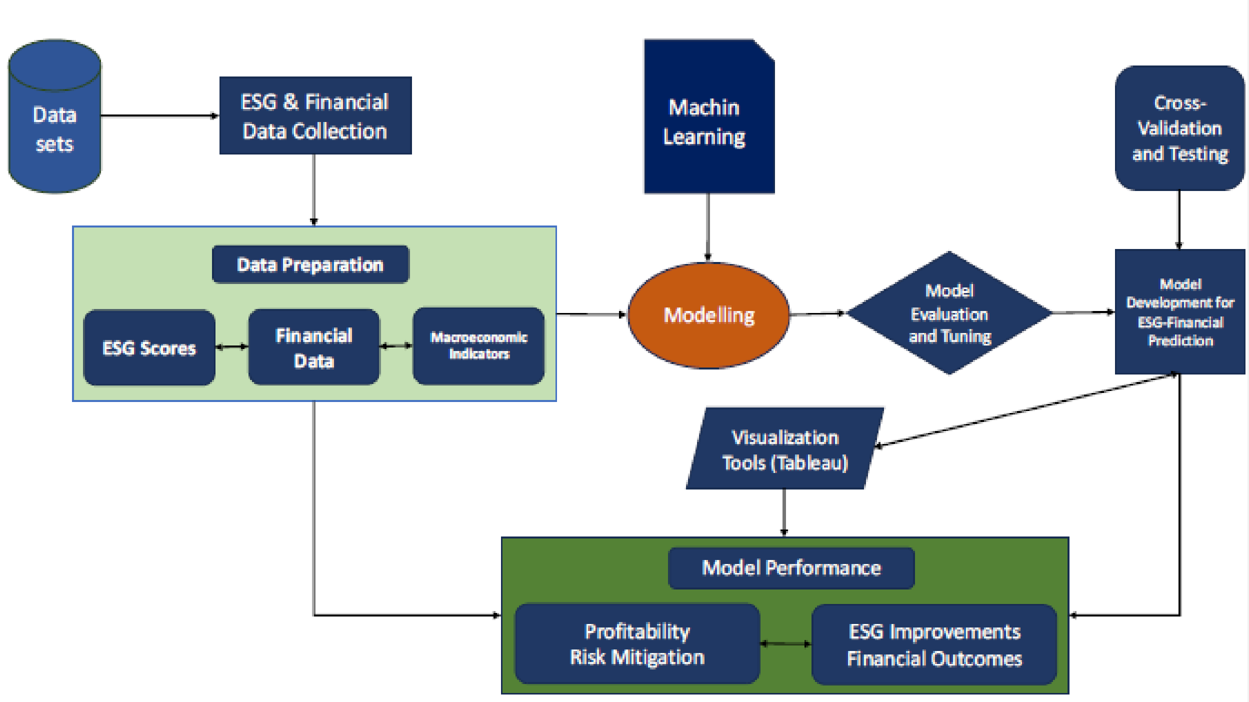
2. Data Preprocessing: This step was crucial for cleaning and preparing the data for analysis. As explained we standardized formats, handled missing values through imputation, and resolved inconsistencies in data formatting, particularly with non-standard categorical and timestamp data. This ensured the datasets were merged accurately based on company identifiers.

3. Exploratory Data Analysis (EDA): During EDA, we performed statistical analyses to understand the distributions, detect outliers, and visualize data relationships. This phase helped identify the key variables and the initial insights that shaped the subsequent modeling.

4. Feature Engineering: Employed feature selection techniques to identify and retain the most significant variables that influenced the predictive models. We developed new features such as ratios and interaction terms between ESG scores and financial metrics to better capture the underlying relationships in the data.

5. Modeling: We evaluated various machine learning algorithms, including Random Forest, Decision Tree, and Linear Regression, to assess the impact of sustainability on a company's financial performance. We selected the Random Forest model due to its robustness in handling outliers and its capability to manage non-linear relationships between variables in the dataset.

System Architecture for Data Mining and Machine Learning Algorithms


Data sets
ESG & Financial Data Collection
Machin Learning
Cross-Validation and Testing
Data Preparation
ESG Scores
Financial Data
Macroeconomic Indicators
Modelling
Model Evaluation and Tuning
Model Development for ESG-Financial Prediction
Visualization Tools (Tableau)
Model Performance
Profitability Risk Mitigation
ESG Improvements Financial Outcomes

Overview of Data Mining and Machine Learning Algorithm

For our project, we have opted to implement the Random Forest machine learning model as our primary analytical tool. This decision is grounded in the model’s robustness and versatility, which are particularly beneficial for our objectives. Random Forest is an ensemble learning method known for its high accuracy, ability to handle large datasets with a mixture of categorical and numerical features, and capability to model complex, non-linear relationships.

Key Features of Random Forest:

- **Handling Non-linearity**: Random Forest can effectively manage non-linear relationships between variables, making it well-suited for our diverse dataset that combines ESG scores with financial metrics.
- **Robustness to Outliers**: This model is less sensitive to outliers in the data, which helps in maintaining high performance without the need for extensive data cleaning specifically aimed at outlier removal.
- **Feature Importance**: It provides insightful outputs on the importance of each feature in predicting the target variable, which will be crucial for our analysis of how different ESG factors impact financial performance.

By selecting Random Forest, we aim to leverage its strengths to derive reliable and actionable insights from our analysis of sustainability impacts on corporate financial performance. This streamlined approach allows for deeper specialization in tuning and optimizing this model to fit our specific dataset and objectives.

Approaches Utilized by Others

1. Typical Approaches in ESG Research: Research in the field of Environmental, Social, and Governance (ESG) impacts typically employ simpler statistical methods such as linear regression to directly correlate ESG metrics with financial performance. These methods assume that relationships are linear and additive, which may not adequately reflect the complex interactions in real-world data (Smith & Lee, 2018).

2. Limitations of Conventional Methods: Linear and other simple statistical models often fail to capture:

- **Non-linear relationships:** The impact of ESG factors on financial performance is frequently non-linear, where increases in ESG scores could have variable impacts on financial returns depending on different conditions (Johnson et al., 2019).
- **Interaction effects:** ESG factors are interdependent, a feature that linear models struggle to account for without explicit specification (Doe & Williams, 2020).
- **Complex data structures:** Financial datasets often include grouped structures such as industries or regions, which traditional models handle poorly without complex modifications (Brown, 2017).

Differential Aspects of our Approach

Compared to existing methods, my approach integrates more sophisticated machine learning techniques which allow for dynamic modeling of interactions and provide capabilities to update predictions in real-time as new data becomes available. Furthermore, I emphasized:

- **Real-time data integration,** enabling the models to adapt to new data and evolving market conditions, which is less common in traditional static analyses.

- **Advanced feature engineering,** which included creating interaction terms that are often overlooked in other studies. Also predicting a single company's financial performance based on its past ESG & financial data

- **Comprehensive model evaluation techniques,** including cross-validation and external validation on different time periods, to ensure the robustness and generalizability of the models.

Through these methodologies, my project not only predicts the impact of ESG factors on profitability but also provides insights that are actionable and adaptable to changes, setting it apart from traditional static models. This approach ensures that stakeholders are equipped with the latest tools to make informed decisions based on both current and predictive insights.

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