Phase 3: Investment Fund

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Introduction

Callaghan Investments is a newly formed investment firm specializing in asset allocation and portfolio management. As part of our goal of onboarding the influx of retail investors entering the market at increased rates, we have recently designed, implimented, and got S.E.C approval of our new fleet of Exchange-Traded Funds (ETFs) covering a variety of sectors such as technology, energy, healthcare, financial, real estate, and cryptocurrency (Bitcoin, Ethereum, and Solana). We created these ETFs to provide our clients and investors with a easy way to diversify their portfolio and manage risk in volatile conditions.

While many investors are satisfied with the basket of stocks provided in the ETFs, recent market research shows a significant portion of investors want to take on more risk by investing in individual stocks. To meet this demand, Callaghan Investments is going to offer a stock screening service for our higher capital investors. This service will recommend stocks which have a high probability of increasing in price over the medium term (3 months to 1 year). To build this stock screener, we are going to create a machine learning model to predict whether a stock is likely to beat it's next quarterly estimated earnings per share (EPS). This will be based off the stock's valuation parameters and historical earnings data.

The reason we are building the model to predict whether a stock will beat its' estimated EPS is because it displays that the company has solid fundamentals, is growing steadily, and will often rise in price after beating its' estimated EPS. An Anderson Review article from UCLA states that positive earnings surprises caused stocks to rise an average of 2.4% in price in the days following the announcement, while companies that did not beat their earnings report dropped an average of 3.5% in price. (https://anderson-review.ucla.edu/when-individuals-concentrate-in-a-stock-earnings-surprises-play-out-differently/). Therefore, building this model is not only good for medium term traders, but also short term traders. This service will provide monthly stock recommendations showing stocks which have the highest probability of beating their earnings report, and therefore having a high likelihood of rising in price.

The Data

The data we are using to creat this predictive model comes from two sources:

- nasdaq.com
  - Nasdaq.com contains a stock screener with a downloadable CSV file which contains the company name, the stock ticker, and the current marketcap (https://www.nasdaq.com/market-activity/stocks/screener).
  - We'll also be using this website to record the companies' previous earnings report, specifically the actual EPS and the predicted EPS.

- yfinance
  - Yfinance is a library used to access historical data from Yahoo Finance. We use this to find values for the stock valuation parameters we will be using in our analysis, such as P/E Ratio, Return on Equity, and Free Cash Flow.

Loading, cleaning, and sorting NASDAQ stock data by market capitalization

We'll start by importing our data by loading the downloaded CSV file from the NASDAQ website. We're going to use the top 5,000 stocks by market cap, sorted from highest to lowest.

```
# Importing pandas library for data manipulation and analysis
import pandas as pd

# Load the CSV file into a DataFrame
csv_file_path =
'/Users/evancallaghan/Downloads/nasdaq_screener_1726538993372.csv'
df = pd.read_csv(csv_file_path)

# Inspect the DataFrame to understand its structure
print(df.head())

# Filter DataFrame to only show the columns 'Symbol', 'Name', and
'Market Cap'
df = df[['Symbol', 'Name', 'Market Cap']]

# Convert 'Market Cap' to numeric if it's not already
# Remove commas, dollar signs, and replace these symbols with empty
spaces
df['Market Cap'] = df['Market Cap'].replace({'\$': '', ',': ''},
regex=True).astype(float)

# Sort the DataFrame by Market Cap in descending order
df_sorted = df.sort_values(by='Market Cap',
ascending=False).head(5000)

print(df_sorted.head())
```

```
  Symbol                                               Name Last Sale
\
0      A               Agilent Technologies Inc. Common Stock   $138.31

1     AA                     Alcoa Corporation Common Stock    $34.50

2   AACG   ATA Creativity Global American Depositary Shares   $0.5025

3   AACT  Ares Acquisition Corporation II Class A Ordina...    $10.80

4   AADI                    Aadi Bioscience Inc. Common Stock     $1.88
```

```
   Net Change % Change     Market Cap        Country  IPO Year
Volume  \
0       1.0000   0.728%  3.974029e+10  United States    1999.0
887040
1       1.9800   6.089%  8.912735e+09  United States    2016.0
10730428
2      -0.0275  -5.189%  1.608006e+07          China    2008.0
25043
3       0.0200   0.186%  0.000000e+00            NaN    2023.0
35074
4       0.0800   4.444%  4.627589e+07  United States       NaN
81942

        Sector                                          Industry
0  Industrials  Biotechnology: Laboratory Analytical Instruments
1  Industrials                                          Aluminum
2  Real Estate                           Other Consumer Services
3      Finance                                      Blank Checks
4  Health Care        Biotechnology: Pharmaceutical Preparations
     Symbol                                  Name    Market Cap
15     AAPL              Apple Inc. Common Stock  3.288959e+12
4208   MSFT   Microsoft Corporation Common Stock  3.206167e+12
4559   NVDA      NVIDIA Corporation Common Stock  2.864613e+12
2819   GOOG  Alphabet Inc. Class C Capital Stock  1.957167e+12
2820  GOOGL   Alphabet Inc. Class A Common Stock  1.945719e+12

# Reset the index of the DataFrame and drop the old index
df_sorted.reset_index(drop=True, inplace=True)

# Update the index to start from 1 instead of 0
df_sorted.index = df_sorted.index + 1

# Display the first few rows of the updated DataFrame
df_sorted.head()

  Symbol                                  Name    Market Cap
1   AAPL              Apple Inc. Common Stock  3.288959e+12
2   MSFT   Microsoft Corporation Common Stock  3.206167e+12
3   NVDA      NVIDIA Corporation Common Stock  2.864613e+12
4   GOOG  Alphabet Inc. Class C Capital Stock  1.957167e+12
5  GOOGL   Alphabet Inc. Class A Common Stock  1.945719e+12
```

Stock Valuation Parameters

Below is a list of the stock valuation parameters we will implement into our model. Due to data limitations, some of these values will not be available. If that is the case, we will remove that parameter and continue the analysis with the remaining attributes.

1. Price to earnings ratio

2. price to book ratio
3. dividend yield
4. earnings per share
5. return on equity
6. debt to equity ratio
7. free cash flow
8. revenue growth
9. beta (volatility)
10. operating margin
11. gross margin
12. net profit margin
13. price to sales ratio
14. current ratio
15. quick ratio
16. interest coverage ratio
17. dividennt payout ratio
18. return on assets
19. return on investment
20. enterprise value
21. enterprise value ooon EBITDA
22. price to free cash flow rate
23. PEG ratio (price/earnings to growth ratio)
24. book value per share

Stock Data Cleanup: Remove all except common stock

For building this model, it is crucial to only include stocks from our DataFrame that are labeled as 'Common Stock' because it represents ownership in the company and dividend claims. The other types of securities in our Dataframe ('Capital Stock', 'Depository Shares', 'Global Notes', and 'Registry Shares'), have differnet structures, risk profiles, and financial treatments. These can and will distort our model because they do not behave like 'Common Stock' in terms of price, earnings growth, or market reaction to financial reports. By removing these, the model can solely rely on securities that accurately reflect a companies' core earnings performance.

```
# Ensure there are no leading or trailing whitespaces in the 'Name'
column
df_sorted['Name'] = df_sorted['Name'].str.strip()

# List of terms to filter out
terms_to_drop = ["Capital Stock", "Depository Shares", "Global Notes",
"ADS",
                 "Registry Shares", "Depositary Shares"
]

# Create a regex pattern to match any of the terms
# //b ensures that the match occues only at the start or end of a word
```

```
# pipe '|' ensures that if any of the terms in 'terms_to_drop' are seen,
# there is a match
pattern = '|'.join([f"\\b{term}\\b" for term in terms_to_drop])

# Apply filtering based on the updated pattern
df_filtered = df_sorted[~df_sorted['Name'].str.contains(pattern, case=False,
                                                         na=False)
]

# Display the filtered DataFrame
df_filtered.head()
```

	Symbol	Name	Market Cap
1	AAPL	Apple Inc. Common Stock	3.288959e+12
2	MSFT	Microsoft Corporation Common Stock	3.206167e+12
3	NVDA	NVIDIA Corporation Common Stock	2.864613e+12
5	GOOGL	Alphabet Inc. Class A Common Stock	1.945719e+12
6	AMZN	Amazon.com Inc. Common Stock	1.940525e+12

```
# Reset the index to account for the new filtering
df_filtered.reset_index(drop=True, inplace=True)
df_filtered.index = df_filtered.index + 1
df_filtered.head()
```

	Symbol	Name	Market Cap
1	AAPL	Apple Inc. Common Stock	3.288959e+12
2	MSFT	Microsoft Corporation Common Stock	3.206167e+12
3	NVDA	NVIDIA Corporation Common Stock	2.864613e+12
4	GOOGL	Alphabet Inc. Class A Common Stock	1.945719e+12
5	AMZN	Amazon.com Inc. Common Stock	1.940525e+12

```
# Count the rows in our new DataFrame to ensure that filtering was done
# and to see how many rows we have left
df_filtered.count()
```

```
Symbol        4682
Name          4682
Market Cap    4682
dtype: int64
```

Import Stock Valuation Parameters from Yahoo Finance

Now we are going to pull financial ratios and valuation parameters for our list of stocks using the yfinance library and organize it into a pandas dataframe. This pull takes a significant amount of time, so in order to save time when running this notebook, I will convert our resulting DataFrame into a CSV file to make it easier to load.

```
# There is a CSV file of this information provided, as this code is
# computationally intensive
# Import the yfinance library for fetching financial data
#import yfinance as yf

# Function to get various financial ratios
#def get_financial_data(symbol):
#    try:
#        stock = yf.Ticker(symbol)
#        info = stock.info

        # Define the parameters and their corresponding keys in the
info dictionary
#        parameters = {
#            'Trailing P/E Ratio': 'trailingPE',
#            'Forward P/E Ratio': 'forwardPE',
#            'Price to Book Ratio': 'priceToBook',
#            'Dividend Yield': 'dividendYield',
#            'Earnings Per Share Trailing': 'epsTrailingTwelveMonths',
#            'Earnings Per Share Forward': 'forwardEps',
#            'Return on Equity': 'returnOnEquity',
#            'Debt to Equity Ratio': 'debtToEquity',
#            'Free Cash Flow': 'freeCashflow',
#            'Revenue Growth': 'revenueGrowth',
#            'Beta (Volatility)': 'beta',
#            'Operating Margin': 'operatingMargins',
#            'Gross Margin': 'grossMargins',
#            'Net Profit Margin': 'profitMargins',
#            'Price to Sales Ratio': 'priceToSalesTrailing12Months',
#            'Current Ratio': 'currentRatio',
#            'Quick Ratio': 'quickRatio',
#            'Interest Coverage Ratio': 'interestCoverageRatio',
#            'Dividend Payout Ratio': 'dividendPayoutRatio',
#            'Return on Assets': 'returnOnAssets',
#            'Return on Investment': 'returnOnInvestment',
#            'Enterprise Value': 'enterpriseValue',
#            'Enterprise Value to EBITDA': 'enterpriseToEbitda',
#            'Price to Free Cash Flow': 'priceToFreeCashflow',
#            'PEG Ratio': 'pegRatio',
#            'Book Value Per Share': 'bookValue'
#        }

        # Extract data
#        data = {param: info.get(key, 'Not Available') for param, key
in parameters.items()}

#        return data
#    except Exception as e:
#        return {'Symbol': symbol, 'Error': str(e)}
```

```python
# List of stock symbols
#stock_symbols = df_filtered['Symbol'].tolist()

# Create lists to store data
#all_data = []

# Fetch financial data for each stock
#for symbol in stock_symbols:
#    data = get_financial_data(symbol)
#    data['Symbol'] = symbol
#    all_data.append(data)

# Create a DataFrame from the collected data
#df_financial_data = pd.DataFrame(all_data)

# Reset the index to start at 1 for readability
#df_financial_data.index = df_financial_data.index + 1

# Display the DataFrame
#df_financial_data.head()

# Save the DataFrame as a CSV file for later use
#df_financial_data.to_csv('df_financial_data.csv', index=False)

# Extract the CSV file from our files and convert it into a DataFrame
df_financial_data = pd.read_csv('data/df_financial_data.csv')
df_financial_data.head()
```

```
  Trailing P/E Ratio Forward P/E Ratio Price to Book Ratio Dividend
Yield  \
0          37.536186         27.493536            60.58402
0.0044
1           35.22195         28.298223           11.032745
0.0078
2           68.57943         35.295135            61.97635
0.00029999999
3          23.255629         19.583218           6.8551126
0.0045
4          45.091682          34.41178             8.57757  Not
Available

  Earnings Per Share Trailing Earnings Per Share Forward Return on
Equity  \
0                Not Available                          8.31
1.5741299
1                Not Available                         14.95
0.35604
2                Not Available                          4.12
1.23767
```

```
3               Not Available                        8.96
0.32101002
4               Not Available                        6.15
0.22558

  Debt to Equity Ratio Free Cash Flow Revenue Growth  ...  \
0              209.059   110846001152          0.061  ...
1               33.657    61280874496           0.16  ...
2               17.221    33725874176          1.224  ...
3                9.324    41104498688          0.151  ...
4               61.175    54328250368           0.11  ...

  Dividend Payout Ratio Return on Assets Return on Investment  \
0         Not Available          0.21464        Not Available
1         Not Available          0.14592        Not Available
2         Not Available          0.55258        Not Available
3         Not Available          0.16483        Not Available
4         Not Available          0.07069        Not Available

  Enterprise Value Enterprise Value to EBITDA Price to Free Cash Flow
\
0    3456762118144                      25.67           Not Available

1    3179720212480                     23.286           Not Available

2    3563218010112                     58.238           Not Available

3    2125729103872                     17.217           Not Available

4    2321747804160                     20.807           Not Available


       PEG Ratio Book Value Per Share Symbol Error
0  Not Available                3.767   AAPL   NaN
1  Not Available               38.693   MSFT   NaN
2  Not Available                2.368   NVDA   NaN
3  Not Available               25.613  GOOGL   NaN
4  Not Available               24.655   AMZN   NaN

[5 rows x 28 columns]
```

Drop Unavailable Columns

Some of the stock valuation parameters we imported are not availble. This could be because the specific company is not obligated to report that information, yahoo finance does not have that particular information, or payment is required to pull that data. Since this data is not available, we're going to drop these columns since they can't be included in our model.

```
# Drop any columns that appear to have 'Not Available'
# or 'NaN' values for the majority of the stocks
df_financial_data = df_financial_data.drop(columns = ["Price to Free
Cash Flow",
                                                      "Return on
Investment",
                                                      "Dividend Payout
Ratio",
                                                      "Interest
Coverage Ratio",
                                                      "Net Profit
Margin",
                                                      "Earnings Per
Share Trailing",
                                                      "Error"],
axis=1)
df_financial_data.head()
```

```
  Trailing P/E Ratio Forward P/E Ratio Price to Book Ratio Dividend
Yield  \
0          37.536186         27.493536           60.58402
0.0044
1           35.22195         28.298223          11.032745
0.0078
2           68.57943         35.295135           61.97635
0.00029999999
3          23.255629         19.583218          6.8551126
0.0045
4          45.091682          34.41178            8.57757  Not
Available

  Earnings Per Share Forward Return on Equity Debt to Equity Ratio  \
0                       8.31        1.5741299              209.059
1                      14.95          0.35604               33.657
2                       4.12          1.23767               17.221
3                       8.96       0.32101002                9.324
4                       6.15          0.22558               61.175

  Free Cash Flow Revenue Growth Beta (Volatility)  ... Gross Margin  \
0   110846001152          0.061              1.24  ...      0.46206
1    61280874496           0.16             0.904  ...   0.69348997
2    33725874176          1.224             1.657  ...   0.75975996
3    41104498688          0.151             1.034  ...      0.58127
4    54328250368           0.11             1.146  ...      0.48406

  Price to Sales Ratio Current Ratio Quick Ratio Return on Assets  \
0             8.822043         0.867       0.745          0.21464
1            12.486235         1.301       1.163          0.14592
2            37.380695         4.269       3.503          0.55258
3             6.349746          1.95       1.761          0.16483
```

```
4             3.5858924         1.089       0.827           0.07069

  Enterprise Value Enterprise Value to EBITDA      PEG Ratio  \
0    3456762118144                     25.67  Not Available
1    3179720212480                    23.286  Not Available
2    3563218010112                    58.238  Not Available
3    2125729103872                    17.217  Not Available
4    2321747804160                    20.807  Not Available

  Book Value Per Share Symbol
0                3.767   AAPL
1               38.693   MSFT
2                2.368   NVDA
3               25.613  GOOGL
4               24.655   AMZN

[5 rows x 21 columns]
```

Merge DataFrames

Now that we have the 'df_financial_data' DataFrame containing valuation parameters associated with each 'Symbol' (stock ticker), we're going to merge it with the 'df_filtered' so that we have one DataFrame containing the financial parameters, 'Symbol', 'Name', and 'Market Cap'. We use 'pd.merge()' to create a new DataFrame called 'df_stocks_data' and merge it based on 'Symbol'.

```
# Merge DataFrames based on shared column 'Symbol'
df_filtered_stocks_data = pd.merge(df_filtered, df_financial_data,
on="Symbol")
df_filtered_stocks_data.head()

  Symbol                                Name    Market Cap Trailing
P/E Ratio  \
0   AAPL             Apple Inc. Common Stock  3.288959e+12
37.536186
1   MSFT  Microsoft Corporation Common Stock  3.206167e+12
35.22195
2   NVDA     NVIDIA Corporation Common Stock  2.864613e+12
68.57943
3  GOOGL  Alphabet Inc. Class A Common Stock  1.945719e+12
23.255629
4   AMZN        Amazon.com Inc. Common Stock  1.940525e+12
45.091682

  Forward P/E Ratio Price to Book Ratio Dividend Yield  \
0         27.493536            60.58402         0.0044
1         28.298223           11.032745         0.0078
2         35.295135            61.97635  0.00029999999
3         19.583218           6.8551126         0.0045
```

```
4         34.41178            8.57757  Not Available

  Earnings Per Share Forward Return on Equity Debt to Equity
Ratio  ...  \
0                       8.31       1.5741299
209.059  ...
1                      14.95         0.35604
33.657  ...
2                       4.12         1.23767
17.221  ...
3                       8.96      0.32101002
9.324  ...
4                       6.15         0.22558
61.175  ...

  Operating Margin Gross Margin Price to Sales Ratio Current Ratio  \
0          0.31171      0.46206             8.822043         0.867
1       0.46583998   0.69348997            12.486235         1.301
2          0.62057   0.75975996            37.380695         4.269
3          0.32312      0.58127             6.349746          1.95
4      0.109589994      0.48406            3.5858924         1.089

  Quick Ratio Return on Assets Enterprise Value Enterprise Value to
EBITDA  \
0       0.745          0.21464    3456762118144
25.67
1       1.163          0.14592    3179720212480
23.286
2       3.503          0.55258    3563218010112
58.238
3       1.761          0.16483    2125729103872
17.217
4       0.827          0.07069    2321747804160
20.807

       PEG Ratio Book Value Per Share
0  Not Available                3.767
1  Not Available               38.693
2  Not Available                2.368
3  Not Available               25.613
4  Not Available               24.655

[5 rows x 23 columns]
```

Remove Rows with Insufficient Data

Looking at our DataFrame, we can see that some of our stocks have a lot of valuation parameters that are not available. Before performing any kind of imputation, we're going to remove rows which have half or more of the valuation parameters unavailable. This is to prevent us from having too many inaccurate data points that are just median values.

```
# Replace 'Not Available' with pd.NA to easily filter the data
df_filtered_stocks_data.replace('Not Available', pd.NA, inplace=True)

# Put all valuation columns into a variable, dropping the descriptive
'Name'
# and 'Symbol' columns
valuation_columns = df_filtered_stocks_data.drop(['Name', 'Symbol'],
axis=1).columns

# Remove rows which have 11 or more missing values in the valuation
columns
df_filtered_stocks_data = df_filtered_stocks_data[
    df_filtered_stocks_data[valuation_columns]
    .isna().sum(axis=1) < 11]

# Print the original number of rows and the newly filtered rows
print(f"Original number of rows: {len(df_financial_data)}")

print(f"Number of rows after filtering:
{len(df_filtered_stocks_data)}")
```

```
Original number of rows: 4682
Number of rows after filtering: 3555
```

```
df_filtered_stocks_data.head()
```

```
  Symbol                                Name    Market Cap Trailing
P/E Ratio  \
0   AAPL             Apple Inc. Common Stock  3.288959e+12
37.536186
1   MSFT  Microsoft Corporation Common Stock  3.206167e+12
35.22195
2   NVDA     NVIDIA Corporation Common Stock  2.864613e+12
68.57943
3  GOOGL  Alphabet Inc. Class A Common Stock  1.945719e+12
23.255629
4   AMZN        Amazon.com Inc. Common Stock  1.940525e+12
45.091682

  Forward P/E Ratio Price to Book Ratio Dividend Yield  \
0         27.493536            60.58402         0.0044
1         28.298223           11.032745         0.0078
2         35.295135            61.97635  0.00029999999
3         19.583218           6.8551126         0.0045
4          34.41178             8.57757           <NA>

  Earnings Per Share Forward Return on Equity Debt to Equity
Ratio  ...  \
```

```
0                       8.31       1.5741299
209.059  ...
1                      14.95         0.35604
33.657  ...
2                       4.12         1.23767
17.221  ...
3                       8.96      0.32101002
9.324  ...
4                       6.15         0.22558
61.175  ...

  Operating Margin Gross Margin Price to Sales Ratio Current Ratio  \
0          0.31171      0.46206             8.822043         0.867
1       0.46583998   0.69348997            12.486235         1.301
2          0.62057   0.75975996            37.380695         4.269
3          0.32312      0.58127             6.349746          1.95
4      0.109589994      0.48406            3.5858924         1.089

  Quick Ratio Return on Assets Enterprise Value Enterprise Value to
EBITDA  \
0       0.745          0.21464    3456762118144
25.67
1       1.163          0.14592    3179720212480
23.286
2       3.503          0.55258    3563218010112
58.238
3       1.761          0.16483    2125729103872
17.217
4       0.827          0.07069    2321747804160
20.807

  PEG Ratio Book Value Per Share
0      <NA>                3.767
1      <NA>               38.693
2      <NA>                2.368
3      <NA>               25.613
4      <NA>               24.655

[5 rows x 23 columns]
```

Data Preprocessing: Median and Constant Value Imputation

Now that we have filterd out stocks with too much unavailable data, we are going to use imputation to fill in the rest of the unavailable values, as we need a number there in order to run numerical calculations on it. To avoid outliers and keep the dispersion of data as close as possible to what it is now, we're going to replace all unavailable values with the median value of the column, with the exception being the 'Dividend Yield' column. In this column, we will replace all 'Not Available' with '0.00', as explained below.

Constant Value Imputation

Looking at the 'Dividend Yield' column, some of the rows contain "Not Available" values. Since Dividend Yield is calculated as 'Annual Dividend Per Share / Current Stock Price', we're going to assume that any companies with a "Not Available" value in their "Dividend Yield" column does not give out a dividend. This means that the Dividend Yield for these companies is '0.00'.

```
# Replace all 'Not Available' values in 'Dividend Yield' with 0.00
df_filtered_stocks_data["Dividend Yield"] = df_filtered_stocks_data[
    "Dividend Yield"].replace(pd.NA, 0.00).fillna(0.00)
df_filtered_stocks_data.head(25)
```

```
   Symbol                                              Name    Market
Cap  \
0    AAPL                             Apple Inc. Common Stock
3.288959e+12
1    MSFT                  Microsoft Corporation Common Stock
3.206167e+12
2    NVDA                     NVIDIA Corporation Common Stock
2.864613e+12
3   GOOGL                  Alphabet Inc. Class A Common Stock
1.945719e+12
4    AMZN                        Amazon.com Inc. Common Stock
1.940525e+12
5    META            Meta Platforms Inc. Class A Common Stock
1.349101e+12
8     LLY                  Eli Lilly and Company Common Stock
8.777562e+11
9     TSM    Taiwan Semiconductor Manufacturing Company Ltd.
8.769189e+11
10   AVGO                          Broadcom Inc. Common Stock
7.660679e+11
11   TSLA                             Tesla Inc. Common Stock
7.244806e+11
12    WMT                           Walmart Inc. Common Stock
6.475615e+11
13    NVO                        Novo Nordisk A/S Common Stock
6.108792e+11
14    JPM                  JP Morgan Chase & Co. Common Stock
5.913959e+11
15    UNH  UnitedHealth Group Incorporated Common Stock (DE)
5.440226e+11
16      V                                           Visa Inc.
5.293435e+11
17    XOM                  Exxon Mobil Corporation Common Stock
5.007510e+11
18   ORCL                     Oracle Corporation Common Stock
4.719790e+11
19     MA                Mastercard Incorporated Common Stock
```

```
4.598019e+11
20     PG       Procter & Gamble Company (The) Common Stock
4.172320e+11
21   COST         Costco Wholesale Corporation Common Stock
4.024906e+11
22    JNJ                    Johnson & Johnson Common Stock
4.019856e+11
23     HD                Home Depot Inc. (The) Common Stock
3.794480e+11
24   ABBV                          AbbVie Inc. Common Stock
3.457265e+11
25     KO              Coca-Cola Company (The) Common Stock
3.107415e+11
26    BAC           Bank of America Corporation Common Stock
3.033995e+11

   Trailing P/E Ratio Forward P/E Ratio Price to Book Ratio Dividend
Yield  \
0           37.536186         27.493536            60.58402
0.0044
1            35.22195         28.298223           11.032745
0.0078
2            68.57943         35.295135            61.97635
0.00029999999
3           23.255629         19.583218           6.8551126
0.0045
4           45.091682          34.41178             8.57757
0.0
5           27.263107         22.794006            8.854049
0.0034
8            84.99783         34.744507            49.68278
0.0064
9           33.902878         21.246187           1.2249168
0.013200001
10          138.52032         27.499495           2.8770201
0.012200001
11          84.790184          95.36681           14.270384
0.0
12          43.994793         31.026402            8.039402
0.0097
13          34.990032         3.7756453           3.8906538
0.0135
14          13.444692         14.349644           2.1004775
0.0207
15           38.54126         19.725695            5.791293
0.0139
16          31.712961         24.373024            15.35339
0.0076
17          15.013699         14.677951           1.9727713
```

```
0.0326
18          48.08483         26.148077          47.92467
0.0084
19         39.245853         31.758354           64.3502
0.0050999997
20         28.806896          22.54444          7.708064
0.0242
21         55.891712         47.140396         17.331171
0.005
22         25.102478         14.283859          5.211021
0.0324
23         27.247816         25.767067           69.4845
0.0219
24          59.31119         14.009017          49.70114
0.0385
25         25.954355         20.861404         10.165772
0.0308
26         16.630436         12.536874         1.2976733
0.0227

   Earnings Per Share Forward Return on Equity Debt to Equity
Ratio  ...  \
0                        8.31        1.5741299
209.059  ...
1                       14.95          0.35604
33.657  ...
2                        4.12          1.23767
17.221  ...
3                        8.96       0.32101002
9.324  ...
4                        6.15          0.22558
61.175  ...
5                        25.3          0.36134
29.811  ...
8                       22.66          0.65318
218.081  ...
9                        8.08          0.28027
24.081  ...
10                       6.17          0.12509
166.032  ...
11                       3.24          0.20389
18.078  ...
12                       2.72       0.18531999
69.566  ...
13                       4.07       0.88725996
47.271  ...
14                      16.74          0.16216
<NA>  ...
15                       29.9          0.15252
```

```
74.683  ...
16                         12.66          0.50708
53.239  ...
17                          7.87       0.14513999
15.394  ...
18                          7.16          1.55578
749.978  ...
19                         16.38        1.7757801
244.839  ...
20                          7.42          0.28766
69.338  ...
21                         19.68          0.30267
42.118  ...
22                          10.6          0.20889
50.958  ...
23                          15.6          4.04933
1095.368  ...
24                         12.13          0.56407
1174.815  ...
25                          2.97           0.3723
167.358  ...
26                          3.66          0.08092
<NA>  ...

   Operating Margin Gross Margin Price to Sales Ratio Current Ratio  \
0           0.31171      0.46206             8.822043         0.867
1        0.46583998   0.69348997            12.486235         1.301
2           0.62057   0.75975996            37.380695         4.269
3           0.32312      0.58127             6.349746          1.95
4       0.109589994      0.48406            3.5858924         1.089
5           0.42765      0.81501             9.326395         2.732
8        0.39773998      0.80906            18.265305         1.273
9        0.47487998      0.54453           0.36870518         2.567
10          0.31765      0.74713             16.99826         1.038
11      0.107889995      0.18229           10.2821045         1.844
12          0.04689      0.24628            1.0209852         0.803
13          0.47429   0.84657997            1.7316614         0.937
14       0.43787998         <NA>            4.1995354          <NA>
15          0.08637      0.22872            1.3858067         0.908
16          0.66122   0.97833997            16.617924         1.283
17          0.13274      0.31535             1.541141         1.348
18       0.30517998   0.71310997             9.631641          0.72
19       0.59301996          1.0            17.543499         1.289
20       0.27763999      0.51756              4.68959         0.754
21          0.03817      0.12613            1.6087513         0.966
22       0.24516001      0.69391            4.1694636         1.029
23          0.13472      0.33495             2.606787         1.133
24          0.28928      0.70335             5.397871         0.645
25          0.30235   0.60433996             5.811433          1.06
```

```
26          0.30769        <NA>           3.7218654         <NA>

   Quick Ratio Return on Assets Enterprise Value Enterprise Value to
EBITDA  \
0        0.745          0.21464    3456762118144
25.67
1        1.163          0.14592    3179720212480
23.286
2        3.503          0.55258    3563218010112
58.238
3        1.761          0.16483    2125729103872
17.217
4        0.827          0.07069    2321747804160
20.807
5        2.568       0.17188999    1442350366720
18.209
8         0.63          0.13946     757866496000
45.747
9        2.238          0.12409    3672532582400
2.043
10       0.841      0.077010006     100720377856
4.387
11       1.214          0.04759    1040004087808
78.526
12       0.183      0.069510005     747954503680
18.342
13       0.742       0.21465999     458086383616
3.596
14        <NA>      0.013259999     205751500800
<NA>
15       0.833          0.06924     608368656384
17.365
16       0.837          0.16174     584800665600
23.417
17       0.978          0.07083     557304119296
7.79
18       0.591      0.072909996     599515660288
27.497
19       0.891       0.22886999     486012649472
28.957
20       0.507          0.10601     417390854144
17.362
21       0.391           0.0836     412516057088
35.802
22       0.705          0.08403     384398131200
12.791
23       0.251          0.15313     468345290752
18.917
24       0.436      0.077199996     365109346304
```

```
14.245
25       0.784          0.08438     301981204480
20.361
26        <NA>     0.0072899996     348427976704
<NA>

   PEG Ratio Book Value Per Share
0       <NA>                3.767
1       <NA>               38.693
2       <NA>                2.368
3       <NA>               25.613
4       <NA>               24.655
5       <NA>               65.186
8       <NA>               15.825
9       <NA>              153.888
10      <NA>               59.221
11      <NA>               21.806
12      <NA>               10.507
13      <NA>                27.07
14      <NA>               115.15
15      <NA>              102.421
16      <NA>               20.077
17      <NA>               61.112
18      <NA>                3.903
19      <NA>                8.087
20      <NA>               21.676
21      <NA>               53.308
22      <NA>               29.144
23      <NA>                5.839
24      <NA>                3.413
25      <NA>                6.153
26      <NA>               35.371

[25 rows x 23 columns]

# Get a list of all column names in the DataFrame
columns_to_impute = df_filtered_stocks_data.count().keys().tolist()

# Exclude non-numeric columns from the list
columns_to_impute = [col for col in columns_to_impute if col not in
['Symbol', 'Name']]

# Convert columns to numeric and impute missing values with the median

# of the respective column
for col in columns_to_impute:
    df_filtered_stocks_data[col] =
pd.to_numeric(df_filtered_stocks_data[col],
                                                 errors ='coerce')
    median_value = df_filtered_stocks_data[col].median()
```

```
    df_filtered_stocks_data[col].fillna(median_value, inplace=True)

df_filtered_stocks_data.head()
```

```
  Symbol                                Name     Market Cap  \
0   AAPL             Apple Inc. Common Stock  3.288959e+12
1   MSFT  Microsoft Corporation Common Stock  3.206167e+12
2   NVDA     NVIDIA Corporation Common Stock  2.864613e+12
3  GOOGL  Alphabet Inc. Class A Common Stock  1.945719e+12
4   AMZN        Amazon.com Inc. Common Stock  1.940525e+12

   Trailing P/E Ratio  Forward P/E Ratio  Price to Book Ratio
Dividend Yield  \
0           37.536186          27.493536            60.584020
0.0044
1           35.221950          28.298223            11.032745
0.0078
2           68.579430          35.295135            61.976350
0.0003
3           23.255629          19.583218             6.855113
0.0045
4           45.091682          34.411780             8.577570
0.0000

   Earnings Per Share Forward  Return on Equity  Debt to Equity Ratio
...  \
0                        8.31           1.57413               209.059
...
1                       14.95           0.35604                33.657
...
2                        4.12           1.23767                17.221
...
3                        8.96           0.32101                 9.324
...
4                        6.15           0.22558                61.175
...

   Operating Margin  Gross Margin  Price to Sales Ratio  Current Ratio
\
0           0.31171       0.46206              8.822043          0.867

1           0.46584       0.69349             12.486235          1.301

2           0.62057       0.75976             37.380695          4.269

3           0.32312       0.58127              6.349746          1.950

4           0.10959       0.48406              3.585892          1.089
```

```
   Quick Ratio  Return on Assets  Enterprise Value  \
0        0.745           0.21464      3.456762e+12
1        1.163           0.14592      3.179720e+12
2        3.503           0.55258      3.563218e+12
3        1.761           0.16483      2.125729e+12
4        0.827           0.07069      2.321748e+12

   Enterprise Value to EBITDA  PEG Ratio  Book Value Per Share
0                      25.670        1.3                 3.767
1                      23.286        1.3                38.693
2                      58.238        1.3                 2.368
3                      17.217        1.3                25.613
4                      20.807        1.3                24.655

[5 rows x 23 columns]
```

```
df_filtered_stocks_data = df_filtered_stocks_data[
    (df_filtered_stocks_data['Symbol'] != "NaN")]
df_filtered_stocks_data.head(10)
```

```
   Symbol                                             Name    Market
Cap  \
0    AAPL                           Apple Inc. Common Stock
3.288959e+12
1    MSFT                   Microsoft Corporation Common Stock
3.206167e+12
2    NVDA                      NVIDIA Corporation Common Stock
2.864613e+12
3   GOOGL                  Alphabet Inc. Class A Common Stock
1.945719e+12
4    AMZN                         Amazon.com Inc. Common Stock
1.940525e+12
5    META             Meta Platforms Inc. Class A Common Stock
1.349101e+12
8     LLY                  Eli Lilly and Company Common Stock
8.777562e+11
9     TSM  Taiwan Semiconductor Manufacturing Company Ltd.
8.769189e+11
10   AVGO                            Broadcom Inc. Common Stock
7.660679e+11
11   TSLA                               Tesla Inc. Common Stock
7.244806e+11

    Trailing P/E Ratio  Forward P/E Ratio  Price to Book Ratio  \
0            37.536186          27.493536            60.584020
1            35.221950          28.298223            11.032745
2            68.579430          35.295135            61.976350
3            23.255629          19.583218             6.855113
4            45.091682          34.411780             8.577570
5            27.263107          22.794006             8.854049
```

8	84.997830	34.744507	49.682780
9	33.902878	21.246187	1.224917
10	138.520320	27.499495	2.877020
11	84.790184	95.366810	14.270384

	Dividend Yield	Earnings Per Share Forward	Return on Equity \
0	0.0044	8.31	1.57413
1	0.0078	14.95	0.35604
2	0.0003	4.12	1.23767
3	0.0045	8.96	0.32101
4	0.0000	6.15	0.22558
5	0.0034	25.30	0.36134
8	0.0064	22.66	0.65318
9	0.0132	8.08	0.28027
10	0.0122	6.17	0.12509
11	0.0000	3.24	0.20389

	Debt to Equity Ratio	...	Operating Margin	Gross Margin \
0	209.059	...	0.31171	0.46206
1	33.657	...	0.46584	0.69349
2	17.221	...	0.62057	0.75976
3	9.324	...	0.32312	0.58127
4	61.175	...	0.10959	0.48406
5	29.811	...	0.42765	0.81501
8	218.081	...	0.39774	0.80906
9	24.081	...	0.47488	0.54453
10	166.032	...	0.31765	0.74713
11	18.078	...	0.10789	0.18229

	Price to Sales Ratio	Current Ratio	Quick Ratio	Return on Assets \
0	8.822043	0.867	0.745	0.21464
1	12.486235	1.301	1.163	0.14592
2	37.380695	4.269	3.503	0.55258
3	6.349746	1.950	1.761	0.16483
4	3.585892	1.089	0.827	0.07069
5	9.326395	2.732	2.568	0.17189
8	18.265305	1.273	0.630	0.13946
9	0.368705	2.567	2.238	0.12409
10	16.998260	1.038	0.841	0.07701
11	10.282105	1.844	1.214	0.04759

```
    Enterprise Value  Enterprise Value to EBITDA  PEG Ratio  \
0       3.456762e+12                      25.670        1.3
1       3.179720e+12                      23.286        1.3
2       3.563218e+12                      58.238        1.3
3       2.125729e+12                      17.217        1.3
4       2.321748e+12                      20.807        1.3
5       1.442350e+12                      18.209        1.3
8       7.578665e+11                      45.747        1.3
9       3.672533e+12                       2.043        1.3
10      1.007204e+11                       4.387        1.3
11      1.040004e+12                      78.526        1.3

    Book Value Per Share
0                  3.767
1                 38.693
2                  2.368
3                 25.613
4                 24.655
5                 65.186
8                 15.825
9                153.888
10                59.221
11                21.806

[10 rows x 23 columns]
```

Classification Variables

Now that we have a substantial amount of quantitative variables, we are going to add two classification variables to our DataFrame: 'Pays Dividend' and 'Earnings Outcome'. Even though we are creating this model to predict 'Earnings Outcome', I included 'Pays Dividend' because it creates a richer feature set, companies that pay dividends have a different risk profile and may be more stable, and further insights can be derived from seeing the influence that dividend payments have on earnigns reports.

Classification Variables: Pays Dividend

We are going to add a 'Pays Dividend' column to the 'df_stocks_data' DataFrame using the values in the "Dividend Yield" column. To do this, we're going to analyze the values in the "Dividend Yield" column and replace all values that are 0.000 with "No" and any other values with "Yes". Since all values in the "Dividend Yield column are 0 or greater, we do not have to specify if the value is positive or not.

```
# Replace all 0.00 values with 0 and any other values with 1
df_filtered_stocks_data['Pays Dividend'] = df_filtered_stocks_data[
```

```
    "Dividend Yield"].apply(lambda x: 0 if x == 0.0000 else 1)
df_filtered_stocks_data.head()
```

```
  Symbol                                Name    Market Cap  \
0   AAPL             Apple Inc. Common Stock  3.288959e+12
1   MSFT  Microsoft Corporation Common Stock  3.206167e+12
2   NVDA     NVIDIA Corporation Common Stock  2.864613e+12
3  GOOGL  Alphabet Inc. Class A Common Stock  1.945719e+12
4   AMZN         Amazon.com Inc. Common Stock  1.940525e+12

   Trailing P/E Ratio  Forward P/E Ratio  Price to Book Ratio
Dividend Yield  \
0           37.536186          27.493536            60.584020
0.0044
1           35.221950          28.298223            11.032745
0.0078
2           68.579430          35.295135            61.976350
0.0003
3           23.255629          19.583218             6.855113
0.0045
4           45.091682          34.411780             8.577570
0.0000

   Earnings Per Share Forward  Return on Equity  Debt to Equity Ratio
...  \
0                        8.31           1.57413               209.059
...
1                       14.95           0.35604                33.657
...
2                        4.12           1.23767                17.221
...
3                        8.96           0.32101                 9.324
...
4                        6.15           0.22558                61.175
...

   Gross Margin  Price to Sales Ratio  Current Ratio  Quick Ratio  \
0       0.46206              8.822043          0.867        0.745
1       0.69349             12.486235          1.301        1.163
2       0.75976             37.380695          4.269        3.503
3       0.58127              6.349746          1.950        1.761
4       0.48406              3.585892          1.089        0.827

   Return on Assets  Enterprise Value  Enterprise Value to EBITDA  PEG
Ratio  \
0           0.21464      3.456762e+12                      25.670
1.3
1           0.14592      3.179720e+12                      23.286
1.3
2           0.55258      3.563218e+12                      58.238
```

```
1.3
3          0.16483      2.125729e+12                          17.217
1.3
4          0.07069      2.321748e+12                          20.807
1.3

   Book Value Per Share  Pays Dividend
0                 3.767              1
1                38.693              1
2                 2.368              1
3                25.613              1
4                24.655              0

[5 rows x 24 columns]
```

Classification Variables: Earnings Outcome

Earnings outcome is the variable we are going to built our model to try and predict. For stock traders, the important values in earnings reports are "Actual EPS" and "Predicted EPS". "Predicted EPS" are predictions done by financial firms prior to the earnings report and "Actual EPS" are the actual earnings as revealed by the company. We can use yfinance to pull this data from yahoo finance, with the limitation being we can ony pull the last 4 quarters of earnings reports. Because this is a computationally intensive program to run on a simple laptop, I saved the output as a HDF5 file for easy access. Once this is done, we will create our target classification variable, which is 'Earnings Outcome'. Earnings outcome will have a value of 1 if the EPS Difference (Actual EPS - Estimated EPS) is greater than 0 and a value of 0 if the EPS Difference is 0 or less. In this case, an earnings outcome of 1 is positive and an earnings outcome of 0 is negative.

```
# This code is computationally intensive and will take some time
# to run. After running, save it as an HDF5 file, as shown below
import yfinance as yf

# Extract the 'Symbol' column from the DataFrame
stock_symbols = df_filtered_stocks_data["Symbol"]

# Dictionary to store earnings data for each stock
earnings_data = {}

# Function to fetch earnings history for a chunk of stock symbols
def fetch_earnings(symbols_chunk):
    for symbol in stock_symbols:
        stock=yf.Ticker(symbol) # Creates a Ticker object for the
stock symbol
        earnings_history = stock.earnings_history # Fetch the earnings
history

        # Check if earnings_history is None (no data returned)
        if earnings_history is not None:
```

```
            # Convert to DataFrame
            earnings_df = pd.DataFrame(earnings_history)

            # Check if the DataFrame has rows
            if not earnings_df.empty:
                print(f"Earnings history for {symbol}:")
                print(earnings_df.head())
                earnings_data[symbol] = earnings_df
            else:
                print(f"No earnings data available for {symbol}")
        else:
            print(f"No earnings data available for {symbol}")

# Process symbols in chunks of 1000
chunk_size = 1000
for i in range(0, len(stock_symbols), chunk_size):
    symbols_chunk = stock_symbols[i:i + chunk_size]
    print(f"Processing chunk {i // chunk_size + 1}...")
    fetch_earnings(symbols_chunk.head(25))


# Save earnings data to an HDF5 file
#with pd.HDFStore('earnings_data.h5', mode='w') as store:
#    for symbal, df in earnings_data.items():
        # Store each earnings DataFrame using its symbol as the key
#        store[symbal] = df

# Initialize an empty dictionary to store the loaded earnings data
loaded_earnings_data = {}

# Open the HDF5 file in read mode
with pd.HDFStore('earnings_data.h5', mode='r') as store:
    # Iterate through all stored keys (symbols) in the HDF5 file
    for symbol in store.keys():
        # Remove leading '/' from the symbol name
        symbol = symbol.strip('/')
        # Load the DataFrame and add it to the dictionary
        loaded_earnings_data[symbol] = store[symbol]

# Combine all DataFrames in the loaded earnings data dictionary into
# a single DataFrame
# Use the dictionary keys (stock symbols) as a multi-index for the
rows
earnings_df = pd.concat(loaded_earnings_data.values(),
                        keys=loaded_earnings_data.keys())

# Reset the multi-index to move the 'symbol' from the index to a
column
# Rename the new column to 'Symbol' for clarity
earnings_df =
```

```
earnings_df.reset_index(level=0).rename(columns={'level_0': 'Symbol'})
earnings_df.head()
```

```
/var/folders/wv/49phbq0x3bj2l3xqln6zr3x40000gn/T/
ipykernel_5559/397766636.py:4: FutureWarning: The behavior of
DataFrame concatenation with empty or all-NA entries is deprecated. In
a future version, this will no longer exclude empty or all-NA columns
when determining the result dtypes. To retain the old behavior,
exclude the relevant entries before the concat operation.
  earnings_df = pd.concat(loaded_earnings_data.values(),
```

```
           Symbol  epsEstimate  epsActual  epsDifference
surprisePercent
2023-10-31      A         1.34       1.38           0.04
0.030
2024-01-31      A         1.22       1.29           0.07
0.057
2024-04-30      A         1.19       1.22           0.03
0.025
2024-07-31      A         1.26       1.32           0.06
0.048
2023-12-31     AA        -0.86      -0.56           0.30
0.349
```

```
# Reset the index and make 'Date' it's own column
earnings_df = earnings_df.reset_index().rename(columns={'index':
'Date'})
earnings_df.head()
```

```
        Date Symbol  epsEstimate  epsActual  epsDifference
surprisePercent
0 2023-10-31      A         1.34       1.38           0.04
0.030
1 2024-01-31      A         1.22       1.29           0.07
0.057
2 2024-04-30      A         1.19       1.22           0.03
0.025
3 2024-07-31      A         1.26       1.32           0.06
0.048
4 2023-12-31     AA        -0.86      -0.56           0.30
0.349
```

```
# Create new column called 'Earnings Outcome' which is a
classification variable
# and the target of our analysis
# All values greater than 0 in the 'epsDifference' column are assigned
1
# and all values that are
# 0 or less are assigned a value of 0
earnings_df['Earnings Outcome'] = earnings_df[
```

```
    'epsDifference'].apply(lambda x: 1 if x > 0 else 0)
earnings_df.head()
```

```
        Date Symbol  epsEstimate  epsActual  epsDifference
surprisePercent  \
0 2023-10-31      A         1.34       1.38           0.04
0.030
1 2024-01-31      A         1.22       1.29           0.07
0.057
2 2024-04-30      A         1.19       1.22           0.03
0.025
3 2024-07-31      A         1.26       1.32           0.06
0.048
4 2023-12-31     AA        -0.86      -0.56           0.30
0.349

   Earnings Outcome
0                 1
1                 1
2                 1
3                 1
4                 1
```

Merge DataFrames

Now that we have a clean DataFrame with our earnings history information, we can merge it with our other DataFrame containing the stock's valuation parameters using the shared column 'Symbol'.

```
# Merge our earnings history DataFrame with our valuation parameters
DataFrame
# using the shared column 'Symbol'

df_stocks_data_merged = pd.merge(df_filtered_stocks_data, earnings_df,
on="Symbol")
df_stocks_data_merged.head()
```

```
  Symbol                                Name    Market Cap  \
0   AAPL             Apple Inc. Common Stock  3.288959e+12
1   AAPL             Apple Inc. Common Stock  3.288959e+12
2   AAPL             Apple Inc. Common Stock  3.288959e+12
3   AAPL             Apple Inc. Common Stock  3.288959e+12
4   MSFT  Microsoft Corporation Common Stock  3.206167e+12

   Trailing P/E Ratio  Forward P/E Ratio  Price to Book Ratio
Dividend Yield  \
0           37.536186          27.493536            60.584020
0.0044
1           37.536186          27.493536            60.584020
```

```
0.0044
2          37.536186         27.493536           60.584020
0.0044
3          37.536186         27.493536           60.584020
0.0044
4          35.221950         28.298223           11.032745
0.0078

   Earnings Per Share Forward  Return on Equity  Debt to Equity Ratio
...  \
0                        8.31           1.57413               209.059
...
1                        8.31           1.57413               209.059
...
2                        8.31           1.57413               209.059
...
3                        8.31           1.57413               209.059
...
4                       14.95           0.35604                33.657
...

   Enterprise Value to EBITDA  PEG Ratio  Book Value Per Share  Pays
Dividend  \
0                      25.670        1.3                 3.767
1
1                      25.670        1.3                 3.767
1
2                      25.670        1.3                 3.767
1
3                      25.670        1.3                 3.767
1
4                      23.286        1.3                38.693
1

        Date  epsEstimate  epsActual  epsDifference
surprisePercent  \
0 2023-12-31         2.10       2.18           0.08            0.038

1 2024-03-31         1.50       1.53           0.03            0.020

2 2024-06-30         1.35       1.40           0.05            0.037

3 2024-09-30         1.60       1.64           0.04            0.025

4 2023-12-31         2.78       2.93           0.15            0.054


   Earnings Outcome
0                 1
1                 1
```

```
2                  1
3                  1
4                  1

[5 rows x 30 columns]
```

Data Cleanup: Remove Unavailable values

Since earnings history is very important to our model, we're going to remove any rows where the EPS Difference is unavailable. Following our data imputation, we'll also finalize our data cleaning by removing any leftover rows which have unavailable or NaN values.

```
# Remove all rows where 'epsDifference' is unavailable

df_stocks_data_merged =
df_stocks_data_merged.dropna(subset=['epsDifference'])
df_stocks_data_merged.count()
```

```
Symbol                          12091
Name                            12091
Market Cap                      12091
Trailing P/E Ratio              12091
Forward P/E Ratio               12091
Price to Book Ratio             12091
Dividend Yield                  12091
Earnings Per Share Forward      12091
Return on Equity                12091
Debt to Equity Ratio            12091
Free Cash Flow                  12091
Revenue Growth                  12091
Beta (Volatility)               12091
Operating Margin                12091
Gross Margin                    12091
Price to Sales Ratio            12091
Current Ratio                   12091
Quick Ratio                     12091
Return on Assets                12091
Enterprise Value                12091
Enterprise Value to EBITDA      12091
PEG Ratio                       12091
Book Value Per Share            12091
Pays Dividend                   12091
Date                            12091
epsEstimate                     12091
epsActual                       12091
epsDifference                   12091
surprisePercent                 11964
Earnings Outcome                12091
dtype: int64
```

```
# Remove any remaining rows that are 'Not Available' or NaN
import numpy as np

df_stocks_data_merged = df_stocks_data_merged.replace("Not Available",
np.nan)
df_stocks_data_merged = df_stocks_data_merged.dropna()
df_stocks_data_merged.count()
```

```
Symbol                          11964
Name                            11964
Market Cap                      11964
Trailing P/E Ratio              11964
Forward P/E Ratio               11964
Price to Book Ratio             11964
Dividend Yield                  11964
Earnings Per Share Forward      11964
Return on Equity                11964
Debt to Equity Ratio            11964
Free Cash Flow                  11964
Revenue Growth                  11964
Beta (Volatility)               11964
Operating Margin                11964
Gross Margin                    11964
Price to Sales Ratio            11964
Current Ratio                   11964
Quick Ratio                     11964
Return on Assets                11964
Enterprise Value                11964
Enterprise Value to EBITDA      11964
PEG Ratio                       11964
Book Value Per Share            11964
Pays Dividend                   11964
Date                            11964
epsEstimate                     11964
epsActual                       11964
epsDifference                   11964
surprisePercent                 11964
Earnings Outcome                11964
dtype: int64
```

```
# This is to make sure that our numerical columns don't
# contain non-numerical values

non_numerical = df_stocks_data_merged.apply(pd.to_numeric,
errors='coerce')
non_numerical_na = non_numerical.isna().sum()

print("Non-numerical values per column:")
print(non_numerical_na)
```

```
Non-numerical values per column:
Symbol                            11964
Name                              11964
Market Cap                            0
Trailing P/E Ratio                    0
Forward P/E Ratio                     0
Price to Book Ratio                   0
Dividend Yield                        0
Earnings Per Share Forward            0
Return on Equity                      0
Debt to Equity Ratio                  0
Free Cash Flow                        0
Revenue Growth                        0
Beta (Volatility)                     0
Operating Margin                      0
Gross Margin                          0
Price to Sales Ratio                  0
Current Ratio                         0
Quick Ratio                           0
Return on Assets                      0
Enterprise Value                      0
Enterprise Value to EBITDA            0
PEG Ratio                             0
Book Value Per Share                  0
Pays Dividend                         0
Date                                  0
epsEstimate                           0
epsActual                             0
epsDifference                         0
surprisePercent                       0
Earnings Outcome                      0
dtype: int64
```

Data Leakage

Data leakage happens when there is information used in the model that directly or indirectly provides the answer to the target variable, leading to overly optimistic model performance. To mitigate this, we need to remove the earnings information, including EPS Difference, EPS Estimate, EPS Actual, and Surprise Percent, as leaving these in will provide the model information to perfectly predict the target variable, Earnings Outcome. On top of this, we are also going to drop 'Date' is that is not needed and cannot be included in the model.

```
# To prevent data leakage, some columns need to be dropped as they
either indirectly
# provide the model with the target value answer or are in perfect
multicollinearity
# with the target variable

df_stocks_data_merged.drop(columns=["epsDifference", "epsEstimate",
```

```
"epsActual",
                                                    "surprisePercent", "Date"],
inplace=True)
df_stocks_data_merged.head()
```

```
  Symbol                                Name    Market Cap  \
0   AAPL             Apple Inc. Common Stock  3.288959e+12
1   AAPL             Apple Inc. Common Stock  3.288959e+12
2   AAPL             Apple Inc. Common Stock  3.288959e+12
3   AAPL             Apple Inc. Common Stock  3.288959e+12
4   MSFT  Microsoft Corporation Common Stock  3.206167e+12

   Trailing P/E Ratio  Forward P/E Ratio  Price to Book Ratio
Dividend Yield  \
0           37.536186          27.493536            60.584020
0.0044
1           37.536186          27.493536            60.584020
0.0044
2           37.536186          27.493536            60.584020
0.0044
3           37.536186          27.493536            60.584020
0.0044
4           35.221950          28.298223            11.032745
0.0078

   Earnings Per Share Forward  Return on Equity  Debt to Equity Ratio
...  \
0                        8.31           1.57413               209.059
...
1                        8.31           1.57413               209.059
...
2                        8.31           1.57413               209.059
...
3                        8.31           1.57413               209.059
...
4                       14.95           0.35604                33.657
...

   Price to Sales Ratio  Current Ratio  Quick Ratio  Return on Assets
\
0              8.822043          0.867        0.745           0.21464

1              8.822043          0.867        0.745           0.21464

2              8.822043          0.867        0.745           0.21464

3              8.822043          0.867        0.745           0.21464

4             12.486235          1.301        1.163           0.14592
```

```
   Enterprise Value  Enterprise Value to EBITDA  PEG Ratio  \
0      3.456762e+12                      25.670        1.3
1      3.456762e+12                      25.670        1.3
2      3.456762e+12                      25.670        1.3
3      3.456762e+12                      25.670        1.3
4      3.179720e+12                      23.286        1.3

   Book Value Per Share  Pays Dividend  Earnings Outcome
0                 3.767              1                 1
1                 3.767              1                 1
2                 3.767              1                 1
3                 3.767              1                 1
4                38.693              1                 1

[5 rows x 25 columns]
```

Scaling

Scaling is the process of transforming quantitative data into a consistent range or scale. This is done to ensure that the values of features in our dataset to not significantly vary in magnitude, as these differences in scale can cause the model to bias larger values. Since the values of some of our columns are fractional and our market cap column contains values up to $1 trillion, the values need to be standardized. Scaling takes all the data and normalizes it to have a mean of 0 and a standard deviation of 1.

Before scaling our values, we need to make sure that all values are numerical (which we have done above) and that there are no infinite values. As you see below, there are some infinite values in our data that need to be removed. We will remove them by replacing them with median imputation. Once this is done, we can normalize the data to a standard scale for modeling.

```
# Upon trying to scale our values for modeling, we were given an error
saying
# some of our values
# were infinite
# This identifies and prints out rows with infinite values

infinity_values = df_stocks_data_merged[
    ["Market Cap", "Trailing P/E Ratio", "Forward P/E Ratio",
     "Price to Book Ratio", "Dividend Yield",
                                        "Earnings Per Share Forward",

     "Return on Equity", "Debt to Equity Ratio", "Free Cash Flow",
                                        "Revenue Growth", "Beta
(Volatility)",
     "Operating Margin", "Gross Margin", "Price to Sales Ratio",
                                        "Current Ratio", "Quick
Ratio",
```

```
    "Return on Assets", "Enterprise Value", "Enterprise Value to
EBITDA",
                                         "PEG Ratio",
    "Book Value Per Share"]].applymap(np.isinf)

# Print out any rows with infinite values
print(df_stocks_data_merged[infinity_values.any(axis=1)])
```

```
/var/folders/wv/49phbq0x3bj2l3xqln6zr3x40000gn/T/
ipykernel_5559/1759544207.py:16: FutureWarning: DataFrame.applymap has
been deprecated. Use DataFrame.map instead.
  "Book Value Per Share"]].applymap(np.isinf)
```

```
      Symbol                                       Name    Market
Cap  \
2360     KEY                       KeyCorp Common Stock
1.534579e+10
2361     KEY                       KeyCorp Common Stock
1.534579e+10
2362     KEY                       KeyCorp Common Stock
1.534579e+10
2363     KEY                       KeyCorp Common Stock
1.534579e+10
4328     IRT  Independence Realty Trust Inc. Common Stock
4.747794e+09
...      ...                                        ...              ..
.
13323   GANX          Gain Therapeutics Inc. Common Stock
3.779248e+07
13428   UNCY     Unicycive Therapeutics Inc. Common Stock
3.541189e+07
13429   UNCY     Unicycive Therapeutics Inc. Common Stock
3.541189e+07
13430   UNCY     Unicycive Therapeutics Inc. Common Stock
3.541189e+07
13431   UNCY     Unicycive Therapeutics Inc. Common Stock
3.541189e+07

       Trailing P/E Ratio  Forward P/E Ratio  Price to Book Ratio  \
2360                  inf          12.327231             1.321914
2361                  inf          12.327231             1.321914
2362                  inf          12.327231             1.321914
2363                  inf          12.327231             1.321914
4328                  inf          78.477875             1.396517
...                   ...                ...                  ...
13323            20.80899          -1.917582             3.728632
13428            20.80899          -1.261972             1.973991
13429            20.80899          -1.261972             1.973991
13430            20.80899          -1.261972             1.973991
13431            20.80899          -1.261972             1.973991
```

```
       Dividend Yield  Earnings Per Share Forward  Return on Equity  \
2360           0.0430                        1.56           0.00967
2361           0.0430                        1.56           0.00967
2362           0.0430                        1.56           0.00967
2363           0.0430                        1.56           0.00967
4328           0.0306                        0.27          -0.00015
...               ...                         ...               ...
13323          0.0000                       -0.89          -1.88827
13428          0.0000                       -0.20          -1.21763
13429          0.0000                       -0.20          -1.21763
13430          0.0000                       -0.20          -1.21763
13431          0.0000                       -0.20          -1.21763

       Debt to Equity Ratio  ...  Price to Sales Ratio  Current Ratio
\
2360                55.0375  ...              3.910379          1.811

2361                55.0375  ...              3.910379          1.811

2362                55.0375  ...              3.910379          1.811

2363                55.0375  ...              3.910379          1.811

4328                65.6610  ...              7.507696          0.374

...                     ...  ...                   ...            ...

13323                6.8530  ...                   inf          2.842

13428                2.0230  ...                   inf          3.366

13429                2.0230  ...                   inf          3.366

13430                2.0230  ...                   inf          3.366

13431                2.0230  ...                   inf          3.366


       Quick Ratio  Return on Assets  Enterprise Value  \
2360         1.221           0.00077      3.775594e+10
2361         1.221           0.00077      3.775594e+10
2362         1.221           0.00077      3.775594e+10
2363         1.221           0.00077      3.775594e+10
4328         0.203           0.01276      7.086861e+09
...            ...               ...               ...
13323        2.644          -0.72955      3.570824e+07
13428        3.193          -0.53371      5.015270e+07
13429        3.193          -0.53371      5.015270e+07
13430        3.193          -0.53371      5.015270e+07
13431        3.193          -0.53371      5.015270e+07
```

```
       Enterprise Value to EBITDA  PEG Ratio  Book Value Per Share  \
2360                        9.694        1.3                14.479
2361                        9.694        1.3                14.479
2362                        9.694        1.3                14.479
2363                        9.694        1.3                14.479
4328                       20.429        1.3                14.930
...                           ...        ...                   ...
13323                      -1.636        1.3                 0.468
13428                      -1.739        1.3                -0.341
13429                      -1.739        1.3                -0.341
13430                      -1.739        1.3                -0.341
13431                      -1.739        1.3                -0.341

       Pays Dividend  Earnings Outcome
2360               1                 1
2361               1                 0
2362               1                 1
2363               1                 1
4328               1                 0
...              ...               ...
13323              0                 0
13428              0                 0
13429              0                 0
13430              0                 0
13431              0                 1

[80 rows x 25 columns]
```

```
# Replace all infinite values the median column values

columns_with_inf = ['Trailing P/E Ratio', 'Forward P/E Ratio', 'Price
to Sales Ratio']
df_stocks_data_merged[columns_with_inf] = df_stocks_data_merged[
    columns_with_inf].replace([np.inf, -np.inf], np.nan)
df_stocks_data_merged[columns_with_inf] = df_stocks_data_merged[

columns_with_inf].fillna(df_stocks_data_merged[columns_with_inf].media
n())
df_stocks_data_merged.count()
```

```
Symbol                          11964
Name                            11964
Market Cap                      11964
Trailing P/E Ratio              11964
Forward P/E Ratio               11964
Price to Book Ratio             11964
Dividend Yield                  11964
Earnings Per Share Forward      11964
Return on Equity                11964
```

```
Debt to Equity Ratio              11964
Free Cash Flow                    11964
Revenue Growth                    11964
Beta (Volatility)                 11964
Operating Margin                  11964
Gross Margin                      11964
Price to Sales Ratio              11964
Current Ratio                     11964
Quick Ratio                       11964
Return on Assets                  11964
Enterprise Value                  11964
Enterprise Value to EBITDA        11964
PEG Ratio                         11964
Book Value Per Share              11964
Pays Dividend                     11964
Earnings Outcome                  11964
dtype: int64

# Module to standardize numerical data by scaling to unit variance
from sklearn.preprocessing import StandardScaler

# Used to perform scaling transformation on the data
scaler = StandardScaler()

# Use StandardScaler() to standardize the values of each column
df_merged_stocks_data_scaled = df_stocks_data_merged.copy()
df_merged_stocks_data_scaled[["Market Cap", "Trailing P/E Ratio",
                              "Forward P/E Ratio", "Price to Book
Ratio",
                              "Dividend Yield", "Earnings Per Share
Forward",
                              "Return on Equity", "Debt to Equity
Ratio",
                              "Free Cash Flow", "Revenue Growth",
                              "Beta (Volatility)", "Operating Margin",

                              "Gross Margin", "Price to Sales Ratio",
                              "Current Ratio", "Quick Ratio", "Return
on Assets",
                              "Enterprise Value", "Enterprise Value to
EBITDA",
                              "PEG Ratio", "Book Value Per Share"]]=
scaler.fit_transform(
        df_stocks_data_merged[["Market Cap", "Trailing P/E Ratio",
                               "Forward P/E Ratio", "Price to Book
Ratio",
                               "Dividend Yield", "Earnings Per Share
Forward",
                               "Return on Equity", "Debt to Equity
Ratio",
```

```
                                "Free Cash Flow", "Revenue Growth",
                                "Beta (Volatility)", "Operating
Margin",

                                "Gross Margin", "Price to Sales Ratio",

                                "Current Ratio", "Quick Ratio",
                                "Return on Assets", "Enterprise Value",

                                "Enterprise Value to EBITDA", "PEG
Ratio",

                                "Book Value Per Share"]]
)

df_merged_stocks_data_scaled.head(10)

  Symbol                                Name  Market Cap  Trailing P/E
Ratio  \
0   AAPL             Apple Inc. Common Stock   26.156192
0.052293
1   AAPL             Apple Inc. Common Stock   26.156192
0.052293
2   AAPL             Apple Inc. Common Stock   26.156192
0.052293
3   AAPL             Apple Inc. Common Stock   26.156192
0.052293
4   MSFT  Microsoft Corporation Common Stock   25.493544
0.021758
5   MSFT  Microsoft Corporation Common Stock   25.493544
0.021758
6   MSFT  Microsoft Corporation Common Stock   25.493544
0.021758
7   MSFT  Microsoft Corporation Common Stock   25.493544
0.021758
8   NVDA     NVIDIA Corporation Common Stock   22.759833
0.461891
9   NVDA     NVIDIA Corporation Common Stock   22.759833
0.461891

   Forward P/E Ratio  Price to Book Ratio  Dividend Yield  \
0           0.042191             2.006386       -0.351307
1           0.042191             2.006386       -0.351307
2           0.042191             2.006386       -0.351307
3           0.042191             2.006386       -0.351307
4           0.044056             0.195750       -0.247011
5           0.044056             0.195750       -0.247011
6           0.044056             0.195750       -0.247011
7           0.044056             0.195750       -0.247011
8           0.060271             2.057262       -0.477075
9           0.060271             2.057262       -0.477075
```

```
   Earnings Per Share Forward  Return on Equity  Debt to Equity Ratio
...  \
0                    0.372867          0.407950              0.108846
...
1                    0.372867          0.407950              0.108846
...
2                    0.372867          0.407950              0.108846
...
3                    0.372867          0.407950              0.108846
...
4                    0.887650          0.129414             -0.173046
...
5                    0.887650          0.129414             -0.173046
...
6                    0.887650          0.129414             -0.173046
...
7                    0.887650          0.129414             -0.173046
...
8                    0.048026          0.331013             -0.199460
...
9                    0.048026          0.331013             -0.199460
...

   Price to Sales Ratio  Current Ratio  Quick Ratio  Return on Assets
\
0             -0.059645      -0.276589    -0.226634          1.220011

1             -0.059645      -0.276589    -0.226634          1.220011

2             -0.059645      -0.276589    -0.226634          1.220011

3             -0.059645      -0.276589    -0.226634          1.220011

4             -0.053199      -0.233823    -0.184657          0.862928

5             -0.053199      -0.233823    -0.184657          0.862928

6             -0.053199      -0.233823    -0.184657          0.862928

7             -0.053199      -0.233823    -0.184657          0.862928

8             -0.009403       0.058645     0.050335          2.976016

9             -0.009403       0.058645     0.050335          2.976016


   Enterprise Value  Enterprise Value to EBITDA  PEG Ratio  \
0          1.976192                    0.007904  -0.000231
1          1.976192                    0.007904  -0.000231
2          1.976192                    0.007904  -0.000231
```

```
3          1.976192                    0.007904  -0.000231
4          1.816486                    0.003603  -0.000231
5          1.816486                    0.003603  -0.000231
6          1.816486                    0.003603  -0.000231
7          1.816486                    0.003603  -0.000231
8          2.037560                    0.066665  -0.000231
9          2.037560                    0.066665  -0.000231

   Book Value Per Share  Pays Dividend  Earnings Outcome
0             -0.033573              1                 1
1             -0.033573              1                 1
2             -0.033573              1                 1
3             -0.033573              1                 1
4             -0.020314              1                 1
5             -0.020314              1                 1
6             -0.020314              1                 1
7             -0.020314              1                 1
8             -0.034104              1                 1
9             -0.034104              1                 1

[10 rows x 25 columns]
```

Baseline Model: Logisitic Regression and Decision Tree

In order to establish a point of reference for evaluating the effectiveness of more complex models, we need to create a baseline model. A baseline model will help us understand whether more advanced models provide meaningful improvements, if the data needs more preprocessing, or if the problem is too challenging for predictive modeling and more or different data is required.

To create this baseline model, we're going to utilize two different modeling approaches: logistic regression and decision trees. Whichever of these two models is a better and more balanced predictor of the outcome of a target variable is the one we will choose as the baseline. Logistic regression is a linear classification algorithm that predicts probabilities for binary outcomes. It is easily interpretable as it produces coefficients for each feature, indicating their influence on the prediction. A decision tree is a non-linear classification algorithm that splits data based on feature values, creating a tree-like structure of decisions. It captures complex relationships between variables and will handle non-linearity better than logistic regression. We are not yet sure whether our data is linear or non-linear, so we need to try both algorithms to see which better fits the data.

One of the first steps in creating a predictive model, after preprocessing, is splitting the data into training and testing sets. The data is usually split 70-80% for training and 20-30% for testing and we do this because if we train the model purely on all available data, it may perform exceptionally well but perform very poorly with new, unseen data, which would indicate overfitting. We use the training set to fit the model and capture the patterns and relationships of the given data. The testing set is used to evaluate the model's performance on unseen data to simulate real-world predictions.

Upon splitting the data into training and test sets and running both models, we will use the following metrics to evaluate the models ability to predict the target variable: Accuracy, Precision, Recall, F1 Score, and AUC.

Accuracy

- = (Number of Correct Predictions / Total Number of Predictions)
- The proportion of correct predictions out of all predictions. Very useful for balanced datasets (equal number of samples in each class), but can be misleading for imbalanced datasets.

Precision

- = (True Positives / (True Positives + False Positives))
- The proportion of true positive predictions out of all positive predictions. It is a measure of how many of hte predicted positives outcomes are actually positive.

Recall (Sensitivity)

- = (True Positives / (True Positives + False Negatives))
- The proportion of true positives out of all actual positive cases. It assesses the model's ability to detect all positive instances.

F1 Score

- = 2 x ((Precision x Recall) / (Precision + Recall))
- Calculates the harmonic mean of Precision and Recall by comining them into a single metric. It provides a balanced measure than accounts for both false positives and false negatives, making it useful for imbalanced datasets.

AUC (Area Under ROC Curve)

- Represents the probability that a randomly chosen positive instance is ranked higher by the model than a randomly chosen negative instance.A higher AUC indicates a better model at distinguishing between positive and negative cases, with value of 1 representing a perfect model and a value of 0.5 representing a model with no predictive power (equivalent to random guessing).

After evaluating the model's performance metrics, we'll create a confusion matrix, which is a table that shows all true positives, false positives, true negatives, and false negatives of a classification model. It helps visualize the model's performance across differnet prediction categories and can help in adjusting thresholds for models like logistic regression to balance precision and recall.

Precision

This service will be providing stocks which have a high probability of beating their earnings report and therefore increasing in value. In this circumstance, a stock beating its' EPS is positive and a stock not beating it's EPS is negative. Callaghan Investments is much more concerned with correctly choosing stocks which do beat it's next earnings report (True Positive), rather than missing out on stocks who end up beating their estimated EPS (False Negative). The worst possible scenario in this case, is prediciting that a stock will beat it's estimated EPS and it does not (False Positive). Because of this, the main metric we are focusing on is Precision. Precision tells us how many positive outcomes are actually positive, or in other words, how many stocks predicted to beat their estimated EPS actually beat their estimated EPS. We are much less focused on Recall and Accuracy because we are not trying to predict if a stock will not beat its' earnings report and are not as concerned with missing out on a stock which does beat it's earnings report. In summation, we will be choosing the model with the highest precision and if there is a tie, we will take F1 score into consideration as that combines Precision and Recall into a single metric.

Logistic Regression Baseline Model

Below, we will run logistic regression on our model and evaluate the output of metrics.

```
# Import train-test split utility
from sklearn.model_selection import train_test_split

# Import Logistic Regression model
from sklearn.linear_model import LogisticRegression

# Import evaluation metrics
from sklearn.metrics import classification_report, roc_auc_score

# Define features (x) and target (y)

# Drop non-feature columns
x = df_merged_stocks_data_scaled.drop(columns=["Earnings Outcome",
"Symbol",
                                               "Name"])

# Target Variable
y = df_merged_stocks_data_scaled["Earnings Outcome"]

# Split data into training and testing sets
x_train, x_test, y_train, y_test = train_test_split(x, y,
test_size=0.2,
                                                    random_state=42)

# Initialize and train Logistic Regression model
log_reg = LogisticRegression()
log_reg.fit(x_train, y_train)

# Evaluate model and print metrics
y_pred = log_reg.predict(x_test)
print(classification_report(y_test, y_pred))
roc_auc = roc_auc_score(y_test, log_reg.predict_proba(x_test)[:, 1])
print(f"ROC AUC: {roc_auc}")
```

```
              precision    recall  f1-score   support

           0       0.54      0.12      0.20       920
           1       0.63      0.93      0.75      1473

    accuracy                           0.62      2393
   macro avg       0.58      0.53      0.48      2393
weighted avg       0.59      0.62      0.54      2393

ROC AUC: 0.6409180465775258
```

Logistic Regression Baseline Model: Confusion Matrix

To help evaluate our logistic regression model, we'll output a confusion matrix which shows the True Positives, True Negatives, False Positives, and False Negatives. Along with this will be our performance metrics, Accuracy, Precision, Recall, F1 Score, and ROC AUC.

```
# Import Evaluation Metrics
from sklearn.metrics import accuracy_score, precision_score,
recall_score
, f1_score, confusion_matrix

accuracy = accuracy_score(y_test, y_pred)  # Calculate accuracy
# Assuming 1 corresponds to 'Beat'
precision = precision_score(y_test, y_pred, pos_label=1)
recall = recall_score(y_test, y_pred, pos_label=1) # Calculate recall
f1 = f1_score(y_test, y_pred, pos_label=1) # Calculate F1 Score
# Calculate ROC AUC Score

roc_auc = roc_auc_score(y_test, log_reg.predict_proba(x_test)[:, 1])

# Output the evaluation metrics
print(f"Accuracy: {accuracy:.2f}")
print(f"Precision: {precision:.2f}")
print(f"Recall: {recall:.2f}")
print(f"F1 Score: {f1:.2f}")
print(f"ROC AUC: {roc_auc:.2f}")

# Display the confusion matrix
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred))
```

```
Accuracy: 0.62
Precision: 0.63
Recall: 0.93
F1 Score: 0.75
ROC AUC: 0.64
Confusion Matrix:
 [[ 113  807]
 [  97 1376]]
```

Logistic Regression Metrics Evaluation

Accuracy

- 0.62
- The model correctly predicted 62% of the test samples.
- This is a pretty low to moderate accuracy level, but since we are not trying to predict both classes equally, we are not as concerned about accuracy. On top of that, our dataset is imbalanced, which means Accuracy is not a very good metric to use.

Precision

- 0.63
- Out of all the times the model predicted "Beat" (class 1), its' predictions were correct 63% of the time
- This precision value is moderate and there is still room for improvement. We want to minimize false positives.

Recall

- 0.93
- The model correctly predicted 93% of the actual "Beat" cases.
- High recall demonstrates that the model is model is very sensitive to identifying true positive cases, but it also means it's capturing many false positives, which is what we are trying to avoid.

F1 Score

- 0.75
- This is a moderate to high F1 Score, but it is being inflated by the very high recall.

ROC AUC

- 0.64
- This is a moderate ROC AUC score and indicates the model is slightly better at distinguishing the classes than random guessing.

Evaluation Summary

- This model has strong recall, however it comes at the cost of precision, which is the metric we want to maximize.

Decision Tree

Now we will create another baseline model, using a decision tree. We'll evaluate and compare the outputs of both models in order to choose a baseline to move forward with.

```python
# Import Decision Tree Classifier
from sklearn.tree import DecisionTreeClassifier

# x and y already defined above
```

```python
# Initialize and train the Decision Tree Classifier
# Set a random state for reproducibility
tree = DecisionTreeClassifier(random_state=42)
tree.fit(x_train, y_train) # Fit the model using the training data

# Evaluate model on the test data
y_pred_tree = tree.predict(x_test) # Generate predictions on the test
set

# Print classification metrics
# Display precision, recall, F1 score, and accuracy
print(classification_report(y_test, y_pred_tree))
# Calculate and display ROC AUC score
roc_auc = roc_auc_score(y_test, tree.predict_proba(x_test)[:, 1])
print(f"ROC AUC: {roc_auc}")
```

```
              precision    recall  f1-score   support

           0       0.52      0.59      0.55       920
           1       0.72      0.66      0.69      1473

    accuracy                           0.63      2393
   macro avg       0.62      0.62      0.62      2393
weighted avg       0.64      0.63      0.64      2393

ROC AUC: 0.6659612149118923
```

```python
# Decision Tree Confusion Matrix

from sklearn.metrics import accuracy_score, precision_score,
recall_score
, f1_score, roc_auc_score, confusion_matrix

# Predict on the test data using the decision tree model
y_pred_tree = tree.predict(x_test)

# Calculate accuracy, precision, recall, F1-score, and AUC (ROC)
accuracy = accuracy_score(y_test, y_pred_tree)
# Assuming 1 corresponds to 'Beat'
precision = precision_score(y_test, y_pred_tree, pos_label=1)
recall = recall_score(y_test, y_pred_tree, pos_label=1)
f1 = f1_score(y_test, y_pred_tree, pos_label=1)

# Decision trees can also give probabilities, so we use predict_proba
for ROC AUC
roc_auc = roc_auc_score(y_test, tree.predict_proba(x_test)[:, 1])

# Output the evaluation metrics
print(f"Accuracy: {accuracy:.2f}")
print(f"Precision: {precision:.2f}")
print(f"Recall: {recall:.2f}")
```

```
print(f"F1 Score: {f1:.2f}")
print(f"ROC AUC: {roc_auc:.2f}")

# Display the confusion matrix
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred_tree))
```

```
Accuracy: 0.63
Precision: 0.72
Recall: 0.66
F1 Score: 0.69
ROC AUC: 0.67
Confusion Matrix:
 [[546 374]
 [506 967]]
```

Decision Tree Metrics Evaluation (UPDATE 11/12/2024: THIS NEEDS TO BE REDONE TO REFLECT THE NEWLY EVALUATED MODE. BASELINE DECISION TREE MODEL WITHOUT CLASS BALANCING)

Accuracy

- 0.63
- The decision tree model correctly predicted 63% of test samples overall.
- This is a moderate accuracy score, but may be misleading because of the class imbalance.

Precision

- 0.72
- When the decision tree model predicted "Beat, it was correct 72% of the time.
- moderate to good Precision score, which indicates the model is reliable when prediciting "Beat".

Recall

- 0.66
- The decision tree model correctly identified 90% of actual "Beat" cases.
- This is a moderate recall score.

F1 Score

- 0.69
- This is a moderate F1 Score and shows the model performs decent in balancing both Precision and Recall for the "Beat" class.

ROC AUC

- 0.65

- This is a moderate score and indicates that the decision tree model has some ability to descriminate between the two classes, "Beat" and "Not Beat".
- The model performs slightly better than random guessing.

Evaluation Summary

- The decision tree has much precision (0.72) than the our baseline logistic regression model (0.63) and therefore performs better in our context.

Logistic Regression Baseline Vs. Decision Tree Baseline

Since Precision is our most important indicator, we are going to use the Decision Tree as our baseline model. Logistic Regression had a lower Precision score and a very high Recall, which means that we would have to do more work in order to lower the Recall in order to increase Precision. The Decision Tree model already improves Precision by lowering Recall, so it is a better baseline model in this context. On top of this, the F1 Score was very similar and it had a more favorable Confusion Matrix.

Imbalanced Dataset: SMOTE and SMOTEEN.

To try and handle our class imbalance between class 0 (not beating EPS) and class 1 (beating EPS), we going to apply a data preprocessing technique called SMOTE (Synthetic Minority Oversampling Technique). It addresses the class imbalance by creating synthetic examples for the minority class instead of simply duplicating existing examples. We do this to reduce bias in our model predictions and increase the potential of pattern recognition in the minority class. If it does not lead to significant improvement over our baseline model, then we will remove SMOTE to prevent overcomplicating our model with unhelpful processing.

After trying SMOTE, we are also going to try SMOTEEN. SMOTEEN combines SMOTE with an editing technique called Edited Nearest Neighbors (ENN), which takes SMOTE and removes noisy or misclassified instances by checking each instance's nearest neighbors and removing instances that do not agree with the majority of their neighbors.

```
# To deal with the imbalance in class weights, we are going to try
applying SMOTE
# to see if it improves our model
from sklearn.tree import DecisionTreeClassifier
from imblearn.over_sampling import SMOTE
from sklearn.model_selection import train_test_split
from sklearn.metrics import (
    accuracy_score, precision_score, recall_score, f1_score,
roc_auc_score
, confusion_matrix, classification_report
)

# Split the data into training and testing sets
x_train, x_test, y_train, y_test = train_test_split(x, y,
test_size=0.2,
                                                    random_state=42,
```

```
stratify=y)

# Apply SMOTE to balance the training data
smote = SMOTE(random_state=42)
x_train_smote, y_train_smote = smote.fit_resample(x_train, y_train)

# Initialize and fit the Decision Tree model
tree_smote = DecisionTreeClassifier(random_state=42)
tree_smote.fit(x_train_smote, y_train_smote)

# Predict on the test data using the SMOTE-enhanced decision tree
model
y_pred_tree_smote = tree_smote.predict(x_test)

# Calculate evaluation metrics
accuracy_smote = accuracy_score(y_test, y_pred_tree_smote)
# Assuming 1 corresponds to 'Beat'
precision_smote = precision_score(y_test, y_pred_tree_smote,
pos_label=1)
recall_smote = recall_score(y_test, y_pred_tree_smote, pos_label=1)
f1_smote = f1_score(y_test, y_pred_tree_smote, pos_label=1)
roc_auc_smote = roc_auc_score(y_test, tree_smote.predict_proba(x_test)
[:, 1])

# Output the evaluation metrics
print(f"Accuracy: {accuracy_smote:.2f}")
print(f"Precision: {precision_smote:.2f}")
print(f"Recall: {recall_smote:.2f}")
print(f"F1 Score: {f1_smote:.2f}")
print(f"ROC AUC: {roc_auc_smote:.2f}")

# Display the confusion matrix
conf_matrix_smote = confusion_matrix(y_test, y_pred_tree_smote)
print("Confusion Matrix:\n", conf_matrix_smote)

# Additional detailed classification report
print("\nClassification Report:\n")
print(classification_report(y_test, y_pred_tree_smote))
```

```
Accuracy: 0.63
Precision: 0.72
Recall: 0.65
F1 Score: 0.68
ROC AUC: 0.65
Confusion Matrix:
 [[556 371]
 [513 953]]

Classification Report:
```

```
              precision    recall  f1-score   support

           0       0.52      0.60      0.56       927
           1       0.72      0.65      0.68      1466

    accuracy                           0.63      2393
   macro avg       0.62      0.62      0.62      2393
weighted avg       0.64      0.63      0.63      2393
```

Model Evaluation: Baseline Decision Tree vs. Decision Tree with SMOTE

Going forward, we are only going to evaluate the models based off Precision, which we are trying to maximize. On top of this, we may also look at the number of True Positives, as maximizing precision too much may lead to too much of a reduction in True Positives, meaning we would have to loosen up the restrictions a little bit in order to have enough stocks for a portfolio.

Baseline Decision Tree Precision: 0.72

Decision Tree with SMOTE Precision: 0.72

With the addition of SMOTE, there was no change in precision. On top of this, the amount of True Positives and False positives remained relativley the same. Because we don't want to add unnecessary complexity to our model, we are going to refrain from adding SMOTE and stick to the baseline Decision Tree Model.

```
# Import necessary libraries
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import (
    accuracy_score, precision_score, recall_score, f1_score,
roc_auc_score,
    confusion_matrix, classification_report
)
from imblearn.combine import SMOTEENN
from imblearn.pipeline import Pipeline

# Define SMOTEEN for handling class imbalance
smoteen = SMOTEENN(random_state=42)

# Define the Decision Tree Classifier
tree_smoteen = DecisionTreeClassifier(random_state=42)

# Create a pipeline with SMOTEEN and Decision Tree
pipeline_smoteen = Pipeline([
    ('smoteen', smoteen),
```

```python
    ('classifier', tree_smoteen)
])

# Fit the pipeline to the training data
pipeline_smoteen.fit(x_train, y_train)

# Make predictions using the pipeline
y_pred_smoteen = pipeline_smoteen.predict(x_test)

# Predict probabilities for ROC AUC
y_pred_proba_smoteen = pipeline_smoteen.predict_proba(x_test)[:, 1]

# Evaluate the model's performance
accuracy = accuracy_score(y_test, y_pred_smoteen)
precision = precision_score(y_test, y_pred_smoteen, pos_label=1)
recall = recall_score(y_test, y_pred_smoteen, pos_label=1)
f1 = f1_score(y_test, y_pred_smoteen, pos_label=1)
roc_auc = roc_auc_score(y_test, y_pred_proba_smoteen)

# Print the evaluation metrics
print("Decision Tree with SMOTEEN Metrics:")
print(f"Accuracy: {accuracy:.2f}")
print(f"Precision: {precision:.2f}")
print(f"Recall: {recall:.2f}")
print(f"F1 Score: {f1:.2f}")
print(f"ROC AUC: {roc_auc:.2f}")

# Display the classification report
print("\nClassification Report:")
print(classification_report(y_test, y_pred_smoteen))

# Display the confusion matrix
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred_smoteen))
```

```
Decision Tree with SMOTEEN Metrics:
Accuracy: 0.62
Precision: 0.74
Recall: 0.59
F1 Score: 0.65
ROC AUC: 0.63

Classification Report:
              precision    recall  f1-score   support

           0       0.51      0.68      0.58       927
           1       0.74      0.59      0.65      1466

    accuracy                           0.62      2393
   macro avg       0.62      0.63      0.62      2393
weighted avg       0.65      0.62      0.63      2393
```

```
Confusion Matrix:
 [[626 301]
 [606 860]]
```

Model Evaluation: Baseline Decision Tree vs. Decision Tree with SMOTEEN

Basline Decision Tree Precision: 0.72

Decision Tree with SMOTEEN Precision: 0.74

Adding SMOTEEN lead to an increase in Precision of 0.02. This is a step in the right direction and because of this, we are going to keep SMOTEEN in our model.

Gradient Boosting

Gradient boosting is an ensemble machine learning technique which creates multiple decision trees sequentially in order to create a stronger, more accurate model. It creates a decision tree, calculates the residuals, trains a new model to predict these residuals, those predictions are combined with the previous models predictions, and it iterates over this until a predetermined level of error is reached. Gradient boosting reduces bias and variance while adding accuracy to the predictions. For these reasons, we are going to try adding it to our baseline decision tree model and evaluate its' performance.

```
# Import necessary libraries
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.metrics import accuracy_score, precision_score,
recall_score
, f1_score, roc_auc_score, confusion_matrix, classification_report

# Define the Gradient Boosting model
tree_gradient_boost = GradientBoostingClassifier(random_state=42)

# Fit the Gradient Boosting model to the training data
tree_gradient_boost.fit(x_train, y_train)

# Make predictions on the test set
y_pred_boost = tree_gradient_boost.predict(x_test)

# Evaluate the model's performance
print("\nGradient Boosting Classification Report:")
print(classification_report(y_test, y_pred_boost))

# Calculate additional metrics
accuracy = accuracy_score(y_test, y_pred_boost)
precision = precision_score(y_test, y_pred_boost, pos_label=1)
recall = recall_score(y_test, y_pred_boost, pos_label=1)
f1 = f1_score(y_test, y_pred_boost, pos_label=1)
```

```
roc_auc = roc_auc_score(y_test,
tree_gradient_boost.predict_proba(x_test)[:, 1])

# Print the evaluation metrics
print(f"Accuracy: {accuracy:.2f}")
print(f"Precision: {precision:.2f}")
print(f"Recall: {recall:.2f}")
print(f"F1 Score: {f1:.2f}")
print(f"ROC AUC: {roc_auc:.2f}")

# Display the confusion matrix
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred_boost))
```

```
Gradient Boosting Classification Report:
              precision    recall  f1-score   support

           0       0.57      0.37      0.45       927
           1       0.67      0.82      0.74      1466

    accuracy                           0.65      2393
   macro avg       0.62      0.60      0.59      2393
weighted avg       0.63      0.65      0.63      2393

Accuracy: 0.65
Precision: 0.67
Recall: 0.82
F1 Score: 0.74
ROC AUC: 0.68
Confusion Matrix:
 [[ 342  585]
 [ 261 1205]]
```

Model Evaluation: Baseline Decision Tree with SMOTEEN vs. Baseline Decision Tree with Gradient Boost

Baseline Decision Tree with SMOTEEN Precision: 0.74

Baseline Decision Tree with Gradient Boost Precision: 0.67

Adding gradient boosting to my baseline decision tree model yielded a Precision value of 0.67, which is lower than the Precision value for my baseline decision. tree with SMOTEEN added. For this reason, I am going to move forward with my baseline decision tree model with SMOTEEN.

Decision Tree with Gradient Boosting and SMOTEEN

For methodolical testing, I tried combining gradient boosting and SMOTEEN to evaluate its Precision power. This is to test whether combining the strengths of SMOTEEN (better handling of imbalance) along with Gradient Boosting (ensemble learning to reduce bias and variance) leads to a stronger model.

```
# Import necessary libraries
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.metrics import (
    accuracy_score, precision_score, recall_score, f1_score,
roc_auc_score,
    confusion_matrix, classification_report
)
from imblearn.combine import SMOTEENN
from imblearn.pipeline import Pipeline

# Define SMOTEEN for handling class imbalance
smoteen = SMOTEENN(random_state=42)

# Define the Gradient Boosting Classifier with hyperparameters
tree_smoteen_gradient_boost = GradientBoostingClassifier(
    n_estimators=100,       # Number of boosting stages
    learning_rate=0.1,      # Step size shrinking
    max_depth=3,            # Maximum depth of the tree
    subsample=1,           # Fraction of samples used for fitting each
base learner
    random_state=42         # For reproducibility
)

# Create a pipeline with SMOTEEN and Gradient Boosting
pipeline_smoteen_gradient_boost = Pipeline([
    ('smoteen', smoteen),
    ('classifier', tree_smoteen_gradient_boost)
])

# Fit the pipeline to the training data
pipeline_smoteen_gradient_boost.fit(x_train, y_train)

# Make predictions using the pipeline
y_pred_smoteen_gradient_boost =
pipeline_smoteen_gradient_boost.predict(x_test)

# Predict probabilities for ROC AUC
y_pred_proba_smoteen_gradient_boost =
pipeline_smoteen_gradient_boost.predict_proba(
    x_test)[:, 1]

# Evaluate the model's performance
accuracy = accuracy_score(y_test, y_pred_smoteen_gradient_boost)
```

```python
precision = precision_score(y_test, y_pred_smoteen_gradient_boost,
pos_label=1)
recall = recall_score(y_test, y_pred_smoteen_gradient_boost,
pos_label=1)
f1 = f1_score(y_test, y_pred_smoteen_gradient_boost, pos_label=1)
roc_auc = roc_auc_score(y_test, y_pred_proba_smoteen_gradient_boost)

# Print the evaluation metrics
print("Gradient Boosting with SMOTEEN Metrics:")
print(f"Accuracy: {accuracy:.2f}")
print(f"Precision: {precision:.2f}")
print(f"Recall: {recall:.2f}")
print(f"F1 Score: {f1:.2f}")
print(f"ROC AUC: {roc_auc:.2f}")

# Display the classification report
print("\nClassification Report:")
print(classification_report(y_test, y_pred_smoteen_gradient_boost))

# Display the confusion matrix
print("Confusion Matrix:\n", confusion_matrix(y_test,
y_pred_smoteen_gradient_boost))
```

```
Gradient Boosting with SMOTEEN Metrics:
Accuracy: 0.63
Precision: 0.74
Recall: 0.62
F1 Score: 0.67
ROC AUC: 0.67

Classification Report:
              precision    recall  f1-score   support

           0       0.52      0.65      0.58       927
           1       0.74      0.62      0.67      1466

    accuracy                           0.63      2393
   macro avg       0.63      0.63      0.62      2393
weighted avg       0.65      0.63      0.63      2393

Confusion Matrix:
 [[603 324]
 [563 903]]
```

Baseline Decision Tree with SMOTEEN vs. Baseline Decision Tree with SMOTEEN and Gradient Boosting

Baseline Decision Tree with SMOTEEN Precision: 0.74

Baseline Decision Tree with SMOTEEN and Gradient Boost Precision: 0.74

There was no increase in the Precision value by adding Gradient boosting to our baseline decision tree model with SMOTEEN, however the F1 score and True Positives increased in the decision tree model with SMOTEEN and gradient boosting (0.67 and 903 respectivley) vs our decision tree model with just SMOTEEN (0.65 and 860 respectivley). In an attempt to raise our Precision value, we are going to take our baseline decision tree model with SMOTEEN and Gradient boosting and increase the threshold.

Hyperparameter Tuning: Threshold Adjustment

With the goal of increasing Precisioon, we are purposley goiong to make our model more conservative and increase the threshold probability of the model predicting class 1 (a stock beating it's EPS estimate). The standard threshold is 0.5, which means if the predicted probability of a stock beating its' earnings report, it will be classified as class 1 (AKA the stock will be predicted to beat it's earnings rerport). If its' predicted probability is less than 0.5, it will be classified as class 0 (AKA the stock is predicted to not beat its' earnings report). By raising the threshold to 0.9, the model will only classify a stock as class 1 (Beating its' EPS estimate) if the probability is greater than 90% of doing so. This should increase precision and decrease recall, but since we only care about precision, we are willing to sacrifice our recall. This is desirable because we want to be sure that when we recommend stocks to our investors, the model is only predicting stocks with a very high probability of beating their EPS estimates.

```
# Import necessary libraries
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.metrics import (
    accuracy_score, precision_score, recall_score, f1_score,
roc_auc_score,
    confusion_matrix, classification_report, precision_recall_curve
)
from imblearn.combine import SMOTEENN
from imblearn.pipeline import Pipeline

# Define SMOTEEN for handling class imbalance
smoteen = SMOTEENN(random_state=42)

# Define the Gradient Boosting Classifier with hyperparameters
tree_smoteen_gradient_boost = GradientBoostingClassifier(
    n_estimators=100,       # Number of boosting stages
    learning_rate=0.1,      # Step size shrinking
    max_depth=3,            # Maximum depth of the tree
```

```
    subsample=1,          # Fraction of samples used for fitting each
base learner
    random_state=42         # For reproducibility
)

# Create a pipeline with SMOTEEN and Gradient Boosting
pipeline_smoteen_gradient_boost = Pipeline([
    ('smoteen', smoteen),
    ('classifier', tree_smoteen_gradient_boost)
])

# Fit the pipeline to the training data
pipeline_smoteen_gradient_boost.fit(x_train, y_train)

# Make predictions using the pipeline
# Predict probabilities for ROC AUC and threshold adjustment
y_pred_proba = pipeline_smoteen_gradient_boost.predict_proba(x_test)
[:, 1]

# Adjust threshold to 0.9
threshold = 0.9  # Adjust this value to tune precision/recall tradeoff
y_pred_adjusted = (y_pred_proba >= threshold).astype(int)

# Evaluate the model's performance with the adjusted threshold
accuracy = accuracy_score(y_test, y_pred_adjusted)
precision = precision_score(y_test, y_pred_adjusted, pos_label=1)
recall = recall_score(y_test, y_pred_adjusted, pos_label=1)
f1 = f1_score(y_test, y_pred_adjusted, pos_label=1)
# Use unadjusted probabilities for ROC AUC
roc_auc = roc_auc_score(y_test, y_pred_proba)

# Print the evaluation maetrics
print("Gradient Boosting with SMOTEEN Metrics (Adjusted Threshold):")
print(f"Accuracy: {accuracy:.2f}")
print(f"Precision: {precision:.2f}")
print(f"Recall: {recall:.2f}")
print(f"F1 Score: {f1:.2f}")
print(f"ROC AUC: {roc_auc:.2f}")

# Display the classification report
print("\nClassification Report (Adjusted Threshold):")
print(classification_report(y_test, y_pred_adjusted))

# Display the confusion matrix
print("Confusion Matrix (Adjusted Threshold):\n", confusion_matrix(
    y_test, y_pred_adjusted))
```

```
Gradient Boosting with SMOTEEN Metrics (Adjusted Threshold):
Accuracy: 0.46
Precision: 0.82
```

```
Recall: 0.14
F1 Score: 0.24
ROC AUC: 0.67

Classification Report (Adjusted Threshold):
              precision    recall  f1-score   support

           0       0.41      0.95      0.58       927
           1       0.82      0.14      0.24      1466

    accuracy                           0.46      2393
   macro avg       0.62      0.55      0.41      2393
weighted avg       0.66      0.46      0.37      2393

Confusion Matrix (Adjusted Threshold):
 [[ 881   46]
 [1255  211]]
```

Model Evaluation: Baseline Decision Tree with SMOTEEN, Gradient Boosting, and Threshold Adjustement

Baseline Decision Tree with SMOTEEN, Gradient Boosting, and Threshold Adjustement

- Precision: 0.82

Through adjusting threshold to 0.9, we had a dramatic increase in our Precision value from 0.74 to 0.84. Through this, we can see how we sacrificed our Recall, as it dropped from a value of 0.63 to 0.16. Our True Positives also had a drop from 919 to 228, but our False Positives are now at 44 instead of 325. Although we had a big drop in True Positives and an inevitable increase in False Negatives, we can be sure that the stocks we recommend to our investors have a much higher liklihood of beating their EPS estimates, while still giving investors an ample number of stocks to choose from.

Hyperparameter Tuning: Subsample

Subsample is a hyperparameter that controls the proportion of training data used to fit each individual tree in the ensemble. When the subsample is set to a value less than 1, the algorithm randomly samples a fraction of the training data before building each tree. The purpose of altering the subsample size is to:

- Reduce overfitting: Using a smaller subset of the data, the algorithm is less likely to memorize noise
- Increase Robustness: Noisy or outlier data points get averaged out, leading to a more stable model
- Improve computational efficiency: Since fewer data points need to be processed, subsampling reduces the computational burden of training each tree

The default value for subsample is 1. We are going to try lowering it to 0.9, 0.8, and 0.7 and evaluate the outputs.

```
# Baseline Decision Tree Model with SMOTEEN and Gradient Boosting:
Subsample = 0.9
# Import necessary libraries
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.metrics import (
    accuracy_score, precision_score, recall_score, f1_score,
roc_auc_score,
    confusion_matrix, classification_report, precision_recall_curve
)
from imblearn.combine import SMOTEENN
from imblearn.pipeline import Pipeline

# Define SMOTEEN for handling class imbalance
smoteen = SMOTEENN(random_state=42)

# Define the Gradient Boosting Classifier with hyperparameters
tree_smoteen_gradient_boost = GradientBoostingClassifier(
    n_estimators=100,        # Number of boosting stages
    learning_rate=0.1,       # Step size shrinking
    max_depth=3,             # Maximum depth of the tree
    subsample=0.9,           # Fraction of samples used for fitting
each base learner
    random_state=42          # For reproducibility
)

# Create a pipeline with SMOTEEN and Gradient Boosting
pipeline_smoteen_gradient_boost = Pipeline([
    ('smoteen', smoteen),
    ('classifier', tree_smoteen_gradient_boost)
])

# Fit the pipeline to the training data
pipeline_smoteen_gradient_boost.fit(x_train, y_train)

# Make predictions using the pipeline
# Predict probabilities for ROC AUC and threshold adjustment
y_pred_proba = pipeline_smoteen_gradient_boost.predict_proba(x_test)
[:, 1]

# Adjust threshold to 0.9
threshold = 0.9  # Adjust this value to tune precision/recall tradeoff
y_pred_subsample9 = (y_pred_proba >= threshold).astype(int)

# Evaluate the model's performance with the adjusted threshold
accuracy = accuracy_score(y_test, y_pred_subsample9)
precision = precision_score(y_test, y_pred_subsample9 , pos_label=1)
recall = recall_score(y_test, y_pred_subsample9 , pos_label=1)
```

```
f1 = f1_score(y_test, y_pred_subsample9 , pos_label=1)
# Use unadjusted probabilities for ROC AUC

roc_auc = roc_auc_score(y_test, y_pred_proba)
# Print the evaluation maetrics
print("Decision Tree with Gradient Boosting and SMOTEEN Metrics
(Subsample = 0.9):")
print(f"Accuracy: {accuracy:.2f}")
print(f"Precision: {precision:.2f}")
print(f"Recall: {recall:.2f}")
print(f"F1 Score: {f1:.2f}")
print(f"ROC AUC: {roc_auc:.2f}")

# Display the classification report
print("\nClassification Report (Subsample = 0.9):")
print(classification_report(y_test, y_pred_subsample9))

# Display the confusion matrix
print("Confusion Matrix (Subsample = 0.9):\n", confusion_matrix(
    y_test, y_pred_subsample9))

Decision Tree with Gradient Boosting and SMOTEEN Metrics (Subsample =
0.9):
Accuracy: 0.46
Precision: 0.84
Recall: 0.16
F1 Score: 0.26
ROC AUC: 0.67

Classification Report (Subsample = 0.9):
              precision    recall  f1-score   support

           0       0.42      0.95      0.58       927
           1       0.84      0.16      0.26      1466

    accuracy                           0.46      2393
   macro avg       0.63      0.55      0.42      2393
weighted avg       0.67      0.46      0.39      2393

Confusion Matrix (Subsample = 0.9):
 [[ 883   44]
 [1238  228]]

# Baseline Decision Tree Model with SMOTEEN and Gradient Boosting:
Subsample = 0.8
# Import necessary libraries
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.metrics import (
    accuracy_score, precision_score, recall_score, f1_score,
roc_auc_score,
```

```
    confusion_matrix, classification_report, precision_recall_curve
)
from imblearn.combine import SMOTEENN
from imblearn.pipeline import Pipeline

# Define SMOTEEN for handling class imbalance
smoteen = SMOTEENN(random_state=42)

# Define the Gradient Boosting Classifier with hyperparameters
tree_smoteen_gradient_boost = GradientBoostingClassifier(
    n_estimators=100,       # Number of boosting stages
    learning_rate=0.1,      # Step size shrinking
    max_depth=3,            # Maximum depth of the tree
    subsample=0.8,          # Fraction of samples used for fitting
each base learner
    random_state=42         # For reproducibility
)

# Create a pipeline with SMOTEEN and Gradient Boosting
pipeline_smoteen_gradient_boost = Pipeline([
    ('smoteen', smoteen),
    ('classifier', tree_smoteen_gradient_boost)
])

# Fit the pipeline to the training data
pipeline_smoteen_gradient_boost.fit(x_train, y_train)

# Make predictions using the pipeline
# Predict probabilities for ROC AUC and threshold adjustment
y_pred_proba = pipeline_smoteen_gradient_boost.predict_proba(x_test)
[:, 1]

# Adjust threshold to 0.9
threshold = 0.9  # Adjust this value to tune precision/recall tradeoff
y_pred_subsample8 = (y_pred_proba >= threshold).astype(int)

# Evaluate the model's performance with the adjusted threshold
accuracy = accuracy_score(y_test, y_pred_subsample8)
precision = precision_score(y_test, y_pred_subsample8 , pos_label=1)
recall = recall_score(y_test, y_pred_subsample8 , pos_label=1)
f1 = f1_score(y_test, y_pred_subsample8 , pos_label=1)
roc_auc = roc_auc_score(y_test, y_pred_proba)

# Print the evaluation maetrics
print("Decision Tree with Gradient Boosting and SMOTEEN Metrics
(Subsample = 0.8):")
print(f"Accuracy: {accuracy:.2f}")
print(f"Precision: {precision:.2f}")
print(f"Recall: {recall:.2f}")
print(f"F1 Score: {f1:.2f}")
```

```
print(f"ROC AUC: {roc_auc:.2f}")

# Display the classification report
print("\nClassification Report (Subsample = 0.8):")
print(classification_report(y_test, y_pred_subsample8))

# Display the confusion matrix
print("Confusion Matrix (Subsample = 0.8):\n", confusion_matrix(
    y_test, y_pred_subsample8))
```

```
Decision Tree with Gradient Boosting and SMOTEEN Metrics (Subsample =
0.8):
Accuracy: 0.46
Precision: 0.86
Recall: 0.14
F1 Score: 0.24
ROC AUC: 0.67

Classification Report (Subsample = 0.8):
              precision    recall  f1-score   support

           0       0.42      0.96      0.58       927
           1       0.86      0.14      0.24      1466

    accuracy                           0.46      2393
   macro avg       0.64      0.55      0.41      2393
weighted avg       0.69      0.46      0.37      2393

Confusion Matrix (Subsample = 0.8):
 [[ 894   33]
 [1258  208]]
```

```
# Baseline Decision Tree Model with SMOTEEN and Gradient Boosting:
Subsample = 0.7
# Import necessary libraries
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.metrics import (
    accuracy_score, precision_score, recall_score, f1_score,
roc_auc_score,
    confusion_matrix, classification_report, precision_recall_curve
)
from imblearn.combine import SMOTEENN
from imblearn.pipeline import Pipeline

# Define SMOTEEN for handling class imbalance
smoteen = SMOTEENN(random_state=42)

# Define the Gradient Boosting Classifier with hyperparameters
tree_smoteen_gradient_boost = GradientBoostingClassifier(
    n_estimators=100,       # Number of boosting stages
```

```python
    learning_rate=0.1,      # Step size shrinking
    max_depth=3,            # Maximum depth of the tree
    subsample=0.7,          # Fraction of samples used for fitting
                            # each base learner
    random_state=42         # For reproducibility
)

# Create a pipeline with SMOTEEN and Gradient Boosting
pipeline_smoteen_gradient_boost = Pipeline([
    ('smoteen', smoteen),
    ('classifier', tree_smoteen_gradient_boost)
])

# Fit the pipeline to the training data
pipeline_smoteen_gradient_boost.fit(x_train, y_train)

# Make predictions using the pipeline
# Predict probabilities for ROC AUC and threshold adjustment
y_pred_proba = pipeline_smoteen_gradient_boost.predict_proba(x_test)
[:, 1]

# Adjust threshold to 0.9
threshold = 0.9  # Adjust this value to tune precision/recall tradeoff
y_pred_subsample7 = (y_pred_proba >= threshold).astype(int)

# Evaluate the model's performance with the adjusted threshold
accuracy = accuracy_score(y_test, y_pred_subsample7)
precision = precision_score(y_test, y_pred_subsample7 , pos_label=1)
recall = recall_score(y_test, y_pred_subsample7 , pos_label=1)
f1 = f1_score(y_test, y_pred_subsample7 , pos_label=1)
roc_auc = roc_auc_score(y_test, y_pred_proba)

# Print the evaluation maetrics
print("Decision Tree with Gradient Boosting and SMOTEEN Metrics
(Subsample = 0.7):")
print(f"Accuracy: {accuracy:.2f}")
print(f"Precision: {precision:.2f}")
print(f"Recall: {recall:.2f}")
print(f"F1 Score: {f1:.2f}")
print(f"ROC AUC: {roc_auc:.2f}")

# Display the classification report
print("\nClassification Report (Subsample = 0.7):")
print(classification_report(y_test, y_pred_subsample7))

# Display the confusion matrix
print("Confusion Matrix (Subsample = 0.7):\n", confusion_matrix
      (y_test, y_pred_subsample7))
```

```
Decision Tree with Gradient Boosting and SMOTEEN Metrics (Subsample =
0.7):
Accuracy: 0.46
Precision: 0.82
Recall: 0.15
F1 Score: 0.25
ROC AUC: 0.67

Classification Report (Subsample = 0.7):
              precision    recall  f1-score   support

           0       0.41      0.95      0.58       927
           1       0.82      0.15      0.25      1466

    accuracy                           0.46      2393
   macro avg       0.62      0.55      0.41      2393
weighted avg       0.66      0.46      0.38      2393

Confusion Matrix (Subsample = 0.7):
 [[ 878   49]
 [1247  219]]
```

Hyperparameter Tuning: Subsample Evaluation

- Subsample = 0.9 Adjusting the subsample to 0.9 not only lead to an increase in Precision from 0.82 to 0.84, the number of True Positives also increased from 211 to 228.

- Subsample = 0.8 A subsample of 0.8 lead to another increase in Precision up to 0.86. The number of True Positives decreased to 208, but that is still a sufficient number of stocks to choose from.

- Subsample = 0.7 A subsample of 0.7 decreased the Precision from 0.86 back to 0.82, which is what we got when our subsample was at the default value of 1. However, it has a slight edge over the default value because it has 8 more True Positive cases.

- Conclusion Judging by the results of adjusting subsample, we are going to modify our model by adjusting the hyperparamter subsample to the value of 0.8. With our goal being maximum Precision power, a subsample of 0.8 brings us closer to that goal while maintaining an abundant basket of stocks to choose from.

Hypeparameter Tuning: n_estimators

In gradient boosting algorithms, simple decision trees called 'weak learners' are iteritively created one at a time, with each one fixing the errors of the one before it until a max number of iterations or accuracy threshold is reached. n_estimators is a hyperparamter in gradient boosting algorithms that controls the number of 'weak learners' (decision trees) that are combined to form the final predictor. Increasing n_estimators can raise computational cost and lead to overfitting, which improves the models performance on the training data, but may not translate those results to unseen data. Decreasing n_estimators can reduce overfitting and improve generalization to new data, but may fail to capture all underlying relationships in the data. So far in our model, n_estimators has been set to 100. We are going to try adjusting this to 50 and 150 and evaluate the results.

```
# Baseline Decision Tree Model with SMOTEEN and
# Gradient Boosting: n_estimators = 50
# Import necessary libraries
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.metrics import (
    accuracy_score, precision_score, recall_score, f1_score,
roc_auc_score,
    confusion_matrix, classification_report, precision_recall_curve
)
from imblearn.combine import SMOTEENN
from imblearn.pipeline import Pipeline

# Define SMOTEEN for handling class imbalance
smoteen = SMOTEENN(random_state=42)

# Define the Gradient Boosting Classifier with hyperparameters
tree_smoteen_gradient_boost = GradientBoostingClassifier(
    n_estimators=50,        # Number of boosting stages
    learning_rate=0.1,       # Step size shrinking
    max_depth=3,             # Maximum depth of the tree
    subsample=0.8,           # Fraction of samples used for fitting
                             # each base learner
    random_state=42          # For reproducibility
)

# Create a pipeline with SMOTEEN and Gradient Boosting
pipeline_smoteen_gradient_boost = Pipeline([
    ('smoteen', smoteen),
    ('classifier', tree_smoteen_gradient_boost)
])

# Fit the pipeline to the training data
pipeline_smoteen_gradient_boost.fit(x_train, y_train)

# Make predictions using the pipeline
# Predict probabilities for ROC AUC and threshold adjustment
y_pred_proba = pipeline_smoteen_gradient_boost.predict_proba(x_test)
[:, 1]

# Adjust threshold to 0.9
threshold = 0.9  # Adjust this value to tune precision/recall tradeoff
y_pred_estimators50 = (y_pred_proba >= threshold).astype(int)

# Evaluate the model's performance with the adjusted threshold
accuracy = accuracy_score(y_test, y_pred_estimators50)
```

```
precision = precision_score(y_test, y_pred_estimators50 , pos_label=1)
recall = recall_score(y_test, y_pred_estimators50 , pos_label=1)
f1 = f1_score(y_test, y_pred_estimators50 , pos_label=1)
roc_auc = roc_auc_score(y_test, y_pred_proba)
# Print the evaluation maetrics
print("Decision Tree with Gradient Boosting and SMOTEEN Metrics
(n_estimators = 50):")
print(f"Accuracy: {accuracy:.2f}")
print(f"Precision: {precision:.2f}")
print(f"Recall: {recall:.2f}")
print(f"F1 Score: {f1:.2f}")
print(f"ROC AUC: {roc_auc:.2f}")

# Display the classification report
print("\nClassification Report (n_estimators = 50):")
print(classification_report(y_test, y_pred_estimators50))

# Display the confusion matrix
print("Confusion Matrix (n_estimators = 50):\n", confusion_matrix(
    y_test, y_pred_estimators50))
```

```
Decision Tree with Gradient Boosting and SMOTEEN Metrics (n_estimators
= 50):
Accuracy: 0.43
Precision: 0.88
Recall: 0.08
F1 Score: 0.14
ROC AUC: 0.67

Classification Report (n_estimators = 50):
              precision    recall  f1-score   support

           0       0.40      0.98      0.57       927
           1       0.88      0.08      0.14      1466

    accuracy                           0.43      2393
   macro avg       0.64      0.53      0.36      2393
weighted avg       0.69      0.43      0.31      2393

Confusion Matrix (n_estimators = 50):
 [[ 911   16]
 [1354  112]]
```

```
# Baseline Decision Tree Model with SMOTEEN and
# Gradient Boosting: n_estimators = 150
# Import necessary libraries
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.metrics import (
    accuracy_score, precision_score, recall_score, f1_score,
roc_auc_score,
```

```
    confusion_matrix, classification_report, precision_recall_curve
)
from imblearn.combine import SMOTEENN
from imblearn.pipeline import Pipeline

# Define SMOTEEN for handling class imbalance
smoteen = SMOTEENN(random_state=42)

# Define the Gradient Boosting Classifier with hyperparameters
tree_smoteen_gradient_boost = GradientBoostingClassifier(
    n_estimators=150,       # Number of boosting stages
    learning_rate=0.1,      # Step size shrinking
    max_depth=3,            # Maximum depth of the tree
    subsample=0.8,          # Fraction of samples used for fitting
                            # each base learner
    random_state=42         # For reproducibility
)

# Create a pipeline with SMOTEEN and Gradient Boosting
pipeline_smoteen_gradient_boost = Pipeline([
    ('smoteen', smoteen),
    ('classifier', tree_smoteen_gradient_boost)
])

# Fit the pipeline to the training data
pipeline_smoteen_gradient_boost.fit(x_train, y_train)

# Make predictions using the pipeline
# Predict probabilities for ROC AUC and threshold adjustment
y_pred_proba = pipeline_smoteen_gradient_boost.predict_proba(x_test)
[:, 1]

# Adjust threshold to 0.9
threshold = 0.9  # Adjust this value to tune precision/recall tradeoff
y_pred_estimators150 = (y_pred_proba >= threshold).astype(int)

# Evaluate the model's performance with the adjusted threshold
accuracy = accuracy_score(y_test, y_pred_estimators150)
precision = precision_score(y_test, y_pred_estimators150 ,
pos_label=1)
recall = recall_score(y_test, y_pred_estimators150 , pos_label=1)
f1 = f1_score(y_test, y_pred_estimators150 , pos_label=1)
roc_auc = roc_auc_score(y_test, y_pred_proba)

# Print the evaluation maetrics
print("Decision Tree with Gradient Boosting and SMOTEEN Metrics
(n_estimators = 150):")
print(f"Accuracy: {accuracy:.2f}")
print(f"Precision: {precision:.2f}")
print(f"Recall: {recall:.2f}")
```

```
print(f"F1 Score: {f1:.2f}")
print(f"ROC AUC: {roc_auc:.2f}")

# Display the classification report
print("\nClassification Report (n_estimators = 150):")
print(classification_report(y_test, y_pred_estimators150))

# Display the confusion matrix
print("Confusion Matrix (n_estimators = 150):\n", confusion_matrix(
    y_test, y_pred_estimators150))
```

```
Decision Tree with Gradient Boosting and SMOTEEN Metrics (n_estimators
= 150):
Accuracy: 0.47
Precision: 0.83
Recall: 0.18
F1 Score: 0.29
ROC AUC: 0.67

Classification Report (n_estimators = 150):
              precision    recall  f1-score   support

           0       0.42      0.94      0.58       927
           1       0.83      0.18      0.29      1466

    accuracy                           0.47      2393
   macro avg       0.63      0.56      0.44      2393
weighted avg       0.67      0.47      0.40      2393

Confusion Matrix (n_estimators = 150):
 [[ 875   52]
 [1208  258]]
```

Hyperparameter Evaluation: n_estimators

- n_estimators = 50

Changing the n_estimators to 50 resulted in a Precision value of 0.88 and a fairly dramatic drop in True Positives from our current best model of 208 to 112 and the True Negatives cut in half from 33 to 16. This shows that the model has a high threshold for only choosing stocks that have a very high probability of beating their estimated earnings.

- n_estimators = 150

Changing the n_estimators to 150 resulted in a Precision value of 0.84, which is a slight step down from our current best model. The True Positives to 258 from the current best model of 208.

Final Model

After creating the a baseline model, we tuned it by applying techniques for data augmentation, preprocessing, and hyperparameter modification. Below is a description of our baseline model and final model.

Base Model

Model Type

- Decision Tree

Final Model:

Model Type

- Decision Tree

Tuning

- SMOTEEN
- Gradient Boosting
- Threshold = 0.9
- Subsample = 0.8
- n_estimators = 50

Testing Dataset vs. Training Dataset Metrics

We are now going to compare and evaluate the metrics of the final model on the testing dataset and the training dataset. The goal of this is not only to see the results of our model for investor recommendations, but to see if there are any major changes in the results once the model is run on the training dataset and testing dataset separately. If the model performs way better on the training set than the test set, this indicates overfitting and the model may be memorizing training data instead of generalizing. If the mode performs poorly on both the training and testing datasets, it indicates underfitting or an oversimplified model. Idealy, performance on both the training dataset and testing dataset should be relativley similar.

```
# Fit the pipeline to the training data
pipeline_smoteen_gradient_boost.fit(x_train, y_train)

# Predictions and evaluation on the training set
y_train_pred_proba =
pipeline_smoteen_gradient_boost.predict_proba(x_train)[:, 1]
y_train_pred = (y_train_pred_proba >= threshold).astype(int)

# Evaluate the model's performance on the training set
train_accuracy = accuracy_score(y_train, y_train_pred)
train_precision = precision_score(y_train, y_train_pred, pos_label=1)
train_recall = recall_score(y_train, y_train_pred, pos_label=1)
```

```python
train_f1 = f1_score(y_train, y_train_pred, pos_label=1)
train_roc_auc = roc_auc_score(y_train, y_train_pred_proba)
train_conf_matrix = confusion_matrix(y_train, y_train_pred)

print("Training Metrics:")
print(f"Accuracy: {train_accuracy:.2f}")
print(f"Precision: {train_precision:.2f}")
print(f"Recall: {train_recall:.2f}")
print(f"F1 Score: {train_f1:.2f}")
print(f"ROC AUC: {train_roc_auc:.2f}")
print()
print("Confusion Matrix (Training Set):\n", train_conf_matrix)
print()

# Predictions and evaluation on the test set
y_pred_proba = pipeline_smoteen_gradient_boost.predict_proba(x_test)
[:, 1]
y_pred_estimators50 = (y_pred_proba >= threshold).astype(int)

# Evaluate the model's performance on the test set
test_accuracy = accuracy_score(y_test, y_pred_estimators50)
test_precision = precision_score(y_test, y_pred_estimators50,
pos_label=1)
test_recall = recall_score(y_test, y_pred_estimators50, pos_label=1)
test_f1 = f1_score(y_test, y_pred_estimators50, pos_label=1)
test_roc_auc = roc_auc_score(y_test, y_pred_proba)

print("Test Metrics:")
print(f"Accuracy: {test_accuracy:.2f}")
print(f"Precision: {test_precision:.2f}")
print(f"Recall: {test_recall:.2f}")
print(f"F1 Score: {test_f1:.2f}")
print(f"ROC AUC: {test_roc_auc:.2f}")
print()

# Display the confusion matrix for the test set

print("Confusion Matrix (Test Set):\n", confusion_matrix(
    y_test, y_pred_estimators50))
```

```
Training Metrics:
Accuracy: 0.49
Precision: 0.86
Recall: 0.20
F1 Score: 0.33
ROC AUC: 0.74

Confusion Matrix (Training Set):
 [[3521  188]
 [4668 1194]]
```

```
Test Metrics:
Accuracy: 0.47
Precision: 0.83
Recall: 0.18
F1 Score: 0.29
ROC AUC: 0.67

Confusion Matrix (Test Set):
 [[ 875   52]
 [1208  258]]
```

Metric Evaluation: Training Dataset vs. Testing Dataset

Upon running our model separately on the training dataset and testing dataset, we can see that the metrics are relativley similar, which means there is a low chance that the model is overfitting or underfitting the data. Below are the results and the % change from the training dataset to the testing dataset

Metrics:	*Training Dataset*	*Testing Dataset*	*% Change*
* Accuracy	0.44	0.43	-2.27%
* Precision	0.89	0.88	-1.12%
* Recall	0.09	0.08	-11.11%
* F1 Score	0.17	0.14	-17.65%
* ROC AUC	0.71	0.67	-5.63

As you can see, the % change in the Precision values (our most important metric) differs between the training dataset and testing dataset by 1.12%. This is a great result because it means the performance on both datasets is relatively similar. The Recall and F1 Score differ by much bigger values, 11.11% and 17.65% respectivley. Although these are significant differences, our model was built around maximizing the Precision value, so we do not need to worry about the variation in Recall values and F1 Scores.

Full Dataset

Below is the output metrics of the full dataset (training dataset + testing dataset).

```
# Model used on full dataset
# Combine the training and testing datasets
x_full = pd.concat([x_train, x_test])
y_full = pd.concat([y_train, y_test])

# Predict probabilities for the entire dataset
y_full_proba = pipeline_smoteen_gradient_boost.predict_proba(x_full)
[:, 1]

# Adjust the threshold for predictions
```

```python
threshold = 0.9  # Adjust this value as needed
y_full_pred_final_model = (y_full_proba >= threshold).astype(int)

# Evaluate the model's performance on the entire dataset
accuracy_full = accuracy_score(y_full, y_full_pred_final_model)
precision_full = precision_score(y_full, y_full_pred_final_model,
pos_label=1)
recall_full = recall_score(y_full, y_full_pred_final_model,
pos_label=1)
f1_full = f1_score(y_full, y_full_pred_final_model, pos_label=1)
roc_auc_full = roc_auc_score(y_full, y_full_proba)
# Print evaluation metrics for the entire dataset
print("Final Model Results:")
print(f"Accuracy: {accuracy_full:.2f}")
print(f"Precision: {precision_full:.2f}")
print(f"Recall: {recall_full:.2f}")
print(f"F1 Score: {f1_full:.2f}")
print(f"ROC AUC: {roc_auc_full:.2f}")

# Display the classification report
print("\nClassification Report on Full Dataset using Final Model:")
print(classification_report(y_full, y_full_pred_final_model))

# Display the confusion matrix
print("Confusion Matrix on Full Dataset using Final Model:\n"
      , confusion_matrix(y_full, y_full_pred_final_model))
```

```
Final Model Results:
Accuracy: 0.49
Precision: 0.86
Recall: 0.20
F1 Score: 0.32
ROC AUC: 0.73

Classification Report on Full Dataset using Final Model:
              precision    recall  f1-score   support

           0       0.43      0.95      0.59      4636
           1       0.86      0.20      0.32      7328

    accuracy                           0.49     11964
   macro avg       0.64      0.57      0.46     11964
weighted avg       0.69      0.49      0.43     11964

Confusion Matrix on Full Dataset using Final Model:
 [[4396  240]
 [5876 1452]]
```

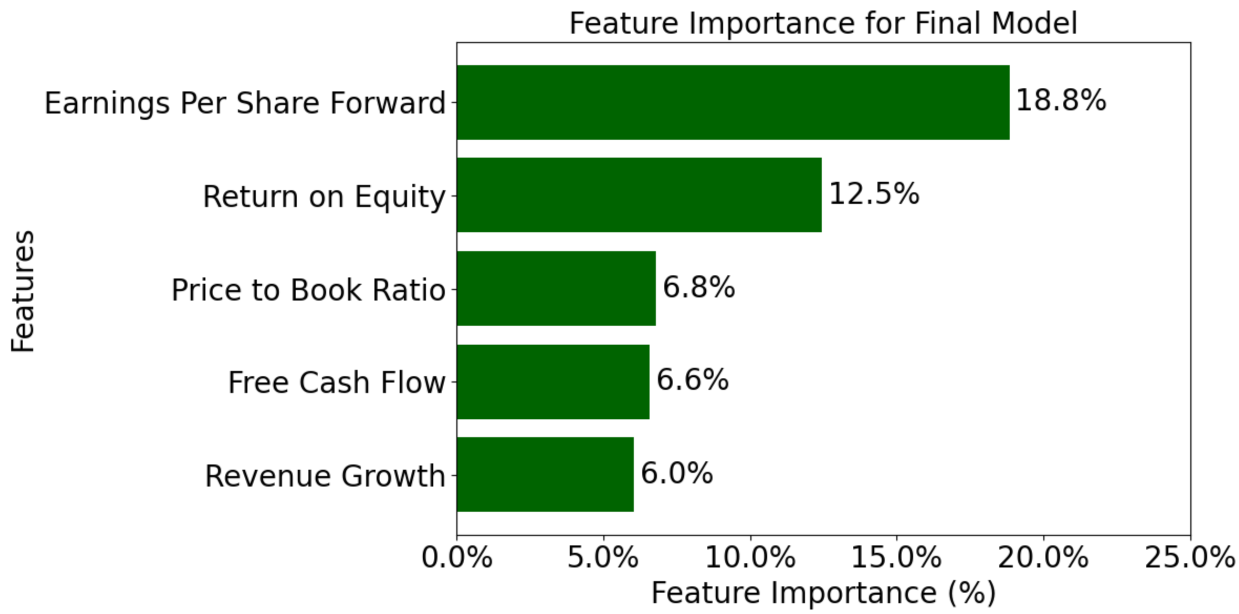
Feature Importance

Out of the 22 parameters used in this model, we want to see which features are contributing the most to the model's predictions. Below we run code to find the relative contribution of each feature.

```
import numpy as np
import matplotlib.pyplot as plt
from matplotlib.ticker import FuncFormatter

# Access feature importances from the trained Gradient Boosting model
feature_importances = pipeline_smoteen_gradient_boost.named_steps[
    'classifier'].feature_importances_

# Create a DataFrame for better readability
importances_df = pd.DataFrame({
    'Feature': x_full.columns,
    'Importance': feature_importances
})

# Sort features by importance
importances_df = importances_df.sort_values(by='Importance',
ascending=False)

# Add percentage contribution for better interpretation
importances_df['Percentage'] = (importances_df['Importance'] /
                                importances_df['Importance'].sum()) *
100

# Display top features
print("Top Feature Importances:")
print(importances_df)  # Adjust the number of top features to display

# Show only top 5 features on the plot
top_5_features = importances_df.head(5)

# Plot feature importances
plt.figure(figsize=(12, 6))
bars = plt.barh(top_5_features['Feature'],
top_5_features['Percentage']
                , color='darkgreen')
plt.xlabel('Feature Importance (%)', fontsize=20)
plt.ylabel('Features', fontsize=20)
plt.title('Feature Importance for Final Model', fontsize=20)

# Adjust tick label font sizes
plt.xticks(fontsize=20)
plt.yticks(fontsize=20)

# Add "%" symbol to x-axis values
```

```
plt.gca().xaxis.set_major_formatter(FuncFormatter(lambda x, _:
f'{x:.1f}%'))

# Add percentage values to the right of the bars
for bar, percentage in zip(bars, top_5_features['Percentage']):
    plt.text(
        bar.get_width() + 0.2,  # Position to the right of the bar
        bar.get_y() + bar.get_height() / 2,  # Vertically centered on
the bar
        f'{percentage:.1f}%',  # Text to display
        va='center',  # Align text vertically
        ha='left',  # Align text horizontally
        fontsize=20
    )

plt.xlim(0, 25)  # Set the x-axis range from 0 to 30


plt.gca().invert_yaxis()
plt.tight_layout()
plt.show()
```

```
Top Feature Importances:
                      Feature  Importance  Percentage
5   Earnings Per Share Forward    0.188414   18.841426
6             Return on Equity    0.124586   12.458632
3         Price to Book Ratio    0.068016    6.801605
8              Free Cash Flow    0.065946    6.594593
9              Revenue Growth    0.060459    6.045852
0                  Market Cap    0.056005    5.600493
4              Dividend Yield    0.047468    4.746797
12               Gross Margin    0.045795    4.579521
16           Return on Assets    0.039407    3.940707
20        Book Value Per Share    0.039394    3.939386
1           Trailing P/E Ratio    0.033917    3.391659
15                Quick Ratio    0.033253    3.325307
2            Forward P/E Ratio    0.031384    3.138401
17           Enterprise Value    0.031102    3.110185
7        Debt to Equity Ratio    0.030910    3.091011
10         Beta (Volatility)    0.024008    2.400769
18  Enterprise Value to EBITDA    0.021966    2.196585
11           Operating Margin    0.021661    2.166056
13        Price to Sales Ratio    0.018292    1.829229
14              Current Ratio    0.018018    1.801783
19                  PEG Ratio    0.000000    0.000000
21              Pays Dividend    0.000000    0.000000
```



Feature Performance Evaluation

The feature contributing most to the features conbtributions is Earnings Per Share Forward at 18.8%%. Earnings Per Share Foward is an estimate of a company's future earnings per share for the next fiscal quarter or year, which is forecasted by financial analysts, investment firms, and research departments. Even though this is predicting what the stock's earnings report will be for the next quarter, it is not an example of data leakage because this is publicly available information and is only an estimate of the future earnings per share value. The next highest contributing feature is Return on Equity at 12.5%%. Return on Equity measures a company's profitability relative to its shareholders' equity. It's indicating how effectivley a companyis using the capital invested by its' shareholders to generate profits.

The rest of the features contribute less than 6% each to the model's prediction, with the exception of PEG Ratio and Dividend Payment, which contribute 0%.

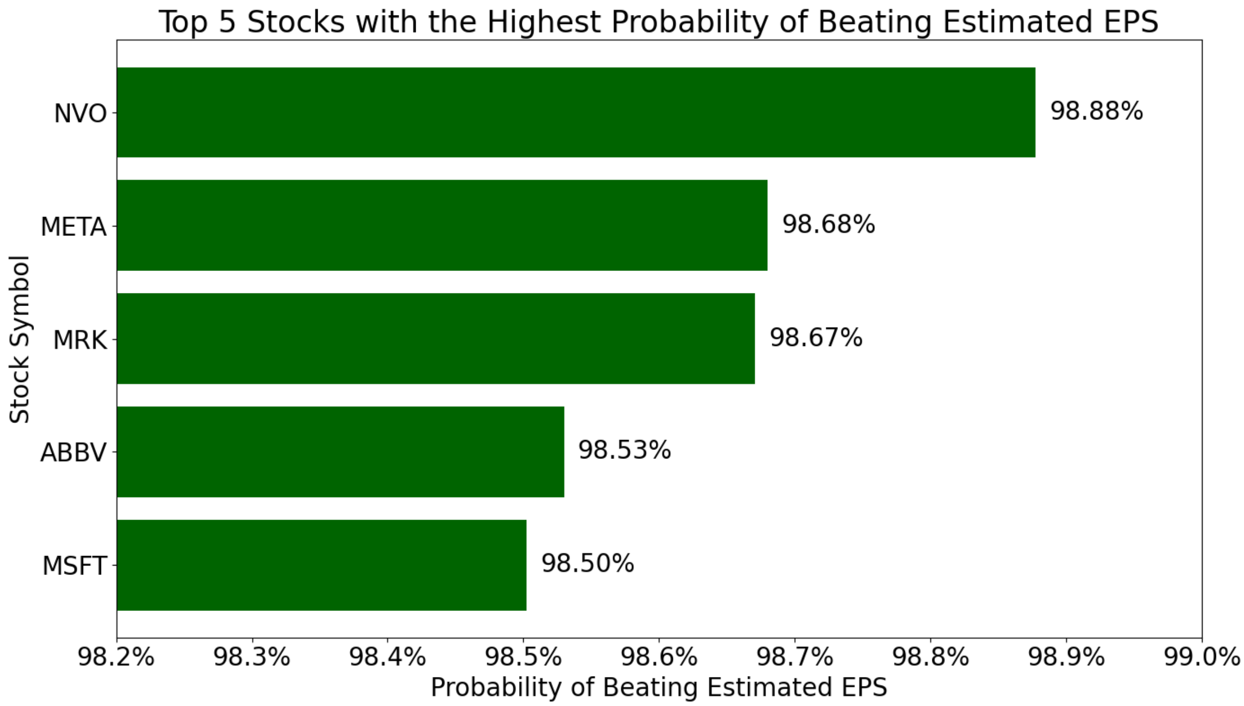
Stocks with Highest Probability of Beating Earnings

We're going to make a list of the top 25 stocks with the highest probability of beating their next estimated EPS, as predicted by the model. To do this, we'll use the y_full_proba, which is a variable we created in our model that retreives the probability that each stock will belong to class 1 (beating their estimated EPS).

```
# Add probabilities and stock identifiers to a dataframe for
# the top 25 highest probability stocks
# Create a new DataFrame in order to keep the x_full DataFrame
x_full_probability = x_full.copy()

# Add a column to the DataFrame called 'Probability' containing
# the y_full_proba values calculated by our model
x_full_probability['Probability'] = y_full_proba
```

```
# Add the 'Symbol' column back into our Dataframe so we can see it
x_full_probability['Symbol'] = df_merged_stocks_data_scaled['Symbol']

# Create a DataFrame showing probabilities sorted (descending),
# stocks grouped by 'Symbol' as we still have one row for each of the
# four quarterly estimated EPS  reports per stock, and extract the top
25
top_25_stocks = x_full_probability.groupby('Symbol',
as_index=False).agg(
    'first').sort_values(by='Probability', ascending=False).head(25)

# Display the top 25 stocks
print("Top 25 Stocks with the Highest Probability of Beating
Earnings:")
print(top_25_stocks[['Symbol', 'Probability']])

Top 25 Stocks with the Highest Probability of Beating Earnings:
     Symbol  Probability
1996    NVO     0.988774
1776   META     0.986799
1849    MRK     0.986706
10     ABBV     0.985300
1863   MSFT     0.985024
1662    LMT     0.984236
1458   INTU     0.984110
2656    SYK     0.983663
1721     MA     0.982952
731     CRM     0.982934
2290   QCOM     0.982636
2872      V     0.982531
1214   GILD     0.982119
89     AGYS     0.981985
2149    PEP     0.981877
1525    JNJ     0.981763
183    ANET     0.981698
2787   TSLA     0.981647
50     ADBE     0.981557
1932   NFLX     0.980907
1393    IBM     0.980716
2168    PGR     0.980403
1490   ISRG     0.980092
2110   PANW     0.979983
1187     GE     0.979315

import matplotlib.pyplot as plt
import pandas as pd

# Your data preparation code remains the same
x_full_probability = x_full.copy()
```

```
x_full_probability['Probability'] = y_full_proba
x_full_probability['Symbol'] = df_merged_stocks_data_scaled['Symbol']

# Aggregate and sort data for the top 25 stocks
top_5_stocks = (
    x_full_probability.groupby('Symbol', as_index=False)
    .agg({'Probability': 'first'})  # Take the first probability per
stock
    .sort_values(by='Probability', ascending=False)
    .head(5)
)

# Multiply probabilities by 100 for percentage values
top_5_stocks['Probability'] = top_5_stocks['Probability'] * 100

# Plotting the top 5 stocks
plt.figure(figsize=(14, 8))
bars = plt.barh(top_5_stocks['Symbol'], top_5_stocks['Probability']
                , color='darkgreen')
plt.xlabel('Probability of Beating Estimated EPS', fontsize=20)
plt.ylabel('Stock Symbol', fontsize=20)
plt.title('Top 5 Stocks with the Highest Probability of Beating
Estimated EPS'
          , fontsize=24)

# Adjust tick label font sizes
plt.xticks(fontsize=20)
plt.yticks(fontsize=20)

# Add probability values to the right of the bars
for bar, probability in zip(bars, top_5_stocks['Probability']):
    plt.text(
        bar.get_width() + 0.01,  # Position to the right of the bar
        bar.get_y() + bar.get_height() / 2,  # Vertically centered on
the bar
        f'{probability:.2f}%',  # Text to display
        va='center',  # Align text vertically
        ha='left',  # Align text horizontally
        fontsize=20
    )

# Add "%" symbol to x-axis values
plt.gca().xaxis.set_major_formatter(FuncFormatter(lambda x, _:
f'{x:.1f}%'))

plt.xlim(98.2, 99)  # Set the x-axis range from 95 to 96

plt.gca().invert_yaxis()  # Invert y-axis for better readability
plt.tight_layout()
plt.show()
```



Conclusion

To wrap up this analysis, we'll end by giving an overall summary of the process we took to build our model, the limitations of data collection and model results, potential solutions to those limitations, future actions to improve our model.

Summary

- Pull the top 5,000 stocks by market cap from the NASDAQ website (https://www.nasdaq.com/market-activity/stocks/screener) which gave us stock ticker, company name, and current market cap value
- Remove any stocks that aren't common shares, such as capital stock, registry shares, and global notes
- Import stock valuation parameters and earnings report history from Yahoo Finance for our list of stocks, remove unavailable parameter values, and impute specific values to maintain consistency in the dataset
- Remove certain columns to prevent data leakage and scale the data in preparation for modeling
- Analyze metrics we will use to evaluate our model and decide which metric is most important for our business goal (Precision value)
- Run the data through two different types of models (Logistic Regression and Decision Tree) and choose which one has the best performance for our specific needs (Decision Tree)
- Implement data preprocessing techniques, tune hyperparameters, and compare the results of each modification to the baseline model to see if there was an increase in model performance. If an increase in performance is observed, keep the modification and

move on to the next technique. Revise the model until performance improves to a sufficient level
- Run the final model on both the training dataset and testing dataset to confirm generalizing (model is not overfit to only work on the training data), run model on full dataset, and create a list of the top 25 stocks with the highest probability of beating their earnings report

Limitations

- Data pulled from Yahoo Finance, while free, is limited in terms of real-time data and historical data. The market cap and valuation parameters are not updated in real time, but appear to be updated periodically, possible on a daily or weekly basis, though the exact timeframe is unknown. On top of this, there is a constraint on how much historical data can be retrieved. For example, only the most recent four quarterly earnings reports are available for stocks.
- Retrieving the original 24 stock valuation parameters for 5,000 stocks took almost an hour to generate. Future projects may lead to a dramatic increase in the number of parameters desired in order to discover new patterns and correlations in the data, increasing processing time exponentially.
- The main method for finding the ideal preprocessing techniques and hyperparameter tunings was trial-and-error. Hyperparameter optimization techniques, like GridSearchCV, reduce the number of models that need to be tested, streamlining the tuning process. Unfortunately, these optimization techniques required more computational resources than my computer could provide, preventing me from utilizing these strategies.
- Our target variable is earnings outcome, which is whether the stock beat their estimated earnings per share. A stock beating it's quarterly estimated earnings per share is a good indicator that the company is doing well fundamentally and has a much higher probability of increasing its' price, as opposed to a company that matched or missed its' estimated earnings per share. However, a company beating its' estimated earnings per share is not a guarantee that the stock will move up, especially in the short term. There are times where a company will greatly exceed its' estimated earnings per share, but the price will fall in the days following the announcement. This that there are other factors besdies beating its' estimated earnings per share that go into an increase in stock price.

Potential Solutions to these Limitations

- Financial data providers, such as Bloomberg Terminal and Alpha Vantage, provide APIs for accessing historical and real-time stock market data. These resources would provide us with accurate real-time data to ensure our model is up-to-date, along with extensive historical data spanning multiple years, rather than being limited to just a year or two. These services are expensive and cost anywhere from hundreds to thousands of dollars per month and have rate limits, which means that only a certain amount of data is able to be pulled every hour.
- There are a few options to reduce processing time for large dataset analysis and computationally intensive modeling. One option is to install one or multiple GPU (Graphics Processing Unit) units, which can significantly increase computational capability for tasks that involve large amounts of data and machine learning models. Another option is to invest in infrastructure, like powerful servers and GPUs, and rent out

space in a data center. These data centers provide cooling, security, maintenance, and monitoring, reducing costs associated with real estate, power, cooling, and personnel. One more option is use Cloud Hosting, which is renting servers and GPUs from data centers or cloud providers, like Amazon Web Services (AWS), Google Cloud, or Microsoft Azure. This is the most cost effective in the short term, as we don't need to purchase or manage the hardware ourself. We pay for the computational power and resources used, and the provider is responsible for maintaining the infrastructure.

- Factors other than a stock beating its' estimated earnings per share may be a better indicator for a stock increasing in price, such as other types of valuation parameters or technical analysis indicators. We may also find that stocks that beat their estimated earnings per share may, on average, experience a percentage increase in price that is greater than the percentage decline when they miss estimates, leading to a long-term upward trend in average price. This would need to be calculated and proven using historical earnings reports and price data.

Future Actions for Improvement

- With the addition of Financial data providers, like Bloomberg Terminal, more stock valuation parameters and ratios will be available, which can be added to the model in order to see if any of them have a significant predictive power.
- Technical analysis (TA) is a method of evaluating future stock price movement using historical data, primarily price and volume. Unlike fundamental analysis, which focuses on a company's financial performance and intrinsic value (this project is based on fundamental analysis), TA is concerned with identifying patterns and trends in the data. TA often uses candlestick charts and uses mathhematical calculations based on price and volume, like Moving Averages (average price over a set period of time, i.e. 5 day MA, 50 day MA etc.), Relative Strength Index (measures the speed and chance of price movements to determine overbought or oversold conditions), Bollinger Bands (indicates price volatility by plotting two standard deviationos away from a moving average), and many more. Since these indicators and patterns are used by stock/commodity traders to determine future price movements, we can try implementing these tools to our model to see if they enhance predictive power.
- In this model, we focused on logistic regression and decision trees. However, other machine learning algorithms and statistical approaches, such as Support Vector Machines (SVM), Neural Networks, and Random Forest. Most of these require greater computational power than the approach taken in this project, but may lead to more robust model.