( + Code ) ( + Text )

## BA870 - Using BERT to Predict a Company's Asset Intensity (Text Analysis)

The goal of this notebook is to show the possibilities of predicting financial outcomes from textual data via DistilBERT transformer model.

This notebook builds uses Business Decriptions from Google Finance

(Example: See textual **Description** of AAPL (in this case from Yahoo Finance))"

#### link text

This Colab notebook uses the following files that are posted on the class webite:

- company\_des.csv with Company descriptions of a large number of companues from Yahoo Finance
- ta.csv and rev.csv with total assets and revenue data. This financial data was downloaded from Yahoo Finance

The steps this ipynb goes through are below:

- 1. Upload stock\_des.csv , ta.csv and rev.csv' from your local machine to the Colab working directory.
- 2. Install and load the necessary libraries.
- 3. Load, merge, clean the data.
- 4. Create the label variable.
- 5. Prepare the predictor.
- 6. Run the DistilBERT model.
- 7. Train logistic regression and evaluate its accuracy.

**Note**. Save this Colab notebook to your Drive via File > Save a copy in Drive to be able to edit it.

## 1. Upload data files

Please upload the necessary files (stock\_des.csv, ta.csv, rev.csv) in your project\_folder folder.

You can upload the files via files.upload() code cell below OR use the upload function in the window to the left (lcik on folder icon and then click on upload icon).

```
# Upload data
from google.colab import files
uploaded = files.upload()
```

Choose Files No file chosen Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable.

Saving assigment3lyushensong.csv to assigment3lyushensong.csv

Saving stock des.csv to stock des.csv

### 2. Install, load the libraries

#### !pip install transformers

```
Requirement already satisfied: transformers in /usr/local/lib/python3.10/dist-packages (4.38.2)
Requirement already satisfied: filelock in /usr/local/lib/python3.10/dist-packages (from transformers) (3.13.
Requirement already satisfied: huggingface-hub<1.0,>=0.19.3 in /usr/local/lib/python3.10/dist-packages (from transformers) (1.
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.10/dist-packages (from transformers) (6.
Requirement already satisfied: pyyaml>=5.1 in /usr/local/lib/python3.10/dist-packages (from transformers) (6.
Requirement already satisfied: regex!=2019.12.17 in /usr/local/lib/python3.10/dist-packages (from transformers) (2.31.
Requirement already satisfied: tokenizers<0.19,>=0.14 in /usr/local/lib/python3.10/dist-packages (from transformers) (4.6
Requirement already satisfied: tqdm>=4.27 in /usr/local/lib/python3.10/dist-packages (from transformers) (4.6
Requirement already satisfied: typing-extensions>=3.7.4.3 in /usr/local/lib/python3.10/dist-packages (from huggingface-Requirement already satisfied: charset-normalizer<4,>=2 in /usr/local/lib/python3.10/dist-packages (from requirement already satisfied: charset-normalizer<4,>=2 in /usr/local/lib/
```

Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.10/dist-packages (from requests->trans1

```
Requirement already satisfied: urllib3<3,>=1.21.1 in /usr/local/lib/python3.10/dist-packages (from requests-->
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.10/dist-packages (from requests-->

import numpy as np
import pandas as pd
import torch
import seaborn as sns
import matplotlib.pyplot as plt
from scipy.stats.mstats import winsorize
import transformers as ppb # pytorch transformers
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import train_test_split

DEVICE = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")

Device: cuda:0
```

## 2. Load, merge, clean the data

torch.cuda.get device name(0)

'Tesla T4'

```
# load the csv files
stock_des = pd.read_csv('stock_des.csv')
stock_data=pd.read_csv('/content/assigment3lyushensong.csv')
stock_data
```

	at	act	curcd	conm	tic	datafmt	popsrc	consol	indfmt	fyear	datadate	gvkey	
	1833.100	1097.900	USD	AAR CORP	AIR	STD	D	С	INDL	2022	2023-05- 31	1004	0
2	63058.000	13572.000	USD	AMERICAN AIRLINES GROUP INC	AAL	STD	D	С	INDL	2023	2023-12- 31	1045	1
	24661.153	1926.967	USD	PINNACLE WEST CAPITAL CORP	PNW	STD	D	С	INDL	2023	2023-12- 31	1075	2
	1491.255	NaN	USD	PROG HOLDINGS INC	PRG	STD	D	С	INDL	2023	2023-12- 31	1076	3
6	73214.000	22670.000	USD	ABBOTT LABORATORIES	ABT	STD	D	С	INDL	2023	2023-12- 31	1078	4
	7590.000	2582.000	USD	API GROUP CORPORATION	APG	STD	D	С	INDL	2023	2023-12- 31	325576	2330
	6161.700	1336.100	USD	NVENT ELECTRIC PLC	NVT	STD	D	С	INDL	2023	2023-12- 31	326688	2331
	3577.900	912.000	USD	ARCOSA INC	ACA	STD	D	С	INDL	2023	2023-12- 31	328795	2332
	507.643	128.066	USD	HYDROFARM HLDNG GP INC	HYFM	STD	D	С	INDL	2023	2023-12- 31	345920	2333
	504.452	294.084	USD	IMMUNITYBIO INC	IBRX	STD	D	С	INDL	2023	2023-12- 31	347007	2334

2335 rows x 19 columns

```
# clean up the column names
stock_data.rename(columns={'tic': 'ticker'}, inplace=True)
```

stock\_data

	gvkey	datadate	fyear	indfmt	consol	popsrc	datafmt	ticker	conm	curcd	act	at
0	1004	2023-05- 31	2022	INDL	С	D	STD	AIR	AAR CORP	USD	1097.900	1833.100
1	1045	2023-12- 31	2023	INDL	С	D	STD	AAL	AMERICAN AIRLINES GROUP INC	USD	13572.000	63058.000
2	1075	2023-12- 31	2023	INDL	С	D	STD	PNW	PINNACLE WEST CAPITAL CORP	USD	1926.967	24661.153
3	1076	2023-12- 31	2023	INDL	С	D	STD	PRG	PROG HOLDINGS INC	USD	NaN	1491.255
4	1078	2023-12- 31	2023	INDL	С	D	STD	ABT	ABBOTT LABORATORIES	USD	22670.000	73214.000
2330	325576	2023-12- 31	2023	INDL	С	D	STD	APG	API GROUP CORPORATION	USD	2582.000	7590.000
2331	326688	2023-12- 31	2023	INDL	С	D	STD	NVT	NVENT ELECTRIC PLC	USD	1336.100	6161.700
2332	328795	2023-12- 31	2023	INDL	С	D	STD	ACA	ARCOSA INC	USD	912.000	3577.900
2333	345920	2023-12- 31	2023	INDL	С	D	STD	HYFM	HYDROFARM HLDNG GP INC	USD	128.066	507.643
2334	347007	2023-12- 31	2023	INDL	С	D	STD	IBRX	IMMUNITYBIO INC	USD	294.084	504.452

2335 rows × 19 columns

ticker

#### stock\_des

		ticker	description					
	0	AAPL	Apple Inc. designs, manufactures, and markets					
	1	MSFT	Microsoft Corporation develops, licenses, and					
	2	AMZN	Amazon.com, Inc. engages in the retail sale of					
	3	FB	Facebook, Inc. develops products that enable p					
	4	GOOGL	Alphabet Inc. provides online advertising serv					
	2847	SIEB	Siebert Financial Corp., through its subsidiar					
	2848	SEAC	SeaChange International, Inc. provides multisc					
	2849	XFOR	X4 Pharmaceuticals, Inc., a clinical-stage bio					
	2850	WLL	Whiting Petroleum Corporation, an independent					
	2851	EVFM	Evofem Biosciences, Inc., a biopharmaceutical					
	2852 rc	ws × 2 col	umns					
	_		ames into one k_data, stock_des, on='ticker')					
ui –	puille	rge(stoc	k_uata, Stock_des, on= ticker )					
df.i	snull(	) <sub>sum()</sub>						
	gvkey datada	2+0	0 0					
	fyear	ace	0					
	indfm		0					
	conso		0 0					
	datafi		0					

0

conm	0
curcd	0
act	569
at	0
invt	41
lct	569
lt	6
ni	0
revt	0
sale	0
costat	0
description	0
dtype: int64	

There are some missing values in the current liabilities, current assets, and inventories variables. Therefore, I decided to drop them, because I can't fill them with median and mean.

```
df = df.dropna()

df.drop(columns=['indfmt','curcd', 'gvkey','datafmt','consol','popsrc'], inplace=True)
```

Drop Unnecessary Columns that does not contain useful information

```
df.head()
```

	datadate	fyear	ticker	conm	act	at	invt	lct	lt	ni	revt	
0	2023-05- 31	2022	AIR	AAR CORP	1097.900	1833.100	624.700	351.500	734.000	90.200	1990.600	1!
1	2023-12- 31	2023	AAL	AMERICAN AIRLINES GROUP INC	13572.000	63058.000	2400.000	22062.000	68260.000	822.000	52788.000	52
2	2023-12- 31	2023	PNW	PINNACLE WEST CAPITAL CORP	1926.967	24661.153	493.547	2889.347	18376.291	501.557	4695.991	4
4	2023-12- 31	2023	ABT	ABBOTT LABORATORIES	22670.000	73214.000	6570.000	13841.000	34387.000	5723.000	40109.000	40

```
df.rename(columns={'act': 'current asset'}, inplace=True)
df.rename(columns={'at': 'total asset'}, inplace=True)
df.rename(columns={'lt': 'liabilities'}, inplace=True)
df.rename(columns={'sale': 'sales/turnover'}, inplace=True)
df.rename(columns={'ni': 'net income'}, inplace=True)
df.rename(columns={'lct': 'current liabilities'}, inplace=True)
df.rename(columns={'revt': 'revenue'}, inplace=True)
df.rename(columns={'invt': 'inventories'}, inplace=True)
```

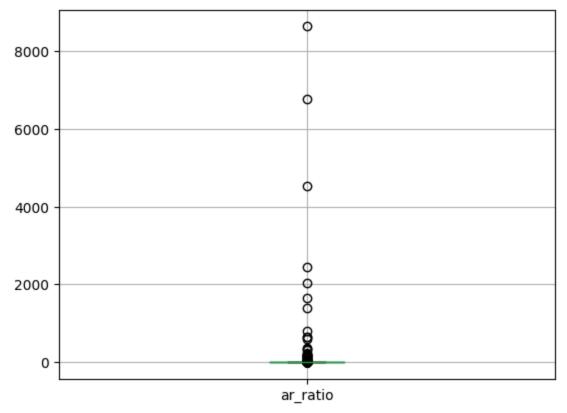
df.head()

	datadate	fyear	ticker	conm	current asset	total asset	inventories	current liabilities	liabilities	net income	l
0	2023-05- 31	2022	AIR	AAR CORP	1097.900	1833.100	624.700	351.500	734.000	90.200	
1	2023-12- 31	2023	AAL	AMERICAN AIRLINES GROUP INC	13572.000	63058.000	2400.000	22062.000	68260.000	822.000	5;
2	2023-12- 31	2023	PNW	PINNACLE WEST CAPITAL CORP	1926.967	24661.153	493.547	2889.347	18376.291	501.557	,
4	2023-12- 31	2023	ABT	ABBOTT LABORATORIES	22670.000	73214.000	6570.000	13841.000	34387.000	5723.000	4(
5	2023-12- 31	2023	AMD	ADVANCED MICRO DEVICES	16768.000	67885.000	4351.000	6689.000	11993.000	854.000	2:

```
# create the assets to revenue ratio
df['ar_ratio'] = df['total asset']/df['revenue']
print(df['ar_ratio'].describe())
df.boxplot(column='ar_ratio');
```

count	1724.000000	
mean	21.877924	
std	302.355441	
min	0.090086	
25%	0.907457	
50%	1.477851	
75%	2.447725	
max	8630.285714	
M	and the second s	£1.

Name: ar\_ratio, dtype: float64



We have 6 outliers with the ratio of 1000+. Let's remove them.

(1690, 15)

Create a binary variable that is 1 if the assets to revenue ratio is above its median and 0 otherwise.

This is the **dependent variable** (label) that we'll try to predict.

```
df['HIGH_ARR'] = (df['ar_ratio'].gt(df['ar_ratio'].median())).astype(int)
```

## Asset Intensity Ratio

```
df['asset_intensity']=df['revenue']/df['total asset']
```

Due to Colab's RAM limitations, limit the description size. We'll only keep 1st sentence of each description. In case if you have Pro subscription you can increase the number of sentences/try random sentences from descriptions/use full descriptions. (Observed improvement is marginal.)

### Three Financial Ratios

- Quick ratio: (Current Assets Inventory) / Current Liabilities The quick ratio measures the liquidity of a company by measuring
  how well its current assets could cover its current liabilities. Here, I want to see how well these companies cover their short term
  liabilities within a shorter time.
- Current ratio: Current Assets / Current Liabilities Similar to Quick Ratio, current ratio measures a company's ability to pay short term liabilities with its current assets. On the other hand, the current ratio is more appropriate to show what resources a company has to pay its short term liabilities within 12 months.
- Return on Assets: Net Income / Total Assets Return on Assets shows a company's profitability based on its total assets. For this assignment, I want to see how efficient companies are using their assets to generate profit.

```
df.columns
```

```
Index(['datadate', 'fyear', 'ticker', 'conm', 'current asset', 'total asset',
            'inventories', 'current liabilities', 'liabilities', 'net income',
            'revenue', 'sales/turnover', 'costat', 'description', 'ar_ratio',
            'HIGH_ARR', 'asset_intensity'],
          dtype='object')
df['quick ratio']=(df['current asset']-df['inventories'])/df['current liabilities']
df['current ratio']=df['current asset']/df['current liabilities']
df['ROA']=df['net income']/df['total asset']
df['quick ratio'].describe()
              1690.000000
    count
                1.955605
    mean
                2.248591
    std
    min
                0.090486
    25%
                0.855237
    50%
                1.276287
    75%
                2.177798
               25.441970
    max
    Name: quick ratio, dtype: float64
df['current ratio'].describe()
              1690.000000
    count
               -0.007352
    mean
                0.263005
    std
               -2.665283
    min
    25%
               -0.023754
    50%
                0.035726
    75%
                0.080925
                5.019803
    max
    Name: ROA, dtype: float64
```

```
df['ROA'].describe()
```

```
count
         1690.000000
           -0.007352
mean
            0.263005
std
min
           -2.665283
           -0.023754
25%
50%
            0.035726
            0.080925
75%
            5.019803
max
Name: ROA, dtype: float64
```

Print out the general information about the three financial ratios that I created.

```
df['HIGH_quick_ratio'] = (df['quick ratio'].gt(df['quick ratio'].median())).astype(int)
df['HIGH_current_ratio'] = (df['current ratio'].gt(df['current ratio'].median())).astype(int)
df['HIGH_ROA'] = (df['ROA'].gt(df['ROA'].median())).astype(int)
```

Create a binary variable that is 1 if the net profit margin/inventory turnover/return on equity ratio is above its median and 0 otherwise.

These are the dependent variables (label) that we'll try to predict.

```
df.head()
```

	datadate	fyear	ticker	conm	current asset	total asset	inventories	current liabilities	liabilities	net income	
0	2023-05- 31	2022	AIR	AAR CORP	1097.900	1833.100	624.700	351.500	734.000	90.200	
1	2023-12- 31	2023	AAL	AMERICAN AIRLINES GROUP INC	13572.000	63058.000	2400.000	22062.000	68260.000	822.000	
2	2023-12- 31	2023	PNW	PINNACLE WEST CAPITAL CORP	1926.967	24661.153	493.547	2889.347	18376.291	501.557	
4	2023-12- 31	2023	ABT	ABBOTT LABORATORIES	22670.000	73214.000	6570.000	13841.000	34387.000	5723.000	
5	2023-12- 31	2023	AMD	ADVANCED MICRO DEVICES	16768.000	67885.000	4351.000	6689.000	11993.000	854.000	

5 rows × 25 columns

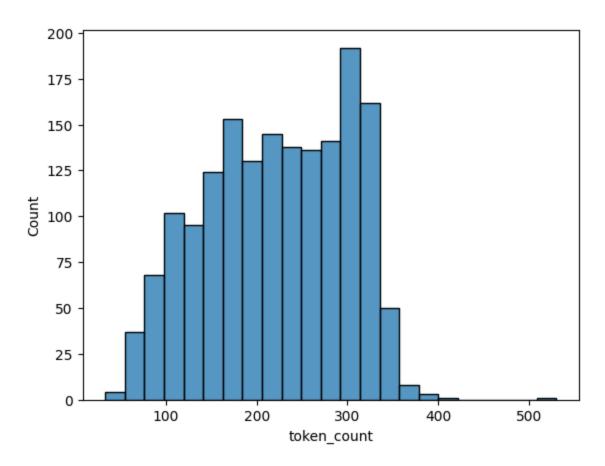
```
from nltk.tokenize import word_tokenize
import nltk
nltk.download('punkt')
# Count the number of tokens in the 'text' column
df['token_count'] = df['description'].apply(lambda x: len(word_tokenize(x)))
print(df.shape)
df
```

[nltk\_data] Downloading package punkt to /root/nltk\_data...
[nltk\_data] Unzipping tokenizers/punkt.zip.
(1690, 24)

	datadate	fyear	ticker	conm	current asset	total asset	inventories	current liabilities	liabilities	net income
0	2023-05- 31	2022	AIR	AAR CORP	1097.900	1833.100	624.700	351.500	734.000	90.200
1	2023-12- 31	2023	AAL	AMERICAN AIRLINES GROUP INC	13572.000	63058.000	2400.000	22062.000	68260.000	822.000
2	2023-12- 31	2023	PNW	PINNACLE WEST CAPITAL CORP	1926.967	24661.153	493.547	2889.347	18376.291	501.557
4	2023-12- 31	2023	ABT	ABBOTT LABORATORIES	22670.000	73214.000	6570.000	13841.000	34387.000	5723.000
5	2023-12- 31	2023	AMD	ADVANCED MICRO DEVICES	16768.000	67885.000	4351.000	6689.000	11993.000	854.000
2321	2023-03- 31	2022	LPG	DORIAN LPG LTD	236.299	1708.914	2.642	94.597	835.068	172.444
2322	2023-12- 31	2023	APG	API GROUP CORPORATION	2582.000	7590.000	150.000	1807.000	4722.000	153.000
2323	2023-12- 31	2023	NVT	NVENT ELECTRIC PLC	1336.100	6161.700	485.400	733.600	3019.600	567.100
2324	2023-12- 31	2023	ACA	ARCOSA INC	912.000	3577.900	401.800	431.200	1245.900	159.200
2325	2023-12- 31	2023	HYFM	HYDROFARM HLDNG GP INC	128.066	507.643	75.354	37.652	217.033	-64.813

1690 rows × 24 columns

import seaborn as sns
sns.histplot(data=df, x="token\_count");



Looks like most descriptions are around 200 to 300 words.

```
import re
# Function to remove unusual characters
def remove_unusual_characters(text):
    pattern = r'[^a-zA-Z0-9.,?!]' # Pattern to match common English characters, numbers, and punctuation
    text = re.sub(pattern, '', text)
    return text

# Apply the function to the 'text' column
df['text'] = df['description'].apply(remove_unusual_characters)

# Remove very long descriptions
lower_threshold = df['token_count'].quantile(0.00)
upper_threshold = df['token_count'].quantile(0.99)

# Trim the DataFrame based on the 1% thresholds
trimmed_df = df[(df['token_count'] >= lower_threshold) & (df['token_count'] <= upper_threshold)]

trimmed_df.head(5)</pre>
```

	datadate	fyear	ticker	conm	current asset	total asset	inventories	current liabilities	liabilities	net income '	ı
0	2023-05- 31	2022	AIR	AAR CORP	1097.900	1833.100	624.700	351.500	734.000	90.200	
1	2023-12- 31	2023	AAL	AMERICAN AIRLINES GROUP INC	13572.000	63058.000	2400.000	22062.000	68260.000	822.000	
2	2023-12- 31	2023	PNW	PINNACLE WEST CAPITAL CORP	1926.967	24661.153	493.547	2889.347	18376.291	501.557	
4	2023-12- 31	2023	ABT	ABBOTT LABORATORIES	22670.000	73214.000	6570.000	13841.000	34387.000	5723.000	
5	2023-12- 31	2023	AMD	ADVANCED MICRO DEVICES	16768.000	67885.000	4351.000	6689.000	11993.000	854.000	

5 rows × 25 columns

```
trimmed_df=trimmed_df[tricker"]!="LLY"] # these 2 have special characters in description, hence remove trimmed_df=trimmed_df[tricker"]!="BIIB"]
trimmed_df=trimmed_df.reset_index(drop=True)

from nltk.tokenize import sent_tokenize
# Function to keep first three sentences
def keep_n_sentences(text):
    sentences = sent_tokenize(text)
    first_three_sentences = sentences[:1]
    return ' '.join(first_three_sentences)

# Apply the function to the 'text' column
trimmed_df['text'] = trimmed_df['text'].apply(keep_n_sentences)

trimmed_df.head(3)
```

	datadate	fyear	ticker	conm	current asset	total asset	inventories	current liabilities	liabilities	net income	 H:
0	2023-05- 31	2022	AIR	AAR CORP	1097.900	1833.100	624.700	351.500	734.000	90.200	
1	2023-12- 31	2023	AAL	AMERICAN AIRLINES GROUP INC	13572.000	63058.000	2400.000	22062.000	68260.000	822.000	
2	2023-12- 31	2023	PNW	PINNACLE WEST CAPITAL CORP	1926.967	24661.153	493.547	2889.347	18376.291	501.557	

3 rows × 25 columns

# Preparing the predictor and DistilBERT model

Note. Please enable GPU in Edit > Notebook settings > Hardware accelerator.

Load a pre-trained BERT model.

model\_class, tokenizer\_class, pretrained\_weights = (ppb.DistilBertModel, ppb.DistilBertTokenizer, 'distilbert-base
# Load pretrained model/tokenizer

# Load pretrained model/tokenizer
tokenizer = tokenizer\_class.from\_pretrained(pretrained\_weights, max\_length=2)
model = model class.from pretrained(pretrained weights)

/usr/local/lib/python3.10/dist-packages/huggingface\_hub/utils/\_token.py:88: UserWarning:

The secret `HF TOKEN` does not exist in your Colab secrets.

To authenticate with the Hugging Face Hub, create a token in your settings tab (<a href="https://huggingface.co/settir">https://huggingface.co/settir</a> You will be able to reuse this secret in all of your notebooks.

Please note that authentication is recommended but still optional to access public models or datasets. warnings.warn(

tokenizer\_config.json: 100% 28.0/28.0 [00:00<00:00, 1.63kB/s]

vocab.txt: 100% 232k/232k [00:00<00:00, 2.69MB/s]

tokenizer.json: 100% 466k/466k [00:00<00:00, 5.43MB/s]

config.json: 100% 483/483 [00:00<00:00, 32.1kB/s]

model.safetensors: 100% 268M/268M [00:01<00:00, 224MB/s]

Tokenize the textual data for DistilBERT.

trimmed df.description[12]

'ABM Industries Incorporated provides integrated facility solutions in the United States and internationall y. The company operates through Business & amp; Industry, Technology & amp; Manufacturing, Education, Aviatio n, and Technical Solutions segments. It provides janitorial, facilities engineering, parking, custodial, land dscaping and ground, and mechanical and electrical services; and vehicle maintenance and other services to rental car providers. The company was founded in 1909 and is headquartered in New York. New York.'

trimmed\_df.text[12]

'ABM Industries Incorporated provides integrated facility solutions in the United States and internationall v.'

```
tokenized = trimmed_df['text'].apply((lambda x: tokenizer.encode(x, add_special_tokens=True)))
```

Pad all lists of tokenized values to the same size.

```
max_len = 0
for i in tokenized.values:
    if len(i) > max_len:
        max_len = len(i)

padded = np.array([i + [0]*(max_len-len(i)) for i in tokenized.values])

np.array(padded).shape
    (1671, 69)
```

Create attention mask variable for BERT to ignore (mask) the padding when it's processing its input.

```
attention_mask = np.where(padded != 0, 1, 0)
attention_mask.shape

(1671, 69)
```

### DistilBERT model

We run the pretrained DistilBERT model on the prepared predictor and keep the result in last\_hidden\_states variable.

# Logistic regression model

Keep the first layer of the hidden states and assign the outcome variable to labels.

trimmed\_df

	datadate	fyear	ticker	conm	current asset	total asset	inventories	current liabilities	liabilities	net income
0	2023-05- 31	2022	AIR	AAR CORP	1097.900	1833.100	624.700	351.500	734.000	90.200
1	2023-12- 31	2023	AAL	AMERICAN AIRLINES GROUP INC	13572.000	63058.000	2400.000	22062.000	68260.000	822.000
2	2023-12- 31	2023	PNW	PINNACLE WEST CAPITAL CORP	1926.967	24661.153	493.547	2889.347	18376.291	501.557
3	2023-12- 31	2023	ABT	ABBOTT LABORATORIES	22670.000	73214.000	6570.000	13841.000	34387.000	5723.000
4	2023-12- 31	2023	AMD	ADVANCED MICRO DEVICES	16768.000	67885.000	4351.000	6689.000	11993.000	854.000
1666	2023-03- 31	2022	LPG	DORIAN LPG LTD	236.299	1708.914	2.642	94.597	835.068	172.444
1667	2023-12- 31	2023	APG	API GROUP CORPORATION	2582.000	7590.000	150.000	1807.000	4722.000	153.000

1668	2023-12- 31	2023	NVT	NVENT ELECTRIC PLC	1336.100	6161.700	485.400	733.600	3019.600	567.100
1669	2023-12- 31	2023	ACA	ARCOSA INC	912.000	3577.900	401.800	431.200	1245.900	159.200
1670	2023-12- 31	2023	HYFM	HYDROFARM HLDNG GP INC	128.066	507.643	75.354	37.652	217.033	-64.813