15.776 HODL Project

I. Curating our own dataset - Extract News Data

Source: refinitive

Also tried: seeking alpha, yahoo finance, and reddit, but not enough data comparing to refinitve

Data Coverage ¶

Company list: 200 comps

1. US list company on NYSE and NASDAQ
2. Technology Sector according to LSEG workspace
3. Market Cap top 200: We have tried top 600 but smaller companies do not have as frequent news coverage as the larger ones
4. Time horizon: from 2024-09-10 to 2025-12-04

A. Refinitive News Data

We extract news data from LSEG workspace, we would attach our code in another file. Our result is news.csv. The screenshots of extracting data at local Refinitiv Workspace are attached as below.

In [1]:
```
import refinitiv.data as rd
from refinitiv.data.content import news
from IPython.display import HTML
import pandas as pd
import numpy as np
from datetime import datetime,timedelta
import time
import warnings
warnings.filterwarnings("ignore")
```

In [3]:
```
rd.open_session()
```

Out[3]:
```
<refinitiv.data.session.Definition object at 0x7f62b7b4f1c0 {name='codebook'}>
```

In [4]:
```
dNow = datetime.now().date()
maxenddate = dNow - timedelta(days = 450) #upto months=15
compNews = pd.DataFrame()
riclist = ['NVDA.O', 'AAPL.O', 'GOOGL.O', 'MSFT.O', 'AVGO.O', 'META.O', 'TSM.N', 'ORCL.N', 'MA.N', 'NFLX.O', 'ASM
L.O', 'PLTR.O', 'BABA.N', 'AMD.O', 'CSCO.O', 'IBM.N', 'SAP.N', 'MU.O', 'CRM.N', 'TMUS.O', 'APP.O', 'AMAT.O', 'SHO
P.O', 'LRCX.O', 'INTC.O', 'UBER.N', 'QCOM.O', 'INTU.O', 'T.N', 'NOW.N', 'VZ.N', 'APH.N', 'SONY.N', 'ACN.N', 'PDD.
O', 'TXN.O', 'ANET.N', 'KLAC.O', 'ARM.O', 'ADBE.O', 'TBB.N', 'PANW.O', 'ADI.O', 'CRWD.O', 'HOOD.O', 'SPOT.N', 'ME
LI.O', 'ADP.O', 'CMCSA.O', 'DASH.O', 'DELL.N', 'CDNS.O', 'NTES.O', 'SNPS.O', 'MRVL.O', 'SE.N', 'SNOW.N', 'INFY.
N', 'ABNB.O', 'COIN.O', 'RELX.N', 'GLW.N', 'NET.N', 'TEL.N', 'RBLX.N', 'AMX.N', 'FTNT.O', 'ADSK.O', 'MSI.N', 'ST
X.O', 'WDAY.O', 'NXPI.O', 'WDC.O', 'RKT.N', 'DDOG.O', 'MSTR.O', 'EA.O', 'ROP.O', 'TTWO.O', 'MPWR.O', 'CRWV.O', 'F
ICO.N', 'RDDT.N', 'BIDU.O', 'TEAM.O', 'CTSH.O', 'GRMN.N', 'ZS.O', 'CPRT.O', 'EBAY.O', 'CLS.N', 'KEYS.N', 'MCHP.
O', 'UI.N', 'FIS.N', 'NOK.N', 'ASX.N', 'CRDO.O', 'CHT.N', 'ERIC.O', 'TER.O', 'TME.N', 'SNDK.O', 'VRSK.O', 'WIT.
N', 'HPE.N', 'VOD.O', 'MTD.N', 'CSGP.O', 'COHR.N', 'CIEN.N', 'CHTR.O', 'ASTS.O', 'ZM.O', 'ALAB.O', 'LDOS.N', 'HP
Q.N', 'TDY.N', 'CYBR.O', 'PSTG.N', 'TEF.N', 'JBL.N', 'IOT.N', 'LITE.O', 'VRSN.O', 'NTAP.O', 'FLEX.O', 'STM.N', 'A
FRM.O', 'ON.O', 'CRCL.N', 'TLK.N', 'GRAB.O', 'BCE.N', 'SSNC.O', 'SATS.O', 'PTC.O', 'CHKP.O', 'VIV.N', 'GFS.O', 'T
OST.N', 'TU.N', 'GIB.N', 'SMCI.O', 'RCI.N', 'TYL.N', 'HUBS.N', 'UMC.N', 'TRMB.O', 'IONQ.N', 'TWLO.N', 'FIG.N', 'C
DW.O', 'U.N', 'PINS.N', 'GDDY.N', 'GWRE.N', 'IT.N', 'LOGI.O', 'Q.N', 'FN.N', 'GEN.O', 'DD.N', 'KSPI.O', 'OKTA.O',
'DOCU.O', 'FFIV.O', 'MTSI.O', 'BMNR.N', 'RBRK.N', 'ALLE.N', 'IREN.O', 'ZBRA.O', 'CACI.N', 'ENTG.O', 'DT.N', 'SNA
P.N', 'JKHY.O', 'TSEM.O', 'BSY.O', 'NTNX.O', 'SNX.N', 'AKAM.O', 'KLAR.N', 'PCOR.N', 'YMM.N', 'CART.O', 'EPAM.N',
'DAY.N', 'SAIL.O', 'BAH.N', 'MANH.O', 'TIMB.N', 'AMKR.O', 'RMBS.O', 'BILI.O', 'LSCC.O', 'SWKS.O', 'QBTS.N', 'PAT
H.N']

for ric in riclist:
    cHeadlines = rd.news.get_headlines("R:" + ric + " AND Language:LEN AND Source:RTRS", start= str(dNow),
                                       end = str(maxenddate), count = 1000)
    cHeadlines['cRIC'] = ric
    if len(compNews):
        compNews = pd.concat([compNews,cHeadlines])
    else:
        compNews = cHeadlines

compNews
```

Out[4]:

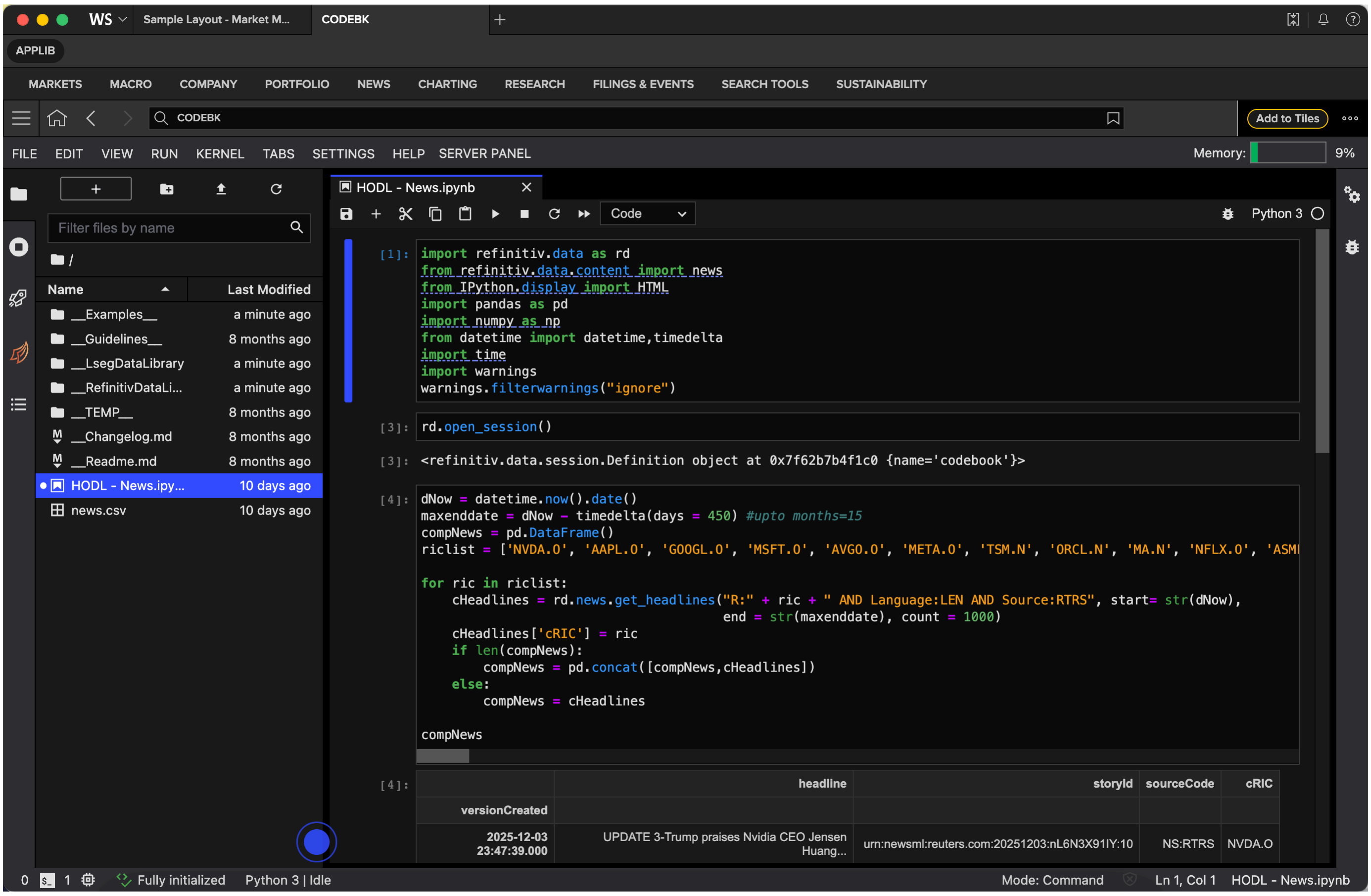
	headline	storyId	sourceCode	cRIC
versionCreated				
2025-12-03 23:47:39.000	UPDATE 3-Trump praises Nvidia CEO Jensen Huang...	urn:newsml:reuters.com:20251203:nL6N3X91IY:10	NS:RTRS	NVDA.O
2025-12-03 21:40:48.000	UPDATE 2-Intel says it will keep networking an...	urn:newsml:reuters.com:20251203:nL6N3X91JO:4	NS:RTRS	NVDA.O
2025-12-03 21:18:09.985	TRUMP: SPOKE TO NVIDIA'S HUANG	urn:newsml:reuters.com:20251203:nS0N3VS01N:1	NS:RTRS	NVDA.O
2025-12-03 20:49:13.000	REFILE-UPDATE 1-Trump met with Nvidia CEO Jens...	urn:newsml:reuters.com:20251203:nL6N3X91GE:4	NS:RTRS	NVDA.O
2025-12-03 19:48:36.000	NVIDIA CEO HUANG SPOKE WITH TRUMP WEDNESDAY -S...	urn:newsml:reuters.com:20251203:nL1N3X9123:1	NS:RTRS	NVDA.O
...	...	...	...	...
2024-09-17 19:50:04.110	NYSE ORDER IMBALANCE <PATH.N> 240046.0 SHARES ...	urn:newsml:reuters.com:20240917:nAQN2JHG4E:1	NS:RTRS	PATH.N
2024-09-16 19:50:06.681	NYSE ORDER IMBALANCE <PATH.N> 303859.0 SHARES ...	urn:newsml:reuters.com:20240916:nAQN2JHA72:1	NS:RTRS	PATH.N
2024-09-13 19:50:04.946	NYSE ORDER IMBALANCE <PATH.N> 65515.0 SHARES O...	urn:newsml:reuters.com:20240913:nAQN2JH302:1	NS:RTRS	PATH.N
2024-09-11 19:50:14.191	NYSE ORDER IMBALANCE <PATH.N> 148641.0 SHARES ...	urn:newsml:reuters.com:20240911:nAQN2JGS38:1	NS:RTRS	PATH.N
2024-09-10 19:50:02.207	NYSE ORDER IMBALANCE <PATH.N> 123576.0 SHARES ...	urn:newsml:reuters.com:20240910:nAQN2JGJLC:1	NS:RTRS	PATH.N

78301 rows × 4 columns

In [5]:
```
compNews.to_csv('news.csv')
```

In [6]:
```
rd.close_session()
```

In [ ]:



[4]:

versionCreated	headline	storyId	sourceCode	cRIC
2025-12-03 23:47:39.000	UPDATE 3-Trump praises Nvidia CEO Jensen Huang...	urn:newsml:reuters.com:20251203:nL6N3X91IY:10	NS:RTRS	NVDA.O
2025-12-03 21:40:48.000	UPDATE 2-Intel says it will keep networking an...	urn:newsml:reuters.com:20251203:nL6N3X91JO:4	NS:RTRS	NVDA.O
2025-12-03 21:18:09.985	TRUMP: SPOKE TO NVIDIA'S HUANG	urn:newsml:reuters.com:20251203:nS0N3VS01N:1	NS:RTRS	NVDA.O
2025-12-03 20:49:13.000	REFILE-UPDATE 1-Trump met with Nvidia CEO Jens...	urn:newsml:reuters.com:20251203:nL6N3X91GE:4	NS:RTRS	NVDA.O
2025-12-03 19:48:36.000	NVIDIA CEO HUANG SPOKE WITH TRUMP WEDNESDAY -S...	urn:newsml:reuters.com:20251203:nL1N3X9123:1	NS:RTRS	NVDA.O
...	...	...	...	...
2024-09-17 19:50:04.110	NYSE ORDER IMBALANCE <PATH.N> 240046.0 SHARES ...	urn:newsml:reuters.com:20240917:nAQN2JHG4E:1	NS:RTRS	PATH.N
2024-09-16 19:50:06.681	NYSE ORDER IMBALANCE <PATH.N> 303859.0 SHARES ...	urn:newsml:reuters.com:20240916:nAQN2JHA72:1	NS:RTRS	PATH.N
2024-09-13 19:50:04.946	NYSE ORDER IMBALANCE <PATH.N> 65515.0 SHARES O...	urn:newsml:reuters.com:20240913:nAQN2JH302:1	NS:RTRS	PATH.N
2024-09-11 19:50:14.191	NYSE ORDER IMBALANCE <PATH.N> 148641.0 SHARES ...	urn:newsml:reuters.com:20240911:nAQN2JGS38:1	NS:RTRS	PATH.N
2024-09-10 19:50:02.207	NYSE ORDER IMBALANCE <PATH.N> 123576.0 SHARES ...	urn:newsml:reuters.com:20240910:nAQN2JGJLC:1	NS:RTRS	PATH.N

78301 rows × 4 columns

[5]:
```
compNews.to_csv('news.csv')
```

[6]:
```
rd.close_session()
```

B. Extract daily prices

In [5]:
```
import yfinance as yf
import pandas as pd
from datetime import datetime, timedelta

tickers = ["AAPL"]

def get_history(tickers, period="1y", interval="1d"):
    dfs = []
    for t in tickers:
        df = yf.Ticker(t).history(
            period=period,
            interval=interval,
            auto_adjust=False,
            actions=False,
            repair=True,
        )
        df["Ticker"] = t
        dfs.append(df)

    return pd.concat(dfs).reset_index()

df_prices = get_history(tickers)
df_prices
```

Out[5]:

	Date	Open	High	Low	Close	Adj Close	Volume	Repaired?	Ticker
0	2024-12-13 00:00:00-05:00	247.820007	249.289993	246.240005	248.130005	247.012817	33155300	False	AAPL
1	2024-12-16 00:00:00-05:00	247.990005	251.380005	247.649994	251.039993	249.909714	51694800	False	AAPL
2	2024-12-17 00:00:00-05:00	250.080002	253.830002	249.779999	253.479996	252.338730	51356400	False	AAPL
3	2024-12-18 00:00:00-05:00	252.160004	254.279999	247.740005	248.050003	246.933182	56774100	False	AAPL
4	2024-12-19 00:00:00-05:00	247.500000	252.000000	247.089996	249.789993	248.665344	60882300	False	AAPL
...	...	...	...	...	...	...	...	...	...
245	2025-12-08 00:00:00-05:00	278.130005	279.670013	276.149994	277.890015	277.890015	38211800	False	AAPL
246	2025-12-09 00:00:00-05:00	278.160004	280.029999	276.920013	277.179993	277.179993	32193300	False	AAPL
247	2025-12-10 00:00:00-05:00	277.750000	279.750000	276.440002	278.779999	278.779999	33038300	False	AAPL
248	2025-12-11 00:00:00-05:00	279.100006	279.589996	273.809998	278.029999	278.029999	33248000	False	AAPL
249	2025-12-12 00:00:00-05:00	277.795013	279.220001	276.820007	278.279999	278.279999	39532887	False	AAPL

250 rows × 9 columns

II. Building NLP Model

A. Dataframe preprocessing

- Following the data extraction steps outlined above, we collected 78,301 news headlines related to 200 companies over a 15-month period.
- We conducted basic data preprocessing, including time conversion, ticker extraction, company name mapping, cleaning of headline, and creation of new column that combines companyname and headline as nlp model inputs.

In [6]:
```
import pandas as pd
import yfinance as yf
from google.colab import files
from sklearn.metrics import classification_report, accuracy_score
```

In [7]:
```
! wget https://raw.githubusercontent.com/ShirleyH17/HODL_Project/refs/heads/main/news.csv
```

```
--2025-12-14 19:33:55--  https://raw.githubusercontent.com/ShirleyH17/HODL_Project/refs/heads/main/news.
csv
Resolving raw.githubusercontent.com (raw.githubusercontent.com)... 185.199.111.133, 185.199.108.133, 18
5.199.110.133, ...
Connecting to raw.githubusercontent.com (raw.githubusercontent.com)|185.199.111.133|:443... connected.
HTTP request sent, awaiting response... 200 OK
Length: 12505941 (12M) [text/plain]
Saving to: 'news.csv'

news.csv            100%[===================>]  11.93M  --.-KB/s    in 0.02s

2025-12-14 19:33:56 (500 MB/s) - 'news.csv' saved [12505941/12505941]
```

In [8]:
```
rnews_df = pd.read_csv('news.csv')
```

In [9]:
```
# extracting relevant columns and renaming
rnews_df = rnews_df[['versionCreated', 'headline', 'cRIC']]
rnews_df.columns = ['time', 'headline', 'cRIC']

# extracting ticker
rnews_df['ticker'] = rnews_df['cRIC'].str.replace(r'\..*', '', regex=True)
rnews_df['time'] = pd.to_datetime(rnews_df['time'])

# mapping ticker to company name
def map_ticker_to_company(tickers):
    mapped = []
    for ticker in tickers:
        try:
            info = yf.Ticker(ticker).info
            name = info.get('shortName', ticker)
        except Exception as e:
            name = ric
        mapped.append({'ticker': ticker, 'CompanyName': name})
    return pd.DataFrame(mapped)


tickers = rnews_df['ticker'].unique().tolist()
ticker_name_df = map_ticker_to_company(tickers)

rnews_df = rnews_df.merge(ticker_name_df, on='ticker', how='left')
```

In [10]:
```
# cleaning headlines
# removing missing values if any
rnews_df = rnews_df[rnews_df['headline'].notnull()]

# removing leading/trailing whitespaces
rnews_df['headline'] = rnews_df['headline'].str.strip()
# removing extra whitespace if any
rnews_df['headline'] = rnews_df['headline'].str.replace(r'\s+', ' ', regex=True)
```

In [11]:
```
# creating column that combine company name and headline as input for nlp models
rnews_df['input'] = rnews_df['CompanyName'] + ': ' + rnews_df['headline']

rnews_df = rnews_df.sort_values(by='time').reset_index(drop=True)

# retrieving a copy in case later usage
rnews_df_copy = rnews_df.copy()

# only leaving useful columns
rnews_df = rnews_df[['time', 'ticker', 'input']]
rnews_df.head()
```

Out[11]:

	time	ticker	input
0	2024-09-10 01:56:58.000	PLTR	Palantir Technologies Inc.: PRESS DIGEST-Briti...
1	2024-09-10 03:00:03.353	SNPS	Synopsys, Inc.: SYNOPSYS POWERS WORLD'S FASTES...
2	2024-09-10 04:00:00.000	CMCSA	Comcast Corporation: COMCAST TECHNOLOGY SOLUTI...
3	2024-09-10 04:00:00.000	CMCSA	Comcast Corporation: COMCAST TECHNOLOGY SOLUTI...
4	2024-09-10 04:00:00.000	CMCSA	Comcast Corporation: COMCAST TECHNOLOGY SOLUTI...

B. Training and Testing DF Creation

- Define a classification_accuracy function which can output accuracy results against benchmark.
- To avoid look ahead bias in later strategy part, we set a strategy date (2024/11/01) and only select train_val and test data before that date. There will be 7448 data, and we will be randomly sampling from it some train_val data, and then the test data, while ensuring that train_val data time is strictly before test data.
- Extract 1000 subsamples and feed it to ChatGPT to generate sentiment classification, and use it as train data to finetune model and improve performance.
- Extract 200 subsamples and feed it to ChatGPT to generate sentiment classification (positive/neutral/negative), and use it as test data / benchmark to evaluate model performance.
- Backup benchmark: human-labeled dataset SEntFiN can be used as a reference for performance.

In [12]:
```
def evaluate_results(actual, prediction):
    print("Accuracy:", accuracy_score(actual, prediction))
    print("\nClassification Report:\n", classification_report(actual, prediction, target_names=['Negativ
e', 'Neutral', 'Positive']))
```

B(1). Generating ChatGPT responses

Based on the abovementioned rules, we select subsamples of data for train_val and test, and then feed it to ChatGPT.

In [13]:
```
# selecting df prior to a strategy date
strategy_date = pd.Timestamp('2024-11-01')
df_before_strategy = rnews_df[rnews_df['time'] < strategy_date].sort_values('time')
df_before_strategy_size = len(df_before_strategy)
print(f'Total data before strategy date: {df_before_strategy_size}')

test_size = 200
train_val_size = 1000

# identifying the cutoff index, making the df where train_val will be sampled from contains around 5/6 o
f total data here
cutoff_idx = int(df_before_strategy_size * train_val_size / (train_val_size + test_size))

cutoff_time = df_before_strategy.iloc[cutoff_idx]['time']
print(f'Cutoff time: {cutoff_time}')

train_val_df = df_before_strategy[df_before_strategy['time'] < cutoff_time].sample(n=train_val_size, ran
dom_state=42).sort_values("time")
test_df = df_before_strategy[df_before_strategy['time'] >= cutoff_time].sample(n=test_size, random_state
=42).sort_values("time")

print(f"Train_val samples: {len(train_val_df)}")
print(f"Test samples: {len(test_df)}")
```

```
Total data before strategy date: 7448
Cutoff time: 2024-10-28 10:24:43
Train_val samples: 1000
Test samples: 200
```

In [14]:
```
# from openai import OpenAI
# from tqdm import tqdm

# # Initialize OpenAI client
# #client = OpenAI(api_key="")

# df = train_val_df.copy()

# system_prompt = """
# You are an expert in financial news sentiment analysis.
# The text contains a company's name followed by a news headline.
# For each headline, classify the sentiment specifically from the perspective of the stock market or inv
estor sentiment.

# Choose ONLY ONE label:
# - Negative (bearish or adverse impact on the stock)
# - Neutral (no clear impact on the stock)
# - Positive (bullish or favorable impact on the stock)

# Return your output in JSON:
# {"input": "<input_text>", "sentiment": "Positive"}
# """

# def classify_sentiment(text):
#     """Call GPT model to classify sentiment."""

#     response = client.chat.completions.create(
#         model="gpt-4.1-mini",
#         messages=[
#             {"role": "system", "content": system_prompt},
#             {"role": "user", "content": text}
#         ],
#         temperature=0
#     )

#     content = response.choices[0].message.content

#     import json
#     try:
#         result = json.loads(content)
#         sentiment = result["sentiment"]
#     except:
#         sentiment = "Neutral"

#     mapping = {"Positive": 1, "Neutral": 0, "Negative": -1}
#     return mapping.get(sentiment, 0)

# sentiment_list = []
# for text in tqdm(df["input"], desc="Classifying Sentiment"):
#     sentiment_list.append(classify_sentiment(text))

# df["sentiment"] = sentiment_list

# df
```

In [15]:
```
#train_val_df = df.copy()
```

In [16]:
```
# system_prompt = """
# You are an expert in financial news sentiment analysis.
# The text contains a company's name followed by a news headline.
# For each headline, classify the sentiment specifically from the perspective of the stock market or inv
estor sentiment.

# Choose ONLY ONE label:
# - Negative (bearish or adverse impact on the stock)
# - Neutral (no clear impact on the stock)
# - Positive (bullish or favorable impact on the stock)

# Return your output in JSON:
# {"input": "<input_text>", "sentiment": "Positive"}
# """

# def classify_sentiment(text):
#     """Call GPT model to classify sentiment."""

#     response = client.chat.completions.create(
#         model="gpt-4.1-mini",
#         messages=[
#             {"role": "system", "content": system_prompt},
#             {"role": "user", "content": text}
#         ],
#         temperature=0
#     )

#     content = response.choices[0].message.content

#     import json
#     try:
#         result = json.loads(content)
#         sentiment = result["sentiment"]
#     except:
#         sentiment = "Neutral"

#     mapping = {"Positive": 1, "Neutral": 0, "Negative": -1}
#     return mapping.get(sentiment, 0)

# sentiment_list = []
# for text in tqdm(test_df["input"], desc="Classifying Sentiment"):
#     sentiment_list.append(classify_sentiment(text))

# test_df["sentiment"] = sentiment_list

# test_df
```

In [17]:
```
# train_val_df.to_csv("train_val.csv", index=False)
# test_df.to_csv("test.csv", index=False)
# files.download("train_val.csv")
# files.download("test.csv")
```

In [18]:
```
def input_column_to_list_of_lists(df, column='input', chunk_size=100):
    """Split the df[column] into a list of lists, each sublist of size chunk_size"""
    input_series = df[column].tolist()
    num_chunks = len(input_series) // chunk_size
    result = [input_series[i*chunk_size:(i+1)*chunk_size] for i in range(num_chunks)]
    return result

# Generate the 10 lists of 100 inputs each and then share with gpt
# train_val_input_lists = input_column_to_list_of_lists(train_val_df, column='input', chunk_size=100)
# test_input_lists = input_column_to_list_of_lists(test_df, column='input', chunk_size=100)
```

In [19]:
```
! wget https://raw.githubusercontent.com/ShirleyH17/HODL_Project/refs/heads/main/train_val.csv
! wget https://raw.githubusercontent.com/ShirleyH17/HODL_Project/refs/heads/main/test.csv
```

```
--2025-12-14 19:34:07--  https://raw.githubusercontent.com/ShirleyH17/HODL_Project/refs/heads/main/train
_val.csv
Resolving raw.githubusercontent.com (raw.githubusercontent.com)... 185.199.108.133, 185.199.109.133, 18
5.199.110.133, ...
Connecting to raw.githubusercontent.com (raw.githubusercontent.com)|185.199.108.133|:443... connected.
HTTP request sent, awaiting response... 200 OK
Length: 128606 (126K) [text/plain]
Saving to: 'train_val.csv'

train_val.csv       100%[===================>] 125.59K  --.-KB/s    in 0.003s

2025-12-14 19:34:08 (36.6 MB/s) - 'train_val.csv' saved [128606/128606]

--2025-12-14 19:34:08--  https://raw.githubusercontent.com/ShirleyH17/HODL_Project/refs/heads/main/test.
csv
Resolving raw.githubusercontent.com (raw.githubusercontent.com)... 185.199.111.133, 185.199.108.133, 18
5.199.110.133, ...
Connecting to raw.githubusercontent.com (raw.githubusercontent.com)|185.199.111.133|:443... connected.
HTTP request sent, awaiting response... 200 OK
Length: 24622 (24K) [text/plain]
Saving to: 'test.csv'

test.csv            100%[===================>]  24.04K  --.-KB/s    in 0s

2025-12-14 19:34:08 (164 MB/s) - 'test.csv' saved [24622/24622]
```

In [20]:
```
mapping = {
    1: "positive",
    0: "neutral",
    -1: "negative"
}
```

In [21]:
```
labeled_train_val_df = pd.read_csv('train_val.csv')
labeled_test_df = pd.read_csv('test.csv')

labeled_train_val_df["sentiment"] = labeled_train_val_df["sentiment"].map(mapping)
labeled_test_df["sentiment"] = labeled_test_df["sentiment"].map(mapping)

labeled_train_val_df['sentiment'] = labeled_train_val_df['sentiment'].str.capitalize()
labeled_test_df['sentiment'] = labeled_test_df['sentiment'].str.capitalize()
labeled_train_val_df = labeled_train_val_df[['input', 'sentiment']]
labeled_test_df = labeled_test_df[['input', 'sentiment']]
```

In [22]:
```
labeled_train_val_df
```

Out[22]:

	input	sentiment
0	Comcast Corporation: COMCAST TECHNOLOGY SOLUTI...	Positive
1	Comcast Corporation: COMCAST TECHNOLOGY SOLUTI...	Positive
2	Comcast Corporation: COMCAST TECHNOLOGY SOLUTI...	Positive
3	Comcast Corporation: COMCAST TECHNOLOGY SOLUTI...	Positive
4	Rubrik, Inc.: RUBRIK INC <RBRK.N>: CIBC RAISES...	Positive
...	...	...
995	CDW Corporation: CDW CORP <CDW.O>: JP MORGAN C...	Negative
996	Micron Technology, Inc.: MORNING BID AMERICAS-...	Neutral
997	ON Semiconductor Corporation: MORNING BID AMER...	Neutral
998	SS&C Technologies Holdings, Inc: SS&C TECHNOLO...	Positive
999	VeriSign, Inc.: VERISIGN, INC <VRSN.O>: CITIGR...	Negative

1000 rows × 2 columns

In [23]:
```
labeled_test_df
```
Out[23]:

	input	sentiment
0	Roblox Corporation: ROBLOX SHARES UP 1% PREMAR...	Positive
1	ON Semiconductor Corporation: BRIEF-onsemi Q3 ...	Positive
2	CDW Corporation: CDW Corp <CDW.OQ> expected to...	Neutral
3	Cisco Systems, Inc.: BRIEF-Lenovo Collaborates...	Positive
4	AT&T Inc. 5.350% Global Notes d: AT&T announce...	Positive
...	...	...
195	Atlassian Corporation: Atlassian raises annual...	Positive
196	Monolithic Power Systems, Inc.: US STOCKS-Wall...	Negative
197	Uber Technologies, Inc.: Newscasts - Trading a...	Negative
198	America Movil, S.A.B. de C.V.: AMERICA MOVIL S...	Positive
199	America Movil, S.A.B. de C.V.: BRIEF-America M...	Positive

200 rows × 2 columns

B(2). Splitting train and validation data

In [24]:
```
labeled_train_df = labeled_train_val_df[:800]
labeled_val_df = labeled_train_val_df[800:]
```
In [25]:
```
labeled_train_df
```
Out[25]:

	input	sentiment
0	Comcast Corporation: COMCAST TECHNOLOGY SOLUTI...	Positive
1	Comcast Corporation: COMCAST TECHNOLOGY SOLUTI...	Positive
2	Comcast Corporation: COMCAST TECHNOLOGY SOLUTI...	Positive
3	Comcast Corporation: COMCAST TECHNOLOGY SOLUTI...	Positive
4	Rubrik, Inc.: RUBRIK INC <RBRK.N>: CIBC RAISES...	Positive
...	...	...
795	ASML Holding N.V. - New York Re: BUZZ-U.S. sto...	Neutral
796	ASML Holding N.V. - New York Re: Newscasts - B...	Negative
797	AT&T Inc.: COMMUNICATIONS WORKERS OF AMERICA -...	Negative
798	AT&T Inc. 5.350% Global Notes d: Eutelsat uses...	Neutral
799	Ericsson: ERICSSON <ERICb.ST>: JP MORGAN RAISE...	Positive

800 rows × 2 columns

In [26]:
```
labeled_val_df
```
Out[26]:

	input	sentiment
800	ASE Technology Holding Co., Ltd: BRIEF-ASE Say...	Positive
801	KLA Corporation: RPT-BUZZ-U.S. stocks weekly: ...	Neutral
802	Leidos Holdings, Inc.: LEIDOS AWARDED $331 MIL...	Positive
803	CACI International, Inc.: CACI AWARDED $805 MI...	Positive
804	Leidos Holdings, Inc.: BRIEF-Leidos Awarded $3...	Positive
...	...	...
995	CDW Corporation: CDW CORP <CDW.O>: JP MORGAN C...	Negative
996	Micron Technology, Inc.: MORNING BID AMERICAS-...	Neutral
997	ON Semiconductor Corporation: MORNING BID AMER...	Neutral
998	SS&C Technologies Holdings, Inc: SS&C TECHNOLO...	Positive
999	VeriSign, Inc.: VERISIGN, INC <VRSN.O>: CITIGR...	Negative

200 rows × 2 columns

B(3). SEntFiN database as a backup benchmark to evaluate model performance

In [27]:
```
! wget https://raw.githubusercontent.com/ShirleyH17/HODL_Project/refs/heads/main/SEntFiN-v1.1.csv
```

```
--2025-12-14 19:34:08--  https://raw.githubusercontent.com/ShirleyH17/HODL_Project/refs/heads/main/SEntF
iN-v1.1.csv
Resolving raw.githubusercontent.com (raw.githubusercontent.com)... 185.199.108.133, 185.199.110.133, 18
5.199.111.133, ...
Connecting to raw.githubusercontent.com (raw.githubusercontent.com)|185.199.108.133|:443... connected.
HTTP request sent, awaiting response... 200 OK
Length: 1191632 (1.1M) [text/plain]
Saving to: 'SEntFiN-v1.1.csv'

SEntFiN-v1.1.csv    100%[===================>]   1.14M  --.-KB/s    in 0.006s

2025-12-14 19:34:08 (177 MB/s) - 'SEntFiN-v1.1.csv' saved [1191632/1191632]
```

In [28]:
```python
import ast

benchmark_df = pd.read_csv('SEntFiN-v1.1.csv', encoding='utf_8')

# retrieving sentiment
benchmark_df['Decisions'] = benchmark_df['Decisions'].apply(ast.literal_eval)
benchmark_df['sentiment'] = benchmark_df['Decisions'].apply(lambda x: list(x.values())[0])

# retrieving entity of the sentence
benchmark_df['entity'] = benchmark_df['Decisions'].apply(lambda x: list(x.keys())[0])

benchmark_df = benchmark_df[['Title', 'entity', 'sentiment']]
benchmark_df.columns = ['input', 'entity', 'sentiment']
benchmark_df['sentiment'] = benchmark_df['sentiment'].str.capitalize()

# creating a subsample for evaluation
benchmark_df = benchmark_df.sample(n=500, random_state=42)
```

C. Rule Based Model Vader

We directly test performance of Vader on test data.

In [29]:
```python
!pip install nltk
import nltk
nltk.download('vader_lexicon')
from nltk.sentiment.vader import SentimentIntensityAnalyzer
```

```
Requirement already satisfied: nltk in /usr/local/lib/python3.12/dist-packages (3.9.1)
Requirement already satisfied: click in /usr/local/lib/python3.12/dist-packages (from nltk) (8.3.1)
Requirement already satisfied: joblib in /usr/local/lib/python3.12/dist-packages (from nltk) (1.5.2)
Requirement already satisfied: regex>=2021.8.3 in /usr/local/lib/python3.12/dist-packages (from nltk) (2
025.11.3)
Requirement already satisfied: tqdm in /usr/local/lib/python3.12/dist-packages (from nltk) (4.67.1)

[nltk_data] Downloading package vader_lexicon to /root/nltk_data...
```

In [30]:
```python
vader = SentimentIntensityAnalyzer()

def analyze_sentiment_vader(df):
    prob_neg = []
    prob_neu = []
    prob_pos = []
    prob_compound = []

    df_copy = df.copy()

    def classify_vader(compound):
        if compound >= 0.05:
            return 'Positive'
        elif compound <= -0.05:
            return 'Negative'
        else:
            return 'Neutral'


    for idx, text in enumerate(df_copy['input']):
        scores = vader.polarity_scores(text)
        prob_neg.append(scores['neg'])
        prob_neu.append(scores['neu'])
        prob_pos.append(scores['pos'])
        prob_compound.append(scores['compound'])

        if (idx + 1) % 5000 == 0:
            print(f'Processed {min(idx+1, len(df_copy))} / {len(df_copy)} headlines.')

    df_copy['vader_prob_neg'] = prob_neg
    df_copy['vader_prob_neu'] = prob_neu
    df_copy['vader_prob_pos'] = prob_pos
    df_copy['vader_compound'] = prob_compound
    df_copy['vader_sentiment'] = df_copy['vader_compound'].apply(classify_vader)
    print('Processing completed.')
    return df_copy
```

In [31]:
```python
vader_results_subsample = analyze_sentiment_vader(labeled_val_df)
print(f'Vader performance on ChatGPT responses:')
evaluate_results(labeled_val_df['sentiment'], vader_results_subsample['vader_sentiment'])

vader_results_subsample_2 = analyze_sentiment_vader(benchmark_df)
print(f'\nVader performance on SEntFin responses:')
evaluate_results(benchmark_df['sentiment'], vader_results_subsample_2['vader_sentiment'])
```

```
Processing completed.
Vader performance on ChatGPT responses:
Accuracy: 0.485

Classification Report:
              precision    recall  f1-score   support

    Negative       0.68      0.44      0.53        39
     Neutral       0.31      0.64      0.41        47
    Positive       0.65      0.44      0.52       114

    accuracy                           0.48       200
   macro avg       0.55      0.50      0.49       200
weighted avg       0.57      0.48      0.50       200

Processing completed.

Vader performance on SEntFin responses:
Accuracy: 0.53

Classification Report:
              precision    recall  f1-score   support

    Negative       0.74      0.42      0.53       156
     Neutral       0.43      0.62      0.50       146
    Positive       0.55      0.56      0.55       198

    accuracy                           0.53       500
   macro avg       0.57      0.53      0.53       500
weighted avg       0.57      0.53      0.53       500
```

D. Pretrained Financial Sentiment Model

D(1) FinBert - ProsusAI/finbert - Fixing parameters

We experimented with pretrained model Finbert, specifically ProsusAI/finbert, keeping its parameters fixed to evaluate its performance against benchmark.

In [32]:
```python
import torch
```

In [33]:
```python
# Load model directly
from transformers import AutoTokenizer, AutoModelForSequenceClassification

model_name = "ProsusAI/finbert"
tokenizer = AutoTokenizer.from_pretrained(model_name)
model = AutoModelForSequenceClassification.from_pretrained(model_name, num_labels=3)
```

```
/usr/local/lib/python3.12/dist-packages/huggingface_hub/utils/_auth.py:94: 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 (https://huggingface.co/s
ettings/tokens), set it as secret in your Google Colab and restart your session.
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(
```

In [34]:
```python
def analyze_sentiment_prosusai_finbert(df):

    df_copy = df.copy()

    device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
    model.to(device)

    model.eval()

    batch_size = 64
    prob_neg = []
    prob_neu = []
    prob_pos = []

    with torch.no_grad():
        for i in range(0, len(df_copy), batch_size):
            batch_texts = df_copy['input'][i:i+batch_size].tolist()

            inputs = tokenizer(batch_texts, return_tensors='pt', truncation=True, padding=True, max_leng
th=512)
            inputs = {k: v.to(device) for k, v in inputs.items()}

            outputs = model(**inputs)
            probs = torch.softmax(outputs.logits, dim=1).cpu().numpy()
            prob_neg.extend(probs[:, 0])
            prob_neu.extend(probs[:, 1])
            prob_pos.extend(probs[:, 2])

            if (i+batch_size) % 5000 < batch_size:
                print(f'Processed {min(i+batch_size, len(df_copy))} / {len(df_copy)} headlines.')

    print('Processing completed.')

    df_copy['prosusai_finbert_prob_neg'] = prob_neg
    df_copy['prosusai_finbert_prob_neu'] = prob_neu
    df_copy['prosusai_finbert_prob_pos'] = prob_pos

    df_copy['prosusai_finbert_sentiment'] = df_copy[['prosusai_finbert_prob_neg', 'prosusai_finbert_prob
_neu', 'prosusai_finbert_prob_pos']].idxmax(axis=1)
    df_copy['prosusai_finbert_sentiment'] = df_copy['prosusai_finbert_sentiment'].map({
    'prosusai_finbert_prob_neg': 'Negative',
    'prosusai_finbert_prob_neu': 'Neutral',
    'prosusai_finbert_prob_pos': 'Positive'
    })

    return df_copy
```

```
In [35]: prosusai_finbert_results_subsample = analyze_sentiment_prosusai_finbert(labeled_val_df)
print(f'ProsusAI/FinBert performance on ChatGPT responses:')
evaluate_results(labeled_val_df['sentiment'], prosusai_finbert_results_subsample['prosusai_finbert_senti
ment'])

prosusai_finbert_results_subsample_2 = analyze_sentiment_prosusai_finbert(benchmark_df)
print(f'\nProsusAI/FinBert performance on SEntFin responses:')
evaluate_results(benchmark_df['sentiment'], prosusai_finbert_results_subsample_2['prosusai_finbert_senti
ment'])
```

```
Processing completed.
ProsusAI/FinBert performance on ChatGPT responses:
Accuracy: 0.25

Classification Report:
              precision    recall  f1-score   support

    Negative       0.11      0.26      0.15        39
     Neutral       0.12      0.09      0.10        47
    Positive       0.49      0.32      0.38       114

    accuracy                           0.25       200
   macro avg       0.24      0.22      0.21       200
weighted avg       0.33      0.25      0.27       200

Processing completed.

ProsusAI/FinBert performance on SEntFin responses:
Accuracy: 0.182

Classification Report:
              precision    recall  f1-score   support

    Negative       0.06      0.05      0.05       156
     Neutral       0.11      0.11      0.11       146
    Positive       0.32      0.34      0.33       198

    accuracy                           0.18       500
   macro avg       0.16      0.17      0.16       500
weighted avg       0.17      0.18      0.18       500
```

D(2) FinBert - yiyanghkust/finbert-tone - Fixing parameters

Given the performance of basic ProsusAI/finbert model is extremely bad, we experimented with yiyanghkust/finbert-tone, keeping its parameters fixed to evaluate its performance against benchmark.

```
In [36]: from transformers import BertTokenizer, BertForSequenceClassification
from transformers import pipeline

finbert = BertForSequenceClassification.from_pretrained('yiyanghkust/finbert-tone',num_labels=3)
tokenizer = BertTokenizer.from_pretrained('yiyanghkust/finbert-tone')

nlp = pipeline("sentiment-analysis", model=finbert, tokenizer=tokenizer)
```

```
Device set to use cuda:0
```

```
In [37]: def analyze_sentiment_yyfinbert(df, model):
    df_copy = df.copy()
    sentences = df_copy['input'].to_list()
    results = model(sentences)
    return pd.DataFrame(results, index=df.index)
```

In [38]:
```python
yyfinbert_results_subsample = analyze_sentiment_yyfinbert(labeled_val_df, nlp)
print(f'yiyanghukst/finbert-tone performance on ChatGPT responses:')
evaluate_results(labeled_val_df['sentiment'], yyfinbert_results_subsample['label'])

yyfinbert_results_subsample_2 = analyze_sentiment_yyfinbert(benchmark_df, nlp)
print(f'\nyiyanghkust/finbert-tone performance on SEntFin responses:')
evaluate_results(benchmark_df['sentiment'], yyfinbert_results_subsample_2['label'])
```

```
yiyanghukst/finbert-tone performance on ChatGPT responses:
Accuracy: 0.55

Classification Report:
              precision    recall  f1-score   support

    Negative       0.80      0.41      0.54        39
     Neutral       0.33      0.87      0.48        47
    Positive       0.96      0.46      0.63       114

    accuracy                           0.55       200
   macro avg       0.70      0.58      0.55       200
weighted avg       0.78      0.55      0.58       200


yiyanghkust/finbert-tone performance on SEntFin responses:
Accuracy: 0.712

Classification Report:
              precision    recall  f1-score   support

    Negative       0.88      0.67      0.76       156
     Neutral       0.53      0.90      0.67       146
    Positive       0.90      0.61      0.73       198

    accuracy                           0.71       500
   macro avg       0.77      0.73      0.72       500
weighted avg       0.79      0.71      0.72       500
```

D(3). FinBert - yiyanghkust/finbert-tone - Enabling finetuning

- We tried enabling all parameters finetuning and only finetuning classifier head, and also tried changing the number of epoch for training. The performance of model when allowing tuning of all parameters is extremely bad, so is the model that has too many training epochs.
- It could be the case that ChatGPT labels are not very consistent/of high quality and thus using it to finetune model actually destroy some useful and quality content in the pretrained model.
- Final decision: we only train one epoch and only tune classifier parameters.

In [39]:
```python
from torch.utils.data import DataLoader, TensorDataset, random_split
from tqdm import tqdm
```

In [40]:

```
finbert = BertForSequenceClassification.from_pretrained('yiyanghkust/finbert-tone', num_labels=3)
tokenizer = BertTokenizer.from_pretrained('yiyanghkust/finbert-tone')

# Only training classifier head
# Have examined that when also training other parameters, bad performance
for param in finbert.bert.parameters():
    param.requires_grad = False
for param in finbert.classifier.parameters():
    param.requires_grad = True

# using labeled_train_df to train the model
texts = labeled_train_df['input'].tolist()
label_map = {"Negative": 0, "Neutral": 1, "Positive": 2}
labels = labeled_train_df['sentiment'].map(label_map).tolist()
labels_tensor = torch.tensor(labels, dtype=torch.long)

# Tokenize
encodings = tokenizer(texts, padding=True, truncation=True, return_tensors="pt", max_length=512)

dataset = TensorDataset(encodings['input_ids'], encodings['attention_mask'], labels_tensor)

# Split into training and validation sets
val_size = int(0.1 * len(dataset))
train_size = len(dataset) - val_size
train_dataset, val_dataset = random_split(dataset, [train_size, val_size])

train_loader = DataLoader(train_dataset, batch_size=8, shuffle=True)
val_loader = DataLoader(val_dataset, batch_size=8)

optimizer = torch.optim.AdamW(finbert.parameters(), lr=1e-5)


finbert.train()
for epoch in range(1):  # tested 3, performance too bad
    total_loss = 0
    for batch in tqdm(train_loader, desc=f"Epoch {epoch+1} Training"):
        input_ids, attention_mask, labels = batch
        optimizer.zero_grad()
        outputs = finbert(input_ids, attention_mask=attention_mask, labels=labels)
        loss = outputs.loss
        loss.backward()
        torch.nn.utils.clip_grad_norm_(finbert.parameters(), max_norm=1.0)
        optimizer.step()
        total_loss += loss.item()

    avg_train_loss = total_loss / len(train_loader)

    # generating validation results
    finbert.eval()
    val_loss = 0
    correct = 0
    total = 0
    with torch.no_grad():
        for batch in val_loader:
            input_ids, attention_mask, labels = batch
            outputs = finbert(input_ids, attention_mask=attention_mask, labels=labels)
            val_loss += outputs.loss.item()
            preds = torch.argmax(outputs.logits, dim=1)
            correct += (preds == labels).sum().item()
            total += labels.size(0)
    avg_val_loss = val_loss / len(val_loader)
    val_accuracy = correct / total

    print(f"Epoch {epoch+1} completed. Train Loss: {avg_train_loss:.4f}, "
          f"Val Loss: {avg_val_loss:.4f}, Val Accuracy: {val_accuracy:.4f}")

    finbert.train()  # back to training mode in case further testing is needed

# using final tuned model to evaluate performance on validation data
nlp_finetuned = pipeline("sentiment-analysis", model=finbert, tokenizer=tokenizer)

tuned_yyfinbert_results_subsample = analyze_sentiment_yyfinbert(labeled_val_df, nlp_finetuned)
print(f'yiyanghukst/finbert-tone performance on ChatGPT responses:')
evaluate_results(labeled_val_df['sentiment'], tuned_yyfinbert_results_subsample['label'])

tuned_yyfinbert_results_subsample_2 = analyze_sentiment_yyfinbert(benchmark_df, nlp_finetuned)
print(f'\nyiyanghkust/finbert-tone performance on SEntFin responses:')
evaluate_results(benchmark_df['sentiment'], tuned_yyfinbert_results_subsample_2['label'])
```

```
Epoch 1 Training: 100%|██████████| 90/90 [00:38<00:00,  2.33it/s]
Device set to use cuda:0

Epoch 1 completed. Train Loss: 8.8853, Val Loss: 9.3106, Val Accuracy: 0.1500
yiyanghukst/finbert-tone performance on ChatGPT responses:
Accuracy: 0.475

Classification Report:
              precision    recall  f1-score   support

    Negative       0.76      0.33      0.46        39
     Neutral       0.29      0.87      0.44        47
    Positive       0.95      0.36      0.52       114

    accuracy                           0.47       200
   macro avg       0.67      0.52      0.48       200
weighted avg       0.76      0.47      0.49       200


yiyanghkust/finbert-tone performance on SEntFin responses:
Accuracy: 0.674

Classification Report:
              precision    recall  f1-score   support

    Negative       0.90      0.64      0.75       156
     Neutral       0.49      0.92      0.64       146
    Positive       0.91      0.52      0.66       198

    accuracy                           0.67       500
   macro avg       0.77      0.69      0.68       500
weighted avg       0.78      0.67      0.68       500
```

E. Support Vector Machine Model (SVM)

In [41]:
```
labeled_train_df['sentiment'].value_counts(normalize=True)
```

Out[41]:

sentiment	proportion
Positive	0.53125
Negative	0.27375
Neutral	0.19500

dtype: float64

In [42]:
```
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.svm import SVC


def fitting_and_predicting_svm(train_df, val_df):

    label_map = {"Negative": 0, "Neutral": 1, "Positive": 2}

    train_df_copy = train_df.copy()
    val_df_copy = val_df.copy()

    train_df_copy['label'] = train_df_copy['sentiment'].map(label_map)

    X_train_texts = train_df_copy['input'].tolist()
    y_train = train_df_copy['label'].tolist()

    X_val_texts = val_df_copy['input'].tolist()

    vectorizer = TfidfVectorizer(
        max_features=5000,
        ngram_range=(1, 2),
        stop_words='english'
    )

    X_train = vectorizer.fit_transform(X_train_texts)
    X_val = vectorizer.transform(X_val_texts)

    svm_clf = SVC(kernel='linear', C=1.0, class_weight='balanced')
    svm_clf.fit(X_train, y_train)

    y_pred = svm_clf.predict(X_val)

    # converting back to sentiments
    reverse_label_map = {0: 'Negative', 1: 'Neutral', 2: 'Positive'}
    y_pred = [reverse_label_map[i] for i in y_pred]
    y_pred = pd.DataFrame({'input': val_df['input'], 'svm_sentiment': y_pred})

    return y_pred
```

In [43]:
```
svm_pred_results = fitting_and_predicting_svm(labeled_train_df, labeled_val_df)
evaluate_results(labeled_val_df['sentiment'], svm_pred_results['svm_sentiment'])
svm_pred_results_2 = fitting_and_predicting_svm(labeled_train_df, benchmark_df)
evaluate_results(benchmark_df['sentiment'], svm_pred_results_2['svm_sentiment'])
```

```
Accuracy: 0.645

Classification Report:
              precision    recall  f1-score   support

    Negative       0.47      0.49      0.48        39
     Neutral       0.47      0.36      0.41        47
    Positive       0.75      0.82      0.78       114

    accuracy                           0.65       200
   macro avg       0.57      0.55      0.56       200
weighted avg       0.63      0.65      0.64       200

Accuracy: 0.494

Classification Report:
              precision    recall  f1-score   support

    Negative       0.58      0.34      0.43       156
     Neutral       0.44      0.27      0.33       146
    Positive       0.48      0.78      0.60       198

    accuracy                           0.49       500
   macro avg       0.50      0.46      0.45       500
weighted avg       0.50      0.49      0.47       500
```

F. Ensemble model combining Vader, FinBert and SVM

For FinBert model, we use the second model (yiyanghkust/finbert-tone without finetuning) given its best performance.

Below we experimented with different methods to ensemble the above three models.

- Method 1: take majority vote
- Method 2: weighted vote
- Method 3: stacked meta model (fit a logistic regression on)

In [44]:
```
from scipy.stats import mode
from sklearn.model_selection import StratifiedKFold
from sklearn.linear_model import LogisticRegression
import numpy as np
```

In [45]:
```
def generate_sentiments_all_models(train_df, val_df):
    """Training model on train_df, return predictions on val_df"""
    train_df_copy = train_df.copy()
    val_df_copy = val_df.copy()

    # when necessary, use train_df to finetune model and evaluate on val_df
    print(f'Generating vader results.')
    vader_val_results = analyze_sentiment_vader(val_df)['vader_sentiment']

    print(f'Generating finbert results.')
    finbert = BertForSequenceClassification.from_pretrained('yiyanghkust/finbert-tone',num_labels=3)
    tokenizer = BertTokenizer.from_pretrained('yiyanghkust/finbert-tone')
    nlp = pipeline("sentiment-analysis", model=finbert, tokenizer=tokenizer)
    finbert_val_results = analyze_sentiment_yyfinbert(val_df, nlp)['label']

    print(f'Generating svm results.')
    svm_val_results = fitting_and_predicting_svm(train_df, val_df)['svm_sentiment']

    ensemble_df = pd.DataFrame({
        'vader': vader_val_results,
        'finbert': finbert_val_results,
        'svm':svm_val_results
        })
    return ensemble_df


def evaluate_all_model_performance(val_df, prediction_df):
    print('For vader:')
    evaluate_results(val_df['sentiment'], prediction_df['vader'])
    print('\nFor finbert:')
    evaluate_results(val_df['sentiment'], prediction_df['finbert'])
    print('\nFor svm:')
    evaluate_results(val_df['sentiment'], prediction_df['svm'])
```

In [46]:
```python
ensemble_df = generate_sentiments_all_models(labeled_train_df, labeled_test_df)
evaluate_all_model_performance(labeled_test_df, ensemble_df)
```

```
Generating vader results.
Processing completed.
Generating finbert results.

Device set to use cuda:0

Generating svm results.
For vader:
Accuracy: 0.5

Classification Report:
              precision    recall  f1-score   support

    Negative       0.50      0.26      0.34        35
     Neutral       0.39      0.80      0.52        54
    Positive       0.67      0.43      0.52       111

    accuracy                           0.50       200
   macro avg       0.52      0.50      0.46       200
weighted avg       0.56      0.50      0.49       200


For finbert:
Accuracy: 0.535

Classification Report:
              precision    recall  f1-score   support

    Negative       1.00      0.40      0.57        35
     Neutral       0.37      0.98      0.54        54
    Positive       0.91      0.36      0.52       111

    accuracy                           0.54       200
   macro avg       0.76      0.58      0.54       200
weighted avg       0.78      0.54      0.53       200


For svm:
Accuracy: 0.605

Classification Report:
              precision    recall  f1-score   support

    Negative       0.47      0.26      0.33        35
     Neutral       0.56      0.35      0.43        54
    Positive       0.63      0.84      0.72       111

    accuracy                           0.60       200
   macro avg       0.56      0.48      0.50       200
weighted avg       0.58      0.60      0.58       200
```

In [47]:
```
# method 1: taking majority vote
def majority_vote(train_df, val_df, test_df):
    train_df_copy = train_df.copy()
    val_df_copy = val_df.copy()
    test_df_copy = test_df.copy()

    # fitting models on train_df and val_df, generating predictions on test_df
    train_val_df = pd.concat([train_df, val_df], axis=0)
    ensemble_df = generate_sentiments_all_models(train_val_df, test_df)
    majority_vote = ensemble_df[['vader', 'finbert', 'svm']].mode(axis=1)[0]
    ensemble_df['majority_vote'] = majority_vote
    ensemble_df['input'] = test_df_copy['input']

    ensemble_df = ensemble_df[['input'] + ['vader', 'finbert', 'svm'] + ['majority_vote']]

    return ensemble_df


ensemble_df_majority_vote = majority_vote(labeled_train_df, labeled_val_df, labeled_test_df)
evaluate_results(labeled_test_df['sentiment'], ensemble_df_majority_vote['majority_vote'])
acc_majority = accuracy_score(labeled_test_df['sentiment'], ensemble_df_majority_vote['majority_vote'])
```

```
Generating vader results.
Processing completed.
Generating finbert results.

Device set to use cuda:0

Generating svm results.
Accuracy: 0.65

Classification Report:
              precision    recall  f1-score   support

    Negative       0.70      0.54      0.61        35
     Neutral       0.50      0.91      0.64        54
    Positive       0.83      0.56      0.67       111

    accuracy                           0.65       200
   macro avg       0.68      0.67      0.64       200
weighted avg       0.72      0.65      0.65       200
```

In [48]:
```
ensemble_df_majority_vote
```

Out[48]:

	input	vader	finbert	svm	majority_vote
0	Roblox Corporation: ROBLOX SHARES UP 1% PREMAR...	Positive	Positive	Negative	Positive
1	ON Semiconductor Corporation: BRIEF-onsemi Q3 ...	Neutral	Neutral	Positive	Neutral
2	CDW Corporation: CDW Corp <CDW.OQ> expected to...	Positive	Neutral	Neutral	Neutral
3	Cisco Systems, Inc.: BRIEF-Lenovo Collaborates...	Positive	Neutral	Positive	Positive
4	AT&T Inc. 5.350% Global Notes d: AT&T announce...	Positive	Neutral	Neutral	Neutral
...	...	...	...	...	...
195	Atlassian Corporation: Atlassian raises annual...	Positive	Positive	Positive	Positive
196	Monolithic Power Systems, Inc.: US STOCKS-Wall...	Positive	Positive	Positive	Positive
197	Uber Technologies, Inc.: Newscasts - Trading a...	Negative	Neutral	Positive	Negative
198	America Movil, S.A.B. de C.V.: AMERICA MOVIL S...	Positive	Neutral	Positive	Positive
199	America Movil, S.A.B. de C.V.: BRIEF-America M...	Positive	Neutral	Positive	Positive

200 rows × 5 columns

In [49]:
```python
# method 2: taking weighted vote
def weighted_vote(train_df, val_df, test_df):
    train_df_copy = train_df.copy()
    val_df_copy = val_df.copy()
    test_df_copy = test_df.copy()

    # fitting models on train_df, generating predictions on val_df
    ensemble_df = generate_sentiments_all_models(train_df, val_df)

    # using the accuracy rate on val_df to determine weight allocation
    acc_vader = accuracy_score(val_df['sentiment'], ensemble_df['vader'])
    acc_finbert = accuracy_score(val_df['sentiment'], ensemble_df['finbert'])
    acc_svm = accuracy_score(val_df['sentiment'], ensemble_df['svm'])
    weights = {
        'vader': acc_vader,
        'finbert': acc_finbert,
        'svm': acc_svm
    }

    def weighted_vote_helper(row, weights):
        scores = {'Negative': 0, 'Neutral': 0, 'Positive': 0}
        for model, pred in row.items():
            scores[pred] += weights[model]
        return max(scores, key=scores.get)

    train_val_df = pd.concat([train_df, val_df], axis=0)
    # using train_df and val_df for training, and then predict on test_df
    ensemble_test_df = generate_sentiments_all_models(train_val_df, test_df)
    ensemble_test_df['weighted_vote'] = ensemble_test_df[['vader', 'finbert', 'svm']].apply(
        lambda row: weighted_vote_helper(row, weights),
        axis=1
    )
    ensemble_test_df['input'] = test_df_copy['input']
    ensemble_test_df = ensemble_test_df[['input'] + ['vader', 'finbert', 'svm'] + ['weighted_vote']]

    return ensemble_test_df


ensemble_df_weighted_vote = weighted_vote(labeled_train_df, labeled_val_df, labeled_test_df)
evaluate_results(labeled_test_df['sentiment'], ensemble_df_weighted_vote['weighted_vote'])
acc_weighted = accuracy_score(labeled_test_df['sentiment'], ensemble_df_weighted_vote['weighted_vote'])
```

```
Generating vader results.
Processing completed.
Generating finbert results.

Device set to use cuda:0

Generating svm results.
Generating vader results.
Processing completed.
Generating finbert results.

Device set to use cuda:0

Generating svm results.
Accuracy: 0.64

Classification Report:
              precision    recall  f1-score   support

    Negative       0.86      0.34      0.49        35
     Neutral       0.49      0.91      0.64        54
    Positive       0.77      0.60      0.68       111

    accuracy                           0.64       200
   macro avg       0.71      0.62      0.60       200
weighted avg       0.71      0.64      0.63       200
```

In [50]:

```python
# Method 3: creating a stacked meta model
from sklearn.model_selection import TimeSeriesSplit

def stacked_meta_model_vote(train_df, val_df, test_df, n_splits=5):
    train_df_copy = train_df.copy()
    val_df_copy = val_df.copy()
    test_df_copy = test_df.copy()
    train_val_df_copy = pd.concat([train_df, val_df], axis=0)

    label_map = {"Negative": 0, "Neutral": 1, "Positive": 2}
    reverse_label_map = {v:k for k, v in label_map.items()}


    # converting train_val_df sentiment values to numeric
    y_encoded = train_val_df_copy['sentiment'].map(label_map).values

    tscv = TimeSeriesSplit(n_splits=n_splits)

    meta_features = np.zeros((len(train_val_df_copy), 3), dtype=int)

    counting = 1
    for train_idx, val_idx in tscv.split(train_val_df_copy):
        print(f'Training TimeSeriesSplit fold {counting}.')
        fold_train = train_val_df_copy.iloc[train_idx]
        fold_val = train_val_df_copy.iloc[val_idx]

        # using fold_train to train svm, and then generate forecast on fold_val
        base_preds = generate_sentiments_all_models(fold_train, fold_val)
        base_preds_encoded = base_preds.apply(lambda col: col.map(label_map)).values
        meta_features[val_idx, :] = base_preds_encoded

        counting += 1

    # Train meta-model on full out-of-fold predictions
    meta_model = LogisticRegression(max_iter=500)
    meta_model.fit(meta_features, y_encoded)


    # training on train_val_df_copy and predict on test_df
    print(f'Generating sentiment labels for test data.')
    test_base_preds = generate_sentiments_all_models(train_val_df_copy, test_df)
    test_meta_features = test_base_preds.apply(lambda col: col.map(label_map)).values

    y_meta_pred = meta_model.predict(test_meta_features)
    y_meta_pred_labels = np.array([reverse_label_map[i] for i in y_meta_pred])

    result_df = test_base_preds.copy()
    result_df['input'] = test_df_copy['input'].values
    result_df['stacked_vote'] = y_meta_pred_labels

    result_df = result_df[['input'] + list(test_base_preds.columns) + ['stacked_vote']]

    return meta_model, result_df



meta_model, ensemble_df_stacked_vote = stacked_meta_model_vote(labeled_train_df, labeled_val_df, labeled
_test_df)
evaluate_results(labeled_test_df['sentiment'], ensemble_df_stacked_vote['stacked_vote'])
acc_stacked = accuracy_score(labeled_test_df['sentiment'], ensemble_df_stacked_vote['stacked_vote'])
```

```
Training TimeSeriesSplit fold 1.
Generating vader results.
Processing completed.
Generating finbert results.

Device set to use cuda:0

Generating svm results.
Training TimeSeriesSplit fold 2.
Generating vader results.
Processing completed.
Generating finbert results.

Device set to use cuda:0

Generating svm results.
Training TimeSeriesSplit fold 3.
Generating vader results.
Processing completed.
Generating finbert results.

Device set to use cuda:0

Generating svm results.
Training TimeSeriesSplit fold 4.
Generating vader results.
Processing completed.
Generating finbert results.

Device set to use cuda:0

Generating svm results.
Training TimeSeriesSplit fold 5.
Generating vader results.
Processing completed.
Generating finbert results.

Device set to use cuda:0

Generating svm results.
Generating sentiment labels for test data.
Generating vader results.
Processing completed.
Generating finbert results.

Device set to use cuda:0

Generating svm results.
Accuracy: 0.635

Classification Report:
              precision    recall  f1-score   support

    Negative       1.00      0.46      0.63        35
     Neutral       0.00      0.00      0.00        54
    Positive       0.60      1.00      0.75       111

    accuracy                           0.64       200
   macro avg       0.53      0.49      0.46       200
weighted avg       0.51      0.64      0.53       200


/usr/local/lib/python3.12/dist-packages/sklearn/metrics/_classification.py:1565: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` p
arameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.12/dist-packages/sklearn/metrics/_classification.py:1565: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` p
arameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.12/dist-packages/sklearn/metrics/_classification.py:1565: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` p
arameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```

G. Final Model

Based on the process above, we concluded that by creating sentiment labels for all three models, and then ensemble them using the method three - created a stacked meta model to generate vote is the best to use. Thus we will train the svm model using train_df, val_df, and test_df, and then generate sentiment labels for all the data after strategy date.

In [51]:
```
# comparing accuracy score and select model
accuracy_scores = [acc_majority, acc_weighted, acc_stacked]
best_idx = accuracy_scores.index(max(accuracy_scores))

# testing on first 100 values in rnews_df['input']
testing_model_df = rnews_df[rnews_df['time'] > strategy_date]

if best_idx == 0:
    print(f'The best performing model is majority_vote, with accuracy {acc_majority:.4f}')
    ensemble_df = majority_vote(labeled_train_val_df, labeled_test_df, testing_model_df)
elif best_idx == 1:
    print(f'The best performing model is weighted_vote, with accuracy {acc_weighted:.4f}')
    ensemble_df = weighted_vote(labeled_train_val_df, labeled_test_df, testing_model_df)
else:
    print(f'The best performing model is stacked_meta_model_vote, with accuracy {acc_stacked:.4f}')
    _, ensemble_df = stacked_meta_model_vote(labeled_train_val_df, labeled_test_df, testing_model_df)

ensemble_df
```

```
The best performing model is majority_vote, with accuracy 0.6500
Generating vader results.
Processed 5000 / 70853 headlines.
Processed 10000 / 70853 headlines.
Processed 15000 / 70853 headlines.
Processed 20000 / 70853 headlines.
Processed 25000 / 70853 headlines.
Processed 30000 / 70853 headlines.
Processed 35000 / 70853 headlines.
Processed 40000 / 70853 headlines.
Processed 45000 / 70853 headlines.
Processed 50000 / 70853 headlines.
Processed 55000 / 70853 headlines.
Processed 60000 / 70853 headlines.
Processed 65000 / 70853 headlines.
Processed 70000 / 70853 headlines.
Processing completed.
Generating finbert results.

Device set to use cuda:0

Generating svm results.
```

Out[51]:

	input	vader	finbert	svm	majority_vote
7448	STMicroelectronics N.V.: STMicroelectronics NV...	Neutral	Neutral	Neutral	Neutral
7449	ASE Technology Holding Co., Ltd: ASE Technolog...	Neutral	Neutral	Neutral	Neutral
7450	Atlassian Corporation: Atlassian Corp reports ...	Neutral	Neutral	Neutral	Neutral
7451	Uber Technologies, Inc.: Uber Technologies Inc...	Neutral	Neutral	Neutral	Neutral
7452	Atlassian Corporation: ATLASSIAN <TEAM.O>: RAY...	Neutral	Positive	Positive	Positive
...	...	...	...	...	...
78296	Netflix, Inc.: UPDATE 1-Paramount raises break...	Neutral	Neutral	Positive	Neutral
78297	Comcast Corporation: UPDATE 1-Paramount raises...	Neutral	Neutral	Positive	Neutral
78298	Snowflake Inc.: UPDATE 3-Snowflake's product r...	Positive	Negative	Negative	Negative
78299	NVIDIA Corporation: UPDATE 3-Trump praises Nvi...	Positive	Neutral	Negative	Negative
78300	Meta Platforms, Inc.: META ANNOUNCES QUARTERLY...	Neutral	Neutral	Positive	Neutral

70853 rows × 5 columns

In [52]:
```
ensemble_df.to_csv('label.csv', index=False)
files.download('label.csv')
```

III. Building Strategy

In [53]:
```
!wget https://raw.githubusercontent.com/annawxyowo/15.776-HODL-Fall2025-TeamProject-NewsSentimentTradin
g/main/data/label-2.csv
```

```
--2025-12-14 19:47:06--  https://raw.githubusercontent.com/annawxyowo/15.776-HODL-Fall2025-TeamProject-N
ewsSentimentTrading/main/data/label-2.csv
Resolving raw.githubusercontent.com (raw.githubusercontent.com)... 185.199.108.133, 185.199.110.133, 18
5.199.111.133, ...
Connecting to raw.githubusercontent.com (raw.githubusercontent.com)|185.199.108.133|:443... connected.
HTTP request sent, awaiting response... 200 OK
Length: 9390107 (9.0M) [text/plain]
Saving to: 'label-2.csv.1'

label-2.csv.1       100%[===================>]   8.96M  --.-KB/s    in 0.02s

2025-12-14 19:47:06 (581 MB/s) - 'label-2.csv.1' saved [9390107/9390107]
```

In [54]:
```
ensemble_df = pd.read_csv('label-2.csv')
ensemble_df
```

Out[54]:

	input	vader	finbert	svm	majority_vote
0	STMicroelectronics N.V.: STMicroelectronics NV...	Neutral	Neutral	Neutral	Neutral
1	ASE Technology Holding Co., Ltd: ASE Technolog...	Neutral	Neutral	Neutral	Neutral
2	Atlassian Corporation: Atlassian Corp reports ...	Neutral	Neutral	Neutral	Neutral
3	Uber Technologies, Inc.: Uber Technologies Inc...	Neutral	Neutral	Neutral	Neutral
4	Atlassian Corporation: ATLASSIAN <TEAM.O>: RAY...	Neutral	Positive	Positive	Positive
...	...	...	...	...	...
70848	Netflix, Inc.: UPDATE 1-Paramount raises break...	Neutral	Neutral	Positive	Neutral
70849	Comcast Corporation: UPDATE 1-Paramount raises...	Neutral	Neutral	Positive	Neutral
70850	Snowflake Inc.: UPDATE 3-Snowflake's product r...	Positive	Negative	Negative	Negative
70851	NVIDIA Corporation: UPDATE 3-Trump praises Nvi...	Positive	Neutral	Negative	Negative
70852	Meta Platforms, Inc.: META ANNOUNCES QUARTERLY...	Neutral	Neutral	Positive	Neutral

70853 rows × 5 columns

In [55]:
```
rnews_df_copy['time'] = pd.to_datetime(rnews_df_copy['time'])
rnews_df_copy['date'] = rnews_df_copy['time'].dt.normalize()
news_clean = rnews_df_copy[['date', 'ticker']]
news_clean = news_clean[news_clean['date']>='2024-11-01']
news_clean.reset_index(drop=True, inplace=True)
strategy_df = pd.concat([news_clean, ensemble_df], axis=1)
strategy_df
```

Out[55]:

	date	ticker	input	vader	finbert	svm	majority_vote
0	2024-11-01	STM	STMicroelectronics N.V.: STMicroelectronics NV...	Neutral	Neutral	Neutral	Neutral
1	2024-11-01	ASX	ASE Technology Holding Co., Ltd: ASE Technolog...	Neutral	Neutral	Neutral	Neutral
2	2024-11-01	TEAM	Atlassian Corporation: Atlassian Corp reports ...	Neutral	Neutral	Neutral	Neutral
3	2024-11-01	UBER	Uber Technologies, Inc.: Uber Technologies Inc...	Neutral	Neutral	Neutral	Neutral
4	2024-11-01	TEAM	Atlassian Corporation: ATLASSIAN <TEAM.O>: RAY...	Neutral	Positive	Positive	Positive
...	...	...	...	...	...	...	...
70848	2025-12-03	NFLX	Netflix, Inc.: UPDATE 1-Paramount raises break...	Neutral	Neutral	Positive	Neutral
70849	2025-12-03	CMCSA	Comcast Corporation: UPDATE 1-Paramount raises...	Neutral	Neutral	Positive	Neutral
70850	2025-12-03	SNOW	Snowflake Inc.: UPDATE 3-Snowflake's product r...	Positive	Negative	Negative	Negative
70851	2025-12-03	NVDA	NVIDIA Corporation: UPDATE 3-Trump praises Nvi...	Positive	Neutral	Negative	Negative
70852	2025-12-04	META	Meta Platforms, Inc.: META ANNOUNCES QUARTERLY...	Neutral	Neutral	Positive	Neutral

70853 rows × 7 columns

In [56]:
```
strategy_df.to_csv("strategy_df.csv", index=False)
files.download("strategy_df.csv")
```

In [57]:

```
tickers = strategy_df['ticker'].unique().tolist()
start_date = strategy_df['date'].min()
end_date   = strategy_df['date'].max()

print("Tickers:", tickers)
print("Date range:", start_date, "to", end_date)

price_df = yf.download(
    tickers,
    start=start_date,
    end=end_date + pd.Timedelta(days=1),
    progress=True,
    auto_adjust='False'
)
```

```
[*                      3%                       ]  6 of 200 completed

Tickers: ['STM', 'ASX', 'TEAM', 'UBER', 'CMCSA', 'EBAY', 'MA', 'RBLX', 'DASH', 'PTC', 'TWLO', 'ADP', 'GD
DY', 'CHKP', 'SONY', 'BIDU', 'LRCX', 'ASML', 'TOST', 'CTSH', 'CHTR', 'DAY', 'VRSK', 'CART', 'T', 'TBB',
'VZ', 'CSGP', 'MRVL', 'TEF', 'ENTG', 'SATS', 'GFS', 'FIS', 'CRM', 'VIV', 'IONQ', 'EPAM', 'SMCI', 'ALAB',
'MCHP', 'NXPI', 'LSCC', 'FN', 'FFIV', 'AFRM', 'INFY', 'MU', 'VOD', 'NOK', 'SHOP', 'COHR', 'LITE', 'KEY
S', 'OKTA', 'LDOS', 'BAH', 'TDY', 'QBTS', 'BCE', 'BSY', 'MSI', 'RCI', 'CSCO', 'PSTG', 'AMAT', 'FLEX', 'A
PP', 'GIB', 'TRMB', 'PLTR', 'ACN', 'DELL', 'DD', 'HOOD', 'TIMB', 'PDD', 'ARM', 'CRWV', 'SPOT', 'WDC', 'T
ME', 'NTES', 'BILI', 'IT', 'HUBS', 'CLS', 'SE', 'EA', 'TTWO', 'JKHY', 'CACI', 'HPE', 'MTD', 'ANET', 'WI
T', 'SAP', 'CRWD', 'IBM', 'LOGI', 'CHT', 'UMC', 'GLW', 'IREN', 'RMBS', 'MTSI', 'TU', 'ROP', 'PINS', 'PAT
H', 'ALLE', 'UI', 'MELI', 'FICO', 'TXN', 'ON', 'SNPS', 'AMX', 'NOW', 'ERIC', 'DT', 'DDOG', 'NTNX', 'SN
X', 'TMUS', 'YMM', 'HPQ', 'AKAM', 'ABNB', 'FTNT', 'NET', 'PANW', 'U', 'RELX', 'SNOW', 'KLAC', 'SNAP', 'R
KT', 'SWKS', 'CYBR', 'NTAP', 'MPWR', 'TSEM', 'JBL', 'GWRE', 'GRAB', 'TER', 'AMKR', 'ADSK', 'ADBE', 'RDD
T', 'IOT', 'ASTS', 'KLAR', 'ZM', 'RBRK', 'ZBRA', 'TYL', 'ZS', 'CDNS', 'APH', 'INTU', 'WDAY', 'KSPI', 'PC
OR', 'CRDO', 'CPRT', 'TEL', 'DOCU', 'MSTR', 'BMNR', 'SSNC', 'CIEN', 'ADI', 'MANH', 'CDW', 'GEN', 'TLK',
'VRSN', 'AVGO', 'STX', 'NFLX', 'GRMN', 'SAIL', 'BABA', 'SNDK', 'FIG', 'COIN', 'CRCL', 'TSM', 'AMD', 'QCO
M', 'ORCL', 'INTC', 'META', 'AAPL', 'Q', 'MSFT', 'GOOGL', 'NVDA']
Date range: 2024-11-01 00:00:00 to 2025-12-04 00:00:00

[*********************100%***********************]  200 of 200 completed
```

In [58]:

```
price_matrix = price_df['Close'].sort_index()
price_matrix
```

Out[58]:

Ticker	AAPL	ABNB	ACN	ADBE	ADI	ADP	ADSK	AFRM	AKAM	ALAB	...	VRSK
Date												
2024-11-01	221.662506	136.460007	340.804321	482.799988	220.886597	282.290894	286.570007	43.220001	100.570000	72.650002	...	273.811310
2024-11-04	220.767532	136.869995	339.059204	481.350006	219.622864	283.936523	287.619995	43.689999	100.040001	69.650002	...	275.540741
2024-11-05	222.199493	137.820007	340.626831	486.420013	213.167114	285.229584	291.790009	45.599998	100.959999	95.910004	...	277.985840
2024-11-06	221.473557	140.910004	351.117035	504.829987	221.640900	298.943451	302.329987	50.000000	104.709999	98.169998	...	277.439178
2024-11-07	226.206924	147.369995	355.632599	500.920013	223.129944	298.620209	305.510010	48.790001	104.400002	94.489998	...	278.641876
...	...	...	...	...	...	...	...	...	...	...	...	...
2025-11-28	278.850006	116.989998	250.000000	320.130005	264.406128	255.300003	303.339996	70.949997	89.519997	157.570007	...	225.070007
2025-12-01	283.100006	118.800003	257.429993	322.850006	265.572021	255.839996	305.119995	69.065002	87.709999	165.190002	...	224.009995
2025-12-02	286.190002	118.500000	261.019989	322.809998	272.009277	257.179993	310.250000	67.019997	86.830002	142.940002	...	224.850006
2025-12-03	284.149994	120.129997	272.850006	326.779999	277.260742	260.220001	307.239990	69.639999	87.970001	152.500000	...	224.479996
2025-12-04	280.700012	120.820000	269.339996	328.730011	276.284210	259.399994	305.850006	68.690002	86.599998	152.509995	...	222.089996

273 rows × 200 columns

In [59]:

```python
import matplotlib.pyplot as plt
sig_map = {"Positive": 1, "Neutral": 0, "Negative": 0}
strategy_df['signal_num'] = strategy_df['majority_vote'].map(sig_map)

agg_signals = (
    strategy_df
    .groupby(['date', 'ticker'])['signal_num']
    .mean()
    .pipe(np.sign)
    .reset_index(name='signal')
)

signal_matrix = agg_signals.pivot(
    index='date',
    columns='ticker',
    values='signal'
)

signal_matrix = signal_matrix.reindex(price_df.index)
signal_matrix = signal_matrix.ffill().fillna(0)
signal_matrix
```

Out[59]:

ticker	AAPL	ABNB	ACN	ADBE	ADI	ADP	ADSK	AFRM	AKAM	ALAB	...	VRSK	VRSN	VZ	WDAY	WDC	WIT	YMM	ZBRA	ZM	ZS
Date																					
2024-11-01	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	...	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2024-11-04	0.0	0.0	1.0	0.0	0.0	1.0	0.0	0.0	0.0	1.0	...	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2024-11-05	0.0	0.0	1.0	0.0	0.0	1.0	0.0	0.0	0.0	1.0	...	1.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2024-11-06	0.0	0.0	1.0	0.0	0.0	1.0	0.0	0.0	0.0	1.0	...	1.0	0.0	1.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0
2024-11-07	0.0	1.0	1.0	0.0	0.0	1.0	0.0	1.0	0.0	1.0	...	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
2025-11-28	0.0	0.0	0.0	1.0	1.0	1.0	1.0	0.0	0.0	1.0	...	0.0	1.0	0.0	1.0	1.0	0.0	0.0	0.0	1.0	1.0
2025-12-01	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.0	1.0	1.0	...	0.0	1.0	1.0	1.0	1.0	0.0	0.0	0.0	1.0	1.0
2025-12-02	1.0	1.0	0.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	...	0.0	1.0	0.0	0.0	1.0	0.0	0.0	0.0	1.0	1.0
2025-12-03	1.0	1.0	1.0	0.0	1.0	1.0	1.0	1.0	1.0	1.0	...	0.0	1.0	0.0	0.0	1.0	1.0	0.0	0.0	1.0	1.0
2025-12-04	1.0	1.0	1.0	0.0	1.0	1.0	1.0	1.0	1.0	1.0	...	0.0	1.0	0.0	0.0	1.0	1.0	0.0	0.0	1.0	1.0

273 rows × 200 columns

```
In [60]: returns = price_matrix.pct_change().fillna(0)
         returns
```

Out[60]:

Ticker	AAPL	ABNB	ACN	ADBE	ADI	ADP	ADSK	AFRM	AKAM	ALAB	...	VRSK	VRSN	
Date														
2024-11-01	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	...	0.000000	0.000000	0
2024-11-04	-0.004038	0.003004	-0.005121	-0.003003	-0.005721	0.005830	0.003664	0.010875	-0.005270	-0.041294	...	0.006316	0.006679	-0
2024-11-05	0.006486	0.006941	0.004623	0.010533	-0.029395	0.004554	0.014498	0.043717	0.009196	0.377028	...	0.008874	0.007253	0
2024-11-06	-0.003267	0.022421	0.030797	0.037848	0.039752	0.048080	0.036122	0.096491	0.037143	0.023564	...	-0.001967	0.041474	-0
2024-11-07	0.021372	0.045845	0.012861	-0.007745	0.006718	-0.001081	0.010518	-0.024200	-0.002961	-0.037486	...	0.004335	-0.003323	-0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
2025-11-28	0.004684	0.002142	0.008675	0.008220	0.028769	0.003814	0.006503	0.031250	0.000783	0.021722	...	0.005270	-0.002691	0
2025-12-01	0.015241	0.015471	0.029720	0.008497	0.004409	0.002115	0.005868	-0.026568	-0.020219	0.048359	...	-0.004710	-0.003849	-0
2025-12-02	0.010915	-0.002525	0.013946	-0.000124	0.024239	0.005238	0.016813	-0.029610	-0.010033	-0.134693	...	0.003750	0.010557	-0
2025-12-03	-0.007128	0.013755	0.045322	0.012298	0.019306	0.011821	-0.009702	0.039093	0.013129	0.066881	...	-0.001646	-0.014704	0
2025-12-04	-0.012141	0.005744	-0.012864	0.005967	-0.003522	-0.003151	-0.004524	-0.013642	-0.015574	0.000066	...	-0.010647	-0.005201	0

273 rows × 200 columns

```
In [62]: prod = signal_matrix.shift(1).to_numpy() * returns.to_numpy()
         strategy_ret = pd.Series(
             prod.mean(axis=1),
             index=signal_matrix.index,
             name="strategy_ret"
         )
         strategy_ret.iloc[0] = 0.0
         strategy_ret
```

Out[62]:

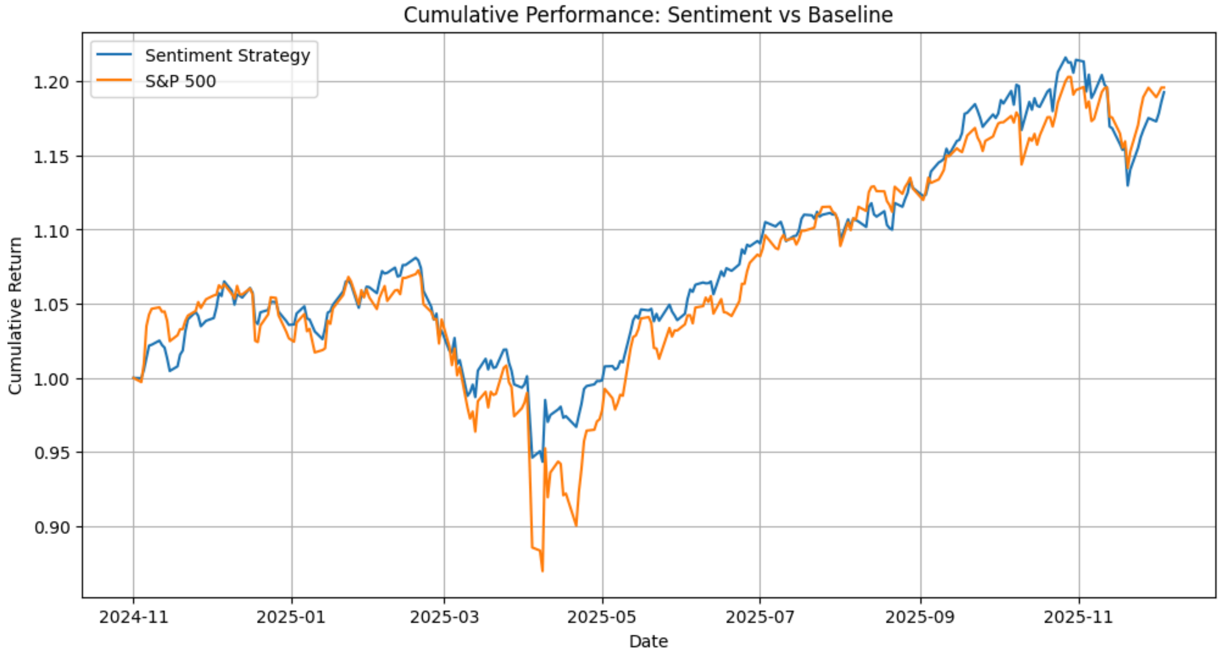
	strategy_ret
Date	
2024-11-01	0.000000
2024-11-04	-0.000193
2024-11-05	0.005561
2024-11-06	0.008078
2024-11-07	0.008145
...	...
2025-11-28	0.007029
2025-12-01	-0.001935
2025-12-02	0.004578
2025-12-03	0.006606
2025-12-04	0.005498

273 rows × 1 columns

dtype: float64

In [63]:
```
start_date = returns.index.min().strftime("%Y-%m-%d")
end_date   = returns.index.max().strftime("%Y-%m-%d")

spx = yf.download("^GSPC", start=start_date, end=end_date)
spx_ret = spx["Close"].pct_change()
spx_ret = spx_ret.reindex(returns.index)
spx_ret = spx_ret.fillna(0)
baseline_ret = spx_ret

def perf_stats(r):
    r = r.squeeze()
    cum = (1 + r).cumprod()
    ret = r.mean()
    std = r.std()
    sharpe = r.mean() / std * np.sqrt(252) if std != 0 else np.nan
    mdd = (cum / cum.cummax() - 1).min()
    return cum, sharpe, mdd, ret

strategy_cum, strategy_sharpe, strategy_mdd, strategy_ret = perf_stats(strategy_ret)
baseline_cum, baseline_sharpe, baseline_mdd, baseline_ret = perf_stats(baseline_ret)

#print("Sentiment strategy Mean Return:", strategy_ret)
print("Sentiment strategy Sharpe:", strategy_sharpe)
print("Sentiment strategy max drawdown:", strategy_mdd)
#print("Baseline Mean Return:", baseline_ret)
print("Baseline Sharpe:", baseline_sharpe)
print("Baseline max drawdown:", baseline_mdd)

plt.figure(figsize=(12, 6))
plt.plot(strategy_cum, label='Sentiment Strategy')
plt.plot(baseline_cum, label='S&P 500')
plt.legend()
plt.title('Cumulative Performance: Sentiment vs Baseline')
plt.xlabel('Date')
plt.ylabel('Cumulative Return')
plt.grid(True)
plt.show()
```

```
/tmp/ipython-input-419062374.py:4: FutureWarning: YF.download() has changed argument auto_adjust default
to True
  spx = yf.download("^GSPC", start=start_date, end=end_date)
[*********************100%***********************]  1 of 1 completed

Sentiment strategy Sharpe: 1.35734563618898
Sentiment strategy max drawdown: -0.12717640243736827
Baseline Sharpe: 0.9827801755251532
Baseline max drawdown: -0.18902206184283943
```



In [65]:

```python
import statsmodels.api as sm

fwd_returns = returns.shift(-1)
signal_matrix = signal_matrix.iloc[:-1]
fwd_returns = fwd_returns.iloc[:-1]
signal_long = signal_matrix.stack().rename("signal")
ret_long = fwd_returns.stack().rename("fwd_ret")
reg_df = pd.concat([signal_long, ret_long], axis=1).dropna()
reg_df_news = reg_df[reg_df["signal"] != 0]
X_pooled = sm.add_constant(reg_df_news["signal"])
y_pooled = reg_df_news["fwd_ret"]

pooled_res = sm.OLS(y_pooled, X_pooled).fit(cov_type="HC1")
print(pooled_res.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                fwd_ret   R-squared:                       0.000
Model:                            OLS   Adj. R-squared:                  0.000
Method:                 Least Squares   F-statistic:                       nan
Date:                Sun, 14 Dec 2025   Prob (F-statistic):                nan
Time:                        20:09:17   Log-Likelihood:                 55341.
No. Observations:               28152   AIC:                        -1.107e+05
Df Residuals:                   28151   BIC:                        -1.107e+05
Df Model:                           0
Covariance Type:                  HC1
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
signal         0.0013      0.000      6.302      0.000       0.001       0.002
==============================================================================
Omnibus:                    14718.538   Durbin-Watson:                   1.563
Prob(Omnibus):                  0.000   Jarque-Bera (JB):           922680.741
Skew:                           1.720   Prob(JB):                         0.00
Kurtosis:                      30.835   Cond. No.                         1.00
==============================================================================

Notes:
[1] Standard Errors are heteroscedasticity robust (HC1)
```